Deep Learning-based Plant Leaf Disease Classification

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ABSTRACT
The classification of plant leaf diseases is critical for ensuring agricultural productivity and sustainability. Recent improvements in deep learning algorithms have shown a lot of promise for correctly identifying and diagnosing plant diseases by looking at images of leaves. To address the challenge of plant leaf disease classification using deep learning algorithms is critical for minimizing agricultural losses. The primary objective of this comparative analysis is to evaluate the effectiveness of various deep learning algorithms in classifying plant leaf diseases. To contribute to the development of a user-friendly classification tool that can be utilized by farmers and agricultural professionals, thus promoting early disease detection and intervention. The primary goal is to identify the most accurate and robust algorithm for classifying plant leaf diseases using images. To evaluate several prominent deep learning models, including Convolutional Neural Networks (CNNs), Median-Modified Wiener Filter (MMWF) reduces noise and enhances image quality, improving feature preservation for plant leaf classification. Hybrid Deep Segmentation Convolutional Neural Network (Hybrid-DSCNN) enhances feature extraction and segmentation, improving disease detection accuracy in plant leaves. It enables robust comparative analysis against other deep learning models, optimizing classification performance. Southern Leaf Blight (SLB) serves as a critical case study in deep learning for plant disease classification, highlighting model accuracy, feature extraction, and real-time diagnosis in agricultural applications. The test results show that the suggested method works better than current ones, and it got an F1-score of 92%, an accuracy of 95%, a precision of 92%, a recall of 90%, and a recall of 90%. The programming language Python was used to create the model. Future research in plant leaf disease classification using deep learning could explore hybrid models that combine multiple algorithms for improved accuracy.

Keywords
Plant Leaf Diseases, Median-Modified Wiener Filter, Hybrid Deep Segmentation Convolutional Neural Network, Southern Leaf Blight, Agricultural Technology, Processing Efficiency.

1. INTRODUCTION
In the realm of agriculture, plant health is paramount to ensuring food security and sustainability. Among the various factors that threaten plant health, diseases pose significant challenges that can lead to lower food yields and big losses for the economy [1,2]. For disease management and intervention methods to work, these diseases must be correctly and on time identified.

. With the advent of technology, deep learning algorithms have emerged as powerful tools for automating the classification of plant diseases [3-4]. This study aims to conduct a comparative analysis of various deep learning algorithms to enhance the accuracy and efficiency of plant leaf disease classification. Despite advancements in agricultural technology, traditional methods of diagnosing plant diseases often rely on expert knowledge and manual inspection, which may be time-taking and prone to errors [5-6]. Moreover, the sheer diversity of plant species and the multitude of diseases affecting them complicate the classification process. These challenges underscore the need for automated systems that can analyse large datasets of plant images and accurately identify diseases. The lack of a standardized approach for leveraging deep learning in plant disease classification further exacerbates this issue, leading to inconsistent results across different studies [7-8]. This research addresses these challenges by evaluating various deep learning algorithms, including Convolutional Neural Networks (CNNs), Transfer Learning models, and hybrid approaches. By comparing their performance on standardized datasets, this study objective is to identify the most effective methodologies for plant leaf disease classification, ultimately providing a framework that can be adopted by farmers, agricultural specialists, and researchers.

