A Survey on Deep Learning Approaches for Crop Disease Analysis in Precision Agriculture

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Abstract

Precision agriculture has emerged as a transformative paradigm in modern farming, leveraging advanced technologies to optimize crop management. This paper presents a comprehensive survey of deep learning approaches for crop disease analysis in precision agriculture. The investigation focuses on four key aspects: leaf disease detection through deep learning techniques, leaf shape-based disease analysis, crop weed detection utilizing deep learning methods, and crop damage detection using aerial images. The survey encompasses a review of recent advancements, methodologies, challenges, and future prospects in each of these domains. By exploring the intersection of deep learning and precision agriculture, this paper aims to provide a holistic understanding of the current state-of-the-art and inspire further research initiatives to enhance crop health monitoring and management.

Keywords: Precision Agriculture, Deep Learning, Crop Disease Analysis, Leaf Disease Detection, Crop Weed Detection, Aerial Image Analysis

1. Introduction

Agriculture is facing more difficulties as a result of the increased need for food production on a worldwide scale to feed a world population that is expanding. The presence of crop diseases poses a major obstacle to attaining maximum agricultural production, resulting in considerable financial damages and endangering global food security [1]. The reliance on physical labor and visual examination in traditional techniques of disease identification and management in crops has been shown to be inadequate, resulting in mistakes, delayed action, and poor disease control. Therefore, there is an urgent want for sophisticated technical remedies to efficiently address crop diseases within the context of precision agricultural systems. The use of state-of-the-art technology in precision agriculture has transformed conventional farming methods to enhance crop production efficiency [2].

The challenges faced by crop disease analysis in precision agriculture have a significant influence on agricultural productivity and food security. A key obstacle is the fast and erratic dissemination of illnesses among crops, which is worsened by several environmental variables including temperature change, humidity, and soil conditions [3]. The labor-intensive and time-consuming nature of manual inspection techniques presents a substantial challenge in promptly and accurately identifying illnesses in large agricultural areas. This results in delayed action and degraded crop health. Moreover, the wide range and fluctuation of crop diseases make it more difficult to accurately diagnose and distinguish between distinct pathologies, hindering the implementation of efficient disease control techniques [4]. Furthermore, the absence of scalable and accurate disease detection tools in conventional agricultural operations obstructs the adoption of preventative remedies, leading to significant economic losses and reduced agricultural productivity. Therefore, there is a critical need for inventive technical solutions that provide automated, precise, and scalable methods for analyzing crop diseases within precision agricultural frameworks [5]. These solutions are necessary to tackle these urgent difficulties and guarantee sustainable food supply.

Deep learning algorithms have the ability to significantly solve the complexity of analyzing crop diseases in precision agriculture systems. Neural networks, namely convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are very effective in analyzing large and detailed agricultural datasets [6]. They are capable of identifying subtle patterns and changes that are suggestive of crop diseases. CNNs excel in image analysis, enabling accurate disease diagnosis via the extraction of features from plant photos. They can detect minute differences in leaf textures, forms, and discolorations that may indicate the presence of illnesses. Conversely, Recurrent Neural Networks (RNNs) have exceptional performance in evaluating data that changes over time, allowing for the prediction of disease outbreaks by leveraging past patterns and environmental influences. Furthermore, the flexibility of deep learning models enables ongoing learning and enhancement, leading to increased precision and scalability as time progresses. The ability of deep learning algorithms to acquire knowledge from large datasets and apply it effectively to new data makes them highly promising tools for precise and reliable analysis of crop diseases in precision agriculture. These algorithms assist in timely detection of diseases, proactive management, and ultimately, improved agricultural productivity.

The latest developments in Deep Learning Approaches for Crop Disease Analysis in precision agriculture have concentrated on using sophisticated methods like transfer learning, generative adversarial networks (GANs), and ensemble learning to improve disease classification accuracy and resilience [7]. The combination of Internet of

Things (IoT) devices and remote sensing technologies has facilitated the generation of large datasets for training models, hence promoting the advancement of complex deep learning models. Moreover, the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in the study of images and time-series data has enabled accurate diagnosis and prediction of diseases [8]. The advancements mentioned have resulted in the creation of disease monitoring systems that operate in real-time. These systems provide farmers valuable information that can be used to take proactive measures in disease management and enhance agricultural production.

This research intends to investigate the effectiveness and progress in using deep learning methods for analyzing crop diseases in precision agriculture. It provides insights into the possible uses and consequences of these techniques in current agricultural operations.

