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Deep Learning Approaches for Plant Disease Diagnosis Systems: A Review and Future Research Agendas

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Abstract. *To identify novel advancements in plant diseases detection and classification systems employing Machine Learning (ML), Deep Learning (DL), and Transfer Learning (TL), this research compiled 111 peer-reviewed papers published between 2019 and early 2023. The literature was sourced from databases such as Scopus and Web of Science using keywords related to deep learning and leaf disease. A structured analysis of various plant disease classification models is presented through tables and graphics. This paper systematically reviews the model approaches employed, datasets utilized, countries involved, and the validation and evaluation methods applied in plant disease identification. Each algorithm is annotated with suitable processing techniques, such as image segmentation and feature extraction, along with standard experimental metrics, including the total number of training/testing datasets utilized, the quantity of disease images considered, and the classifier type employed. The findings of this study serve as a valuable resource for researchers seeking to identify specific plant diseases through a literature-based approach. Additionally, the implementation of mobile-based applications using the DL approach is expected to enhance agricultural productivity.*
Keywords: *a review intelligent plant disease; disease diagnosis systems; deep learning, intelligent plant disease.*

Type of the Paper: Article Review.

1. Introduction

Plants infections are significant concerns as they adversely affect the growth and yield of chili crops. A range of organisms including fungi, bacteria, viruses, and molds contribute to plant diseases, influencing overall crop production. The recent decline in agricultural production has notably affected farmers' livelihoods. Effective plant infection management begins with accurate disease identification. Agricultural groups and plant clinics have traditionally played a key role in identifying plant infection. More recently, these efforts have been enhanced by an online disease diagnosis platform, facilitated by increasing internet penetration. Additionally, the development of smartphone-based tools has gained prominence, leveraging the wide-spread adoption of smartphone technology [1]. Deep Learning utilizes Artificial Neural Networks (ANN), which are modeled after the neurons in the human brain. This network consists of multiple layers, with the term "deep" referring to their depth [2]. By leveraging deep learning techniques, plant disease identification has emerged as a promising approach, as convolutional layers effectively recognize

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plant characteristics such as color and texture. Moreover, comparable performance can be achieved with a 75% reduction in parameters, increasing confidence in deep learning's effectiveness [3]. CNNs can simultaneously identify and classify images; however, this method has limitations and is time-consuming due to its reliance on large datasets. Nevertheless, its adoption is increasing as more publicly available datasets facilitate further research [3–5]. This study identifies research gaps in the existing literature, aiming to systematically map the plant species involved in leaf diseases classification, as well as architecture, datasets, model approaches, and hardware used in addressing these challenges. The authors reviewed 102 papers published between 2019 and 2023, sourced from databases such as Scopus and Web of Science, using keywords related to deep learning and leaf disease. This study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. This paper is structured as follows: Section II presents a comparative analysis of recent DL algorithms employed in plant disease identification and classification. Section III examines empirical findings from previous research on various DL models. Section IV concludes the study and outlines directions for future research.

Research on plant disease identification using deep learning techniques is crucial for ensuring food security and mitigating adverse effects on the growth and yield of chili crops. Early and accurate detection is essential to prevent further losses. Convolutional Neural Networks (CNNs) enhance efficiency and precision in disease identification through leaf imagery, achieving high accuracy even with smaller datasets and optimized model architectures.

The purpose of this research is to analyze various CNN architectures employed in the identification of plant leaf diseases and evaluate the performance of CNN models in classifying leaf diseases based on architecture, datasets, model approaches, and hardware utilized. Novelty of the research, this study offers a comprehensive analysis of the latest CNN architectures applied in the identification and classification of plant diseases, providing a clear mapping of plants involved in the leaf disease classification process and exploring various model approaches and hardware used. This approach is expected to provide new insights and serve as a foundation for further research in this field.

2. Materials and Methods

To systematically and objectively comprehend the existing body of literature, conducting systematic literature review (SLR), as outlined by Kitchenham et al. [6], is essential. An SLR facilitates a comprehensive evaluation of relevant findings and their interpretation within the research context while addressing specific research questions. This approach ensures consistency, reduces bias, and provides a solid foundation for analysis. The research incorporated a dual-phase strategy, beginning with the execution of an SLR following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. Early-stage researchers often rely on the PRISMA framework and employ online databases such as SCOPUS and ScienceDirect, which enforce specific standards regarding publication dates and language limitations [1]. The decision to adopt an SLR approach was influenced by the varied nature of the content in each publication. This procedure involved planning, execution, reporting, and dissemination. The literature review was conducted using the Prisma methodology.

