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Deep Learning Techniques for Identification of Different Malvaceae Plant Leaf Diseases

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Abstract

INTRODUCTION: The precise and timely detection of plant diseases plays a crucial role in ensuring efficient crop management and disease control. Nevertheless, conventional methods of disease identification, which heavily rely on manual visual inspection, are often time-consuming and susceptible to human error. The knowledge acquired from this research paper enhances the overall comprehension of the discipline and offers valuable direction for future progressions in the applicationof deep learning for the identification of plant diseases.[1][2]
AIM: to investigate the utilization of deep learning techniques in identifying various Malvaceae plant diseases.
METHODS: AlexNet, VGG, Inception, REsNet and other CNN architectures are analyzed on Malvaceae plant diseases specially on Cotton, Ocra and Hibiscus, different data collection methods ,Data augmentation and Normalization techniques.
RESULTS: Inception V4 have Training Accuracy 98.58%, VGG-16 have Training Accuracy 84.27%, ResNet-50 have TrainingAccuracy 98.72%, DenseNet have Training Accuracy 98.87%, Inception V4 have Training Loss 0.01%, VGG-16 have Training Loss 0.52%, ResNet-50 have Training Loss 6.12%, DenseNet have Training Loss 0.016%, Inception V4 have TestAccuracy 97.59%, VGG-16 have Test accuracy 82.75%, ResNet-50 have Test Accuracy 98.73%, DenseNet have Test Accuracy 99.81%, Inception V4 have Test Loss 0.0586%, VGG-16 have Test Loss 0.64%, ResNet-50 have Test Loss 0.027%, DenseNet have Test Loss 0.0154% .
CONCLUSIONS: conclusion summarizes the key findings and highlights the potential of deep learning as a valuable tool for accurate and efficient identification of Malvaceae plant diseases.

Keywords: Deep learning, Malvaceae plant diseases, CNN, Image-Based Disease Identification, Internet of Things (IoT) and Edge Computing

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1. Introduction

The precise identification of plant diseases is paramount for the successful management of crops and control of diseases. Traditional methods of disease identification often rely on manual visual inspection, which can be time-consuming, subjective, and susceptible to human error. In recent years, deep learning techniques have emerged as a promising approach for automating disease identification tasks, offering the potential for more accurate and efficient diagnoses. The purpose of this paper is to present a comprehensive analysis of the utilization of deep learning techniques for the identification of various diseases affecting plants from the Malvaceae family.[3]

2. Importance of Accurate Plant Disease Identification:

Malvaceae plants, which encompass economically significant crops such as cotton, hibiscus, and okra, are susceptible to a range of diseases that can have a substantial impact on both yield and quality. The timely and accurate identification of these diseases is of utmost importance in order to implement effective strategies for disease management. Such strategies may include the targeted application of treatments, the cultivation of disease-resistant varieties through breeding techniques, and the implementation of cultural practices.[1]

3. Objectives

The primary aim of this review paper is to investigate the utilization of deep learning techniques in the identification of various diseases affecting Malvaceae plants. Through a comprehensive analysis of existing literature and studies in this field, we seek to assess the methodologies employed, the performance achieved, and the limitations encountered by deep learning models. The findings of this review will provide valuable insights into the potential of deep learning as a precise and efficient tool for the identification of Malvaceae plant diseases.

4. The Economic Significance of Malvaceae Crops

Malvaceae crops hold immense importance in the realm of global agriculture and economies. Notably, cotton stands as one of the most pivotal fiber crops, providing the essential raw material for the textile industry on a global scale. Furthermore, crops such as okra and hibiscus possess substantial commercial value as both sources of food and ornamental plants. The cultivation and trade of Malvaceae crops play a crucial role in rural livelihoods, employment generation, and the overall economic growth of numerous regions.

5. A more profound examination of the unique challenges specific to diseases affecting Malvaceae crops

Malvaceae, a family of flowering plants, encompasses several significant crops including cotton (Gossypium spp.), okra (Abelmoschus spp.), and various ornamental species. While these crops bear exceptional eco-nomic and agricultural value, they also confront distinct disease challenges that can significantly impact their yield and quality. Let us delve into some of the primary disease challenges specific to Malvaceae crops.

