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Article

Deep Learning Techniques for Plant and Soybean Leaf Disease Detection: A Review of Models, Datasets, Gaps, Challenges and Future Directions

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Abstract: Plant diseases have a high impact on agricultural productivity and food security in the world. Plant diagnosis is also critical in avoiding a loss of crops and enhancing agricultural productivity by timely detecting plant diseases. The conventional methods of identifying diseases are by manual inspection and expert knowledge, which are time consuming and have the risk of human error. Over the last few years, deep learning and computer vision methods have evolved as powerful solutions towards automated detection of plant diseases using leaf images. The demand for soybeans as a source of oil and protein on the world market makes them one of the most important crops in the world. Because of this, researchers are now increasingly interested in developing deep learning systems to detect soybean leaf diseases. This paper reviews the recent advancements in the application of deep learning techniques for the identification of plant and soybean leaf diseases. It presents multiple deep learning structures such as convolutional neural networks (CNNs), transformer-based neural networks, hybrids of deep learning, and ensemble techniques. Additionally, the paper discusses the importance of high-quality training data and surveys publicly available datasets used in soybean disease detection. Other important issues analyzed in the study include constraints of the dataset, environmental changes, complexity in computing, and interpretability of the model. Lastly, the paper describes the possible future research directions to enhance the accuracy, robustness, and scalability of automated plant disease detection systems. This review is an overview of the existing studies in the field of deep learning-based detection of plant diseases and an introduction to the study by the prospective researcher in the area of smart agriculture and precision farming technologies.
Keywords: Deep Learning, Plant Disease Detection, Soybean Leaf Disease, Convolutional Neural Networks (CNN), Transformer Models, Hybrid Deep Learning, Transfer Learning, Agricultural Datasets, Precision Agriculture, Computer Vision

1. INTRODUCTION

Agriculture is a critical sector of the global community as it helps to guarantee food production and maintain the global economy. Nevertheless, plant diseases are one of the biggest challenges facing the productivity of agriculture. Fungal, bacterial, viral and pests- generated diseases may severely impact crop quality and quantity. It is therefore important to diagnose plant diseases at the earliest possible stage and ensure proper management of crops to avoid mass agricultural losses.

Traditional plant disease detection methods primarily rely on manual inspection by farmers or agricultural experts. Though such methods are common, they are usually time-consuming and need domain expertise. The visual manifestations of various diseases can be in many ways similar and fine identification becomes difficult even among the professionals. With the increase in agricultural areas and a more advanced farm management system, manual observation is insufficient to improve chances of early disease detection. Manual observation is not a sufficient measure to get the chance to detect the disease in time. The development of artificial intelligence (AI), specifically deep learning and computer vision, has changed the way the surveillance and detection of plant diseases are conducted.

Deep learning method-based systems can analyze images of leaves of vegetation and determine symptoms of diseases with a high accuracy. Conventional neural networks (CNNs), which are among the most popular deep learning structures, have shown outstanding performance in plant disease recognition.

The recent literature has delved into different deep learning methods aiming to identify diseases in different crops like soybean, tomato, potato, apple, and cotton. These methods feed the neural networks with an image of leaves on the agricultural field or in the laboratory to identify the patterns of the diseases [1]. Learning complex features, including color variations, the shape of a lesion, and a certain pattern of texture, is among plant diseases that a variety of models have successfully learned and demonstrated a high classification accuracy.

Soybean is a very significant crop by the world standards; it is extensively utilized in food production, animal, as well as industrial purposes. Nonetheless, the soybean plants are prone to different diseases such as bacterial blight, soybean rust, and leaf spot. These diseases will greatly lower the productivity of crops if they are not identified at an early stage (Farah et al. 2023). Consequently, much attention was devoted by researchers to creating automatic systems of detection of soybean leaf disease using artificial intelligence (deep learning models) [2].

Several deep learning models and datasets have been developed, particularly for soybean disease detection. For example, the SoyNet dataset offers high-resolution images of leaves on soybeans with various diseases to allow researchers to train and test deep learning models more efficiently [3].

This review paper aims to provide a comprehensive summary of existing deep learning techniques for plant and soybean leaf disease detection. The paper presents the latest contributions to this area of research and summarizes widely applied datasets and models, and suggests the problematic aspects and possibilities of future research in the field.

2. RESEARCH GAPS AND MOTIVATION

2.1 Identified Research Gaps

Despite the rapid development of the methods of deep learning in plant disease detection, there are still certain research gaps which can be considered as critical. One of the most crucial issues is the overreliance on the doctored laboratory results. Such datasets typically consist of high-quality images captured under controlled lighting and background conditions. These datasets are not an appropriate representation of the agricultural environment, even though they would be useful for training deep learning models. In real life, various factors have an influence on the images of plant leaves. Consequently, the models which are trained using the laboratory data sets, are not always effective in practice. The other major limitation is the design of the traditional convolutional neural networks. Though these models prove very effective in the extraction of local features like edges, textures, and color variations, they are not well suited for the extraction of multi-scale and global information [4]. Plant diseases can be manifested in various forms and sizes within a leaf, and these may be observed in various parts of the leaf in various areas.

The next major research gap is the little regard to the cross-domain generalization by the researchers. Majority of the models have been trained and evaluated on specific datasets, rendering them less effective when applied to other crops, geographical areas, or imaging situations. Moreover, the problem of the imbalance in the classes in the datasets of plant

diseases is frequently neglected with certain diseases being overrepresented and other ones having a very small number of representations. This results in biased learning and low detection of rare diseases. Moreover, deep learning models are often not interpretable, and farmers and other agricultural experts cannot be sure of the system and how it arrives at its decision-making procedures. The lack of explicable AI mechanisms restricts its use in the real world. The other gap is the lack of resistance to multimodal data being incorporated including environmental conditions, soil conditions, and weather data that can play a significant role in defining the occurrence and progression of the disease.

2.2 Motivation for Proposed Framework

The shortcomings observed in previous research present solid reasons as to why a better deep learning framework should be developed. It is also driven by the desire to come up with a model that can work successfully in the agricultural environment. A model of this kind must be able to combat the difference in light, background, and the orientation of the leaves, but should be very accurate. Compared to feature extraction, convolutional neural networks are weak in their ability to capture global patterns. Transformer-based models, on the other hand, are more contextual and computationally expensive. Therefore, a balanced approach is required that combines the advantages of both techniques while minimizing their limitations. The model must be strong enough to be able to work with various datasets and plant species [5]. This means that one must be able to acquire a variety of patterns and be able to fit in different conditions without having to undergo a lot of retraining. Productivity is also an important factor.