The Fig. 1 below illustrates the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) flow diagram, which is used in systematic literature reviews (SLRs) to systematically and transparently screen and select relevant studies. This diagram consists of several stages, including identification, screening, and inclusion, which structure and streamline the literature selection process.

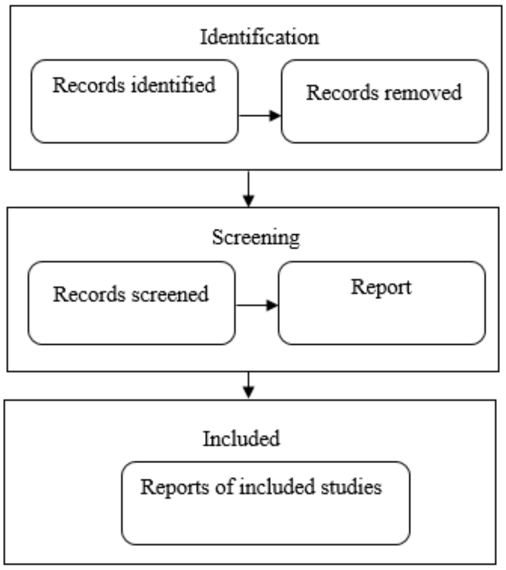

Fig. 1. PRISMA Flow Diagram for SLR [7]

1. Study Identification

   Studies were identified through the Scopus database using the keyword "deep learning leaf disease", retrieving a total of 111 studies. An additional 48 studies were obtained from external sources. Inclusion criteria include studies related to deep learning in leaf disease classification, with available abstracts and relevant content published between 2013 and 2023, from high-quality journals (e.g., Tier Q1-Q3). Exclusion criteria include studies removed before screening for the following reasons: duplicate records (0 studies), did not meet journal quality criteria (Tier Q1-Q3) (19 studies), and lack of an abstract for screening (0 studies).

2. Screening Process

   After removing ineligible studies, 92 studies were screened, with no exclusion at this stage (0 studies). Out of 92 studies sought for full-text retrieval, 38 studies were not retrieved. Ultimately, 54 studies were assessed for eligibility, and after eligibility assessment, 2 studies were excluded for specific reasons.

3. Studies Included in the Final Review
   After completing all stages, 52 studies from the primary database and 11 studies from other sources were included in the final review, resulting in a total 63 research reports in the systematic review.
4. Data Analysis and Leaf Disease Classification
   Studies were categorized based on the deep learning methods used for leaf disease classification. Various deep learning architectures such as CNN, ResNet, VGG, and Transformers were employed. Datasets used were either publicly available or self-developed. Supervised learning models were applied for classification, with fine-tuning of pretrained models. Hardware such as GPU and TPU were employed to accelerate model training. Data Preprocessing involved image augmentation, normalization, and segmentation. Model Training included transfer learning and fine-tuning using available datasets. Model evaluation was conducted using performance metrics such as accuracy, precision, recall, and F1-score to assess model effectiveness.

Feature extraction is crucial for object identification in feature extraction and pattern matching processes [8,9]. Various preprocessing approaches, such as mean reduction and normalization, have been widely used in image processing. These preprocessing steps are also applied in the first layer of every convolutional neural network (CNN) [10,11]. In Google Colab, various techniques have been tested on various CNNs [12]. For instance, AlexNet has been trained on a subset of the ImageNet database containing over one million images, allowing it to classify images into 1000 categories [13,14]. In this algorithm, a pre-trained network is initially loaded, retaining all layers except the last three, which are replaced and retrained using a new dataset. This approach represents a form of transfer learning, where the final layers are adjusted to recalibrate weights. Various CNN-based methods have been applied to plant diseases diagnosis [15,16], including AlexNet, DenseNet [17,18], EfficientNet, GoogleNet [19], Inception [20,21], MobileNet [22], ResNet [23,24], SqueezeNet, VGG [25], VGGNet, Xception [26], YOLO [27,28], Mobile-DANet [29], Faster DR-IACNN [30], SACNN [31], QBPSO-DTL [32], and others. These methods facilitate knowledge discovery from the Intelligent Plant Disease database [33].