5.1. Cotton Diseases

a. Cotton Boll Rot (Anthracnose): This disease, caused by the fungal pathogen Colletotrichum gossypii, impairs cotton bolls, leading to a decline in fiber quality and yield. Effective management entails the utilization of resistant cotton varieties and the application of fungicides.

b. Cotton Root Rot (Phymatotrichopsis): A soilborne fungus (Phymatotrichopsisomnivora) is responsible for cotton root rot, which can prove devastating, particularly in warm and arid regions. Cultural practices such as crop rotation and soil solarization are employed to control this affliction.

c. Cotton Verticillium Wilt: Verticillium wilt (Verticillium dahliae) affects cotton plants, resulting in wilting, leaf chlorosis, and reduced yield. The management of this disease involves crop rotation with non-susceptible plants and the use of resistant cotton varieties.

5.2. Okra Diseases

a. Okra Yellow Vein Mosaic Virus (OYVMV): This viral disease induces symptoms such as yellowing, vein clearing, and mosaic patterns on okra leaves. Common management strategies include aphid control and the usage of virus-free seeds for planting.

b. Okra Powdery Mildew: Powdery mildew (Podosphaeraxanthii) can afflict okra plants, leading to a decline in fruit quality. The control of this disease is achieved through the application of fungicides and ensuring proper spacing for adequate air circulation.

5.3. Diseases Affecting Ornamental Malvaceae

a. Hollyhock Rust: Ornamental Malvaceae plants, such as hollyhocks (Alcea spp.), are susceptible to rust diseases caused by fungi like Puccinia malvacearum. The management of rust involves the use of fungicides and the removal of infected plant parts.

b. Malva Mosaic Virus: This viral disease affects ornamental Malvaceae plants, specifically Lavatera and Malva species, resulting in mottling and yellowing of leaves. The reduction of its spread necessitates the control of aphid vectors and the removal of infected plants.

5.2 Characteristics of Malvaceae plant diseases that set them apart from diseases in other plant families

The diseases that affect Malvaceae crops share commonalities with diseases seen in other plant families. However, there are certain characteristics that set them apart. These unique features are often influenced by the wide range of crops within the Malvaceae family and the specific pathogens that target them. Here are some of the distinctive characteristics of diseases affecting Malvaceae crops:

1. Planting Season
2. Viral Diseases
3. Soilborne Pathogens
4. Host Range
5. Unique Symptoms
6. Impact on Fiber Quality
7. Environmental Sensitivity

In summary, diseases affecting Malvaceae crops possess a unique diversity, host range, and potential impact on economically valuable crops such as cotton. Their susceptibility to viral diseases and soilborne pathogens, as well as the distinct symptoms they exhibit, differentiate them from diseases found in other plant families. Effective disease management strategies for Malvaceae crops should consider these unique characteristics while also addressing specific environmental and regional factors. [7] [8]

6. Limitations and challenges associated with traditional methods of disease identification in the context of Malvaceae crops

Traditional methods of disease identification for Malvaceae crops, which heavily rely on visual inspection, laboratory testing, and expert knowledge, have several limitations and face various challenges. The following are the shortcomings of traditional disease identification methods and highlight the specific challenges faced in the context of Malvaceae crops.

1. Subjectivity and Human Error
2. Limited Scalability
3. Time-consuming and Labor-intensive
4. Dependency on Symptom Expression
5. Limited Expertise and Accessibility
6. Cost and Infrastructure

Deep learning techniques and their specific application to plant disease identification.

This section introduces deep learning techniques and their specific application to plant disease identification, highlighting their potential benefits and advantages over traditional methods.

7. Deep Learning Overview

Deep learning is a branch of machine learning that utilizes artificial neural networks with multiple layers to learn and extract hierarchical representations of data. Convolutional Neural Networks (CNNs), a popular deep learning architecture, have been particularly successful in image analysis tasks. CNNs are designed to automatically learn intricate patterns and features from large datasets, making them well-suited for image-based disease identification. [9] [10].