Alongside increasing the accuracy and power of the developed framework, there is a compelling urge to develop a framework that will be computationally efficient and applicable to real-world agricultural settings. Many farmers use mobile devices or low-power systems and the proposed model must work with the constrained computational resources. Thus, reducing the trade-off between the level of complexity and performance of the model is one of the major goals. The other incentive is to optimize the system scalability in such a way that the system can be extended to other crops other than soybean without having to revamp the system. This would render the solution more feasible and cost-effective to be used in large scale farming. Furthermore, it is important to add flexibility into the model, as it will constantly be informed by new data and new patterns of diseases to adapt to them. This flexibility guarantees flexibility and sustainability in application and relevance of the system in the volatile farming environments.

2.3 Multi-Scale Wide-Residual Framework

The Multi-Scale Wide-Residual Framework has been suggested as a remedy to the shortcomings that have been established by the current methods. The framework is based on multi-scale feature extraction followed by wide-residual learning, which enhances the functionality and stability of the plant disease detection models. Multi-scale feature extraction enables the model to examine aspects at varying scales of detail. This is particularly applicable in the case of plant disease detection since the symptoms can be of different sizes and localities. Other diseases may be in the form of small dots, and others may cover a huge portion of the leaf. The model can capture features of various sizes, thereby identifying small- scale features as well as large-scale features. Massive residual connectivity intensifies the flow of information in the network [6]. In contrast to the traditional deep networks, which might be affected by the problem of vanishing gradients, the wide-residual architectures enable the features to propagate better and learn more efficiently.

In addition, the use of multi-scale processing and multi-scale wide-residual connections also helps in enhancing feature recycling and minimizing redundancy in the network. This allows the model to be very performance-intensive and allow subsistence of computational costs. Side-by-side paths of feature extraction can also be facilitated within the framework, enabling the simultaneous extraction of fine-grained and coarse-grained features, thereby improving the accuracy of detection in complex patterns of disease. The other benefit of this architecture is that it is flexible enough to include attention mechanisms that will further enhance the effectiveness of the model in extracting the most relevant parts of the leaf image. This is especially applicable in situations whereby the signs of a disease are so mild or partially covered. Moreover, it can be expanded to accommodate transfer learning and hybridization with transformer elements to be flexible to future changes in deep learning methods and to achieve sustained performance in plant disease detection systems.

3. BACKGROUND OF PLANT DISEASE DETECTION

The possibility of detecting plant diseases has been researched over a long period of time because of its relevance in agricultural processing. Initial studies put most emphasis on manual disease detection systems. The visual assessment of the leaves was performed by farmers and plant pathologists who were seeking the symptoms like discoloration, lesions and abnormal development patterns. Although the subjectivity and the dependence on the knowledge of the specialists are among the main limitations of such an approach, it is still rather popular.

As digital imaging technology improved, scientists started to apply the method of computer vision to computerize the process of plant disease classification. The initial machine learning models were based on feature extraction methods that were manually formulated. Such techniques included color history, texture features, and shape features among leaf images. The feature extracted was subsequently processed by standard machine learning methods like support vector machines (SVMs) to classify the disease in plants.

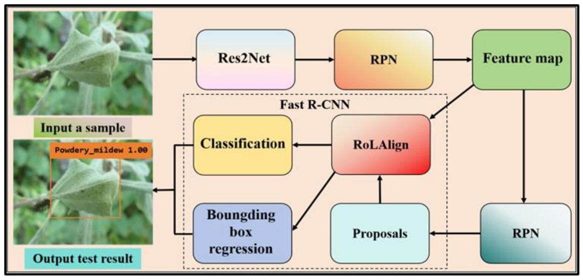

Fig. 1: Plant Leaf Disease Identification by Deep Learning Algorithms

Previous studies have demonstrated the use of color analysis and texture extraction techniques for disease detection in rice leaves and other crops through digital images. Similarly, Support Vector Machine (SVM)-based classification models [7] have been used to detect pests.

Although these methods have moderate success, there are various limitations that they have. Complex features in the images of plant diseases were often not observed using handcrafted features. Moreover, such methods also require a lot of knowledge in the field to develop effective feature extraction methods. Deep learning has done wonders in the detection of plant diseases as there is no need to manually extract features. The automatic learning and hierarchy feature learning of neural networks are carried out directly on image information and they can learn the complex visual patterns that are the features of plant diseases. As a result, deep learning models have realized a high accuracy relative to the traditional machine learning.

4. OVERVIEW OF EXISTING RESEARCH

4.1 Traditional Machine Learning Approaches

As discussed by Yao et al. (2024), the original techniques of plant disease detection have been based on traditional machine learning techniques, which have employed handcrafted feature extraction. The approaches included the methods of extracting features (color, texture, and shape) of leaf images and classifying them. Support vector machines and decision trees are algorithms that have been frequently utilized in this regard.

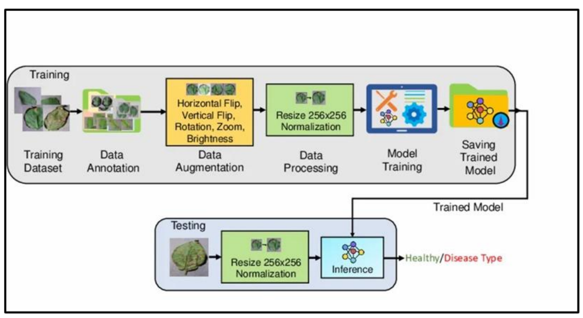

Fig. 2: Traditional Machine Learning Workflow for Plant Disease Detection

To a degree, these techniques have been effective particularly under controlled conditions in which images have been homogeneous and the noise is minimized. They did have a few limitations, however. It has been knowledge-intensive in the domain, and may be time consuming when extracting features. The handcrafted features, too, might not always fit into the detailed patterns to which the presence of plant diseases has been attributed. The greater the number of types of featured diseases, the more difficult were created features that will succeed to differentiate between them. Such challenges led to the application of deep learning algorithms which can automatically find features of the raw data. Other classical machine learning algorithms such as k-nearest neighbours (KNN), random forests, and naive Bayes classifiers have also been applied to detect plant diseases along with other more frequently used algorithms, such as support vector machines and decision trees. The efficacy of these methods largely depends on the efficacy of feature extraction techniques, which dictate how the classification model will work in general. Histogram of oriented gradients (HOG), gray-level co-occurrence matrix (GLCM), and color histogram have been implemented in large numbers as feature engineering approaches to capture the attributes of leaf images [8]. The effectiveness of the specified techniques, however, will mostly rely on the quality of the hand matters and the skills of the researchers to choose the most topical descriptors.