2. Precision agriculture methods

A. Pavithra et al [9] proposed a new model called DL-APDDC, which is especially tailored for applications in Precision Agriculture. The DL-APDDC algorithm is specifically designed to detect and classify plant diseases that occur in both leaves and fruits. At first, the algorithm utilizes U2Net-based background removal to differentiate between areas of leaves and areas of fruits. Afterwards, the Adam optimizer is used in conjunction with the SqueezeNet model to extract features, and the hyperparameters are adjusted by fine-tuning with the Adam optimizer. The categorization of plant diseases is performed via the XGBoost classifier. The effectiveness of the DL-APDDC approach is assessed by conducting experimental validation on a benchmark dataset of plant diseases. The simulation results clearly illustrate the higher performance of the DL-APDDC technique in comparison to other current models.

Chandrabhanu Bajpai et al [10] presented a classification method called DNSVM, which combines DenseNet-201 with support vector machine (SVM) to accurately identify plant leaf diseases. The suggested model was evaluated using the Plant-Village dataset, which is renowned for its wide range of color variations, orientations, and leaf sizes. This dataset offers a complete collection of plant illnesses for analysis purposes. In order to analyze and evaluate the performance of the suggested approach, sugarcane plant leaves were specially used.

Tej Bahadur Shahi et al [11] proposed to provide a comprehensive analysis of the latest developments in the identification of agricultural diseases, with a special emphasis on the use of machine learning and deep learning techniques employing unmanned aerial vehicle (UAV)-based remote sensing. The research first emphasizes the need of using various sensors and image-processing methods to improve the precision of estimating crop diseases by analyzing UAV data. Subsequently, a methodical categorization approach is presented to collect and arrange previous research on the detection of agricultural diseases using UAV data. Moreover, this study offers a comprehensive examination and incorporation of many machine learning and deep learning methodologies to evaluate their efficacy in identifying agricultural illnesses. Ultimately, the paper examines the current obstacles, possible advantages, and future research paths in using UAV-based remote sensing to identify agricultural diseases.

Abdullah Ali Salamai et al [12] proposed is the lesion-aware visual transformer, a novel method that improves the accurate and reliable detection of illnesses in paddy leaves by recognizing distinct lesion features essential for distinction. This approach utilizes an innovative network for extracting contextual characteristics at several sizes. It allows for the depiction of illness features in different scales and channels, spanning both local and global aspects. Additionally, a weakly supervised PLL unit is used to precisely identify unique lesions inside paddy leaves. These lesions act as discerning areas that direct the final classification determination. Additionally, there is an integrated feature tuning unit that aids in modeling links within both the localized and overarching latent spaces. As a result, this improves the way visual meanings of paddy leaves interact with each other in space. The suggested system has been extensively tested against state-of-the-art systems utilizing publicly available paddy disease datasets. These experiments have shown the efficacy and flexibility of the proposed system.

Jinya Su et al [13] conducted an extensive analysis on the current use of UAV sensing systems, including UAV platforms and external sensing units, along with AI algorithms, specifically emphasizing supervised learning algorithms, in Precision Agriculture (PA) applications throughout the entire crop life cycle. This analysis explores the current obstacles and possible future progress of UAV's and artificial intelligence (AI) in the agriculture industry. The objective of this assessment is to provide a prompt and comprehensive technical resource. The main goal of this study is to make a meaningful contribution in addressing future agricultural and nutritional difficulties faced by mankind. This objective will be accomplished by promoting the progress, investigation, and efficient use of AI-driven UAV sensing systems in the field of Precision Agriculture.

Ishana Attri et al [14] emphasized on identifying significant gaps in research, namely in the development of innovative approaches. This study focuses on emphasizing the need of continuous research efforts in this subject.

This highlights the need for continuous study in order to fully use the capabilities of Deep Learning (DL) in the field of smart farming, therefore aiding in the achievement of sustainable agricultural growth.

Prabhjot Kaur et al [15] Employed the MIR-V2, a modified CNN model, in conjunction with transfer learning techniques to accurately detect illnesses in photos of tomato leaves. The model is trained using a combination of a publicly accessible dataset and a dataset collected by the researchers. The datasets include seven different classifications of tomato leaf illnesses and a sample of a healthy leaf. In order to evaluate the effectiveness of the model, many factors are taken into account, such as the dropout rate, learning rate, batch size, number of epochs, and measures of accuracy.