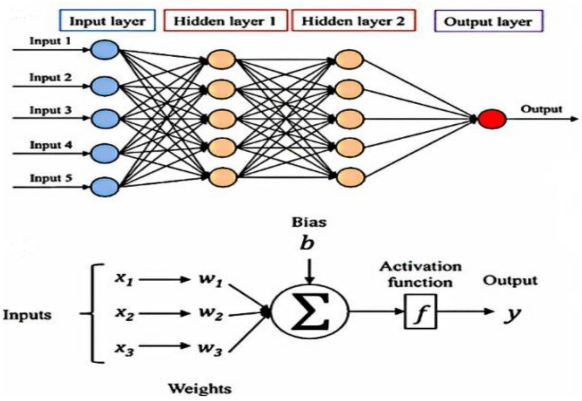


Fig.1. The basic architecture of a deep learning convolution network [12][14]

7.1 Image-Based Disease Identification

Deep learning techniques offer a paradigm shift in disease identification by leveraging the power of image analysis. In the context of plant diseases, deep learning models are trained on large collections of labelLed images representing healthy plants and various disease symptoms. These models learn to extract discriminative features from the images and classify them into different disease categories, enabling automated and accurate disease identification.[11]

7.2 Advantages of Deep Learning for Plant Disease Identification:

Deep learning techniques offer several advantages over traditional methods in the field of plant disease identification:

a. Automatic Feature Learning
b. Adaptability and Generalization
c. Scalability
d. Real-Time and Timely Identification
e. Potential for High Accuracy

7.3. Innovative approaches or adaptations of deep learning techniques tailored to Malvaceae plant disease identification

In recent years, deep learning techniques have revolutionized the field of plant disease identification by enabling more accurate and efficient detection of diseases in crops. To adapt and innovate deep learning approaches for the specific context of Malvaceae plant disease identification, several strategies and technologies can be employed as follows:

- Dataset Collection and Augmentation
- Model Architecture Selection
- Customization and Fine-Tuning
- Data Preprocessing
- Disease Localization

- Transfer Learning
- Real-time Monitoring
- Human-in-the-Loop Systems
- Collaboration and Knowledge Sharing

By incorporating these strategies and innovations, tailored deep learning techniques can greatly benefit the identification and management of diseases in Malvaceae crops, leading to improved crop yield and agricultural sustainability.[13][14]

8. A breakdown of the specific CNN architectures or models used in the studies reviewed

Convolutional Neural Networks (CNNs) have been widely used in various image recognition tasks, including plant disease identification. Here's a breakdown of some specific CNN architectures or models that have been adapted and used for plant disease identification, including their key features and advantages:

8.1 AlexNet

Key Features: AlexNet was one of the pioneering CNN architectures. It consists of five convolutional layers followed by three fully connected layers. It introduced the use of Rectified Linear Units (ReLU) as activation functions and dropout for regularization.

Advantages: AlexNet demonstrated the effectiveness of deep learning for image classification tasks and paved the way for more advanced architectures. While not the most recent, it can still provide good results for plant disease identification when fine-tuned.

8.2 VGG (Visual Geometry Group) Networks

Key Features: VGG networks are characterized by their deep architecture with small 3x3 convolutional filters. They have variations with 16 or 19 weight layers.

Advantages: VGG networks are known for their simplicity and uniform architecture, making them easy to understand and adapt for various tasks. They are suitable for fine-tuning on plant disease datasets.

8.3 ResNet (Residual Networks)

Key Features: ResNet introduced residual connections that allow for very deep networks (e.g., ResNet-50, ResNet-101) without suffering from vanishing gradient problems. Skip connections enable the network to learn residual functions.

Advantages: ResNet architectures have been highly successful for plant disease identification, especially when fine-tuned. Their ability to handle extremely deep networks helps capture intricate features in plant images.

8.4 Inception (GoogLeNet)

Key Features: Inception models utilize multiple parallel convolutional operations with different kernel sizes and strides in a single layer. This allows for the capture of features at various scales.

Advantages: Inception architectures are known for their efficiency and ability to capture both fine and coarse-grained features. They are suitable for plant disease identification tasks with complex and diverse image characteristics.

