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Drone-Assisted Plant Disease Identification Using Artificial Intelligence: A Critical Review

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Abstract: Artificial intelligence has been incorporated into modern agriculture to increase agricultural output and resource efficiency. Utilizing deep learning, particularly convolutional neural networks, for recognizing and diagnosing plant diseases is tempting. In parallel, drone integration in precision agriculture has accelerated, providing new potential for crop monitoring, map creation, and targeted treatments. This study analyzes over 100 significant research articles published between 2018 and 2023, examining the interaction between drones and artificial intelligence in identifying plant diseases. We begin by explaining the value of sensor and drone technology in identifying plant diseases and carefully mapping the area. The various CNN architectures and drone-based approaches essential for precise illness detection and diagnosis are then highlighted in a thorough research review. Our research highlights how this combination can transform how plant diseases are managed completely. This study emphasizes the conceptual underpinnings of this new fusion, even if fulfilling this promise needs additional investigation. In conclusion, we expect changing research paths to direct improvements in this field and integrate AI, deep learning, drones, and plant pathology into a coherent framework with significant agricultural consequences.

Keywords: Artificial Intelligence, Deep Learning, Convolutional Neural Network (CNN), Drone, Plant Diseases, Crop Monitoring.

1. Introduction

Plant diseases are a significant factor that affects food production [1]. They can reduce the quality and decrease the yield of crops [2],[3], and in extreme situations, they can even inhibit the growth of certain crops. To prevent the spread of these diseases, farmers must implement preventative measures such as using bioactive natural products [4], pesticides [5], or fungicides [6]. Hence, staying informed of the most recent advancements in combating diseases and emerging trends in plant diseases is crucial. Therefore, proper crop management is vital to sustain a stable and sufficient food supply, as plant diseases pose a significant risk to agriculture [7]. Early identification of diseases is a valuable strategy for managing them, as it can help limit the spread and progression of the disease [8]. However, current detection techniques, such as visual inspections and laboratory tests, have several limitations [9]. Visual inspections, while helpful, can be prone to subjectivity due to the inspector's background and training. Laboratory tests, on the other hand, can be costly and time-consuming.

To improve plant disease detection methods, ongoing research into new technologies is crucial [10]. For instance, by using Artificial Intelligence (AI) in combination with drones, the detection process can be automated, increasing accuracy. Recent advancements in AI have led to more accurate plant disease detection. AI-based image analysis uses algorithms to identify signs of disease objectively, and deep learning algorithms can increase accuracy by refining disease recognition models with training data [11]. This allows for identifying multi-class diseases at once [12], particularly useful when multiple conditions affect the same plant. The detection of plant diseases is a constantly evolving topic. Therefore, it is essential to continue funding creative approaches to increase the effectiveness of disease management. Drones, also known as Unmanned Aerial Vehicles (UAV), have become crucial tools for detecting and monitoring plant diseases due to their high-resolution imaging capabilities [13]. Their ability to quickly cover large agricultural areas [14] and take images with high precision [15] while reducing time and cost expenditures [16] leads to the presentation of detailed insights into crop viability. Both agriculturalists and researchers may benefit from the data collected, which makes it easier to identify and limit disease outbreaks and evaluate the effectiveness of treatment. Drone technology is crucial in monitoring and controlling plant diseases as it seamlessly integrates with the need for accurate and rapid agricultural activities. The variability in the viewing angles at which drones capture images plays a significant role in disease detection. Certain diseases may be more conspicuous from specific angles, while others remain concealed. Therefore, it becomes essential to formulate strategies that consider this diversity while analyzing plant diseases.

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The present study delves into an exhaustive investigation encompassing the latest amalgamation of specific sides of artificial intelligence with drone technology. This fusion appears indispensable for identifying and comprehending the intricate processes inherent in the manifestations of plant diseases. The study refines its focus to encompass a comprehensive review of the myriad methodological frameworks that harness drone-generated data, extending its applicability to diverse challenges centered around imagery. At the heart of this inquiry lies a meticulous scrutiny of pivotal advancements within Convolutional Neural Network (CNN) technology, characterized by enhancements tailored to elevate CNN's performance within the intricate landscape of precise disease detection using drone imagery. The study aspires to impart nuanced insights into the contemporary milieu in which this interdisciplinary synthesis of artificial intelligence and drone technology is currently situated, a trajectory underscored by analytical rigor. A comprehensive literature study, grounded in the dependable Scopus database, was meticulously conducted to substantiate this overarching aim. This analytical pursuit is inherently propelled by the aspiration to unearth the corpus of existing literature pertinent to the fusion of drone technology and artificial intelligence in the context of plant disease identification within the agricultural sphere. A distinctive search logic was judiciously formulated and subsequently executed with methodical precision. The discernible culmination of this analytical undertaking finds eloquent articulation in Figure 1, graphically charting the temporal evolution of scholarly publications germane to this thematic nexus, spanning the years 2018 to 2023. The conspicuously ascending trend depicted in the graphical representation is a testament to the burgeoning importance and pertinence of this evolving domain of study, calling for special attention. Appearing from its meticulous analytical underpinnings, this study ascends to the status of a potentially invaluable resource, poised to guide and illuminate potential trajectories for research within this sphere. Simultaneously, it gives a comprehensive and erudite overview of this rapidly maturing interdisciplinary amalgamation.

In reference [17], the authors emphasized the challenges to crop productivity, such as weeds, pests, and diseases. The paper proposed precision agriculture with deep learning and UAVs for early plant disease monitoring to enhance agricultural production. The authors Albattah et al. [18] presented an automated framework using deep learning and lightweight drones to identify and categorize insect pests. By employing a customized CornerNet approach with DenseNet-100, the framework improves precision and recall rates for identifying target insects in the field. In Ref. [19], the authors proposed an intelligent method for crop classification that employed a series of images captured by drones and a model based on Convolutional Neural Networks (CNNs). Furthermore, the authors implemented the transfer learning technique to improve the efficiency of the proposed method. The overall detection accuracy rate was 92.93% in Ref. [20]. The authors presented a novel machine learning technique that combined drone technology and the Internet of Things (IoT) to detect and classify rice leaf diseases accurately. The proposed method incorporated a modified transfer learning approach utilizing the VGG-19 architecture. The results of the study proved the efficacy of the proposed technique with an impressive overall accuracy rate of 96.08%, as well as high levels of recall (96.17%), F1-score (96.10%), precision (96.20%), and specificity (99.21%). Albattah et al. [21] proposed a sophisticated drone-based deep-learning approach for precisely identifying and classifying crop leaf diseases. A refined version of the EfficientNetV2-B4 architecture was introduced as the central element of the proposed method. The PlantVillage dataset was utilized as the primary source of experimental data. The obtained results were 99.63% of average precision, a recall of 99.93%, and an accuracy of 99.99%.