Alireza Sanaeifar et al [16] presented a thorough analysis of recent progress in deep learning-based head recognition in cereal plants, focusing on both object detection and picture segmentation techniques. The topic includes a comprehensive examination of the benefits and constraints linked to different deep learning structures and training methods, demonstrating their use in cereal crops such as maize, rice, wheat, and sorghum. Moreover, the study emphasizes the need for future research in the development of strong image processing algorithms, the expansion of deep learning techniques into areas such as unmanned aerial vehicles, and the use of extensive and varied datasets. This work seeks to promote more research and innovation in the dynamic area of precision agriculture by combining advanced computer vision methods. This paper provides a comprehensive assessment of the current advancements in deep learning-based head identification for cereal plants, highlighting the significant potential of this technology in furthering precision agriculture.

Anupong Wongchai et al [17] presented a novel method for monitoring agricultural farms and predicting crop illnesses using advanced deep learning architectures. The monitored data is obtained from an Internet of Things (IoT) module, which is integrated with historical data of cultivation farm photos. The datasets are subjected to preprocessing procedures, which include the elimination of noise and scaling of images, in order to improve the quality of the data. The important features are recovered from the processed data using a convolutional learning approach that incorporates deep attention layers (DAL_CL). The gathered data is then classified using a recursive neural network (RNN) architecture. The suggested system utilizes data categorization and deep learning approaches to evaluate collected data, with the goal of accurately predicting the presence or absence of plant diseases. The main goal is to enhance sustainable agricultural operations by using predictive insights obtained from these methodologies.

Wei Zhao et al [18] optimized the precision of bale recognition with a limited dataset by using a novel computational approach. Firstly, an object identification model is trained using 243 photos acquired under controlled lighting conditions in agricultural fields throughout the fall season. Moreover, domain adaptation (DA), which is a kind of transfer learning, is used to provide training data that covers diverse environmental circumstances while automatically assigning labels. Afterwards, the object detection model is optimized using these generated datasets. The case study findings clearly show a significant improvement in bale identification performance using the suggested methods.

3. Leaf disease direction using deep learning techniques

Yousef Methkal Abd Algani et al [19] presented a novel method for illness identification and classification called Ant Colony Optimization with Convolutional Neural Network (ACO-CNN). This research investigates the efficacy of disease identification in plant leaves by the integration of ant colony optimization (ACO). By using the CNN classifier, visual attributes pertaining to color, texture, and the arrangement of plant leaves from the given photos are extracted. The suggested method's efficacy is assessed using diverse metrics, demonstrating its superiority over current methodologies in terms of accuracy rates and associated performance indicators. These approaches are essential in the process of illness diagnosis, which includes capturing images, separating the images into different parts, removing unwanted elements, and then categorizing them.

Sheng Yu et al [20] presented a novel transformer block that utilizes the transformer architecture to represent distant characteristics and incorporates soft split token embedding to gather specific information from nearby pixels and patches. Furthermore, using the inception architecture with cross-channel feature learning improves the amount of information captured, which is especially beneficial for learning detailed features. The proposed model demonstrates a higher level of accuracy in comparison to previous models that are based on convolutional and vision transformer techniques.

Mohan Bhandari et al [21] The objective was to visually identify nine specific infectious illnesses (bacterial spot, early blight, Septoria leaf spot, late blight, leaf mold, two-spotted spider mite, mosaic virus, target spot, and yellow leaf curl virus) often detected on tomato leaves, as well as distinguish healthy leaves. The model attained a satisfactory average training accuracy by using EfficientNetB5 and a TLD dataset without segmentation.

Alberta Odamea Anim-Ayeko et al [22] presented a ResNet-9 model specifically developed for the purpose of detecting blight disease in photos of potato and tomato leaves. This model has the potential to be a valuable tool for farmers. The first training dataset consisted of 3,990 samples, using the well-known "Plant Village Dataset." After augmenting the training set and doing thorough hyperparameter tuning, the model was trained using the optimal values. Following that, an assessment was carried out on the test set, which consisted of 1,331 photographs.

Ali Arshagi et al [23] proposed CNN methods were used to assess five distinct categories of potato diseases: Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot. The experiment used a dataset including 5000 potato photos and performed a comparative examination of several techniques for classifying potato illnesses, including well-known algorithms like AlexNet, GoogLeNet, VGG, R-CNN, and Transfer Learning. The results suggest that the suggested deep learning approach outperforms existing current approaches in terms of accuracy.