2.1. Classification

Classification, a widely used data mining, utilizes previously categorized samples to develop models for classifying diverse data [34]. Both unsupervised learning [35,36] and transfer learning [37–39] are employed in this process. This technique is often used in plant disease detection, often leveraging CNN with various methods for data classification. The classification process consists of two stages: training and testing. During the training stage, the classification algorithm examines the training data. Subsequently, the testing data is used to evaluate the accuracy of the classification process. If the accuracy is deemed adequate, the generated rules can be applied to new data. The classification training algorithm uses example parameters necessary for accurate discrimination, which are then incorporated into a model known as a classifier.

2.2. AlexNet

This design is a key system in deep learning that has significantly improved ImageNet classification accuracy [40], surpassing traditional methods [41]. The neural network comprises 60 million parameters and 650,000 neurons. It includes five convolutional layers with some max-pooling layers and concludes with three fully connected layers. In total, the network comprises 8 learned layers [42].

2.3. VGGNet

The architecture was developed by the Visual Geometry Group at the University of Oxford [43]. It enhances the performance of AlexNet by substituting large kernel-sized filters with sequentially arranged 3x3 kernel-sized filters [44]. Combining several smaller-sized filters in layers enhances recognition compared to using larger-sized filters [43]. Additionally, incorporating multiple non-linear layers increases the network's depth, enabling more efficient learning of complex features with improved processing speed [45]. In the VGG architecture, three fully connected layers similar to those in the AlexNet network follow the convolutional layers [46]. The width of the first convolutional layer starts at 64, doubling each time a pooling layer is passed through [47].

When tested with ImageNet contest data, the VGGNet system achieved a top-5 accuracy rate of 92.3% [48]. VGGNet has two main variants: VGG-16 and VGG-19. VGG-16 consists of 16 layers, encompassing convolutional layers (3x3), max-pooling layers (2x2), and fully connected layers. Conversely, VGG-19 comprises 19 layers, incorporating convolutional layers, max-pooling, and fully connected layers [49].

2.4. GoogleNet

GoogLeNet developed the concept that many network activations become redundant (having zero values) or excessive due to their interrelationships. This approach emphasizes activations with infrequent connections, ensuring that each input is not always linked to all others. Several methods can reduce such associations, resulting in sparse weights or relationships [33].

A key innovation introduced by GoogLeNet is substituting the fully connected layers at the network’s end with global average pooling, which computes the average of channel values on the 2D feature map after the convolutional layer. By utilizing the network’s depth and scale, GoogLeNet eliminates fully connected layers without sacrificing accuracy.

2.5. Inception

GoogleNet introduced the "Inception" convolutional neural network architecture [50,51], which has evolved through multiple versions, from Inception v1 to Inception v4 [52,53]. These iterations improve the convergence of classification errors in intermediate layers and reduce reliance on large kernel sizes, enhancing efficiency [54,55]. Additional enhancements include convolution factorization and improved normalization [56].

2.6. ResNet

The ResNet technique employs a deeper architecture using a residual module [57–59]. With 152 layers, which is ten times deeper than the previous CNNs [60,61], it emphasizes unique connections and significantly utilizes batch normalization [62,63]. Similar to GoogleNet, ResN*et* applies average pooling before the classification layers [64,65], resulting in higher accuracy than VGG-Net and GoogLeNet [66,67].

3. Results and Discussion

To examine recent advancements in plant disease detection, we conducted a comprehensive literature review using the PRISMA Protocol technique. This approach ensures that our review provides clear, accurate, and transparent information to readers.

We initially identified 111 research articles from the Scopus database using the keyword "deep learning leaf disease", covering studies from 2013 to early 2023. To ensure the quality and relevance, we selected sources with quartile rankings of Q1, Q2, and Q3.

Fig. 2 illustrates the selection and evaluation process based on PRISMA criteria. We included 63 relevant studies for further discussion, highlighting recent advancements and optimal methodologies in plant disease detection using deep learning and transfer learning.

3.1. Country

Research on leaf disease detection using common deep learning architectures has been conducted worldwide. Based on the collected studies, the most frequently mentioned countries include:

a. China: Many studies originate from China, indicating a high interest in deep learning applications for leaf disease detection.
b. India: India also appears several times as the country of origin for these studies, indicating active developments in this field.
c. Malaysia: Several studies from Malaysia highlight regional interest in this technology.