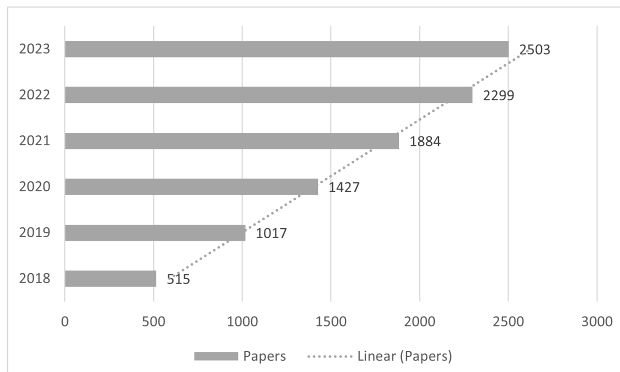

Figure 1. Number of articles by year.

Additionally, Tetila et al. [22] created a novel approach for diagnosing afflictions impacting soybean leaves, utilizing images obtained through unmanned aerial vehicles. They employed open-source implementations of convolutional neural networks, including Inception-v3, VGG-19, ResNet-50, and Xception. The corpus of data utilized in this study consisted of 300 aerial images. The Inception-v3 FT, 75% model, exhibited the highest level of accuracy at 99.04%, followed by ResNet-50, VGG-19 (99.02%), and Xception (98.56%). With F1 scores of 82% for the training dataset and 84% for the test dataset, the authors Lizarazo et al. [23] successfully classified the severity of Verticillium wilt in potatoes from multispectral drone images using machine learning, employing gradient reinforcement machines (GBM). This improves disease identification for this pervasive crop issue. In Ref. [24], the authors compared three CNN models, specifically: 1) RetinaNet, 2) faster R-CNN, and 3) SSD, for the expeditious and accurate detection of objects from uncrewed aerial vehicles. The corpus of data employed in the experiment was the Stanford Drone Dataset (SDD). The results indicated that RetinaNet outperformed the other models in speed and precision in object detection from drones, with an accuracy rate of 86.58%. An improved YOLO-v4 model was offered by the paper's Chen et al.

[25] for the quick and accurate identification and tally of oleanders in aerial images. The improved YOLO-v4 model attained a high detection accuracy of 97.78% and a recall rate of 98.16% after training. The YOLO-v4 optimized model outperformed other models, including YOLO-v4, YOLO-v4 small, YOLO-v3, and Faster R-CNN, regarding recall rate (up to 97.45%) while retaining excellent accuracy. Meanwhile, the study [26] discussed its early and precise identification utilizing RGB aerial photos captured by UAVs. The study's main objectives are to compare several YOLOv5 model architectures and assess their effectiveness in identifying and categorizing verticillium fungus in olive trees and determining their health state.

An unmanned aerial vehicle (UAV) with a Rededge-MX multispectral camera was used by the authors Wenjing et al. [27] to conduct an analysis of wheat scab in a cultivated wheat field, utilizing three algorithms: Partial Least Squares Regression (PLSR), Support Vector Machine Regression (SVR), and Back Propagation Neural Network (BPNN). The study's results demonstrated that, in the multi-source data fusion model, the SVR algorithm exhibited superior performance in terms of efficacy compared to the other algorithms in detecting and monitoring wheat scabs. The authors, Daniel et al. [28], presented approaches for classifying plant seedlings using a dataset containing 4,275 images. The experiment compared the performance of two traditional algorithms, Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN), as well as a Convolutional Neural Network (CNN). The study results indicated that techniques based on CNNs could effectively automate the classification of plant seedlings in agriculture. The CNN achieved a training accuracy of 98.9% and a validation accuracy of 80.21%. Researchers have recently presented several CNN-based approaches for detecting plant leaf diseases. Notably, most of these articles were published after 2018, demonstrating the recent and cutting-edge nature of this approach to agriculture. According to reference [29], weed detection in Chinese cabbage crops was trained using photos from UAVs. CNN achieved a substantially higher overall accuracy of 92.41% compared to the Random Forest (RF) algorithm, which differentiated crops and weeds with an overall accuracy of 86.18%. Stefania et al. [30] developed a feature extraction approach based on AlexNet, VggNet, and ResNet deep learning for plant species identification and plant leaf disease classification. Pre-trained CNNs were employed in this study for feature extraction and were combined with SVMs for sort. The results revealed that the AlexNet model performed exceptionally well, with an accuracy of 99.86% on the dataset analyzed. In Ref. [31], the authors suggested a deep convolutional neural networks-based methodology for detecting illnesses on apple leaves. The AlexNet architecture was employed in this study, and a dataset of 13,689 images was utilized to train the model. The results of the proposed deep CNN model revealed an overall accuracy of 97.62%. Additionally, in [32], an innovative approach using DDMA-YOLO and drone remote sensing was introduced for the accurate detection and monitoring of tea leaf blight (TLB), significantly surpassing conventional methods with a 3.8% increase in average accuracy (AP@0.5) and a 6.5% improvement in recall when compared to the baseline network. In the document [33], upgraded GoogleNet and Cifar10 models, based on deep learning techniques, were proposed for the autonomous detection and diagnosis of maize leaf diseases. The empirical evaluation revealed that both models exhibited high levels of accuracy, with an average identification rate of 98.9% for the GoogLeNet model and 98.8% for the Cifar10 model.