Muhammad E. H. Chowdhury et al [24] proposed the use of a sophisticated deep learning framework that combines the state-of-the-art convolutional neural network, EfficientNet, for the purpose of classifying tomato illnesses. This classification task will be performed using a dataset consisting of 18,161 tomato leaf pictures, which include both plain and segmented forms. The study assesses the efficacy of two segmentation models, namely U-net and Modified U-net, in accurately demarcating the boundaries of the leaves. The text provides a detailed examination of how these models perform in various classification tasks, such as distinguishing between healthy and unhealthy leaves in binary classification, categorizing diseased leaves into six different groups in six-class classification, and classifying unhealthy leaves into ten different types in ten-class classification.

G Ramkumar et al [25] presented a new Deep Learning approach in the field of the Internet of Things (IoT) with the goal of producing precise prediction results. This approach is called Leaf Disease Estimation using Deep Learning Principle (LDEDLP). The LDEDLP technique incorporates advanced technologies such as IoT to accurately identify plant diseases and rapidly notify the appropriate user. The system use image segmentation techniques to accurately identify the damaged region. It then applies classification algorithms to determine the specific illness category. The suggested LDEDLP technique exhibits a notable degree of precision in its predictions, as thoroughly outlined in the subsequent parts of this study.

S. Poornam et al [26] proposed methodology consists of compiling a dataset of plant leaves, followed by preprocessing the images, augmenting the images, and training a neural network. The training step utilizes a dataset obtained from ImageNet. The objective is to differentiate between leaves that are healthy and those that are impacted by illness using the CNN approach. During the preprocessing of images, resizing is performed in order to decrease the time of the training phase. Image augmentation is performed during the training process, when several transformation functions are applied to plant photos. The Neural Network is trained using the Caffenet deep learning framework and utilizes the Rectified Linear Unit (ReLu) activation function inside the CNN. The convolutional base of the CNN produces picture features by applying numerous convolution and pooling layers. Afterwards, the classifier component of the CNN utilizes the retrieved features to classify the pictures, which is done via the fully connected layers. A 10-fold cross-validation function is used to assess performance. The last layer utilizes an activation function, such as softmax, to classify the outputs into different categories.

Mehmet Metin Ozguven et al [27] implemented an optimized Faster R-CNN architecture by adjusting the parameters of a CNN model, designed particularly for the automated detection of leaf spot disease (Cercospora beticola Sacc.) in sugar beet plants. The suggested methodology, which focuses on identifying the severity of an illness utilizing expert systems based on imaging, underwent both training and testing stages. These stages used a dataset consisting of 155 photos. The performance assessment was done using the test findings received from these studies.

Jinzhu Lu et al [28] aimed at analyzing the latest CNN networks that are applicable to the categorization of illnesses affecting plant leaves. The paper succinctly summarized the core tenets of Deep Learning (DL) as they are used in the classification of plant diseases. Moreover, a concise overview was given about the main obstacles faced in CNN-based plant disease categorization, along with their corresponding remedies. Finally, there was a debate of the expected future developments in approaches for classifying plant diseases.

4. Leaf shape based disease analysis using Deep learning

Ramachandran Sangeetha et al [29] presented an improved method that utilizes an advanced deep learning algorithm in agriculture to predict the occurrence of Panama wilt disease by analyzing clinical symptoms. The suggested deep learning model for detecting Panama wilt disease functions as a vital instrument for immediately and reliably identifying diseased plants. It is especially important in large-scale agricultural situations where the fast spread of Panama wilt disease might cause significant harm to crops. Moreover, the use of deep learning models enables the surveillance of treatment efficacy, assisting farmers in making well-informed choices on the most efficient disease management measures. This technique is especially designed to predict the severity of a disease and its effects by examining changes in the color and shape of banana leaves. The present suggested approach is assessed in comparison to its previous iterations to showcase its progress.

Lawrence C. Ngugi et al [30] presented a semi-automatic technique that aims to accelerate the efficient compilation of datasets consisting of individual lesions and pixel maps of leaf pictures. The program specifically addresses the difficulties encountered during the process of dataset creation. The created datasets were then used to train and assess Convolutional Neural Network (CNN) models for lesion classification and semantic segmentation. The results indicate a significant improvement in illness detection accuracy of more than 15% when using GoogLeNet to identify diseases from lesion photos, compared to using full leaf images for disease detection. In addition, the research presents a Convolutional Neural Network (CNN) model that can perform semantic segmentation for both leaves and lesions concurrently in a single iteration.