When choosing a specific CNN architecture for plant disease identification, it's essential to consider factors such as the size of your dataset, available computational resources, and the desired balance between model complexity and accuracy. Many researchers start with pre-trained models and fine-tune them on plant disease datasets to leverage the benefits of transfer learning. Experimentation and model evaluation are crucial to determine the most suitable architecture for your specific application.[15][16]

9. Data preprocessing techniques, including data augmentation or normalization, which are crucial for enhancing model performance

Data preprocessing techniques are crucial for enhancing the performance of deep learning models for plant disease identification. These techniques prepare the dataset for training by improving the quality and consistency of the input data. Here are some important data preprocessing techniques, including data augmentation and normalization:

9.1 Data Augmentation

Purpose: Data augmentation involves creating new training examples by applying various transformations to the original images. It helps in-crease the diversity of the training data and improves the model's ability to generalize to different conditions.

Techniques:

Rotation: Randomly rotate images by a certain angle (e.g., 90 degrees) to account for variations in plant orientations.

Flipping: Horizontally flip images to simulate mirror reflections.

Scaling: Resize images to different scales to simulate variations in plant sizes.

Translation: Shift images horizontally and vertically to simulate changes in plant position within the frame.

Brightness and Contrast Adjustment: Randomly adjust brightness and contrast to simulate changes in lighting conditions.

Noise Addition: Add random noise to images to simulate variations in image quality.

Advantages: Data augmentation helps prevent overfitting, improves model robustness, and enables the model to perform well under different real-world conditions.

9.2 Normalization

Purpose: Normalization standardizes the pixel values in images, ensuring that they have a consistent scale and distribution. This helps in training models more effectively and can improve convergence.

Techniques:

Z-score Normalization: Subtract the mean pixel value from each pixel and divide by the standard deviation. This centers the pixel values around zero with a standard deviation of one.

Min-Max Scaling: Scale pixel values to a specified range (e.g., [0, 1] or [-1, 1]) by subtracting the minimum value and dividing by the range.

Advantages: Normalization ensures that the model is less sensitive to variations in pixel values and makes it easier for the model to learn meaningful features from the data.[17] [18]

10. Highlight of innovative data collection methods or image acquisition technologies used to create the datasets

Innovative data collection methods and image acquisition technologies play a vital role in creating high-quality datasets for plant disease identification. Here are some innovative approaches and technologies used for collecting plant disease-related data:

- Smartphone Apps for Crowdsourcing
- Unmanned Aerial Vehicles (UAVs) or Drones
- Satellite and Remote Sensing Technology
- Automated Robotic Systems
- Plant Phenotyping Platforms
- Crowdsourced Image Databases
- Machine Learning for Data Augmentation
- Collaborative Research Networks

Innovative data collection methods and technologies not only improve the quality and quantity of plant disease datasets but also enable the development of more accurate and robust models for disease identification and management. These approaches contribute to the advancement of precision agriculture and sustainable farming practices. [19] [20]

11. The hyperparameters used during model training, such as learning rates or batch sizes, and their impact on performance

Hyperparameters are critical settings that influence the training process and performance of deep learning models for plant disease identification. The choice of hyperparameters can significantly impact how quickly and effectively a model converges to a solution. Here, we'll discuss key hyperparameters and their impact on model performance:

11.1 Learning Rate:

Definition: Learning rate determines the step size during the optimiza-tion process (e.g., gradient descent). It controls how much the model's weights are updated in each iteration.

Impact:

Too high a learning rate can lead to overshooting the optimal weights, causing divergence and instability during training.

Too low a learning rate can result in slow convergence, as the model makes tiny weight updates.

Optimization: Learning rates are often tuned through techniques like learning rate schedules, where the learning rate is reduced over time, or by using adaptive learning rate algorithms like Adam or RMSprop.

11.2 Batch Size

Definition: Batch size determines the number of data samples used in each forward and backward pass during training.

Impact:

Smaller batch sizes introduce more noise but may lead to faster con-vergence as the model updates its weights more frequently.

Larger batch sizes reduce noise but require more memory and computation.