The remainder of this paper is structured as follows: Section 2 describes the methods employed in this research and presents the drone-assisted detection of plant disease and CNN architecture. Section 3 discusses the CNN applications in plant disease detection, the different CNN models, and the drones used by the authors. Section 4 concludes the paper and presents future directions.

2. Research Method

A. *Research and reading*

This study aimed to comprehensively review the recent literature on the application of artificial intelligence (AI) and drones in the agricultural domain, focusing on identifying and detecting plant diseases. The methodology adopted for this study comprised two main stages: the first stage involved collecting and compiling a sample of 80 relevant research papers that addressed the intersection of deep learning and drone technology concerning plant disease detection. Figure 2 illustrates the method employed in researching and selecting relevant scientific articles. The second stage entailed a thorough analysis and review of the collected literature. In the initial phase of our research, we reviewed a literature search utilizing the Scopus scientific database for papers and articles published between 2018 and 2023. Our research method employed a keyword-based approach with several keywords, such as "plant disease," "drone," "neural network," "CNN," and "deep learning," to cite only a few. Articles that mentioned CNN but did not mention the plant disease were excluded from further analysis. In the second phase, we systematically analyzed the articles selected in the first phase, focusing on addressing the research questions of this study. Such as: what were the methods and dataset utilized in the study? What issues were encountered during the research? What outcomes were achieved? How were the model efficiencies compared? What were the limitations of the study?

A methodical approach was employed, comprising the stages of research, literature review, analysis, and synthesis. A systematic review of the literature was conducted with a focus on selecting relevant data for the study. Examining the methods and performance of artificial intelligence, particularly Convolutional Neural Networks, is a crucial aspect of this current research study. The selection of drones, the process of image collection, and the transmission of information play essential roles in this cutting-edge technology. Therefore, we have conducted a thorough review and

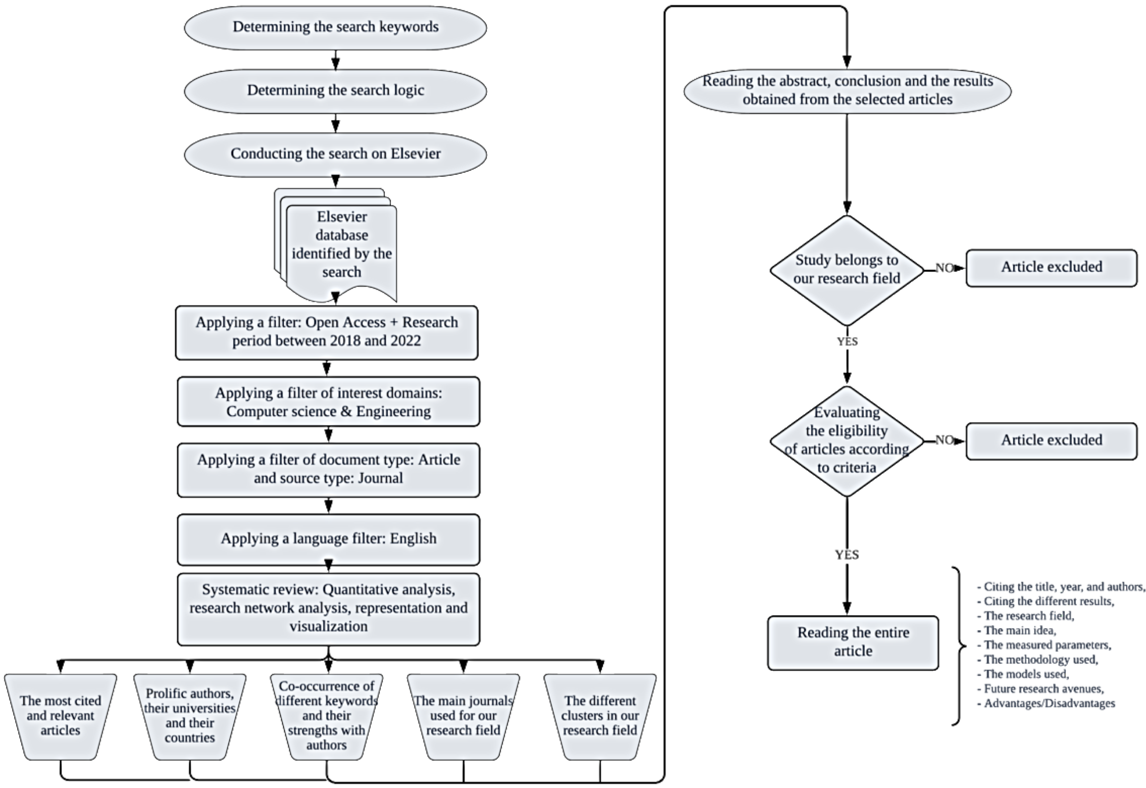

Figure 2. The process of selecting scientific articles.

analysis of relevant studies and compared the performance of CNNs with other current technologies. Additionally, we have summarized the most salient advantages and disadvantages of CNNs and examined and discussed the most significant issues and limitations identified by previous research.

B. Drone-assisted detection of plant disease

1) The growing use of Drones in Agriculture

Unmanned aerial vehicles (UAVs), commonly referred to as "DRONE" (Dynamic Remotely Operated Navigation Equipment [34]), are employed more frequently across a variety of industries, including agriculture. In 2022, agriculture is anticipated to be the second-largest consumer of drones, according to a Goldman Sachs analysis. They may be employed for crop monitoring, mapping, and spraying, increasing efficiency and lowering costs. Additionally, they can aid in precision agriculture by focusing on sectors that require care and conserving resources.

2) Types of Drones utilized in Agriculture

There are two main types of drones: fixed-wing airplanes [35] and rotary-motor helicopters (or quadcopters) [36]. Fixed-wing aircraft have stabilizing tail sections and wings that create lift. They are employed for long-distance travel and high-altitude mapping and are more potent than rotary-engine helicopters. Quadcopters, commonly called "rotary motor helicopters," are multi-rotor drones. They are utilized for operations such as aerial photography and search and rescue missions and are typically smaller.