The other setback with the conventional methods is that they cannot process large volumes of data effectively. Since the volume of agricultural imaging information is increasing at a high rate, the techniques find it difficult to scale up to large sizes, as they require manual preprocessing and feature selection. In addition, conventional models are also adversarial towards noise, variations in illumination and complexities in backgrounds, which are prevalent in real-world agricultural situations. This makes them weaker and less applicable in non-controlled settings .

Also, conventional machine learning methods are typically not adaptable, i.e. a model fitted on one type of crops and disease may not work well when applied on another without substantive adjustment. This is a limitation of generalization that limits their use in a broader scope of agricultural uses. Despite these shortcomings, the traditional methods have been adopted as the framework of automated systems of plant disease detection and can be considered the reference method to compare with other more advanced methods that involve deep learning models [9].

4.2 Convolutional Neural Network (CNN)-Based Studies

The ability to learn hierarchical characteristics of image data automatically has allowed convolutional neural networks to be one of the most popular methods of detecting plant diseases (Jafar et al., 2024). Such models have several layers, such as convolutional layers, pooling layers, and fully connected layers, that collaborate to identify meaningful patterns in leaf images. The CNNs do exceptionally well in recognizing visual features like spots, discoloration, and lesions, which are typically linked to plant diseases. The advantages of CNN-based models are that these tools can be used to work with large volumes of data and have a high classification rate.

These are able to learn not only low-level features like edges and textures, but also high-level features that are complex patterns of a disease. This renders them very efficient in the detection of disease based on images. They are mainly concerned with local feature extraction and might not be capable of extracting global associations in an image. This may make them less useful in instances where the patterns of diseases are spread over various areas of a leaf. Also, the CNN models are known to consume vast quantities of annotated data to be trained, which is typically hard to find in agricultural settings. Such difficulties have prompted researchers to seek other methods that can be used to address these drawbacks.

In addition to their capabilities in estimating hierarchical features, CNN-based models have had major improvements with the emergence of advanced architectures, which includes; AlexNet, VGGNet, ResNet, DenseNet and EfficientNet. The architectures have enhanced the performance of plant disease detection systems through the capability of deeper networks with enhanced feature representation and less overfitting. The vanishing gradient problem is solved thanks to the use of residual connections, which are presented in ResNet and make it possible to train indeed deep networks, thereby increasing the classification accuracy [10].

Other methods like data augmentation and regularization, have also been incorporated in CNN models in order to enhance generalization performance. Simulation of real-world variations such as rotation, flipping, cropping, and brightness adjustment and help decrease overfitting. Also, training has been stabilized with the help of dropout and batch normalization to increase the model robustness.

In spite of these developments, CNNs also have some shortcomings. Dependence on large labelled datasets is one of the key problems because they are generally hard and expensive to acquire in agricultural settings. The data generation system is also time-consuming since it will involve the process of annotating plant disease images using expert knowledge. In addition, CNNs are computationally expensive and they are thus not suitable to run on resource-constrained devices like the smartphones and embedded systems.

The other challenge is that CNN-based models are not interpretable. They can even be true but nobody can very well determine what features are used by the model in its predictions. The methods that have been used to address this issue include grad-CAM and saliency maps but they are not effective in providing an explanation to the model behaviour in full. These inadequacies suggest that there is a greater need to have more effective and understandable models in the process of detecting plant diseases.

4.3 Transfer Learning in Plant Disease Detection

Transfer learning has turned out to be a plausible approach to solve the problem of limited dataset in the detection of plant diseases. This approach uses the already trained models trained on large datasets to provide the general image representation and then fine-tunes it to the specific use [11]. Transfer learning requires little training data and calculation as it utilizes the already known data. In detecting plant disease, transfer learning can be applied so that the researchers can use the already available architectures and modify them to identify disease patterns in leaf images. The advantage of this methodology is enormous in that it can make the model perform to an excellent degree especially when available data is not large and not diverse.

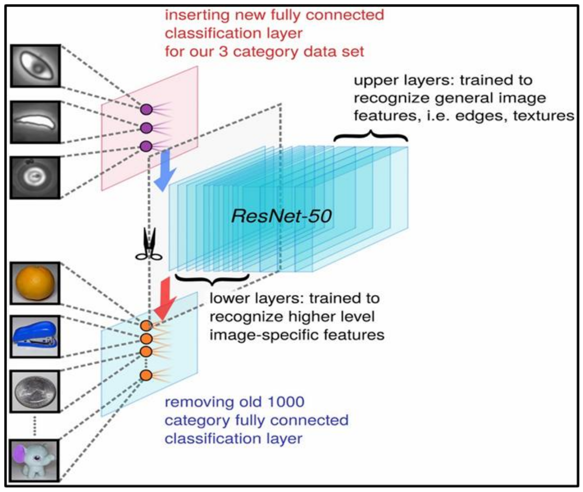

Fig. 3: Transfer Learning Process Using Pre-trained Models

Observed that this approach is time-efficient, as it minimizes the training time required compared to building models from scratch. The pre-trained models are usually created to solve the general image recognition problems and may not be capable of reflecting the peculiarities of plant diseases. This implies that there is a need to fine-tune the model to suit the target domain, which remains computationally expensive. Also, transfer learning can be ineffective in situations where the difference between the source and target data is large. These issues notwithstanding, it is a popular and useful method in the detection of plant diseases. The concept of transfer learning has also become widely adopted because of its capacity to utilize knowledge in huge volumes and use it to solve domain-related problems. InceptionV3, VGG16, ResNet50 and MobileNet are all popular pre-trained models being widely used in plant disease detection. Such models are also usually trained with large datasets such as ImageNet and subsequently optimized on smaller agricultural datasets leading to better performance with less training hours [12].

