Comprehensive Review of Deep Learning Methods for Identifying Okra Plant Diseases

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***Abstract*: Plant diseases and bug pests must be detected quickly, accurately, and efficiently due to the growing requirement for responsible agricultural production. Traditional methods of disease tracking and pest detection are labor-intensive, time-consuming, expensive, and challenging to scale across broad farming regions since they primarily rely on manual field inspection and specialist knowledge. Systematic sickness and identifying insects through visual analysis has been made possible by recent developments in artificial intelligence, and especially the use of deep learning. A thorough analysis of deep learning-based methods for the diagnosis, characterization, and classification of pests in farming and crop diseases is presented in this work. Including popular architectures like Convolutional Neural Networks (CNNs), YOLO-based models, Faster R-CNN, SSD, U-Net, Vision Transformers, and other cutting-edge architectures, the study methodically investigates key AI tasks like object recognition, image classification, lexical and instance segmentation, and change detection. The review also examines how large-scale already trained models, data augmenting, and transfer learning in general might enhance model effectiveness and lower training requirements. Several publicly available and field-gathered information sets, scanning settings, and commonly used criteria for evaluation are also discussed in order to provide comparisons of current approaches. Particular attention is paid to the challenges of everyday agriculture, including variations in lighting and conditions, complex conditions, obstruction, small and advanced lesions, small and unbalanced datasets, cross-class similarity, and limited modeling generalization based across various crops and spatial geographic areas. The paper also identifies significant research gaps related to dataset diversity, model accessibility, computational effectiveness, real-time setup, and the capacity for transfer of algorithms from lab into field environments.**

***Keywords:* deep learning, disease detection, convolutional neural network (CNN), pest identification, image processing**

I. INTRODUCTION

World food security, rural lives, growth in the economy, and a sustainable environment all depend on agriculture. Numerous biotic stressors, especially bacterial infections and insect pests, constantly jeopardize the health and output of agricultural crops. Different periods of agricultural production may be impacted by these risks, which could lower product quality and output. Food supply, agricultural revenue, trade, and rural livelihoods are all significantly impacted by plant pests and diseases, which are estimated by the FAO to be causing loses of up to 40% of worldwide crop production annually [1, 2, 3]. Proper plant health monitoring is even more crucial in light of the growing global trade, population growth, climate change, environmental degradation, and rising food demand. Early and accurate detection is crucial because changes in temperatures, precipitation, and ecological factors can affect the distribution, survival, and intensity of agricultural pests and pathogens [2,4]. As a result, prompt detection of pests and plant diseases is now crucial to agricultural precision and modern crop administration.

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Leaf spots, yellowing, edema, nitric oxide, lesions, abnormal morphology, decay, and tissue injury are only a few of the visible and biological signs of typical plant illnesses and pests. However, depending on the crop variety, pathogen type, disease stage, environmental factors, and relationships between biotic and abiotic pressures, symptoms of illness might differ significantly. While initial stages of infections may cause modest symptoms that are challenging to identify, comparable visual signs may also appear across different medical conditions. Accordingly, the assessment of the place, form, color, consistency, severity, and distribution in space of symptoms is just as important to an accurate diagnosis as the mere presence of apparent symptoms. In traditional agricultural methods, farmers, agricultural outreach agents, or plant pathologists typically make diagnoses by inspection of the eyes. Inspection by hand is time-intensive, laborious, subjective, and challenging to scale to broad agricultural regions, even though expert diagnosis is still crucial. Additionally, there might not be as many qualified specialists available, especially in isolated farming towns. In certain situations, utilizing laboratory-based diagnostic techniques can yield more accurate diagnosis; however, they may necessitate specific tools, skilled workers, standard sample preparation, and extra time. Due to these constraints, automated, reasonably priced, and adaptable methods that enable quick plant health evaluation are required. [5, 6, 7].

The quality and accessibility of farming-related datasets is another significant obstacle. While standard and pest datasets are frequently restricted to certain crops, geographic locations, disease types, or conditions in the environment, deep learning typically gains from vast, diversified, well labeled, and relevant datasets. Biased models and overstated performance might result from imbalanced classes, incorrect annotations, duplication photos, a lack of early-stage symptom instances, and inadequate field variability representation. Additionally, because different datasets, preprocessing techniques, training-test splits, architectures, evaluation metrics, and conditions for experimentation are used by researchers, it can be challenging to compare current work. Therefore, it is not possible to determine if one strategy is actually better or more appropriate for real-world application based just on claimed accuracy [8,9,13].

As a result, this paper offers a thorough analysis of current developments in utilizing deep learning for diseases of plants and pest classification and detection. In addition to discussing the evolution from traditional CNN architectures to contemporary detection systems, transformer-based techniques, transferable learning techniques, and large-scale model training, the review methodically looks at important computational vision tasks like image classification, object detection, semantic and instance division, and change identification. In order to give a comparative perspective of current research, it also looks at frequently used information sets, imaging circumstances, pretreatment techniques, and review measures. By combining these advancements, this review seeks to offer an organized overview of how deep learning has developed as a tool for computerized disease and pest control, what prior research has demonstrated, where current methods are still inadequate, as well as which research avenues hold the greatest promise for creating dependable, scalable, and field-ready agricultural intelligence systems. These developments can decrease crop losses, support prompt action, cut down on needless inputs for agriculture, and promote greener and more efficient farming methods.