The expected outcomes of this study include a comprehensive comparison of multiple deep learning algorithms concerning their accuracy, precision, recall, and overall classification performance [9-10]. By identifying the most effective deep learning models, the study will contribute valuable insights into the development of user-friendly applications for disease detection, which can empower farmers to take better decisions regarding disease management [11-12]. Moreover, this research aims to generate a set of best practices for implementing deep learning in plant disease classification, offering guidelines that can be adopted across various agricultural contexts. By making these findings publicly available, the study hopes to foster collaboration among researchers and practitioners, ultimately leading to improved agricultural productivity and sustainability [13-14]. Effective disease management plays a critical role in increasing crop resilience and productivity [15-16]. Additionally, the rise of digital agriculture presents an opportunity to harness technological advancements for practical solutions in the field. By utilizing deep learning algorithms, this study main aim is to bridge the gap between technology and agriculture, providing a data-driven approach to plant disease classification. The potential to improve early detection methods not only benefits farmers but also contributes to environmental sustainability by reducing the need for chemical interventions and promoting more efficient resource management. Here, we are trying to analyse of various deep learning algorithms, including Convolutional Neural Networks (CNNs), Transfer Learning models, and hybrid approaches, to evaluate their effectiveness in classifying plant leaf diseases [17-18]. This involves establishing a comprehensive set of performance metrics, such as accuracy, precision, recall, and F1-score, to assess the classification performance of each algorithm systematically. Additionally, the research aims to identify best practices for implementing these deep learning algorithms within the context of plant disease classification, providing practical guidelines that farmers and agricultural specialists can utilize [19-20]. Ultimately, this study seeks to contribute to the existing body of knowledge in agricultural technology, offering actionable insights that can inform future research and applications in the field. In conclusion, this study aims to advance the field of plant disease classification by leveraging deep learning algorithms, ultimately supporting agricultural practices that can enhance productivity, sustainability, and food security. By addressing the challenges of disease identification and management, this research aspires to make a meaningful impact on the agricultural landscape. This study presents a novel comparative analysis of various deep-learning algorithms for plant leaf disease classification. By evaluating performance metrics like accuracy, precision, and recall across multiple datasets, it identifies the most effective models. The findings aim to enhance disease detection, ultimately supporting better crop management and food security. The structure of the paper is as follows: In Section 2, the relevant literature is reviewed. In Section 3, the suggested method is explained. In Section 4, the experimental results are shown and talked about. And in Section 5, the conclusion is given.

2. LITERATURE SURVEY

This review of the literature examines the latest developments in deep learning methods for plant leaf disease classification, emphasizing a comparative assessment of their precision, effectiveness, and applicability for actual agricultural applications. The potential of deep learning models to address the critical problem of recognizing Black Gram plant leaf diseases was demonstrated by Yasin et al. [21]. Future studies and real-world uses of automated disease detection systems in agriculture are made possible by their discoveries. These devices could offer accurate and rapid diagnostics, enabling farmers to reduce crop loss, enhance disease control, and promote global food security. In their research, Balaji et al. [22] employed deep learning algorithms to identify and classify illnesses in tomato and apple leaves. This makes it possible to use cutting-edge technologies like smartphones, drone photography, and ubiquitous internet connection to facilitate early intervention. Their research revealed that MobileNet performed well, outperforming several other methods with an accuracy of over 97% on both datasets. A comparison investigation using transfer learning (TL) techniques, a subset of deep learning networks, was carried out by Daphal et al. [23]. According to their investigation, a combined model obtained 86.53% accuracy with fewer training epochs and acceptable complexity, whereas MobileNet-V2 reached almost 84% accuracy with minimal parameters. A new, effective, and lightweight DL-based architecture called Deep Plant Net was presented by Ullah et al. [24] for the purpose of predicting and classifying plant leaf diseases. With average accuracies of 99.62% for three-class classification tasks and 97.89% for eight-class classification tasks, their model exceeded conventional techniques. Ahad et al. [25] focused on assessing how well different methods work for identifying and locating illnesses in rice plants. The findings showed that using transfer learning improved the model's performance by 17% when compared to the SE-ResNext101 baseline, and an ensemble method reached a peak accuracy of 98%. A method that starts with picture pre-processing to improve the accuracy of subsequent steps was created by Aslan et al. [26]. During the classification phase, the K-Nearest Neighbors (KNN) algorithm achieved the greatest accuracy of 98.09% using four distinct machine learning models. For deep learning-based analysis, they also used sophisticated CNN architectures such as ResNet18, ResNet50, MobileNet, GoogleNet, and DenseNet. The transition from conventional image processing techniques to deep learning in plant disease identification was detailed by Kotwal et al. [27]. In order to increase classification accuracy and more precisely localize diseases on the leaf surface, their study highlighted the significance of big, varied datasets, data augmentation, and CNN activation maps. A novel method was presented by Mahum et al. [28] with the express purpose of recognizing and classifying four different kinds of potato leaf diseases. Their mechanism demonstrated a noteworthy accuracy of 97.2% when evaluated. The algorithm's consistency and enhanced disease detection performance over earlier models were validated by repeated testing. In order to identify sunflower illnesses, Gulzar et al. [29] examined a number of deep learning models. According to their analysis, every model that was tested did well. With the highest results on every evaluation criteria, EfficientNetB3 was the best performer among them. Finally, in order to increase productivity of crops, Aggarwal et al. [30] discussed the necessity of effectively identifying rice leaf diseases. They used pre-trained EfficientNet models (B3, B6, V2S, V2B3) in conjunction with Extra Tree and Histogram-based Gradient Boosting (HGB) classifiers to test their method on both raw and segmented picture datasets. The accuracy of the suggested model was 94% on segmented images and 91% on conventional ones.