Optimization: Batch size is often chosen based on available resources (e.g., GPU memory) and the dataset size. Common batch sizes are 32, 64, or 128. [21][22]

12. Specific challenges faced during model training or fine-tuning for Malvaceae plant diseases

Training or fine-tuning deep learning models for Malvaceae plant dis-eases, like any specific agricultural application, comes with its set of challenges. Here are some of the key challenges faced during the model training and fine-tuning process for Malvaceae plant diseases:

- Limited and Imbalanced Data
- Heterogeneity in Disease Symptoms
- Variable Environmental Conditions
- Generalization to Different Malvaceae Species
- Sparse and Noisy Annotations
- Crop Growth Stages
- Transfer Learning Challenges
- Validation and Benchmarking

To address these challenges, researchers and practitioners often employ strategies such as data augmentation, class imbalance handling, fine-tuning of pretrained models, and domain-specific data collection efforts. Collaboration between experts in agriculture, machine learning, and do-main-specific knowledge is crucial to developing effective solutions for Malvaceae plant disease identification and management. Additionally, ongoing research and advancements in the field of computer vision and deep learning can lead to more robust models and methodologies for ad-dressing these challenges. [23][24]

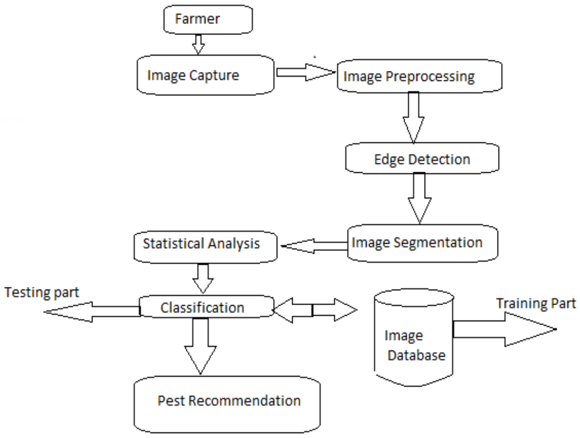


Fig. 2. Advance computing diseases identification System Architecture

12. Detailed Review:

Azath M. et al. (2021) has developed a model utilizing the deep learning technique, Convolutional Neural Network (CNN), to enhance the detection of cotton leaf disease and pests. To accomplish this, the researchers employed common cotton leaf diseases and pests such as bacterial blight, spider mites, and leaf miners. A K-fold cross-validation strategy was implemented to split the dataset, thereby improving the generalization of the CNN model. The researchers accessed nearly 2400 specimens (600 images in each class) for training purposes. The implementation of this developed model was carried out using Python version 3.7.3 and it was equipped with the deep learning package called Keras, which is backed by TensorFlow, and Jupyter, which served as the developmental environment. The achieved accuracy of this model in identifying classes of leaf diseases and pests in cotton plants was 96.4% [25].
Rehan Sarwar., et al. (2021) presents a proposal to train a deep learning Faster R-CNN model on the cotton crop leaf dataset (CCL Dataset) for the purposes of disease detection and classification on leaves, including both healthy and diseased ones. The reference for finding the best feature extractor was the Plant Village dataset, specifically VGG-16, Incep-tionV1, and V2. These models served as the base models in Faster R-CNN. Transfer learning was performed on the CCL Dataset by training the Faster R-CNN inceptionV2 coco model and replacing its output layers with those of the CCL Dataset, enabling the detection and classification of leaf diseases. Experimental results demonstrate a mean average precision (mAP) of 87.1% [26].
Rajani Zambare et al. (2022) have proposed a system that takes a cot-ton plant image as input and preprocesses it to obtain a digitized color image. The leaf image is then segmented, and relevant features are extracted. The subsequent classification of the leaf image is carried out using a CNN model. The experimentation conducted reveals that higher accuracy is achieved by utilizing a CNN model with more than three layers and three hundred epochs for training. The model is further optimized through the addition of a dense layer and flattening. The accuracy obtained for the classification of the model is 99.38% [27].
P. Revathi et al. (2018) have proposed a work centered around Image Edge detection Segmentation techniques. The captured images undergo an initial enrichment process. Subsequently, R, G, B color Feature image segmentation is conducted to identify target regions, specifically disease spots. Further analysis entails the extraction of image features such as boundary, shape, color, and texture, which aid in recognizing diseases and providing pest control recommendations [28].
J. Karthika et al. (2021) have suggested the use of a machine learning model for the detection of cotton plant leaf diseases. This approach is based on image processing techniques and employs SVM classifiers. In this particular study, the author utilized a multiclass cotton leaf disease dataset extracted from Kaggle. Relevant features were extracted using the GLCM (Gray-Level Co-occurrence Matrix) technique [29].