Figure 1: Segmented images manually of Okra plant

The sick leaf is depicted in Figure 1, and the maximum amount of the dataset for these models depends on how complex the image's components are. Consequently, the number of photographs in the dataset was artificially increased by the application of image augmentation techniques. It employs image editing methods like rotation, random translation, and brightness adjustments to corrupt the dataset. A fixed transformation value of 100 and a factor of a random number were used to move each pixel to a predefined position in order to translate it randomly. The brightness of the image was altered by adding or subtracting a random value generated within a specified intensity value. After multiple efforts, a fixed value was achieved to preserve the image's properties. Determining their goals and training a vast number of spectrum image inputs are CNN's biggest challenges. For CNN classifier applications, it has significantly increased the difficulty of classifying the variations from the supplied input data. Analyzing the spectrum mixtures with CNN classifiers is one of the other most challenging aspects. In order to classify a range of agricultural diseases, CNN classifiers typically integrate optimal characteristics such texture, color, and object form. It is easy to train these parameters when the standard images are linear. Such hyper-spectral data can only be trained when there are hundreds of continuous spectral bands. Furthermore, it is highly redundant to extract information from adjacent spectral bands in different spectral areas of a network.

After collecting leaf photographs, we preprocess the leaf images from the same data. For every pair of leaf picture, a training set and a testing set were produced. We achieved an accuracy of more than 98.2% on the test set and validation. The online application, which provides simplified findings and has an easy-to-use user interface, is built upon the model. Plant diseases are a hazard to the world's food supply. This study shows that autonomous disease detection by photo categorization is technically achievable through machine learning with a convolutional neural network technique. A convolutional neural network is trained using a publically available dataset of 54,306 photos of both healthy and diseased plant leaves in order to detect the crop species and disease status of ten distinct classes. The network's residual network architecture yields an accuracy of 98.2%.

Figure 2: The Okra plant

These reduced photographs are used for both prediction and model improvement once the photos have been resized to 256 × 256 pixels. By employing data augmentation techniques including shearing, zooming, flipping, and brightness shift, we were able to almost double the size of the dataset. Data augmentation techniques are commonly employed with deep learning or traditional machine learning algorithms to improve classification accuracy. In this work, the photo augmentation technique was implemented using the Python machine learning module. Procedures like adjusting the width and height, cutting, zooming, rotating horizontally, adjusting brightness, and filling were used for standard class photos. The degree of picture rotation was configured to be created at random. Automatic plant disease detection methods are useful because they minimize the amount of labor required for crop monitoring in large farms and identify disease symptoms early on, such as when they show up on plant leaves. One of the most significant uses of machine vision research is the diagnosis of plant diseases and pests. It is a system that gathers photos of plants and determines if they depict pests or illnesses using machine vision techniques. Changing the weights continuously until CNN learns as efficiently as feasible is the primary goal of optimization strategies. Every technique carries out an updating procedure. Every time the Stochastic Gradient Descent (SGD) method is used, the weights for every instance in the training set are changed. It therefore seeks to accomplish the goal as soon as possible.

Characteristics of the Disease

- *Yellow Vein Mosaic Virus (YVMV)*
- Yellowing of leaves with green veins.
- Mosaic pattern on leaves.
- Stunted growth and deformed pods.

Powdery Mildew

- White, powdery coating on both sides of leaves.
- Leaves turn yellow, dry, and fall off.
- Reduced pod size and yield.

Leaf Spot Disease (Cercospora Leaf Spot)

- Brown or black circular spots on leaves.
- Spots merge and cause leaf blight.
- Severe cases lead to leaf drop.

Fusarium Wilt

- Wilting of lower leaves first.

- Yellowing before wilting.
- Brown streaks inside the stem.
- *Damping Off (Seedling Disease)*
- Seedlings collapse soon after germination.
- Rotting at soil level.

Root-Knot Nematodes

- Swelling (galls) on roots.
- Yellowing leaves and stunted growth.
- Lower yield due to poor root function.

Evaluation of Prevention

- Control bug vectors, including insects and fly species
- Apply insecticides or bactericides as needed.
- Remove and dispose of any infected plants.
- Use cultivars that are resistant to disease.
- Turn your crops around.

II. METHODOLOGY

The Recommended Reporting Items for Systematic Reviews standards were followed in the conduct of this systematic review. This study's primary goal is to use image processing to recognize, distinguish, and assess the various approaches used in Okra plant field management. For the classification, we have applied the transfer learning idea. The primary benefit of employing transfer learning is that, rather than beginning from blank, the model learns from previously discovered patterns when addressing a problem that is comparable to the one at hand. This allows the model to leverage current data rather than starting from scratch. When pre-trained models are used to photo classification, transfer learning is frequently demonstrated. If a model has been trained on a sizable benchmark dataset to address an issue akin to the one, we need to solve, it is said to be pre-trained. For our investigation, CNN pre-trained model weights were employed. This section outlines the procedures used to locate, select, and acquire the data required for this systematic literature review. Finding, assessing, and looking at prior pertinent research that is important to the objectives of the current study is the aim of doing a systematic literature review.

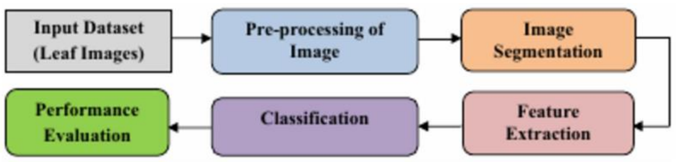

Figure 3: Methodology flow

Pre-Processing: The method used to improve the quality of the input image is called pre-processing. Given that a noisy image directly affects the classification of diseases, it is a crucial stage in the recognition process. To improve an input image of plant leaves, this technique employs three steps: edge enhancement, contrast correction, and denoising. Following pre-processing, exact differentiating evidence using the input photos requires efficient and skilled picture division. It is the only method that can utilize to improve the performance of clear images material. Pre Processing is the necessary stage for image identification of illness of plant. This method uses three steps—edge enhancement, contrast correction, and denoising—to enhance an input image of plant leaves. Effective and proficient image division is necessary for precise differentiating evidence employing the input photos after pre-processing.