3) Drone-assisted crop management: The future of farming

Drones have many applications in agriculture [37], such as monitoring and mapping crops or fields [38], providing farmers with detailed information about crop growth and health [39]. For precise spraying [40], UAVs can be equipped with sprayers to apply pesticides and fertilizers to crops [41]. Drones can monitor irrigation systems for irrigation management to optimize water use and increase crop yields. Drones can also collect soil samples [37] and measure crop growth, which can be used to make data-driven decisions about planting, harvesting, and crop management. Figure 3 depicts unmanned aerial vehicles (UAVs) or drones with various sensors to assess crop conditions. To increase crop quality and minimize field damage, this article will highlight the use of drones in agriculture and showcase the newest and best-performing ones available for monitoring and watching crops. Table 1 lists the various drones utilized by authors. Therefore, image acquisition is essential in creating machine learning models. This step prepares and checks labeled image data [42]. Since agricultural fields have large areas, unmanned aerial vehicles, or drones, must be used to take pictures. These images are then used to train and test machine learning models [43].

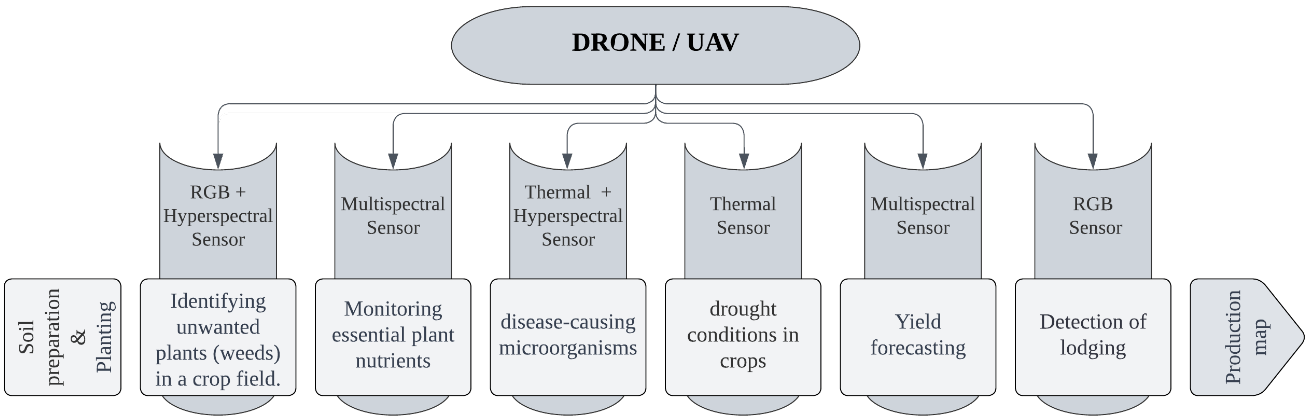

Figure 3. Schematic of methods for information data on a plant's development during its growing season.

Drones equipped with RGB, hyperspectral, multispectral, or thermal sensors are helpful for tasks such as detecting plant diseases, mapping irrigation and weed areas. These drones can also assess crop quality through near-infrared or visible light imaging. Their ability to capture precise ground images using RGB sensors makes them ideal for evaluating plowing techniques at night. Overall, drones are projected to play a crucial role in enhancing the productivity of agriculture and will become a vital tool for farmers shortly.

In the context of modern agriculture, the accurate and timely detection of plant diseases is of paramount importance. Integrating drones with AI-based image analysis technologies into disease monitoring practices presents a groundbreaking solution to this imperative need. This advancement enables early disease outbreak identification and containment, revolutionizing how we safeguard our crops. Geographical constraints do not confine drones equipped with AI; they can hover above fields, offering an unbiased, bird's-eye view of the entire landscape. This unique vantage point allows them to spot infected plants swiftly and without prejudice. Moreover, applying deep learning algorithms to the images captured by these drones can significantly enhance the precision of disease identification. This means multiple diseases can be diagnosed simultaneously, saving time and resources compared to traditional laboratory testing methods. One of the most compelling arguments for integrating drones and AI in disease monitoring lies in its potential to establish an effective and impartial process for identifying and diagnosing plant diseases. This technology democratizes disease detection access, benefiting small and large farmers. It levels the playing field, ensuring that all farmers, regardless of their resources, have access to advanced tools for disease prevention. Moreover, the high-resolution images of crop fields obtained by unmanned aerial vehicles (UAVs) go beyond disease detection. They enable us to identify crops and weeds accurately, even during their early growth phases. This capability empowers precision agricultural techniques that efficiently manage weed issues while reducing costs and minimizing environmental harm. By identifying weeds early in the growing season, farmers can make targeted interventions, reducing the need for excessive herbicide use and promoting sustainable farming practices. Furthermore, drone photography provides farmers with comprehensive insights into their fields. It is an invaluable tool for monitoring crop development, pinpointing disease or stress zones, and making informed decisions regarding crop management. This, in turn, enhances productivity and resource utilization while minimizing waste.

However, as the reviewer aptly pointed out, the proliferation of drones in agriculture raises ethical and environmental questions. The paper acknowledges the pressing need to delve into these aspects further to ensure that the benefits of drone adoption in disease monitoring are balanced with responsible stewardship of both the environment and societal ethics. Ethical considerations may revolve around privacy, data security, and equitable access to technology, while environmental concerns may pertain to drone fleets' energy consumption and ecological impact. Exploring these dimensions is essential to ensure drones' holistic and sustainable integration into the agricultural landscape.

Chew et al. [57] developed a deep learning algorithm for identifying various crop types, such as bananas, legumes, corn, and others, through an RGB camera mounted on a drone. The results demonstrated the effectiveness of the proposed model in detecting crops with a high degree of accuracy. A new method for classifying agricultural progress in rice-wheat rotation fields using RGB unmanned aerial vehicle (UAV) images has been proposed by researchers Song et al. [58], using a Regional Mean Model (RA) model. Authors Zhu et al. [27] used a UAV equipped with multispectral cameras to classify and apply wheat scab using algorithms such as random forest and support vector machine. In Ref. [59], the authors used RGB and

TABLE I. Summary of the various drones used by authors.