Xihuizi Liang et. al. (2021) presents a few-shot learning framework that can be used for cotton leaf disease spot classification task. the classification of cotton leaf spots by small sample learning, a metric-based learning method was developed to extract cotton leaf spot features and classify the sick leaves. The threshold segmentation and SVM were com-pared in the extracting of leaf spots. The results showed that both of these two methods can extract the leaf spot in a good performance, SVM expended more time, but the leaf spot extracted from SVM was much more suitable for classifying, thus SVM method can retain much more information of leaf spot, such as color, shape, textures, which can help classification the leaf spot. In the process of leaf spot classification, the two-way parallel convolutional neural network was established for building the leaf spot feature extractor, and a feature classifier is constructed [30].
Caldeira, R.F. et. al. (2021) proposed deep-learning models to identify lesions on cotton leaves on the basis of images of the crop in the field. the present research provides a solution based on deep learning in the screening of cotton leaves which makes it possible to monitor the health of the cotton crop and make better decisions for its management. With the learning models GoogleNet and Resnet50 using convolutional neural networks, a precision of 86.6% and 89.2%, respectively, was obtained. Compared with traditional approaches for the processing of images such as support vector machines (SVM), Closest k-neighbors (KNN), artificial neural networks (ANN), and neuro-fuzzy (NFC), the convolutional neural networks proved to be up to 25% more precise, suggesting that this method can contribute to a more rapid and reliable inspection of the plants growing in the field [31].
Shantanu Kumbhar et. al. (2019) proposed a deep-learning model and develop an application that recognizes cotton leaf diseases. For availing user need to upload the image and then with the help of image processing get a digitized color image of a diseased leaf and then proceed with ap-plying CNN to predict cotton leaf disease [32].
Chen, J. et. al. (2020) proposed a transfer learning of the deep convolutional neural networks for the identification of plant

leaf diseases and consider using the pre-trained model learned from the typical massive datasets, and then transferring to the specific task trained by our own data. The VGGNet pre-trained on ImageNet and Inception module are selected in our approach. Instead of starting the training from scratch by randomly initializing the weights, initializing the weights using the pre-trained networks on the large, labeled dataset, ImageNet. The proposed approach presents a substantial performance improvement with respect to other state-of-the-art methods; it achieves a validation accuracy of no less than 91.83% on the public dataset [33].

Sukhwinder Kaur et. al. (2022) Detecting plant diseases using Deep Learning can help farmers protect and minimize the damage to the crops. Using pre-trained models such as VGGNet19 and modifying a few parameters can significantly increase the accuracy in classifying images of plants. Transfer learning is a great method that can reduce the time and computation power required to train the models. Using VGGNet19 and adding a few layers can provide better results for classifying and detecting diseases in plants. Also, these methods can be used to predict and classify images for a wider range of plants and other crops [34].

Chohan et al. (2020) proposed a Plant Disease detector that uses pictures of plants to detect diseases. A convolutional Neural Network with multiple convolution and pooling layers is used on the PlantVillage dataset with 15 percent data chosen for testing. They proposed that this model could be integrated with drones and other systems for disease detection in plants [35].

Sibiya et. al. (2019) utilized CNN (GUI) in maize to detect diseases like northern corn leaf blight, grey leaf spot, and common rust with accuracies 99.9%, 91% and 87%, respectively. The healthy leaf detection per-centage was at 93.5% and the overall accuracy was 92.85% [36]

12.1 Summary of Research Gaps

• Azath M. et. al. (2021) [25] did not propose any specific techniques for feature extraction. The author solely relied on the deep CNN method for feature extraction. However, CNN has its limitations, making it challenging to handle hidden features in images and requiring more time for image processing.