Iraq, the United States, Turkey, Egypt, and Korea also appear on the list, though less frequently than China and India. Fig. 3 presents publication data, highlighting the global scope of research on leaf disease detection using deep learning. The findings indicate that this remains an active research area, with certain countries leading in publication volume.

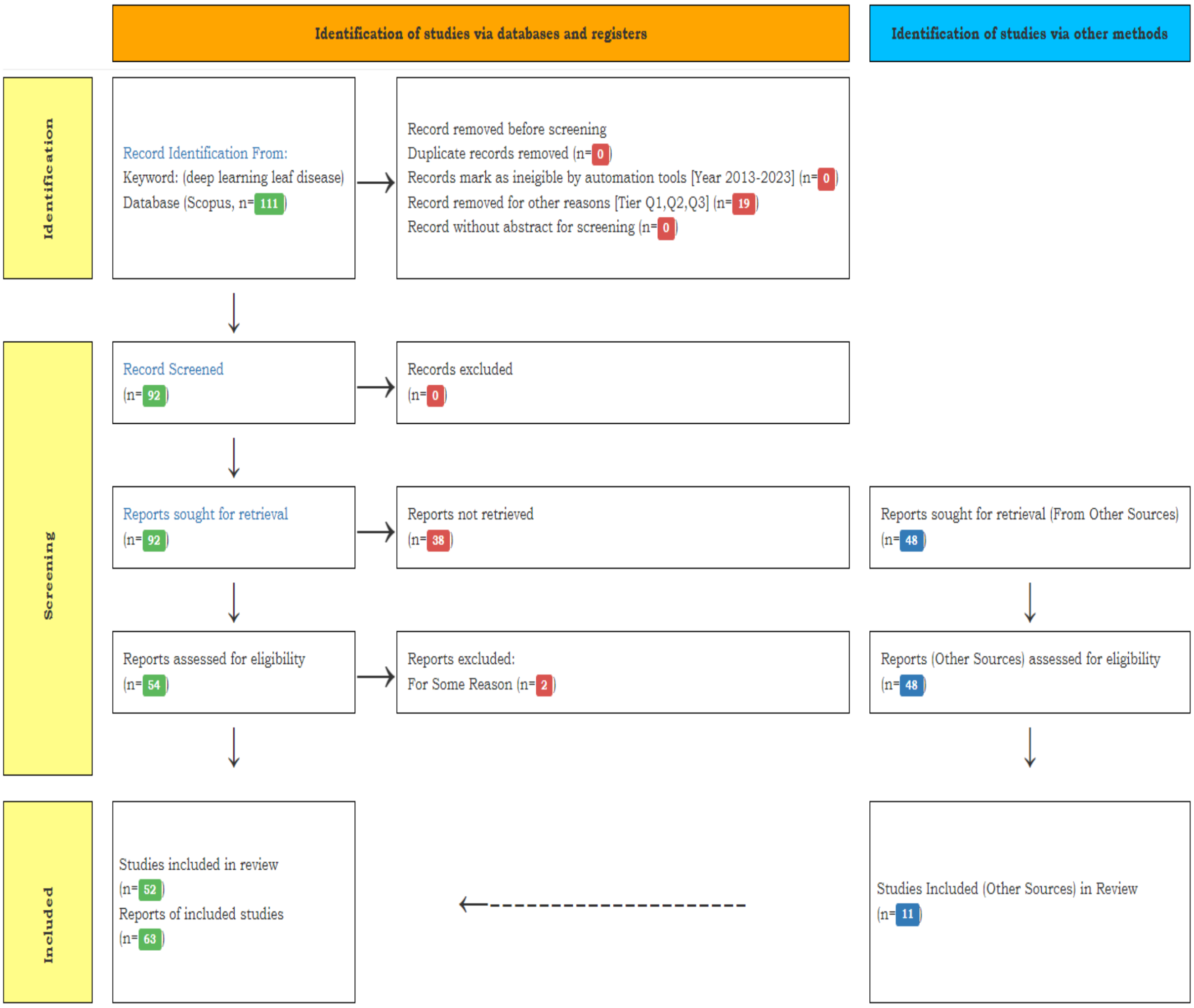

Fig. 2. Classification of research [7]

3.2. Architecture

Several deep learning architectures have been widely utilized for leaf disease detection, including:

a. VGG (such as VGG-16 and VGG-19): Frequently cited for its depth and effectiveness in various computer vision tasks.
b. ResNet (like ResNet50, ResNet101): Incorporates "skip connections," to enable deeper network training and mitigate the vanishing gradient problem.
c. Inception and its variants, like InceptionV3: Optimized for efficient computational resource use in network training.
d. EfficientNet: Gaining interest due to its computational efficiency.