Image Segmentation: Diseased Plant Picture is sent to the segmentation step following pre-processing. While splitting, every image is split up into a vast number of parts or areas. The number of parts is primarily determined by the application and user needs. The plant leaves are segmented using AHKM-FCM. During image segmentation, the image is precisely and sharply divided into segments. A fragment of an image composed A previously removed group of the outlines in the picture is the end product of image segmentation. Segmentation's primary objective is to efficiently alter or streamline the image's existing representation in order to do the evaluation. Segmentation of images efficiently separates the image for further processing. Every pixel is given a value during the photo segmentation process. The leaf sections are divided into afflicted or unaffected segments in this differentiation.

Features Extraction: Post segmentation, it gets place to perform the extraction of features and it occurs by using 13 characteristics of leaf images. Five Feature extraction involved the extraction of feature groups. They are geometric features, leaf-related traits, characteristics of color, texture, and fractals. Most studies on the recognition of plant leaf pictures only takes into account the texture, color, and leaf characteristics. The geometrical and fractal properties in this study were taken into account as well. Following their retrieval, these attributes were categorized into three main categories: shape, color, as well as texture. These features are fed into the classifier as input for further processing. The method is just conducted in order to clearly compare the data set and the derived findings, given the expected presence of illnesses that have affected the leaves.

Picture Categorization: In this particular area the task is identified those Okra plant whose incoming leaf picture can respond. The central component of the algorithm consists of an iterative recognition process that contrasts properties from the input image with feature vectors matching the pre-built dataset's pictures of plant leaves. This is crucial because even a single sick plant potentially spread the illness. Furthermore, most farmers are not sufficiently knowledgeable about these disorders and effective solutions. The expense of recruiting specialists could be high, and handling pesticides improperly will damage the environment. As a result, we have developed a brand-new approach to deal with this problem.

Performance Evaluation: Using a variety of measurement criteria, the confusion metrics are utilized to assess overall performance. Divergent measurements were used to build and examine the model. The actions that follow look into how the suggested model works.

Significance of Research

Global food security and economic growth depend on agriculture, yet crop yield, quality, and sustainability are still seriously threatened by plant diseases and insect pests [1, 2, 3]. The primary method of traditional detection is manual inspection by farmers and specialists, which is labor-intensive, subjective, time-consuming, and challenging to implement on a broad scale [4, 5, 6]. Additionally, traditional image-processing techniques that rely on manually created features are not very resilient in a variety of environmental circumstances. By directly learning pertinent properties from photos, recent developments in deep learning, especially convolutional neural networks (CNNs), have greatly enhanced automated plant disease and pest identification. While transfer learning and pre-trained models have improved performance with limited agricultural data, research has moved beyond image classification to object detection, segmentation, and change detection [7, 8, 9, 10]. Nevertheless, there are still issues, such as small lesions and pests, complicated field backgrounds, imbalanced and restricted datasets, computational demands, and inadequate model generalization to actual situations [8,11–13]. Thus, this study examines current deep-learning methods for plant disease and pest detection, emphasizing key methods, datasets, assessment strategies, difficulties, unmet research needs, and new directions like explainable AI, computing at the edge, lightweight models, and real-time precision agriculture. The review's objectives are to compile existing information and pinpoint viable paths for precise, scalable, and field-ready agricultural tracking systems.

This paper first examines common datasets and conventional plant disease and pest detection techniques in order to lay the groundwork for the investigation. They successfully highlight the benefits of deep learning approaches in determining the cause of parasites and plant diseases by reviewing the uses and drawbacks of conventional methods. The foundation of deep learning model training is datasets, which are also crucial for the use of the use of deep learning software in professional settings of plant diseases and pests. Tiny, white, powdery, spherical to uneven patches initially appear on the exteriors of the top and bottom leaves. Stem cells, petioles, and leaves can all become infected areas. The disease initially affects older leaves before migrating to new ones. Ultimately, the impacted foliage transforms into dead and yellow in color. taurica develops: Light-green to bright-yellow spots show up on the top edges of plants throughout the first moments of infection. These areas later develop necrosis. Infected leaves curl inwardly and show a powdery, white growth on the undersides. When there are many scars, they typically mix to induce dropping of leaves and broad chlorosis. Newer leaves are impacted as the disease progresses. Fruits on afflicted plants may become burnt due to continuous direct daylight.