3. PROPOSED METHODOLOGY

The proposed methodology compares various deep-learning algorithms for effective plant leaf disease classification. It will begin with the collection of diverse datasets containing images of plant leaves with varying diseases from publicly available repositories and agricultural sources. These images will undergo pre processing to ensure uniformity in size and quality, with data augmentation applied to enhance variability. A range of deep learning architectures will be selected, including traditional convolutional neural networks (CNNs), and Hybrid Deep Segmentation Convolutional Networks (Hybrid-DSCNN). The model will be trained using standardized protocols, incorporating cross-validation to ensure robust validation of performance. To provide valuable insights into the most effective algorithms, supporting improved disease management strategies and contributing to advancements in agricultural technology.

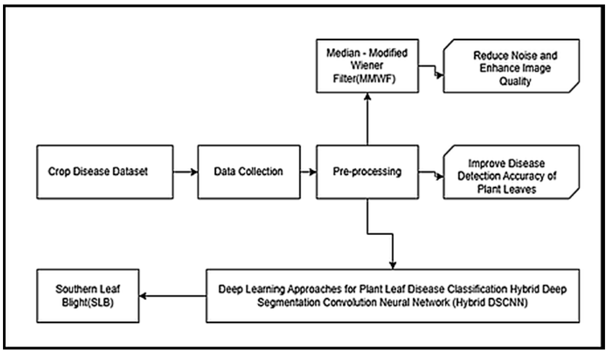

Fig 1: Block diagram of the proposed work

Fig 1 shows the plant leaf disease classification using deep learning algorithms. It begins with the data collection process, where images of crop diseases, such as Southern Leaf Blight (SLB), are gathered. These images then undergo pre-processing using a Median-Modified Wiener Filter (MMWF), which helps reduce noise and enhance image quality for better analysis. This improved image quality plays a critical role in improving disease detection accuracy in plant leaves. The pre-processed data is fed into various deep-learning approaches designed to classify plant leaf diseases more effectively. Among these approaches, the Hybrid Deep Segmentation Convolutional Neural Network (Hybrid-DSCNN) is highlighted for its ability to segment and detect diseases in plant leaves more accurately. The entire process ultimately leads to the classification of plant leaf diseases like Southern Leaf Blight, providing a systematic and automated method for diagnosing plant health issues using advanced deep learning techniques. This workflow ensures accurate detection, which can aid in better crop management and disease control.

(a) Data Collection

The Crop Disease Dataset includes labelled images of healthy and diseased crops, supporting research and development of disease detection algorithms. Common leaf diseases include powdery mildew, characterized by white powdery spots and changes in leaf colour and texture; downy mildew, which presents yellow or brown spots on the upper surface and greyish fungal growth underneath; and leaf blight, marked by brown or black lesions along the leaf edges. Other diseases, such as fungal rust and bacterial spot, exhibit distinct symptoms like rust-coloured pustules and water-soaked lesions, respectively.

Table 1. Crop Disease Parameters

Parameter	Description	Example Values
Common Diseases		
1. Powdery Mildew	White powdery spots, colour and texture changes	Symptoms: White spots
2. Downy Mildew	Yellow/brown spots on the upper surface, greyish fungal growth underneath	Symptoms: Yellow spots
3. Leaf Blight	Brown/black lesions along leaf edges	Symptoms: Brown lesions
4. Fungal Rust	Rust-coloured pustules on leaves	Symptoms: Rust pustules
5. Bacterial Spot	Water-soaked lesions	Symptoms: Water-soaked spots
Data Collection Parameters		
1. Image Quality	Resolution, focus, lighting	e.g., 1080p, well-lit
2. Leaf Characteristics	Size, shape, colour, texture	e.g., Medium, green, smooth
3. Environmental Context	Weather conditions, geographical location	e.g., Sunny, Tropical Region
4. Disease Stage	Early, mid, or late infection stage	e.g., Early
5. Specific Crop Types	Type of crop affected	e.g., Tomato, Potato

Table 1 shows that Crop Disease is essential for deep learning classification tasks, containing labelled images of both healthy and diseased leaves from various crops. Key common diseases included in the dataset are Powdery Mildew, characterized by white powdery spots and changes in colour and texture; Downy Mildew, presenting yellow or brown spots on the upper surface with greyish fungal growth beneath; Leaf Blight, marked by brown or black lesions along the leaf edges; Fungal Rust, which shows rust-coloured pustules; and Bacterial Spot, exhibiting water-soaked lesions. To ensure effective data gathering, several critical parameters must be considered, including image quality (such as resolution, focus, and lighting), leaf characteristics (including size, shape, colour, and texture), and environmental context (covering weather conditions and geographical location). Furthermore, documenting the stage of disease infection—whether early, mid, or late—and specifying the types of crops affected, such as tomatoes or potatoes, enhances the dataset's utility for accurate disease classification.