• Muhammad Suleman Memon et. al. (2022) [26] recommended the utilization of deep learning for leaf disease detection. Nevertheless, the author did not provide any suggestions for noise elimination and feature extraction techniques. Consequently, there exists a problem in extracting the relevant features from leaf disease images.

• Xihuizi Liang et. al. (2021) proposed the threshold method for image segmentation. Nonetheless, this method is subject to certain limitations, including sensitivity to noise and inadequate performance in images with a closely related color spectrum [30].

• Yasamin Borhani et. al. (2022) suggested the use of a deep learning model for plant disease detection, employing vision transforms learning. The author employed a traditional deep learning approach for feature extraction. Nevertheless, traditional deep learning methods for feature extraction possess drawbacks, as deep learning models that perform well on benchmarked datasets may encounter difficulties when applied to real-world datasets. Thus, it is necessary to develop new methods for extracting relevant features from real-time images.

13. Challenges and limitations encountered in implementing deep learning for Malvaceae plant disease identification

Despite the promising potential of deep learning techniques for the identification of Malvaceae plant diseases, several challenges and limitations need to be considered when implementing these techniques. This section highlights the key challenges encountered in applying deep learning for Malvaceae plant disease identification and discusses their implications.

- Overfitting and Generalization
- Interpretability and Explainability
- Transferability across Crop Varieties
- Ethical Considerations and Privacy
- Robustness to Environmental Variations
- Limited and Unbalanced Datasets:

Addressing these challenges and limitations is critical to harness the full potential of deep learning techniques for Malvaceae plant disease identification. Future research should focus on developing robust models, curating comprehensive and diverse datasets, improving interpretability, and optimizing computational efficiency. Collaborative efforts between researchers, agricultural stakeholders, and policymakers are necessary to overcome these challenges and promote the adoption of deep learning-based solutions in the field of Malvaceae plant disease management.

14. Result Analysis:

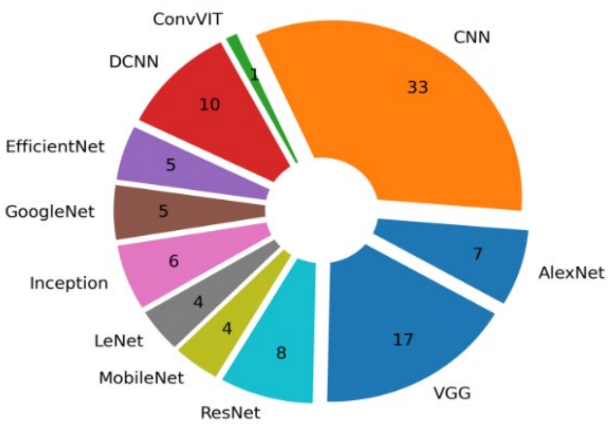
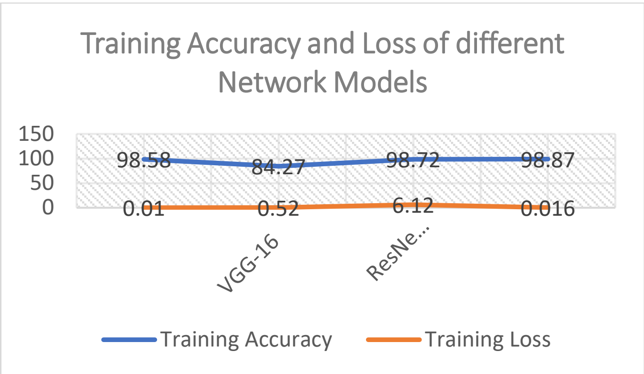


Fig. 3. Distribution of the widely applied CNN algorithm in 100 reviewed studies [9]