Figure 4: Shows the diseased Okra plant

III. LITERATURE REVIEW

Year	Author Name	Technique	Methodology	Results
August, 2019	Yogesh Popat Khade Raj Kumar, Ramesh Kumar Yadav [6]	"Qualitative genetic analysis was done in segregating generations."	The percentage prevalence (PDI) of YVMV illness and the number of days until the disease's initial onset (vein emptying of any kind on any bush) were assessed. The proportion of diseased plants in the population at 30, 60, and 90 days after sowing was tallied and reported as an amount for YVMV incidences.	This came to light that a significant prevalence of infection was caused by the early onset of YVMV illness symptoms. The plants that had YVMV illness prior to flowering had the lowest yield. They were therefore chosen for the genetic examination to mimic their parents. DOV-66 was identified as the genetic make-up most resistant to YVMV illness in a previous investigation.
August, 2020	Yogendrayadav, Praveen Kumar Maurya, Tridip Bhattacharjee, Swadesh Banerjee, Subrata Dutta, Asit Kumar Mandal, Arup Chattopadhyay And Pranab Hazra [7]	biochemical parameters	No precautions were made for the white fly infection in order to permit the number of mosquito vectors to increase during the growing season. From 20 days after sowing (DAS) to 80 DAS, the vegetative openness of each plant in the group to both YVMD and OELCuD was assessed at 20-day intervals.	The extent of the condition differed significantly between the two opposing cross combos' offspring. On the other hand, the F2 population of the VRO178 * BCO-1 cross showed a high illness severity (44.06%).
May, 2024	Ranjana Thakuria, Jeevitha N, Lavanya S, Kruthika S, Sahana M G [8]	Convolutional Neural Networks (CNNs)	Acquired a varied collection of plant photos from public collections, encompassing both normal and diseased species. used a CNN model architecture that included fully connected layers for identifying objects, layers with maximal pooling for downsizing, convolutional layers for acquiring features, and ReLU activation techniques for discontinuity.	CNN-based models have shown impressive skills in correctly recognizing unhealthy plant specimens from photos when a strong methodology that includes data collection, model training, hyperparameter tweaking, and deployment is used. Farmers have benefited from the effective use of CNN models in plant disease detection systems.
May, 2025	Maanyatha Mahesh, Suloni Praveen, Swathi Meghana K R, Supriya T C, Shraddha C [9]	CNN, Deep learning, and other machine-learning algorithms	Researchers gathered information for 2000 photos of both healthy and diseased okra leaves and arranged them into train, validation, and test folders. Finding the yellow vein mosaic disease in okra leaves is the aim. The first step in creating datasets is to take pictures of the okra crops. Numerous research describe how to classify and detect plant diseases. In machine learning and neural networks, several algorithms are used, such as those that employ categorization and regression techniques.	The amount of time wasted manually identifying an infectious onslaught has decreased with the use of machine intelligence and deep learning techniques. Numerous suggested tasks have effectively attained a proficiency level between 93% and 98%. In order to help landowners, crops, and levels of nutrients, we are working to train such a model to generate better, greater precision and quicker results than earlier published projects.
September, 2024	Robertas Damasevicius, Faheem Mahmood, Yaseen Zaman, SobiaDastgeer and Sajid Khan [10]	Machine Learning Models, Image Processing and Deep Learning approaches, Convolutional Neural Networks (CNNs), VGG-16	This investigation looks at ways to identify bacterial, fungal, and viral diseases of leaves in plants. Fifty thousand carefully chosen images of both healthy and ill farming plant leaves are included in the dataset. plant leaf diseases caused by bacteria, fungi, and viruses. This study's primary objective is to accurately categorize stems into four groups: bacteria, fungi, virus, and good.	Initially, the accuracy, precision, recall, and F1 score of deep learning methods are evaluated. To find out which technique worked better and why, the outcomes are examined.

October, 2021	Rashidul Hasan Hridoy, Maisha Afroz , Faria Ferdowsy [11]	Image Augmentation techniques, deep learning models such as InceptionResNetV2, Xception, ResNet50, MobileNetV2, VGG16, and Alex Net.	The overall total of photos is raised to 124760 after employing image augmentation techniques, and each image is periodically assigned to training, testing, and test images by 80%, 15%, and 5%, respectively. To improve the ability to identify objects of CNNs with less photos, a number of image method of augmentation were widely used in DL-based recognition systems.	Fifty thousand carefully chosen images featuring robust and sick farmed plant leaves make up a data set. scabby yellowing, rust, blistering, mites, mossy foliage wrinkles, coloration, bacterial spot, and shrinking are among the various fungal, bacterial, and viral diseases that impact the leaves of crops. The aim of this research is to accurately categorize leaves into four groups: bacteria, fungi, virus, and benign.
April, 2020	Meenaxi M Raikara, Meena S Mb Chaitra Kuchanurc, Shantala Girraddid, Pratiksha Benagi [12]	Deep Learnig models(AlexNet, GoogLeNet and ResNet50)	To eliminate noise from the photos, they undergo pre-processing. To make the dataset the same size, the photos are shrunk to 224x224x3 pixels. The method's visual representation and CNN's structure are both utilized. These networks are trained by transfer learning. The user can remove any layer that is pertinent to the new dataset as well as some of the layers using transfer learning. A fully connected layer is the final CNN layer with learnable weights. Since there are four classes in the study, the final layer is swapped out for a new fully-connected layer with four axons.	Overall accuracy, sensitivity, specificity, and precision are computed using the CM data. The proportion of test samples that are correctly identified is known as accuracy. The proportion of tuples that are positive and that the classifier predicts would be positive is known as sensitivity. Precision is the same as sensitivity and can also be referred to as exactness.
January, 2025	Hany S. El-Mesery , Ahmed H. ElMesiry, Evans K. Quaye, Zicheng Hu, Ali Salem [13]	Machine Learning, SOM (Self-Organizing Map) algorithm	This investigation describes how okra segments are dried using a method that combines convection and optical heating, and how this impacts the okra's phytochemical content and physicochemical properties. Fresh okra pods (Abelmoschus esculentus L.) of comparable sizes, shapes, and colors were bought at a nearby market. After that, they were kept for a day at 4 C in a refrigerator. Before the experiment started, the okra pods were removed and let to stand at room temperature for an hour. The main objective of this kind of treatment was to inactivate enzyme activity.	The elevated degree and enhanced sunshine from the okra slices are the causes of this phenomenon. An et al. (2024) claim that increasing the infrared beam's degree can cause food to dry more quickly. The higher solar intensity causes a greater temperature discrepancy on the surface of the item or deeper slices, which accelerates the rate at which moisture dries as well as lowers the total quantity of moisture removal required.
March, 2022	Aravind Krishnaswamy Rangarajan & Edwin Jayaraj Balu & Muni Sekhar Boligala & Arjun Jagannath & Badri Narayanan Ranganathan [14]	Deep Learning Model (Squeeze Net and ResNet-18), Class Activated Mapping (CAM)	Using the drone with different workloads in an increasing sequence starting with an initial weight of 100 gms proved the laborious investigation. Using MATLAB Simulink, a simulated experiment was conducted to choose the proper instrument rating in the battery conversion process. The semiconductor's design and the voltage that signals it produced	For the duration of the instruction, the learning rate remained constant. First, both algorithms reported inferior minibatch and validation accuracy since they begin with pretrained parameters and the parameters of the added layer are random. Squeeze Net reported a validation accuracy and loss of 43.4% and 0.934 at the conclusion of their initial iteration.
December, 2024	Elham Tahsin Yasin, Kemal Tutunc, Murat Koklu [15]	Machine Learning Algorithms (k-Nearest Neighbors (kNN), Support Vector Machine (SVM), and Logistic Regression (LR)), Feature Extraction Methods ((Deep Loc, Squeeze Net, and VGG19))	Machine learning methods were used in this study to classify a dataset of pictures of okra. The subsequent section contains the dataset's specifics. 501 photos in all were used, and each one was subjected to a feature determination procedure. To compare the outcomes, three distinct feature extraction techniques were used. Ten folds were employed while dividing the collected features into tests and training sets using the cross-validation approach.	Findings for the identification of okra ripeness using several methods for removing features (Deep Loc, Squeeze Net, and VGG19) and machine learning algorithms (kNN, SVM, and LR) are shown in terms of the area under the ROC curve (AUC), classification accuracy, precision, recall, and F1-score.
December, 2024	Pitchakon Papan, Witsarut Chueakhunthod, Chanwit Kaewkasi, Wanploy Jinagool, Akkawat Tharapreuksapong, Arada Masari, Sumana Ngampongsai, Kanlayanee Sawangsalee, and Piyada A. Tantasawat [16]	Artificial neural network (ANN) model, deep learning framework, EfficientNet-B3 architecture	2220 mung bean (Vigna radiata (L.) R. Wilczek) leaves, both asymptomatic and symptomatic for Cercospora leaf spot (CLS), were taken from 65-day-old plants of nine parental cultivars/lines: V4718, V4758, V4785, Chai Nat (CN)72, CN84-1, CN3, Kamphaeng Saen (KPS)1, Suranaree University of Technology (SUT)1, and KING. Additionally, ten promising breeding linesz and H4 were collected, which varied in resistance to CLS and powdery mildew. A Fuji Xerox DocuPrint CM305df (Fuji Xerox, Tokyo, Japan) was used to scan each mung-bean leaf at a resolution of 2480 × 3507 pixels with 24 bits of color depth per pixel. The images were then stored in TIFF format.	Cercospora canescens-infected mung bean leaves of various severity and healthy leaves comprised our own datasets. 90% of the photographs (396-410) in each class were chosen at random to be used as the training set, and the remaining 10% (43–45 images) were used as the validation set. Python was used for the ANNs' training and data augmentation. Thus, EfficientNet-B3 was chosen for additional field testing with a smartphone.