Transfer learning is one of the main solutions to this problem, as it enables the resolution of the problem of small labeled data. The model is able to identify meaningful features using a small dataset by using pre-trained weights. This renders it especially applicable to agricultural purposes where it is difficult to collect and tag data. Transfer learning also lowers the computational demands relative to model training on clean data, thus it is also less likely to be accumulated into real-world use. Nevertheless, transfer learning has its own limitations. Transfer learning is reliant on the degree of resemblance between the source domain and the target domain. When the given source data is dissimilar to the target data, the features transmitted might not be applicable, and the results will be a decreased performance. The effectiveness of the model may be obstructed by this problem called negative transfer.

Moreover, it can be intricate and time-consuming to carefully select hyperparameters and layers to be retrained to fine-tune pre-trained models. The challenges notwithstanding, transfer learning is a potent method in the process of plant disease detection and remains popular because of its efficiency and effectiveness in terms of handling small data situations.

4.4 Transformer-Based Models

Transformer models are a notable advancement in deep learning, particularly in respects that require an understanding of associations among information in a worldwide scale. In contrast to CNNs, transformers process image in global form and long-range dependencies are well recalled using attention, the method of transformers. This attribute makes them very appropriate in detecting intricate and minute trends when it comes to plant disease detection. In the first image in the plant disease detection, the transformer models can be applied to see more than one part of a leaf at once and determine the association between the two or more. This has resulted in improved fine-grained classification and hard-to-detect disease patterns with transformer-based methods. Despite the strengths, transformer models have serious challenges. These models require large volumes of training data and are computationally intensive. This renders them a bit inapplicable in real time scenario in the agricultural sectors especially where resources are limited [13]. Transformer based models have complexities in terms of practical implementation and optimization of agricultural systems. In transformer-type models, a larger amount of data is required, the computation power is also required and specialized hardware to train and deploy, as compared to what would otherwise be accessible in a resource-constrained environment. Transformer model architecture relies on attention mechanisms which are more complex to design, tune or interpret compared to traditional CNN-type models (i.e., CNN). Consequently, they are highly challenging to maximize their output when applied to devices with limited resources like mobile phones or edge systems that are employed by farmers in real agricultural farms. These constraints point to the need to have more efficient models that can accomplish the same task with less computational demands.

Transformer-based models introduce a major advance in deep learning models by emphasizing attention instead of convolution mechanisms. Vision Transformers (ViTs) and their derivatives like Swin Transformer as well as MaxViT have demonstrated encouraging performances in image classification as well as animal disease detection. Such models divide images into patches and interpret them as patterns, enabling the capture of global relationships across the entire image.

Transformer based models are one of the strongest models as they are capable of long-range association of disparate parts of an image. This comes in handy, especially in the case of plant diseases, where the symptoms can be spread over an area of many sections of a leaf. Transformers, unlike CNNs, provide a more global representation of the image. Recent research has shown that transformer-based models have been found to be more accurate on the fine-grained classification tasks than their traditional CNN counterparts. They are also very useful in identifying the nuances of similar categories of diseases which is generally a difficult task in plant pathology.

These models however, have high data and computing requirements. During training of transformers, large datasets and high-performance hardware is required which might be unattainable in most agricultural environments. Moreover, transformers are harder to implement and optimize than CNNs, and it can reduce their use in the real world. To solve these issues, scientists are looking at hybrid solutions involving the use of transformers alongside the CNNs to balance between both performance and efficiency [14]. Despite the constraints mentioned, the transformer-based model is regarded as an avenue of future research in detecting plant diseases because it has a better capacity to convey the global context.

4.5 Hybrid Deep Learning Models

Hybrid deep learning models are developed by using more than one technique to take advantage of the benefits of other architectures. Hybrid algorithms are commonly used in the detection of plant diseases to combine the strengths of convolutional neural networks with other algorithms and enhance the representation of features and accuracy of classification. The hybrid systems are supposed to integrate local and global characteristics in the image of leaves by combining various models. Among the most significant benefits of hybrid models, it can be noted that they allow the analysis to be more complete than in the case of single models.

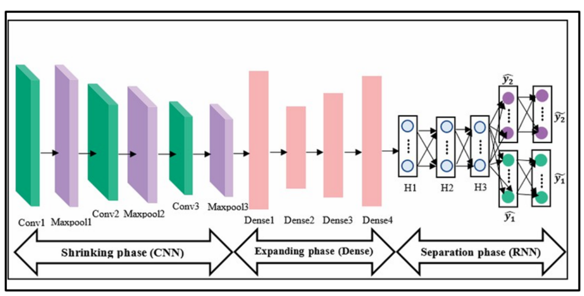

Fig. 4: Hybrid Deep Learning Architecture Combining Multiple Models

Hybrid approaches that combine convolutional networks with other learning techniques enhance the model's capability to identify complex disease patterns. It leads to better accuracy and strength, particularly in problematic situations. Nevertheless, hybrid models introduce additional complexity, increasing computational requirements and complicating model design and optimization due to the integration of multiple components. This may limit their application in the real-world agricultural setting where simplicity and efficiency matter.

Hybrid deep learning models combine both types of architectures, i.e., CNN-type architecture and transformer-type architecture, to overcome the limitations of either of these architectures individually. CNNs excel at extracting local features efficiently; however, they do not capture the global context of any given input pattern (i.e., the relationship between all portions of the input data); thus, they may not provide a complete representation of all data.

Alternatively, transformer models capture the relationship between all parts of an input but are expensive to compute [15]. A hybrid model that uses both architectures (i.e., CNN + transformer) will yield sufficient accuracy and efficiency with respect to the previously mentioned input representation, thereby improving performance overall. Hybrid methods combine various models into a unified approach that seeks to exploit the advantages of each method without reducing their disadvantages. These models offer a better representation of image features since it represents both local and global information.

As an example, CNN-transformer hybrid models combine the local feature extraction through convolutional layers with global dependencies through transformer layers. It has been demonstrated that this combination enhances classification accuracy and strength, particularly in complicated situations where the patterns of the disease are spread throughout the image. Another example can be outlined as CNNs and GNNs integration, in which CNNs acquire visual characteristics and GNNs acquire ties between different locations in the image. In doing this, the model will be able to understand more about patterns in space and relationships, and will be better able to detect.