Muhammad Shoaib et al [31] implemented a methodology using a deep learning framework to detect and classify illnesses that impact tomato plants. The system used picture data of plant leaves. An innovative framework, using a newly created convolutional neural network, was used. The network was trained on a dataset of 18,161 photos of tomato leaves, both segmented and non-segmented. This research effort used the Inception Net model, using a supervised learning strategy, to accurately identify and categorize different tomato illnesses. To identify and define areas impacted by illness, two advanced semantic segmentation models, U-Net and Modified U-Net, were used. The purpose of these models is to categorize the pixels of plant leaves into two distinct groups: Region of Interest (ROI) and background. The study also examines the efficacy of models employing binary classification (differentiating between healthy and diseased leaves), six-class classification (identifying healthy leaves and different categories of diseased leaves), and ten-class classification (distinguishing healthy leaves and multiple varieties of diseased leaves).

Kaihua Wei et al [32] emphasized assessing the comprehensibility of deep learning models in different agricultural categorization tasks using a dataset that included fruit leaves. The aim was to determine whether the classification model primarily extracts the visual features of leaves or the textural properties of leaf lesions throughout the process of feature extraction. The dataset was organized into three separate studies, each covering various areas. The experiments included VGG, GoogLeNet, and ResNet models, together with the ResNet-attention model. Additionally, three interpretable methodologies were implemented. The results indicated that the ResNet model achieved the best level of accuracy in all three studies.

K. Anitha et al [33] proposed research to identify and characterize leaf smut, bacterial blight, and brown spot illnesses by analyzing photos of damaged leaves obtained from a range of plant species, such as Apple (20), Cercospora (60), Rice (100), Grape (140), and wheat (180). An innovative segmentation method is presented, designed particularly to accurately extract the region of interest (ROI) from damaged leaves in the presence of a dynamic backdrop. The textural characteristics of the segmented regions of interest (ROIs), which include both 1st and 2nd order weighted principal component analysis (WPCA) features, are determined after the segmentation process. The characteristics consist of essential statistical parameters, including kurtosis, skewness, mean, and variance, as well as other statistical properties such as smoothness, energy, correlation, homogeneity, contrast, and entropy. Afterwards, the textural characteristics of the chosen segmented region are fed into four distinct classifiers, and among them, the Enhanced Deep Convolutional Neural Network exhibits the best degree of precision.

Shengyi Zhao et al [34] presented a new deep convolutional neural network that integrates an attention strategy to improve the detection of various tomato leaf diseases. The neural network structure consists of residual blocks and attention extraction modules, which are skilled at accurately capturing complex characteristics related to various disorders. The suggested model consistently achieves improved identification accuracy, as shown by detailed experimental comparisons.

Mateus Coelho Silva et al [35] presented a technique for predicting the accurate form of leaves and assessing defoliation using a Conditional GAN. The technique was trained and validated using a dataset consisting of leaf photos from 33 different species. Moreover, the model was assessed by using a supplementary dataset comprising of photos of leaves from 153 diverse species. The results indicate that this model outperforms previous research and has the ability to work efficiently with different leaf shapes, including those from species that were not part of the training dataset.

Nisar Ahmad et al [36] The proposed approach enables the automated identification of plant diseases by following a systematic procedure that includes pre-processing, isolating the impacted leaf region, calculating features using GLCM, selecting relevant features, and performing classification. The investigation included the calculation of six color attributes and twenty-two texture attributes. The categorization of plant diseases was performed via Support Vector Machines (SVM) employing a one-vs-one methodology.

Rakesh Chandra Joshi et al [37] proposed a computerized method that use deep learning to identify viral infections in Vigna mungo, a widely cultivated leguminous plant in the Indian subcontinent. The detection of viral infections in these plants is a challenge owing to the unpredictable changes in leaf image qualities generated by the infection, resulting in a diverse pattern throughout the leaf structure. In order to tackle this issue, the research project compiled a collection of Vigna mungo leaf photos from various categories. These images were then segmented and augmented to enhance the diversity of the dataset. The convolutional neural network, VirLeafNet, is trained using a diverse set of leaf pictures that include healthy leaves, leaves with moderate infections, and leaves with severe infections, throughout numerous epochs. This approach has the capability to be integrated with drones in order to provide comprehensive study of agricultural areas. The suggested technique provides a fully automated, non-invasive, and fast categorization of leaf pictures into several categories in real-time.