May, 2021	MTVasumathi, M kamarasan [17]	combined (CNN) Convolutional Neural Networks , Long-Short Term Memory (LSTM) deep learning model	Given the deep characteristics that were retrieved using CNN and LSTM networks, a deep model is suggested in the current study. Fully connected layers are used for gathering the deep characteristics. The LSTM layer receives the retrieved deep features as input. Following the LSTM layer, which is an entirely linked layer, the images are sorted into either normal or abnormal categories, denoted by class labels 0 and 1, respectively, using a softmax layer and a classification layer. Before adjusting the deep network parameters in the current investigation, that we acquired deep features using instances.	Using the DSLR and iPhone cameras, pictures of produce are taken while visiting twelve farms. The photos were taken during the day. A few of the photos were taken from the Cofilab and Kaggle datasets.The Python toolkit was used to implement the suggested model. An 8-core CPU with four performance and four efficiency cores, an 8-core GPU, a 16-Neural engine, and 8GB of unified memory were used in the experiment. 38% of the dataset was utilized to test the proposed model during the trials, whereas 62% of the dataset was used for training.
June, 2023	Shraddha C, Maanyatha M, Suloni Praveen, Supriya T C, Swathi Meghana K R [18]	CNN, Deep learning, other machine-learning techniques	The suggested approach seeks to identify leaf segments from a range of complicated situations and categorize them as either healthy or early-stage bacterial wilt-infected plants. First, the database is separated into test and training sets. Training sets are also subjected to the ground-truth production process, which produces a database of ground truths that match training sets. Training sets and their matching ground truths are processed by the semantic segmentation module using U-net. Additional test sets are fed into the semantic segmentation module in order to get the segmented output. The classification is done using the Resnet18 model.	An accuracy of 63% is achieved at a learning rate of 0.001 when the effectiveness of semantic segmentation using U-Net is first assessed with a batch size of 16, 240 steps per epoch, and 30 epochs. On the subsequent try, we used batch size 8, learning rate of 0.0001, and 80 epochs to get an accuracy of 94.51% and a validation reliability of 91.33% with 11.78% loss. But the information set, image capture settings, preprocessing methods, network structure, and analysis criteria all have a significant impact on how well the model performs. Contextual variability continues to be a significant obstacle for accurate illness detection, as studies utilizing field-acquired pictures generally show lower and more changeable performance than those using regulated or baseline data sets [15–18]. For instance, CNNs were able to achieve over 99% accuracy based on the Plant Village dataset; however, when models were tested under more realistic circumstances, efficiency significantly declined. The efficacy of preconditioned CNN models for detecting plant diseases was demonstrated by outstanding classification results using transfer-learning-inspired architectures, which evaluated multiple deep learning algorithms and reported classification precision above 99% for an extensive set of plant pathology pictures, adding to the possible application of CNN-based techniques.

IV. RESULTS

In this section the outcomes shows that deep learning specially convolutional neural networks (CNNs), has rapidly improve the digital identification and categorization of many plants and their illnesses. [26]. Nevertheless, these results also indicate that high accuracy on controlled datasets does not necessarily translate into equivalent performance in field environments. Recent studies have therefore emphasized the importance of diverse field datasets, data augmentation, transfer learning, and improved preprocessing to enhance model generalization [21, 22, 23, 24, 25]. The reviewed results further show that modern architectures can automatically extract discriminative features from plant images, reducing the dependence on traditional handcrafted feature engineering. However, challenges remain in recognizing early-stage symptoms, small lesions, overlapping disease patterns, complex backgrounds, and visually similar diseases. Overall, the evidence from prior studies confirms that deep learning provides a strong foundation for automated plant disease detection, while continued improvements in dataset diversity, model architecture, preprocessing, and real-world validation are necessary to achieve robust and generalizable performance.