Drone model	Sensor type	Application	Method	Reference
DJI Matrice 600 Pro	Pika-L 2.4 hyperspectral sensor	Morphophysiological traits in sugarcane	MAPE: SPAD–NDVI-LAI	Poudyal et al., 2023 [44]
DJI Phantom 4	RGB Camera	Automatic weed classification	Faster RCNN	Ajayi and Ashi, 2023 [45]
DJI Phantom 4 Pro	RGB	Spinach seed yield	Mask R-CNN	Ariza-Sentís et al., 2023 [46]
DJI Mavic2 Pro	RGB	Rice Bakanae Disease	YOLOv3-RestNETV2 101	Kim et al., 2023 [47]
DJI Mavic 2 Pro	RGB	Pommier disease classification	GAN	Prasad et al., 2022 [48]
DJI Tello 2	RGB	Recognizing objects in the form of fruits	CNN YOLOv5	Rahmania et al.,2022 [49]
Solo 3DR	Multispectral Sequoia de Parrot	Detection and location of drought-stressed areas of the potato crop	CNN Retina-UNet-Ag	Butte et al.,2022 [50]
DJI Matrix 600 Pro	Multispectral Rededge-MX	Monitor Wheat Scab	PLSR – SVR - BPNN	Zhu et al., 2022b [27]
DJI Phantom 3 Professional	RGB	Automatic recognition of soybean leaf diseases	SLIC	Tetila et al., 2020 [22]
DJI Matrice 600 pro	Hyperspectral Pika L	Detection of target spot and bacterial spot diseases in tomato	MLP - STDA	Abdulridha et al., 2020 [51]
DJI M200 series	Hyperspectral - Nano-Hyperspec LiDAR – LiAir 200	Detection of PSB Stress	RF	Panday et al., 2020 [52]
DJI Phantom 4	RGB Orthomosaic	Fertilizer application level and yield of rice and wheat crops	NDVI	Guan et al., 2019 [53]
DJI S1000	Hyperspectral Firefly UHD 185	Automatic detection of yellow rust in winter wheat fields	DCNN	Zhang et al., 2019 [54]
DJI Matrice 100	Multispectral ADC-Lite	Detection of spider mite-infested cotton	CNN - SVM	Huang et al., 2018 [55]
Modified Mikrokopter	TAU II 320 Multispectral – TetraCam ADC Snap RGB - Canon EOS M 10	Precision Viticulture	NDVI	Matese and di Gennaro, 2018 [56]

hyperspectral imagery for potato yield prediction. A drone-based LiDAR technology was used by Getzin et al. [60] to identify gaps in the vegetation of a forest meadow. In their paper [61], Crusiol et al. used thermal imaging from a drone to monitor the water status of soybean plants. Mao et al. [62] explored the impact of frost damage on tea plant development due to climate change and the limitations of labor-intensive visual evaluation methods. It recommends employing a powerful CNN-GRU model with multimodal remote sensing data (MS, TIR, RGB) acquired by a DJ M200 V2 UAV for precise and objective assessment of cold damage in tea plants. In addition, in [63], the DJI Matrice 210 drone was utilized to estimate the yield of Vicia faba L. using machine learning methods like SVM, RR, PLS, KNN, and RF. The study [64] tackled the issue of off-target dicamba damage in soybean crops using DJI Phantom 4 Pro drone imagery combined with the DenseNet121 deep learning model. Meanwhile, Kierdorf et al. [65] employed a DJI Matrice 600 hexacopter to analyse cauliflower flower growth, and Lizaraz et al. [23] utilized a Tarot FY680 hexacopter drone to identify and categorize potato Verticillium wilt illness.

One of the most pressing challenges in deploying drones for plant disease identification lies in the diversity of the data they collect. Drones have become an invaluable tool in modern agriculture, allowing for efficient and large-scale monitoring of crops. However, the images captured by these drones can vary significantly in several key aspects, including resolution, viewing angle, quality, and format. This diversity can pose substantial hurdles in harnessing artificial intelligence's (AI) power to identify plant diseases accurately and reliably. The variation in resolution among collected images can result from the drone's altitude, camera specifications, and environmental conditions during flight. Lower-resolution images might lack the detail required for precise disease diagnosis, while higher-resolution images may consume substantial storage and computational resources. Balancing these factors becomes crucial for practical implementation.

C. Crop health monitoring using Deep Learning techniques

1) Convolutional Neural Networks (CNN)

Convolutional Neural Networks have become one of the most representative neural networks in deep learning [66], inspired by living creatures' natural visual perception mechanisms [67]. They are widely used in pattern recognition for image processing [68]. Multiple-layer neural network architectures called CNNs continually extract abstract representations of the input data by building on the layers behind them. The basic architecture of a typical CNN is illustrated in Figure 4. Image analysis for the automated diagnosis of plant diseases has significantly advanced according to deep learning methods, notably CNNs. This might result in the creation of mechanical imaging systems in agriculture for jobs like weed detection and the diagnosis of plant diseases. These tools can help farmers embrace excellent agricultural practices and more productive farming methods, increasing food security. Using deep learning in agriculture can significantly enhance the effectiveness and efficiency of farming methods while promoting environmentally sustainable practices. The diagnosis and identi-

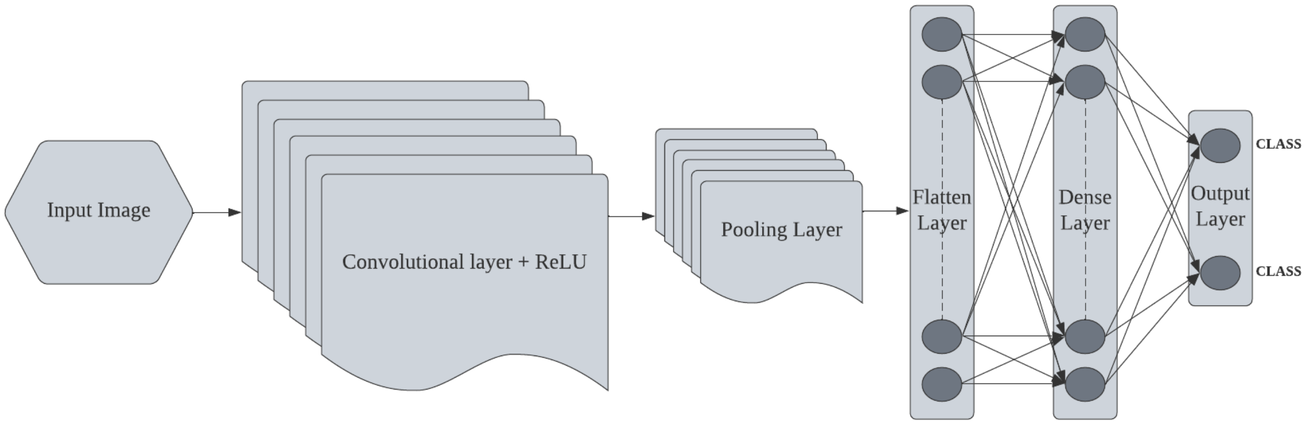

Figure 4. The architecture of a typical CNN.