Despite their advantages, hybrid models present novel difficulties in the architecture design and training. They also require extra computational resources and parameters that are highly tuned and this factor can render only a few of them to be carried out in the real world. Also, more complexity can translate to a longer training process and consumes more energy. Nevertheless, the hybrid models provide a good path in developing advanced plant disease detection models regarding accuracy, robustness and generalization [16]. They are suitable in addressing the different challenges that exist in the area of agricultural image analysis since it incorporates different paradigms of learning.

4.6 Publicly Available Datasets for Plant and Soybean Disease Detection

The accessibility of quality datasets is highly significant in the models and testing of deep learning that detects plant diseases. These datasets present models with data (training and validation) to which they learn features that they use to accurately categorize the disease. Over the past few years, a number of publicly available datasets have been developed, which consist of annotated images of plant foliage that have been affected by various diseases. The majority of these datasets consist of images in controlled settings with uniform backgrounds and perfect lighting, which simplify model training but can decrease their usefulness. In this way, one should be aware of the nature and constraints of such existing datasets to come up with efficient models of disease detection. The next section introduces a review of publicly accessible datasets which were utilized in detecting plant and soybean disease.

Plant disease modeling (data) sets play a crucial role in the process of designing and testing plant disease detectors (Hassan et al. (2022). Majority of the existing studies have been anchored on publicly availed data sets which consist of labeled images of plant leaves under controlled conditions. Such data sets can be used in training and benchmarking models because the data sets are high quality, and their categories are accurate. However, lack of diversity in such datasets can be deemed as one of the largest limitations. The photos are generally captured at ideal environments and have continuous sources of light and a background which might not be reflective of reality of agricultural settings [17]. Therefore, the trained predictive models that are based on these sets of data may perform well in testing but not in practice.

In order to address this issue, scholars use data augmentation techniques to artificially diversify datasets. This sort of manipulation involves image manipulation, specifically through the application of transformations like rotation, scaling and other color manipulations. Despite being helpful, those methods cannot give the variability of the real-world environment. There is a growing need to get more detailed datasets with pictures taken under different environmental conditions.

Other than the commonly used datasets, such as PlantVillage and SoyNet, other datasets have been created to aid the study of plant disease detection. These datasets can be of varying size, diversity and quality which have a significant influence on model performance. Controlled datasets provide clean and well-labeled images, although they are not necessarily intended to be applied to the real world, due to lack of diversity. Researchers have tackled dataset scarcity through data augmentation and synthetic data production technologies. Data augmentation represents the artificial increase of dataset size through the transformation of existing images (i.e., changing properties like rotation, scale, inversion). GANs (Generative Adversarial Networks) further contribute to improving the diversity of datasets, enabling generalization of deep learning models via the generation of new realistic images to utilize for training. These strategies contribute to better generalization of the models but do not necessarily reflect the ground reality.

KSFs (Key Success Factors) assist in conducting processes successfully; therefore, dataset annotation using expert-generated correct labels is a KSF of great importance for creating reliable, deep-learning models and to assure the model achieves a high level of success detecting diseases. Data set annotation is the other KSF. that needs expert knowledge in order to correctly classify diseases. It will be labor intensive, subject to human error and may compromise the quality of the data set. Also, the imbalance in the number of classes can be observed in most of the datasets, where the number of some diseases is comparatively high, resulting in bias in model predictions. To deal with such problems, there is an increasing demand for large scale, varied and publicly available data sets that contain images taken in varying environmental conditions. Researchers, agricultural institutions, and farmers can form a collective partnership to produce more holistic datasets that are realistic. High-quality and variety of data sets are important factors in the effectiveness of deep learning models [18]. Thus, to enhance the development of plant disease detection studies and guarantee the feasibility of such models, it is important to enhance the process of data collection and annotation.

4.7 Comparative Analysis of Existing Studies

Conducted a review of the differences between traditional machine learning and deep learning techniques, such as Convolutional Neural Networks (CNNs), Transformers, and Hybrid (CNN + Transformer) models, based on existing research comparing these methodologies. While traditional methods' algorithms are much simpler and interpretable than CNNs and Transformers, deep learning involves more complex algorithms capable of producing higher accuracy, requiring significantly more data and computing resources. Simple and interpretable traditional machine learning techniques do not have the ability to model complex patterns. Convolutional neural networks are highly utilized and offer good performance, yet they do not perform well in global feature extraction and need large datasets. Transfer learning enhances efficiency using the pre-trained models; thus, it is applicable in situations where data is limited. It might not, however, adapt completely to domain-specific features.

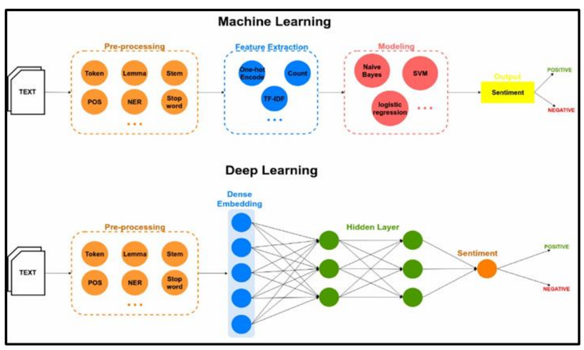

Fig.5: Comparative Analysis of Different Deep Learning Models

The models based on transformers have sophisticated features for capturing global relationships; however, due to the high computation demands, their usage is restricted in practice. Hybrid models have sought to capitalize on the strengths of various approaches giving better accuracy, but they bring forth further complexity. This comparison displays that there is no single approach that can address all the problems in detecting plant diseases [19]. In order to achieve high accuracy, high generalization and high computational efficiency, a balanced structure is needed.

A comprehensive comparison analysis reveals that each technique possesses distinct capabilities tailored to the specific requirements of the application. Existing machine learning algorithms are easily comprehensible, classical, and consume less computing resources; hence, they can be used in simple applications. However, they cannot acquire more complex designs and perform poorly under different environment. CNN-based models are highly accurate and popular in terms of their effectiveness in analysing images. They, on the other hand, require huge datasets and cannot be effective in capturing the global setting. Transfer learning can address a problem of the insufficient data with the pre-trained models and presupposes the similarity of domains and successful fine-tuning.