We used the standard open-access Okra plant dataset, which consists of diseased plant leaves, for both training and testing. The CNN model must be developed and trained so that the same network may be used for different crop classes. The images of both sick plant leaves, which were collected under controlled conditions, are available in a publicly accessible dataset. indicates how well existing CNN designs perform when tested on a variety of illness classifications. Given the models, data sources, pre-processing techniques, and evaluation of the overall efficacy of the proposed CNN models, the image demonstrates the poor performance of the models across multiple illness classifications. The findings indicated that most CNN models could only process unstructured raw picture input to a limited extent.

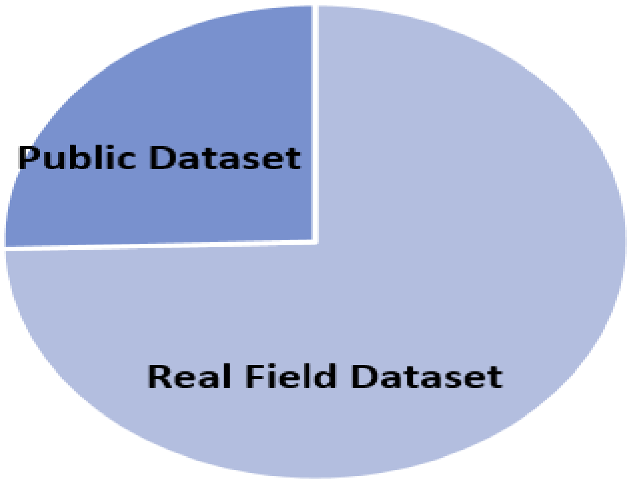

Figure 5: Pie Chart of Used Dataset

Challenges in CNN Implementation

This stage focuses on discussing a few some of the remaining obstacles. The results could be useful for better image preprocessing, classification, and later early crop disease identification. CNN's major hurdles are figuring out their objectives and training a large number of spectrum picture inputs. Classifying the changes from the provided input data has become much more challenging for CNN classifier applications. One of the other most difficult parts is utilizing CNN classifiers to analyze the spectrum mixes. CNN classifiers frequently incorporate ideal attributes including texture, color, and object shape to categorize a variety of agricultural diseases. When the standard pictures are linear, training these parameters is simple. Only when there are hundreds of continuous spectral bands can such hyperspectral data be trained. Additionally, extracting information from neighboring spectral bands in different spectral regions of a network is very redundant. There are still issues with using more advanced CNN technology. Because different researchers have varied ideas about how to use automated techniques like computer vision and image processing, few problems cannot be handled with them. The scope of the models that have been put forth thus far is limited, and they rely on the context of data collection. It might lead to the capturing of unique behaviors that complicate picture processing for disease classification and prediction. The following other concerns have been found to have the biggest impact:

- It takes more than simply new computer vision technology to diagnose illnesses automatically.
- The setting in which the data that was input was gathered may significantly affect the analysis of ailment categorization.
- Because the signs of illness are not well defined,
- it is challenging to tell which portions are healthy and which are sick.
- The visual similarities in the indications of sickness may require the present procedures to rely on distinctions to discriminate.
- It was excluded from the evaluation of the severity of the illness and its management.
- Although they are inaccurate, CNN models trained on smaller datasets may be more accurate.
- Any CNN running on a CPU will have a higher computational cost than one running on a GPU.

V. DISCUSSION

Crop identification of diseases is crucial because it affects the productivity of agriculture and the availability of food worldwide. Conventional methods of disease identification frequently depend on labor-intensive field investigations and inspection by hand, which are laborious and vulnerable to mistakes by humans. However, in recent years, the development of optical sensors in conjunction with machine learning (ML) algorithms has presented an appealing answer to this issue, allowing for the quick and accurately finding of crop diseases. Prior research has shown that photographic techniques are capable of recognizing a variety of plant illnesses, exhibiting their capacity to pick up weak visual cues that indicate infectious agents or physical stress. Producers may use cellphones to snap pictures of their crops, which they can then send to a remote cloud platform where machine learning algorithms will analyze and give analysis. An Android smartphone deep learning model for sugarcane disease diagnosis. The model showed promise as a practical and affordable instrument that uses the farmer's current smartphone for in-field diagnosis, with an accuracy of 65%. Photographers mounted on UAVs and ground-based devices may swiftly and effectively monitor wide regions by taking high-resolution pictures of the vegetables [19].

Precision agriculture relies heavily on remote sensing technologies to help with resource management, early problem identification, and ecologically friendly methods. Unmanned aerial vehicles (UAVs) are now useful instruments for gathering comprehensive Recent advances in data handling and satellite imagery have made it possible to obtain data on ailments of plants with high geographical, chronological, and spectral precision [20].

A thorough examination and evaluation of recent studies is necessary to give a broad overview of the changing approaches in the surveillance of plant diseases and to systematically evaluate the possibilities and constraints of such approaches, especially in light of the expanding corpus of academic research focused on UAV-based disease detection. To gather information and determine current research trends in UAV-based plant illness detection uses and monitoring, this study conducts a thorough quantitative literature evaluation. The findings show a global gap in the field's research, with the largest contributors (43 out of 103 articles) are Asian nations [21, 22, 23, 24]. Webbing reduces transpiration and photosynthetic activity, stunts plant growth, causes premature leaf drying that leads to leaf fall, and eventually kills the entire plant. Even an expert would have a high chance of misidentifying red spider mites due to their more vague or undecided taxonomic categorization. The cases of mite species confusion and misidentification would be significantly reduced by an integrative strategy utilizing morphological and genetic data. ITS2 sequence divergence can be used to distinguish between closely related species and species complexes. Researchers have also examined how temperature and relative humidity affect the biology of red spider mites and found that the ideal temperature range for mite survival is between 30 and 35°C. okra, or Abelmoscus esculentus (L.) Moench, is a vegetable with significant commercial value. the top spot in okra production, accounting for 62% of global production. Six mite pest species are said to be the main culprits behind okra infestations. The red spider mite, Tetranychus sp. (Arachnida: Tetranychidae), is one of the most significant phytophagous mite groups. Spider mites provide a possible threat to agriculture due to their very polyphagous nature, high developmental rate and fertility, dispersal to new host plants, arrhenotokous parthenogenesis, quick development of pesticide resistance, and extremely small size. An average of 9.15–100% of vegetable crop output was lost as a result of mite infestation [22].

