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Harnessing Deep Learning for Plant Disease Identification

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Abstract: Deep learning is a branch of artificial intelligence. In recent years, with the advantages of automatic learning and feature extraction, it has been widely concerned by academic and industrial circles. It has been widely used in image and video processing, voice processing, and natural language processing. At the same time, it has also become a research hotspot in the field of agricultural pl ant protection, such as plant disease recognition and pest range assessment, etc. The application of deep learning in plant disease recognition can avoid the disadvantages caused by artificial selection of disease spot features, make plant disease feature extraction more objective, and improve the research efficiency and technology transformation speed. This review provides the research progress of deep learning technology in the field of crop leaf disease identification in recent years. In this paper, we present the current trends and challenges for the detection of plant leaf disease using deep learning and advanced imaging techniques. We hope that this work will be a valuable resource for researchers who study the detection of plant diseases and insect pests. At the same time, we also discussed some of the current challenges and problems that need to be resolved.

***Index Terms* -** plant disease; deep learning; convolutional neural networks (CNN**).**

1.INTRODUCTION

Plant diseases can significantly impact crop yields and food production. Detecting diseases early is crucial for effective treatment and crop protection. Traditional methods rely on manual inspection, which can be slow and prone to errors. A more efficient approach involves using computer-based image analysis to examine plant leaves.Diseased leaves often show visible changes in color, texture, shape, and size. However, manually analyzing these images is time-consuming and requires expertise. Artificial Intelligence (AI) offers a faster and more precise solution. Specifically, Convolutional Neural Networks (CNNs), a type of AI, excel at identifying patterns in images.For plant disease detection, CNNs are trained using a large dataset of leaf images, each labeled with different diseases. Once trained, these networks can rapidly analyze new images, identify diseases, and even suggest possible treatments. This enables farmers to take timely action and safeguard their crops more effectively.

Convolutional Neural Networks (CNNs)

A Convolutional Neural Network (CNN) is a specialized AI model designed for image recognition and analysis. It plays a vital role in computer vision and deep learning applications, such as object detection and image segmentation.Unlike traditional neural networks that treat images as numerical data, CNNs process images by recognizing spatial structures. They can detect features, such as shapes and patterns, by analyzing different sections of an image. This ability makes them highly effective for image-based tasks, including plant disease identification.One of the key components of a CNN is the convolutional layer. This layer uses small filters, known as kernels, that move across an image, examining small sections at a time. By doing so, CNNs can extract essential features, such as edges, textures, and distinct patterns, which are crucial for identifying diseases in plant leaves.

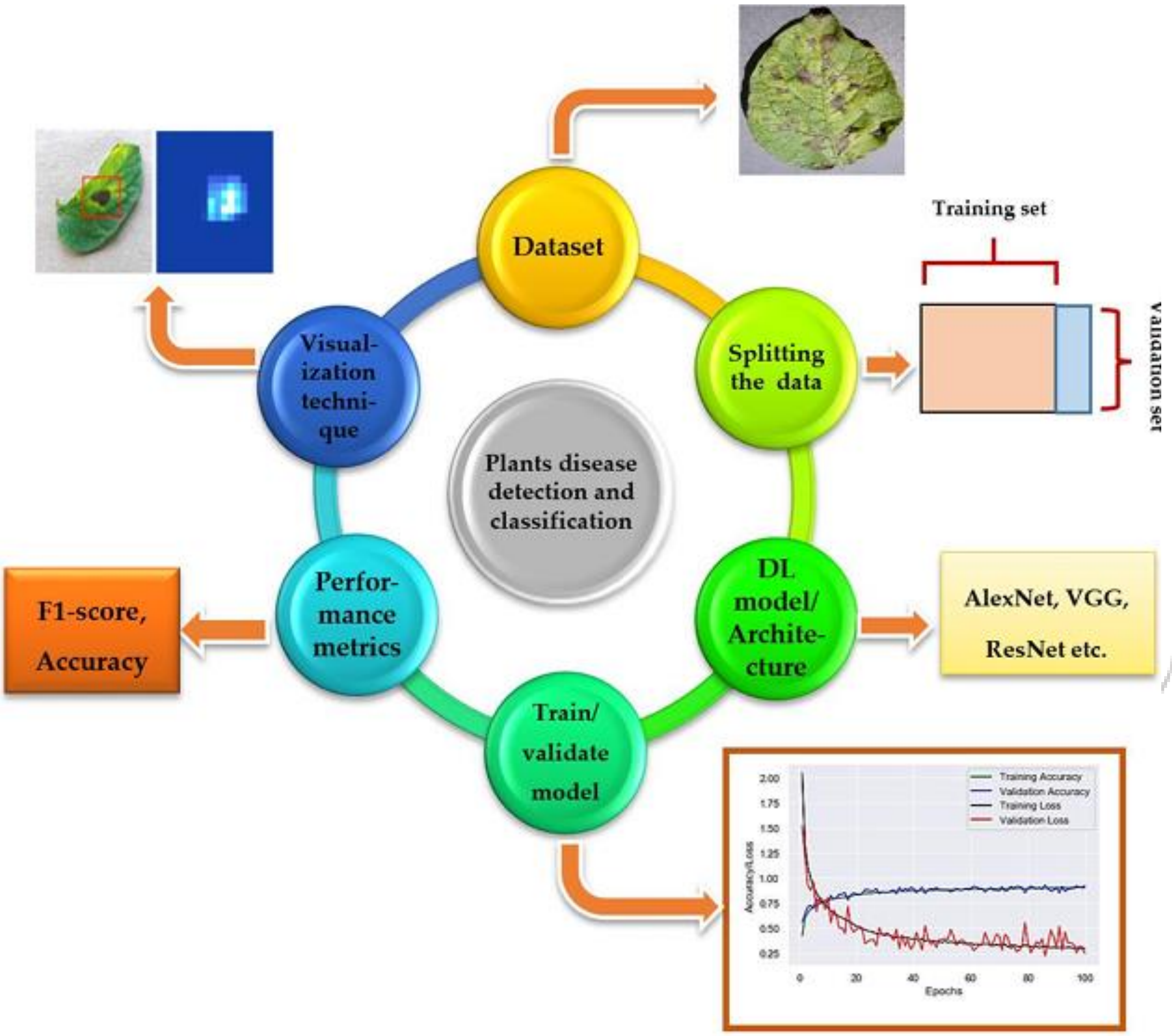

Figure 1. Flow diagram of DL implementation: First, the dataset is collected [25] then split into two parts, normally into 80% of training and 20% of validation set. After that, DL models are trained from scratch or by using transfer learning technique, and their training/validation plots are obtained to indicate the significance of the models. Then, performance metrics are used for the classification of images (type of particular plant disease), and finally, visualization techniques/mappings [55] are used to detect/localize/classify the images.