Large datasets enhance model accuracy and generalization. For example, one study utilized a dataset of 217,000 leaf images from Egypt, demonstrating the impact of extensive training data on model performance.

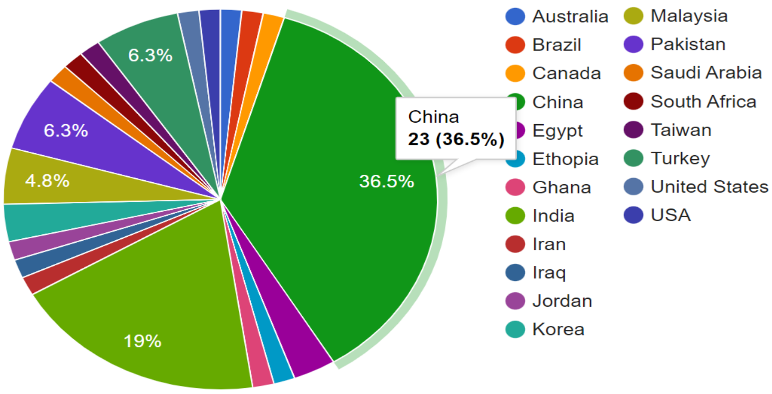

Fig. 3. Classification of research sources using the prism of protocol

3.3. Dataset

Researchers use various datasets for leaf disease detection through deep learning and transfer learning. Common datasets approaches include:

a. Specific Plant Datasets: Many studies focus on specific types of plants, such as Scorch Leaf, Bean Leaves, Chili Leaf, allowing models to be specialized based on unique plant characteristics.
b. Country-Specific Datasets: Some datasets originate from specific countries, such as China, Iraq, and Malaysia, reflecting the need to detect leaf diseases under distinct climatic and environmental conditions.
c. Large-Scale Datasets: Some studies utilize extensive datasets, such as those containing 217,000 images, to train more in-depth and accurate models.
d. General Datasets: Datasets like PlantVillage, which include various types of plants and diseases, support the development of models capable of detecting multiple diseases across different species.

Overall, dataset selection depends on the research objectives, whether to focus on specific disease, adapt models to local conditions, or develop generalized solutions for leaf disease detection.

3.4. Category

Based on the findings from the provided paper, the architectural approaches in plant disease detection can be summarized from the perspectives of transfer learning and unsupervised learning:

a. Unsupervised Learning

Various architectures are employed for plant disease detection, including SqueezeNet, EfficientNetB3, VGG-16, AlexNet, DenseNet121, ResNet24, ResNet50, VGG-19, InceptionV3, DenseNet201, and others. These models are assessed using accuracy, precision, recall, and F1 score. Hardware configurations range from Intel Core CPUs and Nvidia GPUs, to Google Colab servers with high-capacity GPUs and RAM.

b. Transfer Learning:

Transfer learning is widely used, employing architectures such as AlexNet+TL, ResNet18+TL, GoogleNet+TL, Inception-v3, DenseNet-201, MobileNet, VGG-16, and others. Evaluation metrics remain consistent with unsupervised learning, including accuracy, precision, recall, and F1 score. Hardware infrastructure includes high-performance GPUs, CPUs, and cloud platforms like Google Colab.

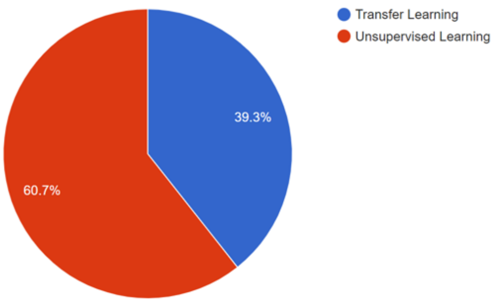

Fig. 4. Percentage of Machine Learning Approach Categories

Both unsupervised and transfer learning approaches dominate plant disease detection, with architectures tailored to dataset requirements and specific challenges (Fig. 4). The selection of architecture depends on factors such as dataset size, problem complexity, and available computational resources.