Okra's qualities, including its soft stems, seeds, succulent pods, fresh leaves, buds, and blooms, allow it to be used for a variety of purposes. Given that it possesses higher concentrations of food nutrients including proteins, calcium, vitamins C, and carbs, its economic significance cannot be overstated. In addition to being a healthy source of oil and protein, okra seeds can be used in place of coffee [18]. The knot in the root. The main nematodes that affect okra globally, including in Nigeria, are nematodes. They damage almost every crop and are widely dispersed, which lowers agricultural productivity. The primary species influencing the development of okra is Meloidogyne incognita. When the nematode population above the economic threshold level, meloidogyne species induce wilting, chlorosis, stunted development, and the creation of galls in the roots of most crops. This frequently results in root destruction, poor growth, low yield, and crop failure [23].

Concerns about the widespread use of chemical control techniques in agricultural production across the world have grown in recent years, mostly because of their harmful effects on creatures that are not the intended targets. The significance of technology-driven solutions for plant disease management in agriculture is highlighted by this circumstance. One such technological advancement that has shown promise for the early identification of plant diseases is thermal imaging technology [11]. Plants are frequently stressed by infections, which causes the temperature at the infection site to rise or fall. It is hypothesized that thermal imaging might be used to detect these temperature changes in plant tissues that are ill in the early stages. The semi-fibrous plant known as okra (Abelmoschus esculentus) belongs to the Mallow family. In moderate areas, it is cultivated as a single plant; in hot climates, it is grown as a perennial. Although okra is cultivated for its fruit, its leaves, seeds, flower parts, and stems also have valuable commercial uses [28].

A key topic in agricultural computational modeling is comprehending how plant diseases and pests affect crop performance. In the past, efforts were made to create theoretical models that took into consideration how genotype, environment, and management interact to explain how pests and diseases affect yield separately. In 1982, the idea of a manufacturing situation was first presented. Another component of a production scenario that involves farmer crop management is pest and disease control. This widely recognized classification of yield levels groups water and nitrogen stress as limiting factors to feasible output and considers crop genetics as a factor determining prospective yield [12]. Three different kinds of yield were identified in a subsequent investigation. In agricultural systems, insect pests play a major role in crop output and storage losses. In tropical nations, these parasites are thought to be responsible for 60–70% of losses, mostly in stored goods. Our globe is home to an astonishingly diverse range of animal species, including insects. Aside from the open water, insects can be found in swamps, woods, deserts, and other extremely hostile settings. With an unmatched degree of adaptation and a vastly larger population than any other animal group, insects are genuinely amazing beings. Both humans and the environment are greatly impacted by insects, which are essential to our ecology. Insect pests seriously damage crops, farm animals, and people [25].

Okra is a significant vegetable that is cultivated for its soft, green fruits, which may be prepared in a number of ways. Among other minerals, it is abundant in calcium, potassium, and vitamins. If you have the right ingredients, it's quite easy to make and fry. You may chop the soft fruits into little pieces, boil them, and serve them with soup. Crude fiber-containing mature fruit and stems that are used in industry. The finest information carriers are models, which represent decision makers' ideas and imaginations about their domains in abstract terms using symbols or numbers rather than real, tangible objects. Users of the knowledge-based system AIES can ascertain the appropriate feasibility assessment for the establishment of agro-industries, which takes into account the connections between the various aspects of the decision-making process in the areas of marketing, technical, legal, financial, economic, and environmental feasibilities. In some cases, growers of vegetables have a fantastic chance to make more money quickly than growers of fruits. Vegetable farming is a short-term venture that yields higher earnings than orchards, which are a long-term enterprise. The most essential food for human health is vegetables. Vitamins, minerals, salts, sugars, protein, carbohydrates, calcium, and water are all found in these veggies. In addition to their nutritional worth, all vegetables are beneficial to human health [26, 27].

Diseased farming plants is effected by the outcome of Crops production of the nation. Plants are usually closely monitored by growers or other professionals to identify and detect diseases. However, this procedure is frequently costly, laborious, and imprecise. Finding a spot on the leaves of the infected plant is one way to identify plant diseases. This work aims to develop a disease recognition model that is backed by the classification of leaf images. We are using image processing with a convolution neural network (CNN) to identify plant illnesses. An artificial neural network type designed especially to analyze pixel input and utilized in image identification is called a convolutional neural network (CNN) [27]. The fungus Sclerotinia sclerotiorum (Lib.) de Bary is the cause of white mold, a serious biotic stressor that affects field and horticultural crops all over the world. This disease results in significant yield losses by causing plants to wilt and eventually die.The pathogen has a poor population structure and a homothallic mating system. The illness often spreads in environments with prolonged precipitation and rather low temperatures. Defense responses against S. sclerotiorum are supported by a series of molecular and physiological processes that are triggered at each stage of infection. Molecular indicators can aid in the quick detection of this plant disease. Changing the agricultural microclimate, using fungicides, lowering the sources of inoculum, and creating resistant plant kinds are all examples of effective management techniques. The best outcomes are frequently obtained through integrated methods that combine such tactics [28, 29].