fication of plant diseases have been commonly achieved through the utilization of images in the past. This section reviews the pre-trained and customized convolutional neural network (CNN) models that the authors have developed. An examination of various studies from the past indicates that most researchers utilized transfer learning to meet their objectives rather than constructing a new CNN model from scratch. This approach allowed for the efficient and expedient completion of research projects and attaining goals in the past. The CNN model has been subsequently applied in various transfer learning research endeavors.

2) Pre-trained convolutional neural networks

A standard method for classifying images is to employ pre-trained CNNs, often used in image classification models. The models of pre-trained CNNs may need more layers to categorize images as their complexity and variety rise correctly. The model's training may become more challenging and time-consuming as a result. Despite this difficulty, pre-trained CNNs continue to be beneficial for classifying images because of their capacity to learn from and extract beneficial characteristics from massive datasets. Knowing how pre-trained CNNs perform in picture classification requires understanding their fundamental principles, such as transfer learning and feature extraction. There are many pre-trained models: AlexNet [69], VGG-16 [70], InceptionResNetV2 [71], DenseNet [72], ResNet [73], and YOLO [74]. Figure 5 illustrates the chronology of the most dominant models of pre-trained CNNs.

Quality issues, such as those arising from weather conditions, lighting, and camera stability during flight, can introduce variability in image quality, potentially degrading the accuracy of disease identification algorithms. To address these challenges, it becomes imperative to employ robust preprocessing techniques. These techniques enhance image quality and reduce noise, ensuring that AI models receive clean and consistent data. Furthermore, the CNN model is a potent tool, particularly in image classification. Its versatility and adaptability shine through transfer learning, which allows it to excel in various roles. The model can be pre-trained on extensive databases and applied to various research endeavors by customizing layers or adding new ones to align with specific tasks. This adaptability renders CNNs invaluable for diverse research applications, making them a cornerstone.

Sharma et al. [75] proposed using convolutional neural network (CNN) models, which were trained on segmented image data, as a viable solution for the task. To evaluate the effectiveness of this approach, the performance of the S-CNN model, which was trained on segmented images, was compared to that of the F-CNN model, which was introduced on complete images. The results showed that the S-CNN model achieved a high accuracy of 98.6 %. The article [76] presented a novel CNN-based approach for detecting rice diseases. The proposed model was trained using 20,639 images from the Plant Village dataset, consisting of infected and healthy leaves of potatoes, tomatoes, and bell pepper. The results of our experiments indicated that the proposed CNN-based model achieved an accuracy of 98.90 % with no evidence of overfitting. Hassan et al. [77] employed depth-separable convolution to replace standard convolution in the CNN models, using the InceptionV3, Inception-ResNetV2, MobileNetV2, and EfficientNetB0 architectures. The disease classification accuracy rates attained by the implemented models were 98.42 %, 99.11 %, 97.02 %, and 99.56 %, respectively.

Elfatimi et al. [78] proposed a CNN-based system for classifying bean leaf diseases. The MobileNet CNN model demonstrated high accuracy, with an average identification rate of 98.49 %. In addition, the authors in [79] proposed a 14-layer deep convolutional neural network (14-DCNN) model for detecting 42 leaf diseases in 16 different plant species using a dataset of 20,639 images. On the training dataset, the model achieved high accuracy (99.96 %), recall (99.7966 %), and F1 score (99.7968 %). In the paper [80], Memon et al. proposed a deep meta-learning model for accurate identification of several cotton leaf diseases with