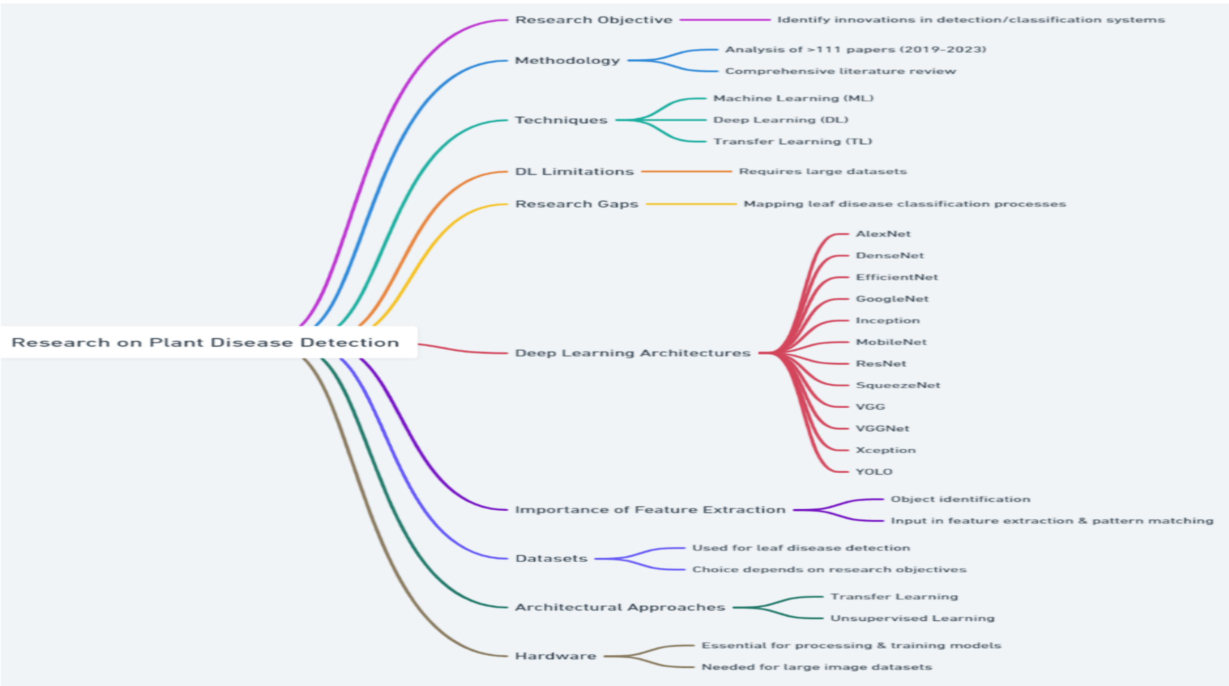

Fig. 5. Research Gap Mindmap

3.5. Hardware

Advanced hardware is crucial for processing large datasets leaf disease detection using deep learning. Commonly used hardware includes:

a. Nvidia GPU: Models such as the Nvidia GTX850M, Nvidia GTX 1050 ti, Nvidia RTX 2070, and Nvidia Tesla V100 enable parallel computation, significantly accelerating model training.
b. Intel Core CPU: Examples include Intel(R) Core(TM) i7-4712MQX and Intel(R) Core(TM) i7-4510U. While GPUs enhance training speed, CPUs remain essential for general operations and data management.
c. Google Colab Server: This cloud platform offers access to high-performance GPUs, such as the 69K GPU graphics card, reducing the need for costly local hardware.

For large datasets, robust hardware is crucial for efficient data processing, enabling researchers to experiment with various architectures, optimize models, and accelerate development cycles.

A. Research GAP

This study highlights advancements in plant disease detection and classification utilizing machine learning (ML), deep learning (DL), and transfer learning (TL).