2. Plant Disease Detection Using Well-Known Deep Learning Models

This Many advanced deep learning (DL) architectures have emerged following the introduction of AlexNet, which significantly improved image recognition, segmentation, and classification tasks. Various researchers have explored these state-of-the-art architectures for detecting and categorizing plant diseases. Additionally, some studies have introduced improved versions of DL models and novel visualization techniques to enhance performance.Among the widely used datasets, the PlantVillage dataset has gained significant attention. It consists of 54,306 images covering 14 different crop species and 26 plant diseases. To assess the effectiveness of different DL models, researchers have employed various performance metrics.

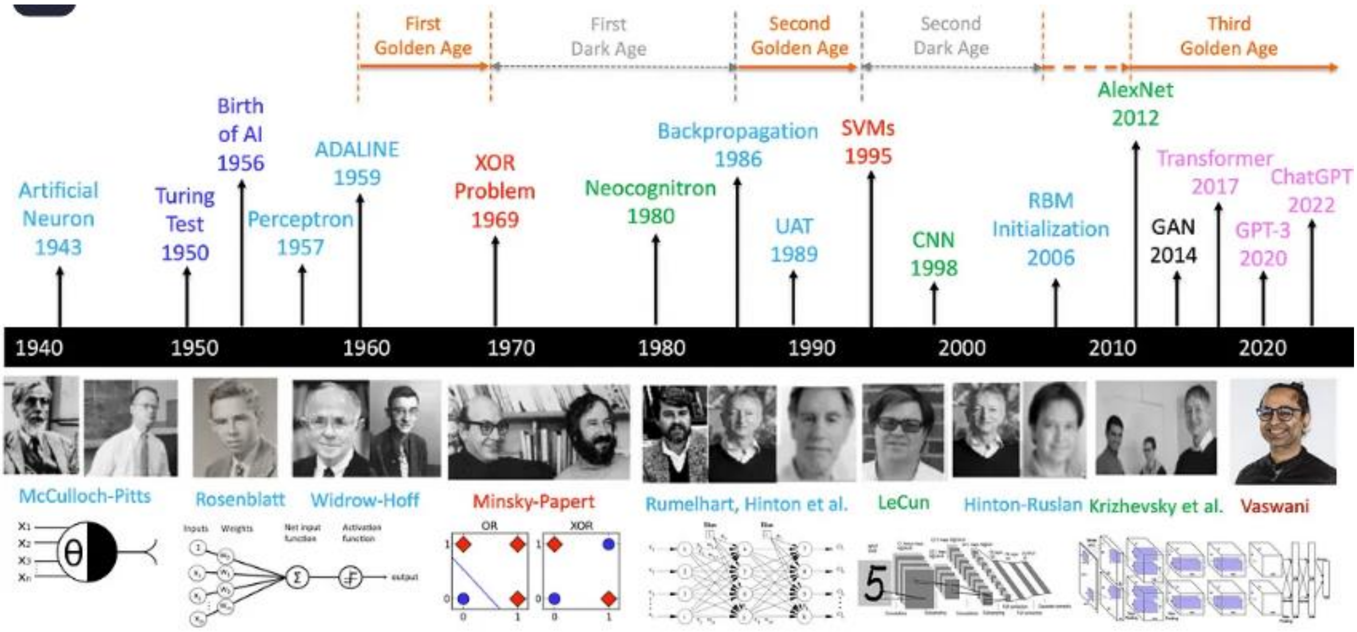

Figure 2. Summary of the evolution of various deep learning models from 2025 until now.

2.1. Studies Without Visualization Techniques

Several studies have utilized Convolutional Neural Networks (CNNs) for plant disease classification without applying visualization methods. For instance, one study used CNNs to classify maize plant diseases and employed histogram techniques to demonstrate the model's significance. Another study applied CNN-based architectures such as AlexNet, GoogLeNet, and ResNet to identify diseases in tomato leaves. Among these models, ResNet demonstrated the highest accuracy.

For banana leaf disease detection, the LeNet architecture was implemented, with classification accuracy (CA) and F1-score being the primary evaluation metrics in both color and grayscale image modes. Another study compared five CNN models—AlexNet, AlexNetOWTbn, GoogLeNet, Overfeat, and VGG—finding that VGG outperformed the others.

In an additional study, three classifiers—Support Vector Machines (SVM), Extreme Learning Machine (ELM), and K-Nearest Neighbor (KNN)—were combined with leading DL models such as GoogLeNet, ResNet-50, ResNet-101, Inception-v3, InceptionResNetV2, and SqueezeNet. Among these, ResNet-50 paired with an SVM classifier achieved the best results based on sensitivity, specificity, and F1-score.

Furthermore, a separate study employed the Inception-v3 model to detect cassava disease, while another study classified cucumber plant diseases using two CNN variants, obtaining a maximum accuracy of 82.3%. Researchers also replaced traditional plant disease detection techniques with Super-Resolution Convolutional Neural Networks (SRCNN) to improve classification.

For tomato plant disease detection, AlexNet and SqueezeNet v1.1 were tested, with AlexNet proving to be the superior model in terms of accuracy. A comparative study was also conducted to determine the most effective DL architecture for plant disease identification. Additionally, another study classified six tomato plant diseases using AlexNet and VGG-16, providing a detailed performance comparison based on classification accuracy.