Transformer based models are good in the modelling of global relations and in addressing the complex pattern, albeit they are computationally costly and demand high amount of data. Hybrid models are models that aim to execute the advantages of the different approaches, hence resulting in improved outcomes at an increased complexity.

Other factors of interest are model scalability and deployability. Real-time applications can benefit well with lightweight models and transfer learning techniques, but more advanced models, involving transformers and hybrid models can be dedicated to research and high-performance systems.

Generally, the comparative analysis indicates that a balanced set in respect to accuracy, efficiency, scalability, and interpretability is required. The future study should consider trying to come up with models that have a way of integrating the perfection of the different methods but minimizing their failures and what will emerge will be more practical and efficient plant diseases detection systems [20]. To analyze the current literature - summarized in Table 1 - demonstrates that the traditional machine learning, CNN-based, transformer and hybrid deep learning methods possess their own unique possibilities and limitations to detect plant diseases.

Table 1: Comparative Analysis of Existing Plant Disease Detection Studies

Reference	**Model/Architecture**	**Dataset(s) Used**	**Performance Metrics**	**Key Limitations**
Duhan et al. (2026)	Lightweight DL Models	Plant datasets	Efficient and fast performance	Slight reduction in accuracy
Sumith and Rashmi (2026)	DL + Super Resolution	Leaf & canopy datasets	Improved image quality and detection	Increased model complexity
Zhao et al. (2025)	CNN, Hybrid DL Models	PlantVillage, Multiple datasets	High classification accuracy	Limited real-world applicability
Khan et al. (2025)	CNN-based DL	Various datasets	Improved detection efficiency	Dataset imbalance, noise
Pranta et al. (2025)	MaxViT	Soybean dataset	High accuracy, speed	Requires large data
Dolatabadian et al. (2025)	ML + DL	Crop datasets	Moderate–high accuracy	Feature sensitivity
Goyal et al. (2025)	Hybrid DL + Hyperspectral	Hyperspectral datasets	High precision	High cost, complexity
Radočaj et al. (2025)	UAV + DL	UAV datasets	Field-level detection	High computation
Shinde & Attar (2025)	UAV-based DL	Soybean UAV dataset	Large-scale detection	Environmental variability
Yao et al. (2024)	Multi-prediction DL	Leaf datasets	High precision/ recall	High complexity
Yani et al. (2024)	CV + DL	Mixed datasets	Reliable performance	Poor generalization
Jafar et al. (2024)	AI-based models	Agricultural datasets	Accurate detection	Interpretability issues
Al Mamun et al. (2024)	Self-supervised learning	Limited labelled data	Reduced labelling need	Lower accuracy
García-Vera et al. (2024)	ML + Hyperspectral	Hyperspectral datasets	Detailed identification	Expensive

Dhaka et al. (2023)	IoT + DL	Smart agriculture datasets	Real-time monitoring	Infrastructure dependency
Hassan et al. (2022)	ML Models	Plant datasets	Basic performance	Low accuracy for complex diseases

5. DEEP LEARNING ARCHITECTURES FOR PLANT DISEASE DETECTION

Deep learning architecture has become the core of the new technology in plant disease detection, especially within the provisions of automated image diagnostics. Recent progress in the field of artificial intelligence has allowed researchers to come up with neural network models that can learn intricate visual features of plant leaf images. These architectures have contributed to a tremendous enhancement of the quality and efficiency of plant disease detectors in comparison with the conventional machine learning models that perform handcrafted features. In the last ten years, several deep learning models have been introduced to solve the problems that surround plant disease classification such as convolutional neural networks (CNNs), transfer learning techniques, transformers, and hybrid deep learning [21]. All these architectures play their own role in enhancing the accuracy of classification, computational efficiency and robustness in the analysis of agricultural image dataset.

5.1 Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) are the most popular deep learning model of detecting plant diseases. CNNs have proven to be the most appropriate models when it comes to analyzing images since they can identify spatial features of an input image automatically using convolutional operations. The architecture of a common CNN system is composed of multiple layers, such as convolutional layers, pooling layers, activation functions and fully connected layers. These layers collaborate in the detection of patterns including textures, forms and color differences in images. Plant disease detector tasks In plant disease detection tasks, CNNs are trained to identify the symptoms of a disease (e.g. leaf spots, discoloration, bad growth patterns, etc.) directly on raw image data.

Several studies have demonstrated the effectiveness of CNN-based models in plant disease detection. For example, a sophisticated deep learning system was developed to detect and classify plant leaf diseases at an early stage, demonstrating high accuracy when trained on large image datasets to identify symptomatic patterns. These models employ deep convolutional layers to learn hierarchical features that can be both higher level semantic features associated with disease symptoms and lower level features such as edges and textures.

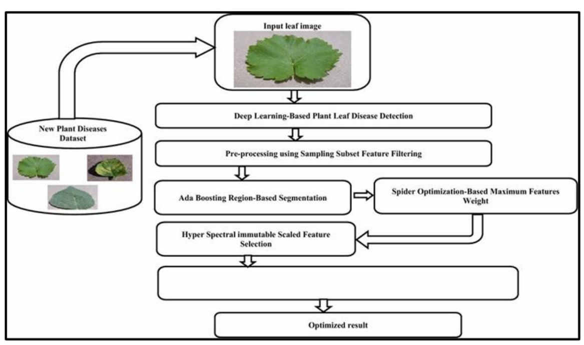

Figure 6: “Architecture diagram for plant disease detection”

Along with the overall disease detection of plants, CNN architectures have also widely been applied to the detection of the soybean leaf disease. Scholars have developed dedicated CNNs that are able to make images of soybean leaves and categorize different types of diseases based on their visual symptoms [22]. These models have patterns that can be effectively detected and these are lesions, yellowing and necrotic spots on leaf, which are common with soybean diseases. CNNs are most successful in recognizing the different kinds of diseases that can be visually similar since they can extract the spatial information of images.

The other significant development in CNN-based plant disease diagnosis is the development of lightweight CNN model to be applied in real farm environments. These smaller-sized architectures reduce the level of computation and provide high classification. Lightweight networks are tailored specifically to the mobile and edge computing, which has limits on computational resources. An example would be to implement smaller CNN models as smartphone apps or integrated into systems which can assist farmers to determine what is ailing their plants in the field. This diagnostic potential can boost the management of crops and reduce crop losses as agricultural diseases can be identified and treated in time.