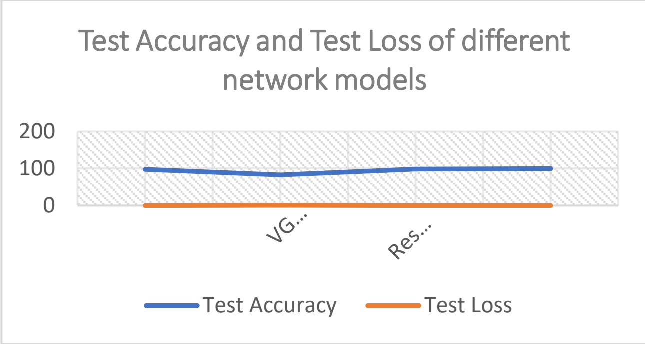
Above analysis illustrates the distribution and number of studies categorized by the algorithm used in the approach development process. Among the 100 summarized studies, the newly developed architecture was the most widely used architecture in plant diseases using CNN.A total of 10 studies, representing 22.2% of the summarized studies, used new architecture. While we observed that Alexnet is the second most commonly used CNN algorithm. In addition, we presented in Figure 7 the accuracy characteristics of 7 CNN architectures used in 100 reviewed studies to detect plant leaf diseases. It could be seen that almost all models converged by the 100th epoch of training reported accuracies of more than 99%. Models such as AlexNet and VGG yielded the highest accuracy when compared to the other models such as ResNet and MobileNet[15].
In agricultural production, early diagnosis of crop disease is essential for high yields. To maintain a high production rate, the latest technologies should be implemented in the early diagnosis of plant disease. It was observed from the literature study that deep learning models are efficient in image classification, and transfer learning-based models are efficient in eliminating training complexity and huge dataset requirements. Hence, in this work, we evaluated four pre-trained models—VGG-16, ResNet-50, Inception V4, and DenseNet-121—to determine the model that was best capable of classifying various plant diseases.

14.1 Comparative performance analysis of various network models [12].

Network Models	Training Accuracy (%)	Training Loss (%)	Test Accuracy (%)	Test Loss (%)
Inception V4	98.58	0.01	97.59	0.0586
VGG-16	84.27	0.52	82.75	0.64
ResNet-50	98.72	6.12	98.73	0.027
enseNet-121	98.87	0.016	99.81	0.0154



Above graph shows relation between training Accuracy and Training loss for different network models



Above graph shows relation between Test Accuracy and Test loss for different network models.

15. Future directions and recommendations for further advancements in this field

In this section, we offer valuable insights into future directions and recommendations for further progress in the field of deep learning techniques used for the detection of plant diseases within the Malvaceae family. These recommendations aim to address the current limitations and challenges and foster the development of more precise, resilient, and practical solutions for disease identification.

- Expansion and standardization of datasets
- Transfer Learning and Model Adaptation
- Explainable and Interpretable Deep Learning Models
- Integration with Internet of Things (IoT) and Edge Computing

By addressing these future directions and recommendations, the field of deep learning techniques for the identification of Malvaceae plant diseases can progress towards more accurate, reliable, and practical solutions. Continuous research, interdisciplinary collaboration, and close engagement with agricultural stakeholders will drive advancements, ultimately benefiting crop management, disease control, and the overall productivity of Malvaceae crops.

16. Conclusion

In conclusion, this paper has delved into the application of deep learning techniques for the identification of various Malvaceae plant diseases. Through an analysis of existing literature and studies, we have identified key findings that underscore the potential of deep learning as a valuable tool for precise and efficient disease identification in Malvaceae crops.
Our analysis of relevant studies has demonstrated the effectiveness of deep learning techniques in identifying different Malvaceae plant diseases. These studies have showcased the capabilities of deep learning models in distinguishing between healthy and diseased plants and classifying various disease types. The achieved accuracies

have surpassed those of traditional methods, thereby highlighting the potential of deep learning for enhancing crop management and disease control.

Looking ahead, future advancements in deep learning for the identification of Malvaceae plant diseases should focus on expanding and standardizing datasets, improving transfer learning techniques, enhancing model interpretability, integrating with IoT and edge computing, fostering collaboration among stakeholders, addressing ethical considerations, and conducting thorough validation and field testing.

By conducting this comprehensive review, our aim is to contribute to the existing knowledge base, provide valuable insights, and guide future research efforts in leveraging deep learning techniques for the identification of plant diseases within the Malvaceae family.

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