Table 1. Comparison of state-of-the-art deep learning models.

Deep Learning Models	Parameters	Key Features and Pros/Cons
LeNet	60k	First CNN model. Few parameters as compared to other CNNmodels. Limited capability of computation
AlexNet	60M	Known as the first modern CNN. Best image recognition performance at its time. Used ReLU to achieve better performance. Dropout technique was used to avoid overfitting
OverFeat	145M	First model used for detection, localization, and classification of objects through a single CNN. Large number of parameters as compared to AlexNet
ZFNet	42.6M	Reduced weights (as compared to AlexNet) by considering 7×7 kernels and improved accuracy
VGG	133M–144M	3×3 receptive fields were considered to include more number of non-linearity functions which made decision function discriminative. Computationally expensive model due to large number of parameters
GoogLeNet	7M	Fewer number of parameters as compared to AlexNet model. Better accuracy at its time
ResNet	25.5M	Vanishing gradient problem was addressed. Better accuracy than VGG and GoogLeNet models
DenseNet	7.1M	Dense connections between the layers. Reduced number of parameters with better accuracy
SqueezeNet	1.25M	Similar accuracy as AlexNet with 50 times lesser parameters. Considered 1×1 filters instead of 3×3 filters. Input channels were decreased. Large activation maps of convolution layers
Xception	22.8M	A depth-wise separable convolution approach. Performed better than VGG, ResNet, and Inception-v3 models
MobileNet	4.2M	Considered the depth-wise separable convolution concept. Reduced parameters significantly. Achieved accuracy near to VGG and GoogLeNet
Modified/Reduced MobileNet	0.5/0.54M	Lesser number of parameters as compared to MobileNet. Similar accuracy as compared to MobileNet
VGG-Inception	132M	A cascaded version of VGG and inception module. The number of parameters were reduced by substituting 5×5 convolution layers with two 3×3 layers. Testing accuracy was increased as compared to many well-known DL models like AlexNet, GoogLeNet, Inception-v3, ResNet, and VGG-16.

2.2. Deep Learning Models and Visualization Techniques for Plant Disease Detection

Several deep learning (DL) models have been combined with visualization techniques to enhance the understanding of plant diseases. One such approach introduced saliency maps to highlight disease symptoms in plants. In another study, the CaffeNet CNN model was used to classify 13 different plant diseases, achieving a classification accuracy (CA) of 96.30%, outperforming previous methods like Support Vector Machines (SVM). Various filters were also applied to pinpoint affected areas on plant leaves.

Similarly, researchers utilized the PlantVillage dataset to test AlexNet and GoogLeNet architectures, evaluating their performance based on precision, recall, F1-score, and overall accuracy. The study uniquely assessed three scenarios—color, grayscale, and segmented images—to compare both CNN models. The results indicated that GoogLeNet outperformed AlexNet, and the activation maps from the initial layers clearly revealed disease spots.

A modified LeNet model was implemented to detect diseases in olive plants using segmentation and edge mapping techniques. Another study focused on four cucumber diseases and compared the accuracy of different classifiers, including Random Forest, SVM, and AlexNet. Image segmentation was employed to visualize the symptoms of plant diseases.

A novel DL model, known as the teacher-student network, introduced an innovative visualization method to identify diseased areas in plants. Another approach combined DL models with detection algorithms to mark plant diseases along with prediction probabilities. This study tested multiple object detectors—Faster R-CNN, R-FCN, and SSD—with well-known architectures like AlexNet, GoogLeNet, VGG, ZFNet, ResNet-50, ResNet-101, and ResNeXt-101. Among them, ResNet-50 paired with the R-FCN detector achieved the highest accuracy. Additionally, bounding boxes were used to highlight disease-affected regions.

For banana leaf disease and pest detection, three CNN models—ResNet-50, Inception-V2, and MobileNet-V1—were evaluated alongside Faster R-CNN and SSD object detectors. Another study tested various CNN combinations and generated heat maps to analyze disease probability, while receiver operating characteristic (ROC) curves were used to measure model performance. Feature maps were also included for rice disease detection.

The LeNet model was applied to identify and classify soybean plant diseases. A comparative study on tomato plant disease detection using AlexNet and GoogLeNet showed that GoogLeNet performed better and introduced occlusion techniques to pinpoint diseased regions. Researchers also explored VGG-based models, such as VGG-FCN and VGG-CNN, for detecting wheat plant diseases and visualizing disease features at different network layers.

For detecting Fusarium wilt in radish, a VGG-CNN model was used along with K-means clustering to highlight affected areas. A semantic segmentation approach with CNN was also proposed for detecting cucumber plant diseases. Another technique focused on identifying individual disease symptoms using a DL model.

A deep CNN framework was designed for identifying, classifying, and quantifying eight types of soybean plant stress. Another study used CNN models to detect rice plant diseases, with feature maps indicating disease patches. A deep residual neural network was extended to develop a mobile application capable of identifying plant diseases through hotspot detection.

A hotspot-based algorithm was also used to extract affected areas from segmented images, ensuring color consistency. This method described each hotspot using two descriptors: one for color information and another for texture analysis. Cucumber diseases were identified using a dilation convolutional neural network, while another study proposed an advanced visualization technique combining correlation coefficients with AlexNet and VGG-16.

Lastly, an innovative approach combined color space analysis and vegetation indices with the LeNet CNN model to detect grapevine diseases.

Table 2. Visualization mapping/techniques used in several approaches.