Other architectural improvements achieved using CNNs are residual connections, depth wise separable convolutions and attention modules in addition to their powerful feature extraction capability. The improvements make CNNs to create increased precision and reduced complexity in calculations. Using attention-based CNNs the most important area of the leaf image can be focused on which is the infected area improving classification performance. Moreover, CNNs can also be utilized with segmentation models to localize disease areas before classification, which can be more interpreted and accurate.

The other interesting one is, ensemble CNN models where a series of CNN architectures are put one on top of the other in order to increase the predictability accuracy. The ensemble methods reduce the bias and variance of the model and lead to more reliable performance on the datasets [23]. Reference CNNs however are currently still to be optimized in regards to tuning parameters, training time and deployment productivity especially in real-time use in agriculture.

The following is a simple algorithm of a CNN-based plant disease detection model. It seems to be not arranged properly and does not contain all information. The perfect algorithm or flowchart would be used to state what is to be done to come up with this model, and help the reader figure out how to obtain detection of plant disease using a CNN-based model. This information may be explained such as adding a diagram to aid the procedures written.

"Input: Leaf Image I

Preprocess I (resize, normalize)

For each convolution layer:

Apply filters to extract feature maps Apply activation function (ReLU)

Apply pooling (reduce dimensions) Flatten feature maps

Pass through fully connected layers Output: Disease class prediction"

5.2 Transfer Learning Approaches

Transfer learning has been an important method in improving disease detection of plants particularly in situations in which the training data are limited. Instead of feeding raw data to a deep learning model when training a deep learning model, transfer learning is created by using pre-trained neural networks that have been trained on huge image datasets such as ImageNet. These models contain preexisting visual characteristics that can be tweaked to a different activity, e.g., to classify plant diseases.

The popular pre-trained architectures applied to transfer learning are VGGNet, ResNet, Inception, and DenseNet. These models are first trained using millions of images as represented in thousands of classes facilitating them to acquire generalized visual representations. Researchers subsequently fine-tune the later layers of these networks using plant disease datasets, enabling the models to learn specialized patterns for disease identification.

Transfer learning has a number of benefits in plant disease detection study. First, it saves on a lot of training time since the model already includes useful features representations. Second, it is more effective in the scenarios of small datasets, which is a typical problem in agricultural studies [24]. Transfer learning models can be transferred to small datasets of agricultural images with high classification performance with the knowledge gained using large-scale datasets. Therefore, transfer learning is a popular method used to come up with effective and accurate systems of detecting plant diseases.

In addition, methods of transfer learning may be classified into feature extraction methods and fine-tuning methods. In feature extraction pre-trained models are provided as fixed feature extractors, with only the target dataset being trained in the final classification levels. Fine-tuning, on the contrary, is a process of modifying certain, or all, model layers to fit the target field more closely. Fine-tuning can be considered more accurate but will consume more computation and need more parameter choices.

The other benefit associated with transfer learning is that it is compatible with lightweight models like MobileNet and EfficientNet which are only made to run on mobile and edge devices. Such models allow detecting diseases in the field in real-time, thus they are very practical to farmers.

Also, transfer learning facilitates domain adaptation methods in which models are adapted to lessen the disparity between the source and target datasets. This is more especially relevant in fields of agriculture where the environmental conditions differ considerably [25]. Although this is effective, the choice of pre-trained model and transfer strategy is a major challenge with a direct effect on the model performance.

5.3 Transformer-Based Models

Over the past years, transformer-based architectures have become viable and effective alternatives to conventional CNN models in computer vision. Transformers are based on attention-based processes as opposed to convolution processes to analyze image data. The attention mechanism also allows the model to determine correlations across various parts of an image which enables it to determine complex variations that might not be easily identified by convolutional filters.

The use of transformer models has shown encouraging performances in the task of detecting plant diseases. The SoyaTrans model, which was created specifically to provide a fine- grained classification of soybean leaf diseases, is among the most notable. Compared to conventional CNN models, this transformer design achieves a high classification rate by using attention mechanisms to assess minute changes in the visual representation of disease symptoms.

The fact that transformer models can learn global contextual information in images renders them highly effective on complex classification tasks in which there are different disease categories. Contrary to CNNs, which mostly emphasize local characteristics, transformers are able to examine long-range correlation of the whole image. It is their ability to detect subtle differences in patterns of the disease that might be scattered in an area spanning a number of regions within a leaf.

New developments in models based on transformers have proposed hybrid vision transformers and hierarchical transformers that enhance efficiency and scalability. To minimize computational complexity and explore the features of modeling global dependencies, models like Swin Transformer apply shifted window mechanisms. These advancements render transformers more useful in real-life situations, such as detection of plant diseases.

The other major advantage of transformers is that they have the capability of integrating multimodal data. Say, transformers may also fuse image information with other environmental data (i.e. temperature, humidity) to enhance prediction of diseases. This feature creates opportunities for accurate agriculture and intelligent farming systems [26].

Nevertheless, the transformer models continue to be challenged by the stability of training and the data requirement. Their performance sometimes needs large-scale datasets that in the case of agricultural research data are not always accessible. Researchers are looking into self- supervised and semi-supervised learning techniques that minimise the use of labelled data to get around issue.

Transformer-based models are regarded as a promising area of research due to its capacity to adapt, scale, and effectively model intricate relationships in visual data.

5.4 Hybrid Deep Learning Models

Hybrid deep learning models are another interesting method for identifying plant diseases. These models combine different deep learning techniques to improve feature representation and classification. Unlike single-model approaches, hybrid models can efficiently integrate local and global image data because they are modeled using distinct neural network architectures.

The integration of convolutional neural networks and graph neural networks (GNNs) can be regarded as one of the examples of a hybrid framework. In this method, visual features of leaf images are extracted by CNNs, and GNNs are applied to calculate connections between various feature parts. The combination of this allows the model to reproduce fine structural patterns of plant disease images.

A recent work suggested that a hybrid CNN-GNN model based on soybean disease detection includes convolutional feature extraction and relational learning via a graph. The method proved to be better at classifying images, using both spatial and relational data in the image set.

Hybrid models are particularly useful in agricultural applications where data exhibit complex patterns and involve multiple disease types. With a combination of complementary deep learning techniques, these models can be more accurate and have high generalization levels than traditional single-architecture methods [27]. As a result, hybrid deep learning models are further under consideration as the development of a sophisticated solution for the automated disease detection system in plants.