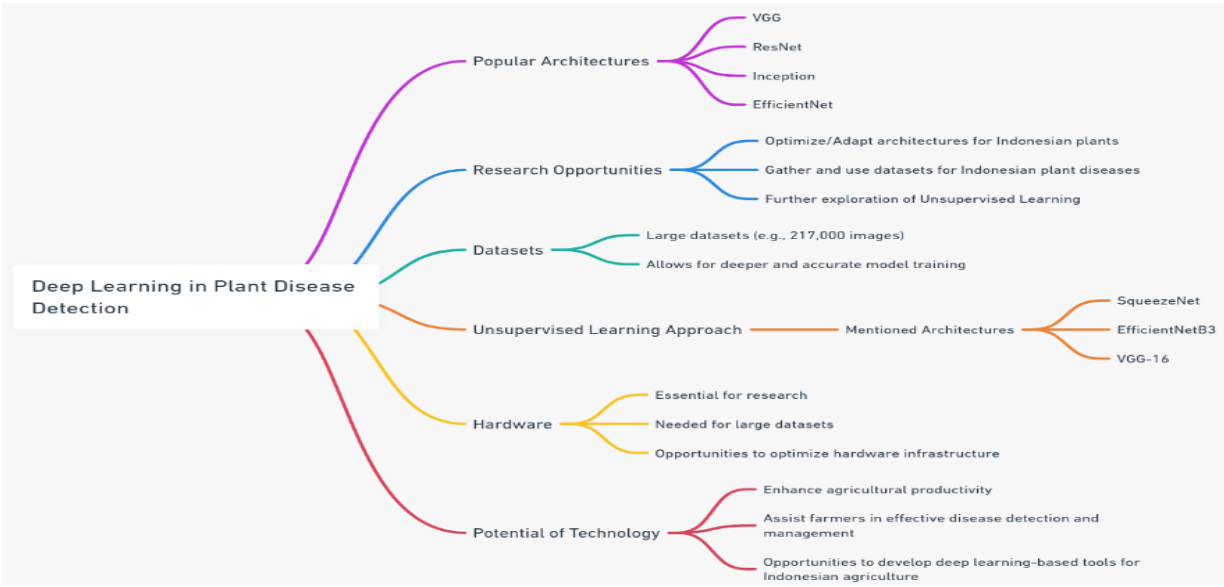

Fig. 6. Research the Future mindmap.

As shown in Fig. 5, more than 111 papers published between 2019 and early 2023 have been analyzed to examine the approaches used in plant disease detection. While deep learning has demonstrated significant potential, its reliance on large dataset remains a limitation. This study identifies research gaps in the existing literature to enhance understanding of leaf disease classification across various plant species. It also documents the utilization of various deep learning architectures, such as AlexNet, DenseNet, EfficientNet, GoogleNet, Inception, MobileNet, ResNet, SqueezeNet, VGG, VGGNet, Xception, YOLO, and others. Feature extraction is essential for object identification in the feature extraction and pattern matching processes. To explore recent advancements in plant disease detection, a comprehensive literature review was conducted. Various datasets are used for leaf disease detection using deep learning and transfer learning approaches, with dataset selection depending on the research objective. This study summarizes architectural approaches from the perspectives of transfer learning and unsupervised learning. In research related to leaf disease detection using deep learning. Additionally, advanced hardware is essential for processing and training models on large datasets, Feature extraction plays a crucial role in identifying an object when used as input in the feature extraction and pattern matching processes. To understand the latest developments and methodologies used in plant disease detection, a comprehensive literature review was conducted. Various datasets are used by researchers for leaf disease detection with deep learning and transfer learning approaches. The choice of dataset often depends on the research objective. Based on the findings from the provided paper, there is a summary of architectural approaches from the perspectives of transfer learning and unsupervised learning. In research related to leaf disease detection using deep learning, advanced hardware is essential for processing and training models on datasets with a large number of images.

B. Future Research Agenda

Numerous deep learning architectures, including VGG, ResNet, Inception, and EfficientNet, are widely recognized for their effectiveness in leaf disease detection. Research opportunities exist in optimizing or adapting these architectures for specific plant conditions in Indonesia. Some studies have used extensive datasets, with up to 217,000 images, enabling deeper and more accurate model training. Similar datasets focusing on common plant diseases in Indonesia could be developed to enhance model performance. Additionally, unsupervised learning approaches have been applied to plant disease detection, with architectures such as SqueezeNet, EfficientNetB3, and VGG-16 frequently cited. Research opportunities exist in further exploring unsupervised learning approaches for plant disease detection in Indonesia. While specific hardware details are not fully presented in the summary, advanced hardware remains essential, especially for processing large datasets. Optimizing hardware infrastructure could enhance efficiency in model training and development. This research shows the great potential of this technology in enhancing agricultural productivity by enabling early and accurate plant disease detection. There is an opportunity to develop deep learning-based applications tailored to agricultural conditions in Indonesia.