Visualization Techniques/Mappings
Visualization of features having filter from first to final layer
Visualize activations in first convolutional layer
Saliency map visualization
Classification and localization of diseases by bounding boxes
Heat maps were used to identify the spots of the disease
Feature map for the diseased rice plant
Symptoms visualization method
Feature and spatial core maps
Color space into HSV and K-means clustering
Feature map for spotting the diseases
Image segmentation method
Reconstruction of images on discriminant regions, segmentation of images by binary threshold theorem, and heat map construction
Saliency map visualization
Saliency map, 2D and 3D contour, mesh graph image
Activation visualization
Segmentation map and edge map

For an accurate assessment of deep learning (DL) models in plant disease detection, it is essential to test them in real-world environments. Many previous studies have relied on datasets with plain backgrounds, which do not accurately reflect natural growing conditions.However, some research has incorporated realistic backgrounds, providing a better evaluation of model performance

Visualization Methods in Plant Disease Detection

Various visualization techniques have been applied to understand how DL models identify plant diseases. Figures 4–11 illustrate their effectiveness.

In Figure 4, feature maps extracted from different hidden layers of a DL model show how features are recognized at various stages. The initial layer (a) captures basic elements like pixels and edges, while deeper layers (h) focus on specific structures in the plant image, helping to detect diseases more effectively.

Figure 5 compares two visualization techniques: heat maps and saliency maps. Heat maps highlight diseased areas with red markers. However, in one instance (d), a diseased region was not detected. This issue was addressed using the saliency map technique, which applied guided backpropagation [55]. The saliency map successfully identified all diseased areas, proving to be a more reliable method than heat maps.

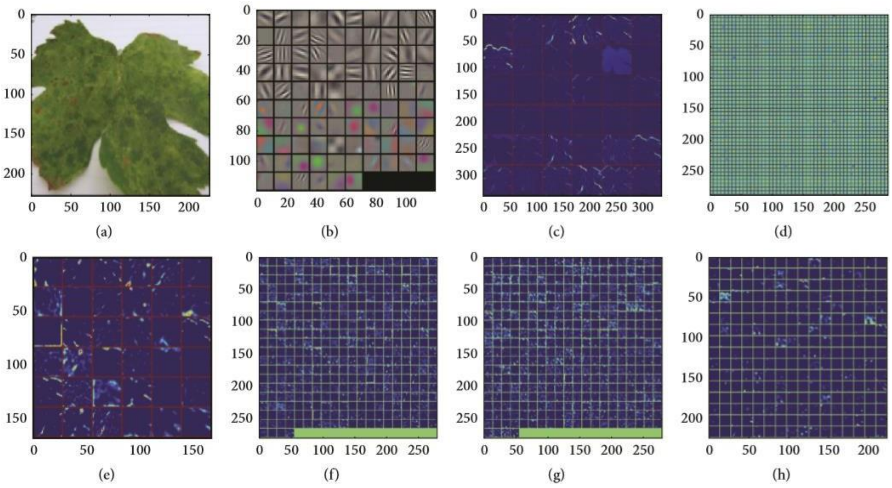

Figure 4. Feature maps after the application of convolution to an image: (**a**) real image, (**b**) first convolutional layer filter, (**c**) rectified output from first layer, (**d**) second convolutional layer filter,(**e**) output from second layer, (**f**) output of third layer, (**g**) output of fourth layer, (**h**) output of fifth layer.

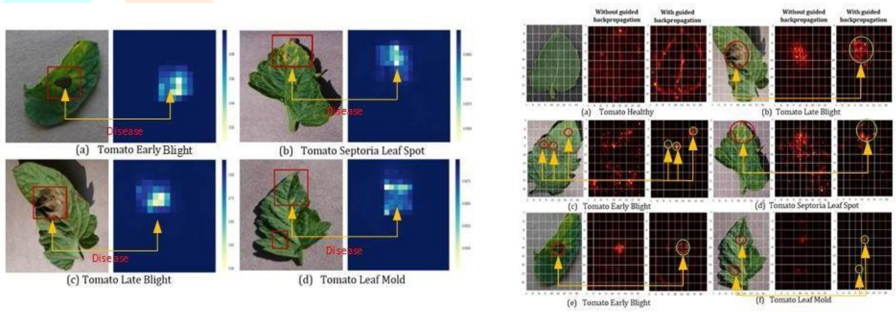

Figure 5. Tomato plant disease detection by heat map: on left hand side (a) tomato early blight,(b) tomato septoria leaf spot, (c) tomato late blight and (d) tomato leaf mold) and saliency map; on right hand side (a) tomato healthy, (b) tomato late blight, (c) tomato early blight, (d) tomato septoria leaf spot, (e) tomato early blight, (f) tomato leaf mold).

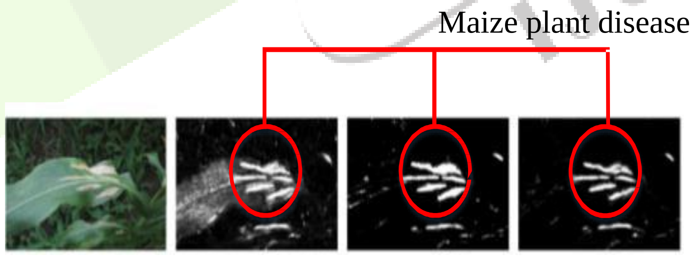

Figure 6. Detection of maize disease (indicated by red circles) by heat map ,represents the heat map to detect the disease in maize plants. First, the image was represented in the form of the probability of each portion containing disease. Then, the probabilities were placed into the form of a matrix in order to denote the outcome of all the areas of the input image.

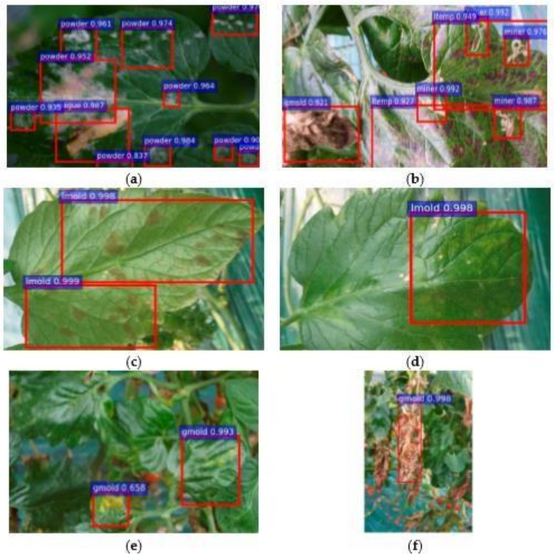

Figure 7. Bounding box indicates the type of diseases along with the probability of their occurrence . A bounding box technique was used in Figure 7 in which (a) represents the one type of disease along with its rate of occurrence, (b) indicates three types of plant disease (miner, temperature, and gray mold) in a single image, (c,d) shows one class of disease but contains different patterns on the front and back side of the image, (e,f) displays different patterns of gray mold in the starting and end stages.