Kaizhou Li et al [38] employed CNN models to classify different degrees of ginkgo leaf defects. More precisely, the study used both the VGGNet-16 and Inception V3 models for this objective. A total of 1322 original photos taken in laboratory settings and 2408 original images collected from outdoor circumstances were used for training after undergoing preprocessing processes in this investigation.

5. Crop weed detection using deep learning techniques

Fengying Dang et al [39] presented a new dataset called CottoWeedDet12, which has been carefully selected to include weeds that have a major influence on cotton output in the southern parts of the United States (U.S.). The dataset consists of 5648 photos that depict 12 different categories of weeds. In all, there are 9370 annotations of bounding boxes. The photographs were gathered in cotton fields, under natural lighting circumstances, to capture a wide range of weed development phases. This research includes a groundbreaking effort to develop a comprehensive benchmark that showcases 25 cutting-edge YOLO object detectors. The detection techniques consist of seven iterations: YOLOv3, YOLOv4, Scaled-YOLOv4, YOLOR, YOLOv5, YOLOv6, and YOLOv7. This extensive series of iterations provide a strong foundation for evaluating weed identification using this dataset.

Ignazio Gallo et al [40] presented the Chicory Plant (CP) dataset, a newly developed dataset designed to evaluate the effectiveness of state-of-the-art deep learning methods in object recognition. The CP dataset consists of more than 3000 RGB photos that were taken using a UAV system. These images capture chicory plantations at different phases of crop and weed development. The collection also includes 12,113 bounding box annotations that are primarily used to detect weed targets, particularly Mercurialis annua. The research thoroughly investigated the identification of cannabis-related objects by using the most recent version, YOLOv7. The trials were performed on two datasets: the CP dataset and a publically accessible dataset called Lincoln beet (LB). The LB dataset was previously used in conjunction with a prior iteration of YOLO to delineate and classify both weeds and crops. The findings obtained from YOLOv7 on the CP dataset demonstrated improved performance compared to other YOLO versions evaluated in the research, which is encouraging.

Yingxiang Feng et al [41] examined seedling cotton as the primary object of analysis, specifically exploring the use of three different advanced deep learning algorithms—YOLOv5, YOLOv7, and CenterNet—for the purpose of recognizing and quantifying cotton seedlings. The research used pictures obtained from Unmanned Aerial Vehicles (UAVs) to gather multispectral photos at six distinct phases throughout the cotton seedling period. The goal is to develop a model that can be used during all phases of cotton seedling development. YOLOv7 demonstrated improved performance in both identification and counting tasks throughout all phases of data collection, according to the results. Furthermore, the T4 dataset consistently exhibited superior performance in each corresponding test set.

Jiging Chen et al [42] developed YOLO-sesame model to improve the accuracy and efficiency in detecting sesame weeds. This is an expansion of the YOLOv4 method that incorporates an attention mechanism. This approach combines local significance pooling with the SPP layer and utilizes the SE module as a crucial component. Furthermore, it utilizes an adaptable spatial feature fusion structure at the feature fusion level to tackle difficulties associated with significant fluctuations in target size and specifications. The empirical findings demonstrate that the YOLO-sesame model, introduced in this study, outperforms well-established models such as Fast R-CNN, SSD, YOLOv3, YOLOv4, and YOLOv4-tiny in terms of its detection capability.

Najmeh Razfar et al [43] presented a weed identification method that uses deep learning models to accurately identify weeds in a soybean plantation, based on visual information. Five discrete deep learning models were used, including MobileNetV2, ResNet50, and three customized Convolutional Neural Network (CNN) models. The implementation of MobileNetV2 and ResNet50 on a Raspberry Pi controller was done for the purpose of conducting a comparative comparison. The 5-layer CNN architecture, particularly built for weed recognition, demonstrated significant accuracy levels using a dataset of 400 pictures and 1536 segments.

A. Subeesh et al [44] explored the viability of deep learning approaches (namely, Alexnet, GoogLeNet, InceptionV3, Xception) for identifying weeds in bell pepper fields using RGB photos. The models underwent training using varying numbers of epochs (10, 20, 30) and batch sizes (16, 32). Additionally, hyperparameters are adjusted to get the best possible performance.