Fig. 6 illustrates research opportunities, commonly used architectures (e.g., VGG, ResNet, and EfficientNet), the role of large datasets, unsupervised learning approaches, and the importance of hardware in supporting deep learning-based plant disease detection, particularly in Indonesia.

4. Conclusions

Based on the literature review in the provided paper, several key points can be concluded based on several criteria:

1. Countries: Research related to leaf disease detection using deep learning approaches has been conducted in various countries worldwide. The most active countries in this field include China, India, and Malaysia. This indicates that leaf disease detection using deep learning technology is an active research area globally.
2. Architecture: some of the most popular deep learning architectures in leaf disease detection include VGG (such as VGG-16 and VGG-19) and ResNet (such as ResNet50, ResNet101). Inception and EfficientNet have demonstrated effectiveness in various computer vision tasks and have been extensively applied in leaf disease detection research.
3. Dataset: various datasets utilization for leaf disease detection. Some datasets are dedicated to specific types of plants, while others cover various types of plants and their diseases. Larger datasets, such as those containing 217,000 images, enable deeper and more precise model training.
4. Category: From a categorical standpoint, unsupervised learning methods have been applied in plant disease detection. Among the architectures mentioned in this category are SqueezeNet, EfficientNetB3, VGG-16, which are evaluated using metrics such as accuracy, precision, recall, and F1 score.
5. Hardware: Although specific hardware information is not fully presented in the summary, advanced hardware remains crucial in this research, especially when handling large-sized datasets.

This research aims to identify various research deviations in the existing literature by analyzing research markers involved in the leaf disease classification process, including architecture, dataset, approach model, and hardware used to address the problem. This objective has been successfully achieved concerning architectural criteria, as the Inception and EfficientNet architectures have demonstrated effectiveness on various computational applications. A dataset with a large number of images, such as 217,000 images, is considered a good dataset. Unsupervised learning methods, including SqueezeNet, EfficientNetB3, VGG-16 are recognized as effective good deep learning models. The learning model’s performance was assessed based on accuracy, precision, recall, and F1 scores.

The findings suggest that selecting the right architecture and dataset is crucial for achieving accurate and reliable disease detection. Utilizing architectures such as Inception and EfficientNet, along with large datasets, can significantly improve the effectiveness of leaf disease detection. However, this research has certain limitations, particularly the lack of detailed information on the hardware used, which may affect model performance, especially when processing large datasets. Additionally, applying these models in real-world agricultural settings requires further exploration to address practical challenges. Based on these findings, several recommendations for future research can be made. First, further studies should focus on identifying optimal hardware capable of efficiently processing large datasets to enhance model performance. Second, exploring hybrid models that integrate supervised and unsupervised learning may improve detection accuracy. Lastly, developing more diverse datasets that include various plant species and diseases from different regions with varying climates will enhance the robustness of the models.

Overall, this paper offers comprehensive insights into recent advancements in leaf disease detection using deep learning techniques. With various approaches and technologies employed, this research highlights the potential of deep learning in enhancing agricultural productivity and assisting farmers in detecting and managing plant diseases more effectively.

Abbreviations

ML	Machine Learning
TL	Transfer Learning
ANN	Artificial Neural Networks
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
CNN	Convolutional Neural Network
SLR	Systematic Literature Review

Data availability statement

All data is available in the authors' articles contained in the references. If necessary, data will be shared upon request by the readers.

CRediT authorship contribution statement

Verry Riyanto: Conceptualization, Methodology, Resources, Formal analysis, Investigation, Data curation, Funding acquisition, Writing – review & editing, Writing – original draft. **Sri Nurdiati**: Validation, Data curation, Formal analysis, Conceptualization. **Marimin**: Validation, Data curation, Formal analysis, Methodology, Conceptualization & review. **Muhamad Syukur**: Validation, Data curation, Formal analysis, Conceptualization. **Shelvie Nidya Neyman**: Validation, Data curation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare there was no known competing financial interests or personal relationships that could have appeared to influence the work reported.

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