A new visualization approach was introduced, as illustrated in Figures 8 and 9. In Figure 8a, the input image was processed within a student-teacher architecture, generating a refined version of the image. Following this, a single-channel heat map was created by applying a simple aggregation method to the channels of the regenerated image (Figure 8b). To enhance clarity, a binary threshold algorithm was then applied, making disease symptoms more distinct.

Figure 9 presents a comparison of the proposed technique with existing visualization methods. On the left side, techniques such as LRP-Z, LRP-Epsilon, and gradient-based methods struggled to clearly highlight diseased areas on plant leaves. Although the Deep Taylor approach provided better results, it still only partially identified the affected regions. On the right side, Grad-CAM demonstrated imperfect localization of plant diseases. This limitation was effectively addressed by the newly proposed technique, which incorporated a decoder to improve accuracy in highlighting diseased areas.

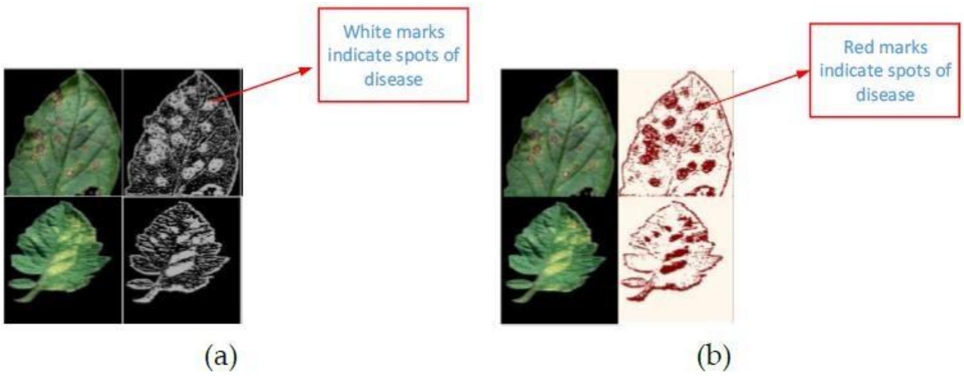

Figure 8. (a) Teacher/student architecture approach; (b) segmentation using a binary threshold algorithm.

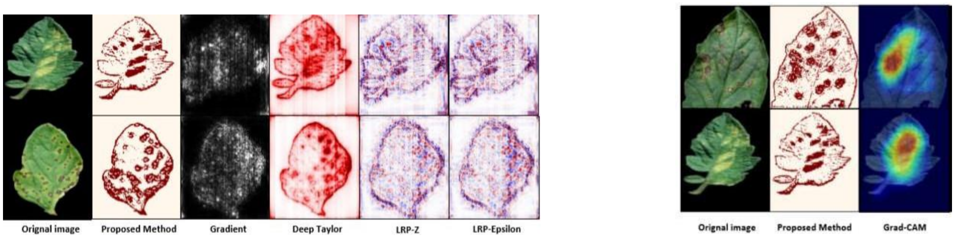

Figure 9. Comparison of Teacher/student approach visualization map with the previous.

To assess the effectiveness of Convolutional Neural Networks (CNNs) in distinguishing various plant diseases, feature maps were generated, as depicted in Figure 10. The results demonstrate the strong performance of the proposed CNN model, as it successfully highlights diseased areas on plant leaves with clarity and accuracy.

Figure 11 presents the use of segmentation and edge detection techniques for identifying plant diseases. In the segmentation map, the affected regions of the leaf are distinctly marked. Specifically, areas that appear yellow in the original image are represented as white regions in the segmentation output, clearly indicating the diseased portions.

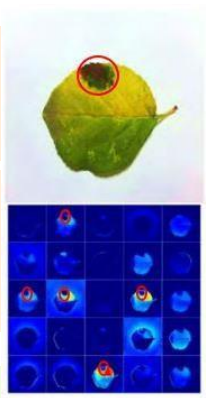

Figure 10. Activation visualization for detection of apple plant disease to show the significance of a VGG-Inception model (the plant disease is indicated by the red circle).

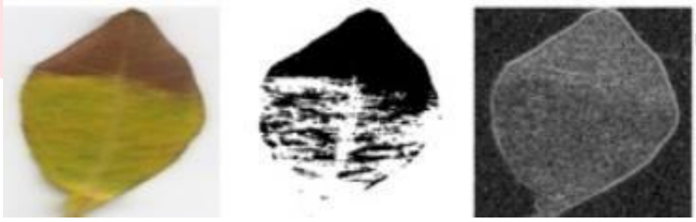

Figure 11. Segmentation and edge map for olive leaf disease detection.

2.3. Novel and Enhanced Deep Learning Architectures for Plant Disease Detection

Recent research has introduced modified and newly developed deep learning (DL) architectures to enhance the accuracy and transparency of plant disease detection. For example, an improved version of GoogLeNet and the Cifar-10 model was proposed in [86], demonstrating superior performance over AlexNet and VGG, with an impressive accuracy of 98.9%. Similarly, in [87], a novel DL model was designed to outperform traditional approaches such as SVM, AlexNet, GoogLeNet, ResNet-20, and VGG-16, achieving an accuracy of 97.62% in classifying apple plant diseases. To enhance model robustness, the dataset was expanded using multiple augmentation techniques, including 90°, 180°, and 270° rotations, mirror symmetry, contrast adjustments, sharpness variations, brightness changes, Gaussian noise application, and PCA jittering. The significance of dataset augmentation was further illustrated through detailed plots.