Anand Muni Mishra et al [45] presented a concise summary of progress in the identification and categorization of weeds, achieved via the integration of cutting-edge artificial intelligence and image processing approaches. More precisely, it provides detailed information on the four crucial stages in identifying and categorizing weeds: pre-processing, segmentation, feature extraction, and classification. Furthermore, the study explores the difficulties faced in this domain, including leaf occlusion, overlapping, various lighting circumstances, and changing development phases. It also presents the methods put out by researchers to tackle these obstacles.

Kavir Osorio et al [46] proposed to compare three different approaches for weed estimate in lettuce fields utilizing deep learning image processing algorithms, in comparison to assessments conducted by field specialists. The primary approach is support vector machines (SVM) that make use of histogram of oriented gradients (HOG) as the feature descriptor. The second method utilizes YOLOv3, using its resilient architecture specifically designed for object identification. The third method use Mask R-CNN, a region-based convolutional neural network, to perform instance segmentation on individual weed entities. In addition, these techniques were enhanced by including a normalized difference vegetation index (NDVI) as a background subtractor, aiding in the removal of non-photosynthetic objects from the study.

Muhammad Hamza_Asad et al [47] validated the proposed approach by using high-resolution color photos acquired from canola fields. The study provides a performance evaluation by comparing deep learning meta-architectures such as SegNet and UNET, as well as encoder blocks like VGG16 and ResNet-50.

Kun Hu et al [48] proposed Graph Weeds Net (GWN), a recently developed deep learning architecture designed to accurately classify different kinds of weeds in complex rangelands using standard RGB photos. GWN employs a method of collecting certain patterns within defined picture scopes and creates complex graph structures at several scales to categorize weeds. Furthermore, GWN provides valuable information about important areas of the picture, allowing robotic systems working inside the images to take appropriate actions.

6. Crop damage detection using Areal Images

Bruno Moraes Rocha et al [49] aimed to identify and evaluate the arrangement of crop rows, while quantifying the distances between them, by using aerial photography of sugarcane fields. This entails use a compact Remotely Piloted Aircraft to capture photographs of the designated regions, producing orthomosaics for future examination. The K-Nearest Neighbor technique is used to classify each orthomosaic and pinpoint particular areas of interest. The direction of the planting rows is determined by using an RGB gradient filter. Additional analysis entails using morphological operations and computational geometry models to detect and delineate the rows and gaps inside the planting row segment. In order to verify the results, the crop rows that have been mapped are compared with manually collected data.

Marianna Crognale et al [50] presented and compared four independent computer vision techniques for detecting damage using image processing: Otsu method thresholding, Markov random fields segmentation, RGB color detection approach, and K-means clustering algorithm. One strategy for the first way is to segment grayscale pictures by using a thresholding technique to produce binary outputs. Markov random fields use a probabilistic approach to allocate labels that represent spatial connections among pixels in a picture. The RGB approach evaluates the size of defects by using color detection. The K-means method groups photos together by calculating their Euclidean distance. The benefits and constraints of each approach are discussed, while emphasizing the difficulties involved with their implementation. A case study is provided to showcase the effectiveness of these strategies in identifying deterioration in civil infrastructures. The results illustrate the effectiveness of image processing methods in detecting different forms of corrosion and fractures, making the suggested methodologies valuable instruments for forecasting the advancement of deterioration in civil infrastructures.

Akshay Dhande et al [51] analyzed many datasets and assesses the effectiveness of context-aware classification algorithms. These strategies are used together to improve the efficiency of multimodal augmented picture classification applications via correlated analysis. By using this analytical technique, the system is able to forecast crop losses with more efficiency in comparison to independent models. The software is particularly designed to detect regions impacted by natural calamities, assisting agricultural specialists in performing precise remedies. The results of this suggested model are compared to several newly created state-of-the-art approaches.

Abdelmalek Bouguettaya et al [52] conducted a comprehensive analysis of the latest developments in using deep learning-based computer vision techniques in conjunction with UAV technology for the purpose of identifying and managing agricultural diseases.