Attention mechanisms, feature fusion strategies, multi-branch architecture can also be added to hybrid models to increase performance. Using feature fusion allows the combination of the results of multiple models enhancing feature representation. Multi-branch architecture allows computing various features of the input image at the same time, e.g. texture and structure, which improves accuracy of classification.

The other trend which is emerging is the use of CNN-transformer hybrid, where CNN layers are used to extract local features and transformer layers extract global dependencies. This collaboration offers a middle way solution that compensates the flaws of each architecture. Besides, pruning and quantization may be applied to optimize hybrid models, reducing their computational cost and thereby being more suitable to be deployed in resource-constrained settings.

The hybrid models have high generalization abilities and resilience in different datasets though they are complex. They come in handy especially when dealing with every tricky situation like the similarity of symptoms of diseases to be dealt with and also noises in the background.

An illustration (in the form of pseudocode) of how hybrid CNN and Transformer models function together to produce plant disease detection predictions is depicted below. This pseudocode illustrates how the local features extracted by the CNN are fused with the global relationships captured by the Transformers before passing them through a classification layer for final classification. This illustration must also be in algorithm or architectural diagram format.

"Input: Leaf Image I Preprocess I

CNN Module:

Extract local features F_local Transformer Module:

Divide image into patches

Apply attention mechanism to get F_global Fusion Layer:

Combine F_local and F_global Classification Layer:

Predict disease class Output: Final prediction"

6. DATASETS FOR SOYBEAN LEAF DISEASE DETECTION

The datasets are essential in training and evaluating the deep learning models. Good quality data sets allow models to obtain various patterns of disease, and generalization will be best.

The SoyNet dataset has been one of the most prominent datasets applied in the detection of soybean diseases. This dataset consists of high-resolution images of soybean leaves affected by various diseases and was developed to facilitate the training of deep learning models.

Plant disease data is broadly divided into two:

1. Lab datasets that have regulated lighting and grounds.

2. Real-life field data in agricultural settings.

The use of laboratory data sets can be useful as it gives quality images, but they do not however depict the actual situation in the field. Datasets in the field are more difficult since the datasets involve variations in light, background clatter, and the orientation of the leaves.

Techniques of data augmentation are common among augmenting the diversity of datasets. Some typical augmentation methods are rotation, flipping, scaling and color transformation. The methods assist in avoiding overfitting and enhancing model robustness.

This section repeats some of the previous information from earlier sections about datasets,

although it is retained if it focuses specifically on soybean datasets. In addition to retaining the content of this section, also include greater detail about the characteristics and attributes of soybean datasets which includes their size, annotation method and limitations in actual field conditions. Moreover, expand on the unique effects of environmental variability on disease detection in soybeans as well as the necessity for extra data due to these environmental variabilities. Finally, include challenges such as class imbalances and domain shifts in relation to soybean datasets. Through adding crop specific information and greater theoretical background, this section is a unique and justified section as opposed to a repetitive one.

7. APPLICATIONS OF DEEP LEARNING IN AGRICULTURE

Deep learning-based systems of detecting plant diseases can be utilized in agriculture in multiple ways.

Disease diagnosis via smartphone is one of these applications. The deep learning models can recognize an alleged disease immediately; plant farmers can use mobile devices to take pictures of the leaves on the planes.

Crop monitoring by drones is another service. The aerial shots of the farmland can be taken by the unarmored aerial vehicles (UAVs), and plant diseases can be identified on a mass level automatically [28].

Artificial intelligence in smart farming systems is also included with deep learning models. These systems involve sensors, cameras and artificial intelligence to constantly scan crop health and present real-time information to the farmers.

Precision agriculture is an important application of such technologies, and data-driven decision-making facilitates crop management optimization and decreases pesticide application.

8. CHALLENGES IN PLANT DISEASE DETECTION

Even with the great advancements, numerous problems still exist in the development of plant disease detection systems that will be reliable.

Dataset Limitations

A large portion of datasets regarding plant diseases is somewhat small and lacking in diversity. Small datasets may cause the overfitting of the model and inefficient generalizations to the real data.

Environmental Variability

The practical agricultural situation has dissimilar lighting conditions, background clutter, and the position of the leaves. These are able to lower the accuracy of deep learning models that are trained using controlled datasets.

Similar Disease Symptoms

Various plant ailments are also known to resemble other ailments as they have comparable visual signs; hence classifying them becomes challenging.

Computational Requirements

Prominent deep learning models are extremely resource-intensive, and thus they may not be able to be deployed in resource strained systems.

Model Interpretability

Deep learning models are deemed as black boxes and it is hard to see how they make decisions.

9. FUTURE RESEARCH DIRECTIONS

Future studies need to understand how to come up with bigger and more heterogeneous datasets to assist in the detection of plant diseases. The joint data collection programs can be used to enhance the quality of datasets and reflect actual agricultural scenarios.

Lightweight deep learning architectures come in sizes, and so researchers should also investigate how to realize them to run efficiently on mobile devices and edge computing systems.

The other promising trend is integration of various sources of data like hyperspectral imaging, weather data and ground data to enhance accuracy of detecting disease.

To establish trust among the farmers and agricultural experts, it is also necessary to enhance explainability in deep learning models.

10. CONCLUSION

The recent advancement in deep learning has greatly facilitated the technical revolution with respect to the identification of plant diseases through the automated analysis of images of plant leaves. Other deep learning models such as CNNs, transformer models and hybrid networks have been shown to perform well in the detection of plant diseases.

The economic significance of the crop has given increased attention to the detection of soybean disease. The creation of particular datasets SoyNet, and the use of complicated deep learning networks have facilitated major advancements in this direction.

Nevertheless, there are still several challenges such as constraints of datasets, environmental uncertainty, and computational complexity. To solve these problems, the interaction of researchers, agricultural specialists, and developers of technologies will be needed.

Additional studies should be conducted in the future to develop powerful, scalable and understandable disease detectors capable of functioning as an effective in vivo agricultural device. With the development of artificial intelligence and computer vision, it can be assumed that the creation of intelligent agricultural devices that will be able to contribute to the process of crop health monitoring and to promotion of sustainable food production can be conducted.

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