In another study, a CNN model named LeafNet was introduced in [88] for the classification of tea leaf diseases, achieving superior accuracy compared to Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) models. Research in [89] explored two modified versions of MobileNet—modified MobileNet and reduced MobileNet—both of which achieved accuracy comparable to VGG, with reduced MobileNet reaching an impressive 98.34% classification accuracy. Due to its reduced number of parameters, it significantly lowered training time compared to VGG. Additionally, a state-of-the-art DL model called PlantDiseaseNet was proposed in [90], proving to be particularly effective in real-world agricultural environments.

Furthermore, [85] introduced the VGG-Inception architecture, which classified and detected five types of apple plant diseases. This model surpassed the performance of AlexNet, GoogLeNet, different ResNet versions, and VGG by integrating inter-class detection and activation visualization, allowing for a more precise diagnosis of plant diseases.

A bar chart, as illustrated in Figure 12, provides an overview of the most frequently utilized DL models in plant disease detection. The AlexNet model appears to be the most commonly used across multiple research studies, followed closely by GoogLeNet, VGG-16, and ResNet-50. Additionally, several improved and cascaded versions of existing models—such as improved Cifar-10, VGG-Inception, cascaded AlexNet with GoogLeNet, modified MobileNet, LeNet, and GoogLeNet—have been employed for plant disease classification.

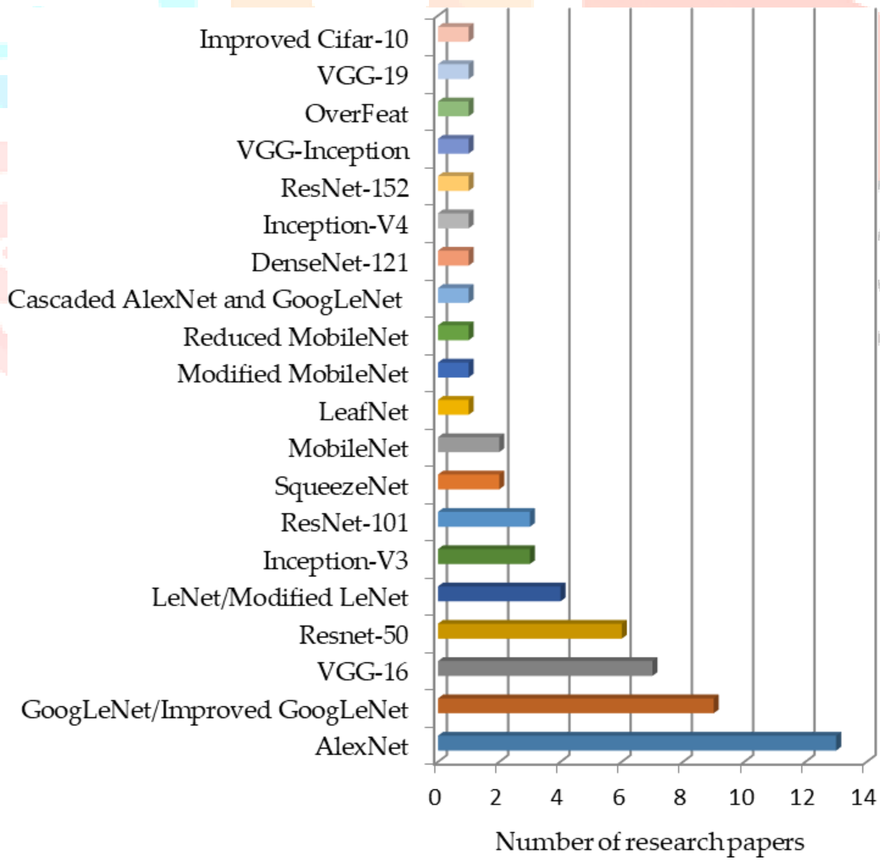

Figure 12. Deep learning models used in the particular number of research papers.

3. Hyperspectral Imaging and Deep Learning for Plant Disease Detection

For the early detection of plant diseases, various imaging techniques have been utilized, including multispectral imaging, thermal imaging, fluorescence imaging, and hyperspectral imaging (HSI). Among these, HSI has recently gained significant attention in research. For instance, a study employed HSI for detecting diseases in tomato plants by identifying specific regions of interest. A feature ranking-KNN (FR-KNN) model was applied, yielding promising results in distinguishing between healthy and diseased plants. Similarly, another study used HSI to detect apple plant diseases and addressed redundancy issues through an unsupervised feature selection technique called Orthogonal Subspace Projection.

HSI has also been applied for detecting leaf diseases in peanuts by identifying sensitive spectral bands and hyperspectral vegetation indices. A tomato disease detection study employed Support Vector Machine (SVM) classifiers using HSI, evaluating performance based on F1-score, accuracy, specificity, and sensitivity.

Machine learning (ML) techniques have increasingly been integrated with HSI for plant disease detection. Research highlighted various ML techniques for agricultural applications using hyperspectral imaging, while another study applied HSI with three ML models for detecting leaf rust disease. In wheat disease detection, a Random Forest (RF) classifier was utilized alongside multispectral imaging, achieving an accuracy of 89.3% . Similarly, another study used SVM with hyperspectral data, obtaining an accuracy exceeding 86%. While numerous ML-based approaches leveraging HSI exist, this section focuses on deep learning (DL) techniques for hyperspectral imaging.

Deep Learning in Hyperspectral Image Classification
DL has been widely applied in classifying hyperspectral images across various fields, including medical applications. For instance, hyperspectral imaging was used for the classification of head and neck cancer. Another study proposed a DL model utilizing contextual information to leverage both spectral and spatial features. A novel 3D-CNN architecture [104] provided a rapid and accurate approach for hyperspectral image classification by incorporating spatial information in addition to spectral data, unlike previous CNN methods [105]. Furthermore, a study [106] utilized CNN for hyperspectral image classification and applied dropout and L2 regularization techniques to mitigate overfitting.