The strain on agricultural products to fulfill the globe's growing need is at an all-time high in the modern world due to population growth. Even with advancements like plants that have been manipulated intelligent farming, and composting, there remain a number of areas that require attention. Plant diseases are one of the primary areas of attention that are mostly ignored. There is little to no room to think about plant well-being and disease detection in many impoverished nations with limited access to human healthcare. As a result, ailments of plants cause a significant loss of yield [29]. Global kiwifruit output increased from 2.84 megatons in 2010 to almost 4.46 megatons in 2021, according to statistics data. Iran produced more than 0.29 megatons of kiwifruit in 2021, placing it fifth among kiwifruit producers. The most accurate classifier to distinguish between infected and non-contaminated kiwifruits was the linear discriminant analysis (LDA), which was created using SNV-filtered spectral data. In the cross-validation and assessment phases, its accuracies were 96.67% and 96.00%, respectively. Prior to the onset of disease signs, the system was able to identify infected samples [30].

Figure 6: Okra having the powdery mildew

Figure 7: Okra with southern blight disease

Figure 8: Twisting of stem and leaf petiole of Okra

Figure 9: Enation of infected leaves of Okra

Figure 10: The Loopers (cabbage looper) of Okra

Figure 11: Okra's yellow vein mosaic disease

There are small, spherical, dark-colored, wet lesions on pods, leaves, and branches that swell up and get sticky; White, cottony fungal growth covers the blossoms; Insufficient moisture can cause cottony white growth to appear on scratches, and the vine as a whole or its subsidiary branches may wither. A tiny pinhead enation may be seen on the bottom surface of the leaves. This enation gets harsh and warty. decrease in leaf size. Along enation, the stem, lateral branches, and petioles of the leaves twist. Curling is seen on the leaves. Patches of green and yellow alternate on the diseased leaves. The stems and leaf stalks become twisted at the advanced stage. Veins get chlorotic and transparent. The fruits are tiny and have a yellowish green hue. Rapid leaf withering, yellowing foliage, browning of the stem above and below soil, browning of the branches, and possibly a fan-like mycelial mat covering the stem. Leaves may have a powdery white coating; if the plant is severely diseased, the leaves may roll upward and appear burnt. Patches may even combine to cover the entire plant. Caterpillars are pale green with white lines down either side of their bodies; leaves may have large or little holes in them; damage is frequently substantial. yellow-stippled leaves that could look bronzed; leaf webbing; mites can be seen as tiny, usually invisible until the plant shows signs, moving specks on the webs or underneath of leaves are best viewed with a hand-held lens; Petals may drop from the growth before they develop yellow.

VI. CONCLUSION AND FUTURE WORK

Deep learning's potential in managing plant pests and diseases is clear because of its strong feature extraction and data processing skills, which offer notable benefits in tasks like object detection and image categorization. To guarantee the usefulness and scalability of these technologies, significant restrictions and difficulties still exist and need to be resolved. Model training is another important constraint. Before being used, deep learning models need a lot of processing power and a lengthy training period. In order to overcome this difficulty, numerous studies have looked into model light weighting strategies, which increase training effectiveness by lowering the amount of model parameters. Future studies should concentrate on creating end-to-end plant pest and disease detection systems and using deep learning models on terminal devices. Because harvesting practitioners frequently need clear decision-making procedures to trust predictive models while taking necessary steps, deep learning algorithms' insufficient comprehension further restricts their practical application. In order to bridge the gap between technology developments and real-world agricultural applications, future initiatives should prioritize the creation of interpretable frameworks that offer actionable information.

To fully utilize deep computing in plant pest and disease management, these present constraints must be addressed. CNN classifiers for image processing have a lot of potential for applications like pattern identification in a variety of sectors, plant disease diagnosis, and food production quality management. The taxonomy of eggplant is expanded by the consequences of this study, which may have uses in other plant and agricultural species. This invention has the potential to improve crop classification and agricultural research. Convolutional Neural Networks (CNNs), a type of deep learning, have demonstrated exceptional efficiency and accuracy in identifying and classifying eggplants in a range of contexts. Because CNNs effectively extract and learn features like shape, texture, and color, they are robust against environmental changes like light and occlusion. Because of this breakthrough's huge potential for agricultural automation, farmers will be able to improve crop monitoring, quality evaluation, and harvesting operations with less human work.

Future studies might focus on improving dataset diversity, fine-tuning hyperparameters, and integrating the system with edge computing for on-field applications. Deep learning techniques, which offer accurate and automated diagnosis of a variety of plant diseases, have shown impressive effectiveness in the identification of eggplant infections. Convolutional Neural Networks (CNNs) and other deep learning models can evaluate eggplant images to precisely detect symptoms including fungal infections, leaf spots, and discoloration. These models eliminate the need for human inspection, allowing for early disease detection and timely intervention—a critical component in boosting agricultural productivity and reducing losses. Additionally, because deep learning-based systems may be connected to Network of Things and mobile applications for continuous disease monitoring, they are helpful tools for modern precise farming. Prospective studies may focus on enhancing modeling generalization by combining several datasets, optimizing architectures, and developing lightweight models suitable for deployment on edge devices. New algorithms with improved performance and more data sets can be added to improve accuracy. One can also generate a valid set by experimenting with different methods. development of a hybrid strategy with two heads. In addition to automated and boring methods, a variety of dynamic equipment will be used to do dynamic analysis. A simple yet powerful probability-based classifier, Transfer Learning handles some of the time-consuming tasks for you. It can also be used to find some useful parameters for other machine learning techniques. can be employed by farmers in isolated locations to identify disease. The method might be used to detect diseases in other Solanaceae plants, such potatoes, tomatoes, and peppers, to enable broader application in agricultural disease control. In ultimately, because of its remarkable image processing capabilities, deep learning has enormous promise and research value in recognizing of plant pests and diseases.

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