Mara Gabbrielli et al [53] employed Sentinel-2 vegetation indicators to detect frost damage in four white mustard (Sinapis alba L.) farms located in Northern Italy. The research included calculating the initiation of frost occurrences by analyzing several vegetative indicators, including EVI, NDRE, NDVI, MMSR, and CCCI. Later, the extent of frost damage at a smaller field level was assessed and charted using measurements taken on the ground during the 2021/2022 season. When evaluating the extent of frost damage, MMSR showed better results than other vegetation indices, with CCCI and EVI doing similarly well. The methodology used to detect the initiation of frost occurrences was mostly effective, demonstrating a little lag of one to four days in the two most successful instances (NDRE). Moreover, the maps generated to show frost damage were in good agreement with actual variations in space. The research confirms the practicality of using vegetation indicators to identify frost damage in cover crops, allowing for the evaluation of the effectiveness of terminating cover crop winterkill in agricultural areas. Nevertheless, it is advisable to do more research that includes extensive field monitoring of white mustard under a wider range of circumstances, as well as an expansion of calibration and validation techniques.

Kishore Dutta et al [54] developed a method to automatically identify illnesses in cruciferous crops using color vegetative indices and Otsu's thresholding methodology. This methodology enables the segmentation of sick leaves, providing an early detection procedure. The approach was applied to aerial RGB photos taken under different sunshine circumstances, including several kohlrabi plants against backdrops of barren dirt and weeds. Our study demonstrates the effectiveness of using the M-statistic in improving the vegetative index set to accurately differentiate between healthy leaves, sick leaves, and various environmental backdrops. The research highlights the significance of tailoring vegetative indices according to individual crop kinds in order to accurately identify unhealthy plant portions using image processing techniques. The ramifications of this method in precision agriculture are comprehensively investigated.

Parthasarathy Velusamy et al [55] provided a comprehensive analysis of the efficient techniques used in agricultural settings for precise crop monitoring and pest management, employing unmanned aerial vehicles (UAVs) or drones. The article provides a thorough analysis and comparison of several kinds of UAVs and their specific functions in the early identification of agricultural diseases. Furthermore, it investigates the use of aerial, satellite, and remote sensing technologies for disease identification, while also evaluating their Quality of Service (QoS).

Sujata Butte et al [56] developed a technique using deep neural networks to analyze aerial photos of potato crops. The main objective is to demonstrate the automated detection of healthy and diseased crops on an individual plant level. The main objective is to detect early plant senescence caused by drought stress in 'Russet Burbank' potato plants. The paper presents a new and innovative deep learning model called Retina-UNet-Ag, specifically developed for the purpose of identifying crop stress. The suggested architecture is a modified iteration of Retina-UNet, integrating connections from lower-level semantic mappings into the feature pyramid network. Moreover, the research presents a variety of aerial field photos obtained using a Parrot Sequoia camera. The collection consists of accurately documented bounding boxes that outline both healthy and troubled areas of plants.

Mohd Yazid Abu Sari et al [57] proposed the use of UAV’s and RGB photography to monitor the development phases of rice crops and the general condition of paddy fields. The research used unmanned aerial vehicles (UAVs) outfitted with RGB digital cameras to collect data from the paddy fields. The results underscore the need of early surveillance of rice crops to assess their state. Hence, the examination of aerial photos acquired by UAVs may greatly improve the management of rice crops, eventually seeking to increase rice crop yields.

Chenghai Yang et al [58] provides a succinct overview of how remote sensing and precision agriculture technologies are used to detect and manage crop diseases. The main objective is to demonstrate the use of aerial and satellite imaging, together with variable rate technologies, for the identification and mapping of cotton root rot, a detrimental fungal infection that impacts cotton crops. The paper explores the use of site-specific fungicide treatment by using prescription maps generated from this imaging to effectively manage diseases. The purpose of these approaches and insights is to provide practical direction to researchers, extension professionals, producers, crop consultants, and agricultural equipment and chemical dealers on how to use remote sensing to diagnose and control diseases in crops.

Conclusion

In conclusion, this survey delves into the intricate landscape of deep learning applications in precision agriculture, specifically addressing critical issues related to crop disease analysis. The examination of leaf disease direction, leaf shape-based analysis, crop weed detection, and crop damage detection reveals the remarkable progress achieved in these domains. However, challenges such as dataset scarcity, model generalization, and real-world deployment persist. The survey underscores the need for collaborative efforts between researchers, practitioners, and agricultural stakeholders to overcome these challenges. As deep learning continues to evolve, the integration of innovative techniques, such as transfer learning and ensemble methods, holds promise for enhancing the robustness and scalability of crop disease analysis systems. Ultimately, the insights gleaned from this survey contribute to the ongoing discourse on leveraging deep learning for precision agriculture, fostering sustainable farming practices and ensuring global food security.

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