Beyond CNN-based models, recurrent neural network (RNN) architectures have also been integrated with HSI, as reported. In the field of plant disease detection, several studies have combined HSI with DL models to enhance disease symptom visualization. A hybrid classification method combining Deep Convolutional Neural Networks (DCNN), Logistic Regression (LR), and Principal Component Analysis (PCA) demonstrated improved classification accuracy compared to previous methods. A comprehensive review of DL applied to HSI [110] provided insights into model selection, overfitting mitigation strategies, and performance improvements.

To counteract overfitting and enhance accuracy, a comparative study examined multiple DL models, including 1D/2D-CNN (where 2D-CNN performed better), LSTM and GRU (both suffering from overfitting), and hybrid 2D-CNN-LSTM/GRU architectures (which still faced overfitting issues). Consequently, a novel hybrid model named 2D-CNN-Bidirectional LSTM/GRU (2D-CNN-BidLSTM/GRU) was introduced for hyperspectral imaging, effectively addressing overfitting and achieving an F1-score of 0.75 and an accuracy of 0.73 for wheat disease detection.

A groundbreaking study proposed a hyperspectral proximal-sensing approach utilizing Generative Adversarial Networks (GANs) to detect tomato plant diseases before visible symptoms appeared, as illustrated in Figure 13. Similarly, a 3D-CNN approach was designed for hyperspectral imaging to detect Charcoal Rot disease in soybeans, achieving an accuracy of 95.76% and an F1-score of 0.87. Saliency map visualization was applied, revealing that the most critical wavelength was approximately 733 nm, falling within the near-infrared (NIR) spectrum.

In another study, hyperspectral imaging combined with DL was used to detect potato virus, achieving a precision score of 0.78 and a recall of 0.88. Additionally, a multiple Inception-ResNet model was developed to detect yellow rust in wheat using both spatial and spectral data from hyperspectral UAV images (Figure 14). This model achieved an accuracy of 85%, significantly outperforming the RF-classifier, which attained only 77%.

Table3. Comparison of several DL approaches in terms of various performance metrics.

DL Architectures/Algorithms	Datasets	Selected Plant/s	Performance Metrics (and Their Results)
CNN	PlantVillage	Maize	CA (92.85%)
AlexNet, GoogLeNet, ResNet	PlantVillage	Tomato	CA by ResNet which gave the best value (97.28%)
LeNet	PlantVillage	Banana	CA (98.61%), F1 (98.64%)
AlexNet, ALexNetOWTBn, GoogLeNet, Overfeat, VGG	PlantVillage and in-field images	Apple, blueberry, banana, cabbage, cassava, cantaloupe, celery, cherry, cucumber, corn, eggplant, gourd, grape, orange, onion	Success rate of VGG (99.53%) which is the best among all
AlexNet, VGG16, VGG 19, SqueezeNet, GoogLeNet, Inceptionv3, InceptionResNetv2, ResNet50, Resnet101	Real field dataset	Apricot, Walnut, Peach, Cherry	F1(97.14), Accuracy (97.86 ± 1.56) of ResNet
Inceptionv3	Experimental field dataset	Cassava	CA (93%)
CNN	Images taken from the research center	Cucumber	CA (82.3%)
Super-Resolution Convolutional Neural Network (SCRNN)	PlantVillage	Tomato	Accuracy (~90%)
CaffeNet	Downloaded from the internet	Pear, cherry, peach, apple, grapevine	Precision (96.3%)
AlexNet and GoogLeNet	PlantVillage	Apple, blueberry, bell pepper, cherry, corn, peach, grape, raspberry, potato, squash, soybean, strawberry, tomato	CA (99.35%) of GoogLeNet
AlexNet, GoogLeNet, VGG- 16, ResNet-50,101, ResNetXt-101, Faster RCNN, SSD, R-FCN, ZFNet	Image taken in real fields	Tomato	Precision (85.98%) of ResNet-50 with Region based Fully Convolutional Network(R-FCN)
CNN	Bisque platform of Cy Verse	Maize	Accuracy (96.7%)
DCNN	Images were taken in real field	Rice	Accuracy (95.48%)
AlexNet, GoogLeNet	PlantVillage	Tomato	Accuracy (0.9918 ± 0.169) of GoogLeNet
VGG-FCN-VD16 and VGG-FCN-S	Wheat Disease Database 2017	Wheat	Accuracy (97.95%) of VGG-FCN-VD16
VGG-A, CNN	Images were taken in real field	Radish	Accuracy (93.3%)
AlexNet	Images were taken in real field	Soybean	CA (94.13%)
AlexNet and SqueezeNet v1.1	PlantVillage	Tomato	CA (95.65%) of AlexNet
DCNN, Random forest, Support Vector Machine and AlexNet	PlantVillage dataset, Forestry Image dataset and agricultural field in China	Cucumber	CA (93.4%) of DCNN

Table3. Cont.