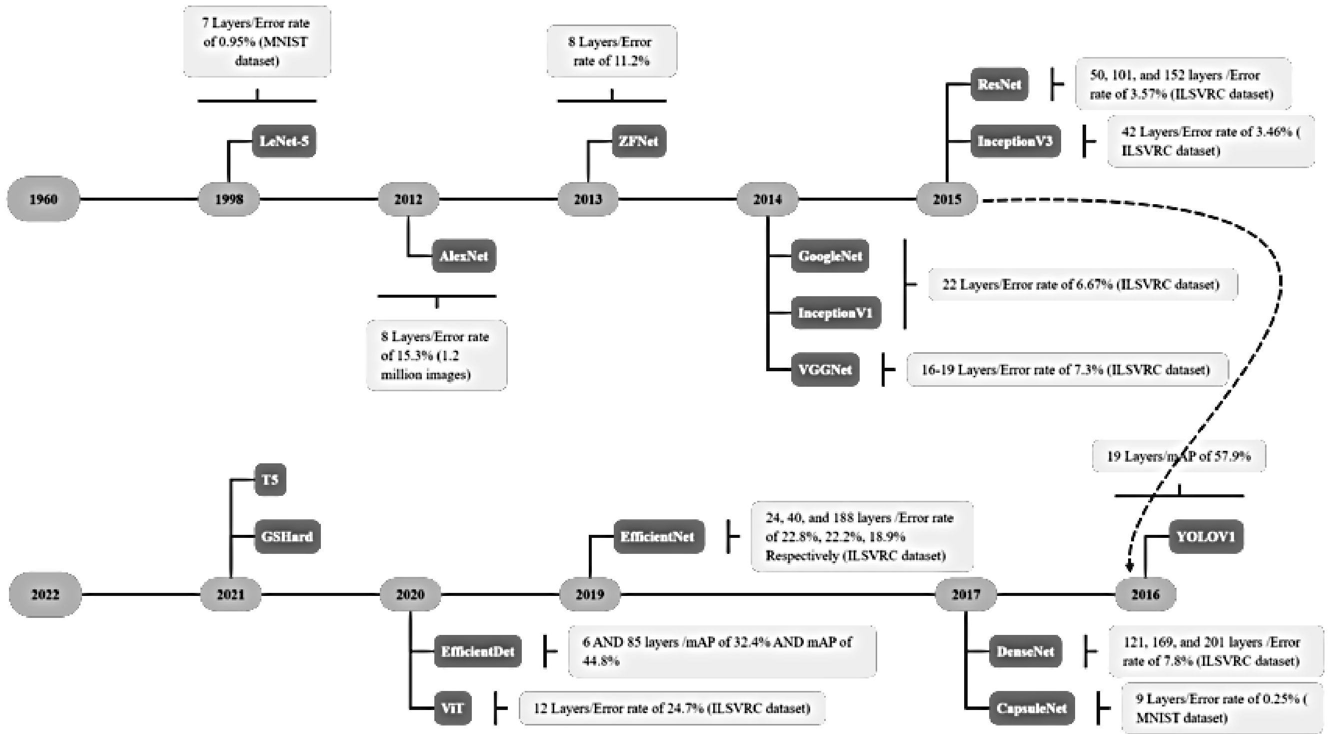

Figure 5. Chronology of the most dominant models of pre-trained CNNs.

98.53 % accuracy, trained on a dataset of 2385 healthy and diseased cotton leaf images using pre-trained models VGG16, ResNet50, Inception V3, and a deep meta-model. About [81], the authors introduced an Internet of Things (IoT) centered system for identifying plant diseases. They employed semantic segmentation techniques, encompassing FCN-8s, CED-Net, SegNet, DeepLabv3, and U-Net with CRF.The SegNet-CRFs system performed well compared to the other methods, using a CNN-based model on a dataset of 588 images. A method for classifying two types of weeds in rice fields using semantic segmentation was presented in a document [82] by Kamath et al. Three models—SegNet, PSPNet, and UNet—were tested on 2695 images. The model PSPNet achieved the highest accuracy at over 90 % for identifying both classes and plant shapes. Jiang et al. used the VGG16 model to identify diseases in rice and wheat plants [83]. The experiment's outcomes were compared to those of other cutting-edge models. The VGG16 model's overall accuracy for rice and wheat plants was 97.22 % and 98.75 %, respectively. Furthermore, their paper [84] suggested a CNN-based model for classifying wheat varieties throughout various growing seasons. Based on ResNet and SENet, the CMPNet in the study ranked wheat at the seed stage with great accuracy reaching 99.51 %.

3. Results And Discussion

During this investigation, a comprehensive and exhaustive review was undertaken to delve into the symbiotic integration of artificial intelligence and drone technology within the agricultural domain. This inquiry pivoted toward a specific focus on employing convolutional neural network (CNN) methodologies for identifying crop diseases. The overarching objective spanning the temporal ambit of 2018 to 2023 entailed presenting a holistic portrayal of the contemporaneous state-of-the-art landscape concerning CNN-based plant leaf disease detection. Central to this pursuit was a meticulous dissection, encompassing an in-depth analysis of diverse CNN architectures, frameworks, and the encompassing application datasets. Within this analytical vista, nuanced examinations unveiled various typologies of drones that have found recent applicability within the agricultural sphere, accompanied by an exploration of the array of sensors deployed for data collection. The amplitude of this analysis extended to encompass a thorough evaluation of dataset magnitudes and the consequential experimental outcomes of various models harnessed for identifying plant leaf diseases. Notably, the recent chronology has witnessed a marked escalation in research endeavors revolving around integrating CNN methodologies for identifying plant leaf diseases. Table 2 encapsulates all pertinent data, encompassing authors' utilization frequency of diverse models, as a testament to fostering informed comparative analyses and facilitating methodological selection for researchers. Remarkably, the column devoted to the authors' frequency of model deployment serves as an emblematic indicator of the varying degrees of utilization, thereby offering a compass to delineate the extensiveness of their application. In crystallizing the synthesis of these multifarious analyses,

TABLE II. Summary of the different UAVs and the deep learning models used by authors.

Reference	Year	Dataset Source	Application	Drone/UAV	Method	Results	Frequency
[85]	2023	Personalized	Artichoke	DJI Phantom 4 Pro	YOLOv5	92.00%	*****
[86]	2023	Personalized	Rubber Tree	DJI Phantom 4 multispectral	Boruta–SHAP - SVM	98.16%	*****
[87]	2023	Personalized	Soybean	DJI P4 Multispectral	AlexNet	99.07%	*****
[88]	2023	Personalized	Wheat	DJI 4 pro	LSTM-PSPNet	95.20%	*****
[89]	2022	Personalized	Pine	DJI Yu Mavic2 DJIFC200 camera DJI M600	YOLOv4	94.56%	*****
[90]	2022	dos Santos et al. 2017	Weed	-	CNN LVQ	99.44%	*****
[21]	2022	PlantVillage	Multiclass plant	-	EfficientNetV2	99.63%	*****
[91]	2022	Personalized	corn	DJI Phantom 4	ResNet18	97.00%	*****
[92]	2022	Personalized	Sugarcane	DJI P4 multispectral	XGB, RF, and KNN	94.00%	*****
[93]	2021	Personalized	Olive	DJI-Phantom 4	Mask R-CNN	94.51%	*****
[94]	2021	Personalized	Maize	DJI Phantom 3	TD-CNN R-CNN	95.90% 97.90%	***** *****
[95]	2020	Personalized	Soybean	DJI S1000+	DNN	84.50%	*****
[96]	2020	Personalized	Crop Row	SenseFly eBee	CRowNet	93.58%	*****
[97]	2020	Personalized	Vine	Scanopy Quadcopter	SegNet	92.00%	*****
[98]	2020	Personalized	Banana	DJI Phantom 4 Pro	VGG-16	85.00%	*****
[99]	2019	Personalized	Citrus trees	SenseFly eBee	CNN	96.24%	*****
[54]	2019	Personalized	Wheat	DJI S1000	DCNN	85.00%	*****
[100]	2019	Personalized	Opium poppy	DJI	YOLOV3	96.37%	*****
[101]	2019	Personalized	Wheat	DJI Phantom 4	CNN	91.43%	*****
[102]	2018	Personalized	Maize	DJI S1000	ANN	94.40%	*****
[103]	2017	Personalized	Soybean	DJI Phantom 3	ConvNets	99.50%	*****

the investigation's core ethos emerges as an illumination of the burgeoning landscape wherein the converging realms of artificial intelligence, drone technology, and plant disease identification coalesce. This not only shapes the contours of contemporary research but also stands as a cardinal embodiment of the multifaceted potential and critical nuances that this fusion embodies.