DL Architectures/Algorithms	Datasets	Selected Plant/s	Performance Metrics (and Their Results)
Teacher/student architecture	PlantVillage	Apple, bell pepper, blueberry, cherry, corn, orange, grape, potato, raspberry, peach, soybean, strawberry, tomato, squash	Training accuracy and loss (~99%,~0–0.5%), validation accuracy and loss (~95%, ~10%)
Improved GoogLeNet, Cifar-10	PlantVillage and various websites	Maize	Top-1 accuracy (98.9%) of improved GoogLeNet
MobileNet, Modified MobileNet, Reduced MobileNet	PlantVillage dataset	24 types of plant	CA (98.34%) of reduced MobileNet
VGG-16, ResNet-50,101,152, Inception-V4 and DenseNets-121	PlantVillage	Apple, bell pepper, blueberry, cherry, corn, orange, grape, potato, raspberry, peach, soybean, strawberry, tomato, squash	Testing accuracy (99.75%) of DenseNets
User defined CNN, SVM, AlexNet, GoogLeNet, ResNet-20 and VGG-16	Images were taken in real field	Apple	CA (97.62%) of proposed CNN
AlexNet and VGG-16	PlantVillage	Tomato	CA (AlexNet)
LeafNet, SVM, MLP	Images were taken in real field	Tea leaf	CA (90.16%) of LeafNet
2D-CNN-BidGRU	Real wheat field	wheat	F1 (0.75) and accuracy (0.743)
OR-AC-GAN	Real environment	Tomato	Accuracy (96.25%)
3D CNN	Real environment	Soybean	CA (95.73%), F1-score (0.87)
DCNN	Real environment	Wheat	Accuracy (85%)
ResNet-50	Real environment	Wheat	Balanced Accuracy (87%)
GPDCNN	Real environment	Cucumber	CA (94.65%)
VGG-16, AlexNet	PlantVillage, CASC-IFW	Apple, banana	CA (98.6%)
LeNet	Real environment	Grapes	CA (95.8%)
PlantDiseaseNet	Real environment	Apple, bell-pepper, cherry, grapes, onion, peach, potato, plum, strawberry, sugar-beets, tomato, wheat	CA (93.67%)
LeNet	PlantVillage	Soybean	CA (99.32%)
VGG-Inception	Real environment	Apple	Mean average accuracy (78.8%)
Resnet-50, Inception-V2, MobileNet-V1	Real environment	Banana	Mean average accuracy (99%) of ResNet-50
Modified LeNet	PlantVillage	Olives	True positive rate (98.6 ± 1.47%)

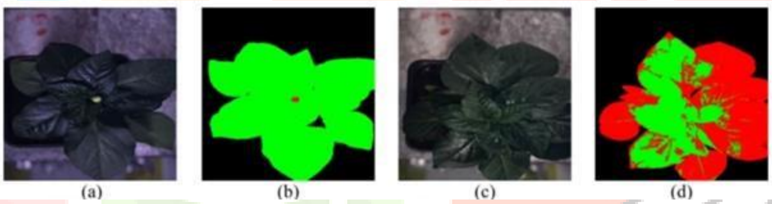

Figure 13. Sample images of OR-AC-GAN (a hyperspectral imaging model).

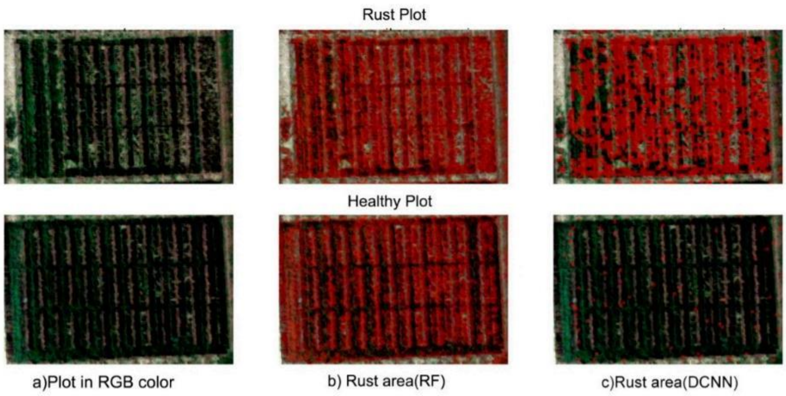

Figure 14. Hyperspectral images by UAV: (a) RGB color plots, (b) Random-Forest classifier, and (c) proposed multiple Inception-ResNet model.

While deep learning (DL) models and architectures have been developed for hyperspectral image classification in plant disease detection, this field remains an active area of research. Further advancements are needed to improve accuracy under varying conditions such as different illumination levels and real-world backgrounds. Enhancing these models will contribute to more reliable disease detection across diverse agricultural settings.

Figure 13 illustrates the results obtained from the method proposed. In these images, the green-colored regions represent healthy parts of the plant, whereas the red areas indicate infected sections. The images labeled (a) and (b) correspond to healthy plants, as they do not exhibit any red markings. However, image (c) shows an infected plant, which is confirmed by its corresponding processed image in (d), where red regions highlight the diseased portions.

A comparison between the proposed Deep Convolutional Neural Network (DCNN) and the Random Forest (RF) classifier using RGB-colored hyperspectral images is presented in Figure 14. The red-colored markings indicate rust-infected areas. Observing the first row, images (b) and (c) demonstrate a similar rust identification pattern. However, in the healthy plot, image (b) (processed by RF) contains a significant red-labeled area, whereas image (c) (processed by DCNN) shows less misclassification. This suggests that the RF model incorrectly classified a healthy region as diseased, whereas the DCNN model demonstrated better accuracy in distinguishing between healthy and infected sections.

4.Conclusions and Future Directions:

This review explored various deep learning (DL) approaches for detecting plant diseases and summarized visualization techniques used to identify disease symptoms. While significant advancements have been made in the past few years, there are still several research gaps that need to be addressed:

- Many studies have relied on the PlantVillage dataset to evaluate DL models. While this dataset provides a large number of images covering different plant species and diseases, its plain background does not reflect real-world conditions. Future research should focus on models that perform well in complex, natural environments.
- Hyperspectral and multispectral imaging have gained prominence in various research domains. Integrating these technologies with advanced DL models could enable early disease detection, even before symptoms become visible.
- More effective visualization techniques should be developed to accurately pinpoint diseased areas on plants. This will help reduce unnecessary pesticide, herbicide, or fungicide application, leading to cost savings and environmental benefits.
- Since the severity of plant diseases evolves over time, DL models must be refined to track and classify diseases throughout their progression, ensuring timely and precise detection at every stage.
- DL models should be robust under varying lighting conditions. Datasets should include images captured in diverse agricultural settings to enhance model adaptability to real-world scenarios.
- A thorough investigation is necessary to identify factors affecting disease detection accuracy, such as dataset size, class distribution, learning rates, and environmental conditions.

5.References

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