This work also generates significant contributions that extend beyond its immediate temporal scope and considerably positively impact future developments in improved illness detection systems. For aspiring researchers and seasoned practitioners in the complex field of precision agriculture, this research gives a viewpoint that has tangible value by providing thorough insights into the delicate interaction of artificial intelligence and drone technology. Notably, these contributions reinforce innovative ideas and are innately based on critical thought, as shown by the critical evaluation that forms the foundation of the whole research. This critical viewpoint is a clear guide for future research, inspiring a study into the technological nuances and methodological depths that call for reinforcement and recalibration. Furthermore, this study's effects extend beyond the borders of research, echoing ongoing projects driven by the need to boost crop yields and strengthen food security in the agricultural environment. The blending of artificial intelligence with drone technology to detect plant diseases exemplifies how advanced technological convergence offers a fruitful ground for creativity. However, this innovation strikes a balance when coupled with a thoughtful critique that sparks a lively interaction between development and meticulous analysis. The scope of the study goes beyond merely disseminating results; it encompasses a ground-breaking engagement with advancing scientific and agricultural paradigms. It underlines how advancement rooted in careful research and self-reflection may change academic discourses and the more general parameters of farm subsistence and resilience.

This technological advancement can radically shift agricultural monitoring by providing farmers with precious information to maximize crop development and output.

Drones have the potential to bring improved crop monitoring precision while reducing operational costs through productive interaction with neural networks. This combination gives farmers quick access to the information they need to make timely and essential crop decisions. The multifaceted effectiveness of this combination extends to the preventive sphere, where it facilitates the early diagnosis of illnesses and infections, preventing their spread and the ensuing harm to crops. Large-scale agricultural operations benefit significantly from the seamless integration of drones and neural networks because of their versatility, which allows for thorough coverage of expansive terrains. Our study's findings support the suggested method's pronounced accuracy in detecting illnesses early in various plant species. This confirms the method's significance as a revolutionary tool in the armory of precision agriculture and emphasizes the method's effectiveness and potential for widespread adoption.

Our comprehensive review highlights the revolutionary potential of using drones and deep learning methods to detect plant diseases. This convergence promises increased efficacy and accuracy in disease identification and can potentially change the entire landscape of agriculture. Our evaluation also reveals significant gaps in existing research, highlighting the critical need for more investigation to strengthen the groundwork for this new study area. This further research demands a purposeful effort to increase the generalizability of results through a broader range of situations and a larger dataset for reliable model validation. Additionally, the importance of the temporal component rises, necessitating real-time drone-based crop monitoring to provide the procedure with dynamic adaptability. To ensure effective disease management, it is essential to thoroughly assess the algorithms' ability to detect a broad spectrum of illnesses. The variability in image collection formats poses challenges in creating standardized datasets for AI model training. This format diversity highlights the need for effective data normalization techniques to prevent biases and enhance model generalization. Developing advanced image preprocessing methods tailored to drone-collected data is critical. These techniques should focus on standardizing image resolution, improving image quality, and addressing variations in viewing angles. Furthermore, adapting AI models to handle the inherent variability in drone-captured images is paramount. Transfer learning, involving pre-training models on diverse datasets and fine-tuning them with drone-collected data, can be a valuable approach to address these challenges comprehensively.

Parallel to this, a comprehensive strategy necessitates addressing practical problems, such as operating costs, implementation difficulties, data security, user-friendliness, and privacy issues. The route of critical dialogue, thorough comparison, and nuanced interpretation of findings warrant further significance within our study in light of the reviewer's significant point. This would incorporate the complex factors that affect the trajectory of developments in this field and increase the academic quality of the study and the robustness of its findings.

4. Conclusions and Future Work

The convergence of artificial intelligence and drone technology has swiftly emerged as a pivotal locus of inquiry in recent years, precipitating a rapid expansion of scholarly endeavors within plant disease detection. Drones have become essential for maintaining agricultural health because of their high-resolution photography capabilities and Convolutional Neural Networks (CNNs) analytic capability. The convergence of these technologies has created a powerful link that can detect early warning indications of plant diseases, radically transforming how disease monitoring is conducted in agriculture. The variety of their data poses serious challenges. A multi-faceted strategy is needed to overcome these obstacles, including creating sophisticated pre-processing methods and modifying artificial intelligence models. The research trajectory in this area has significantly advanced because of the rapidly developing improvements in CNN architectures and training approaches. This development has symbolized improved illness detection precision and quicker processing times. The effects of this advancement could have a far-reaching cascading impact, reducing the spread of diseases, increasing agricultural output, and improving management effectiveness. As a result, the use of CNNs and drones to identify plant diseases is expected to increase in both acceptance and usefulness. But significant obstacles must be overcome to improve this integrated system. These difficulties show themselves while processing varied datasets and coping with erratic changes in lighting and weather. Despite these enormous obstacles, a crucial turning point in plant disease detection and diagnosis is approaching. The development of robust CNN architectures, the automation of detection procedures, and the creation of insightful decision-making models are all crucial to these prospects for the future. The combination of drone technology and artificial intelligence for plant disease monitoring is set to unleash a range of transformational possibilities. This development is based not only on a keen analysis of the problems at hand but also on a vigorous search for novel solutions that radically alter the outlines of agricultural health management.

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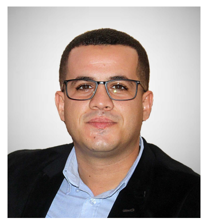

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