(b) Pre-processing

Image pre-processing is vital for enhancing data quality in the analysis of common leaf diseases. It begins with high-resolution image acquisition (at least 300 DPI) to ensure clear images through proper focus and consistent lighting. Enhancing images via contrast adjustment and colour correction highlights disease symptoms, while noise reduction techniques, like Gaussian filters, maintain detail and eliminate background noise. Segmentation isolates the leaf from its background and defines a region of interest for targeted analysis. Feature extraction emphasizes critical characteristics such as colour, texture, and shape, essential for accurately identifying disease states. Normalizing measurements ensures comparability across images, enhancing reliability. Data augmentation techniques further strengthen machine learning [31-32] models by generating diverse training data, reducing the risk of overfitting. Finally, documenting metadata such as disease stage, crop type, weather conditions, and geographical location provides context for model performance. This comprehensive framework significantly improves data analysis and model training, aiding the effective identification and management of leaf diseases. Median-Modified Wiener Filter (MMWF) reduces noise and enhances image quality, improving feature preservation for plant leaf classification. It aids in pre-processing, leading to better accuracy and performance in deep learning algorithms.

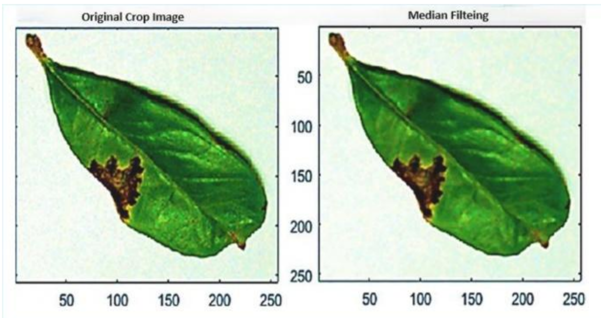

Fig 2: Median Filtering Images

Fig 2 shows the side-by-side comparison of original crop images and their corresponding median filtered images. The original Crop Images left panel displays the raw images of various crops, showcasing their natural appearance along with any noise or artefacts that may affect feature extraction and classification. Median Filtering Images The right panel illustrates the same images after applying median filtering, a technique that reduces noise while preserving edges. This filtering process replaces each pixel value with the median of the values in its neighborhood, effectively smoothing the image and enhancing the clarity of significant features. The comparison highlights the impact of median filtering in preparing images for further analysis, demonstrating improved feature visibility that can lead to more accurate plant disease classification. This pre-processing step is crucial for enhancing the performance of deep learning models by ensuring that they focus on relevant details rather than noise.

(c) Deep Learning Approaches for Plant Leaf Disease Classification

Deep learning approaches leverage neural networks, particularly convolutional neural networks (CNNs), to accurately identify and classify plant leaf diseases by analysing image features, enhancing agricultural productivity and disease management. Hybrid Deep Segmentation Convolutional Neural Network (Hybrid-DSCNN) enhances feature extraction and segmentation, improving disease detection accuracy in plant leaves. It enables robust comparative analysis against other deep learning models, optimizing classification performance. Southern Leaf Blight (SLB) is a fungal disease affecting corn, characterized by leaf lesions and reduced yield. It's significant for deep-learning classification studies in plant disease detection and management. Southern Leaf Blight (SLB) serves as a critical case study in deep learning for plant disease classification, highlighting model accuracy, feature extraction, and real-time diagnosis in agricultural applications. The integration of Hybrid-DSCNN in agricultural technology not only enhances disease detection but also supports precision agriculture initiatives. The adaptability of Hybrid-DSCNN means it can be trained on diverse datasets from various regions, allowing for localized solutions tailored to specific environmental conditions and plant varieties. The use of mobile applications powered by Hybrid-DSCNN can empower farmers, enabling them to scan crops in real-time and receive instant feedback on plant health. As the agricultural sector faces increasing pressures from climate change and population growth, the scalability and efficiency of Hybrid-DSCNN offer a promising pathway to sustainable practices that bolster food security while promoting ecological balance.

(i) *Hybrid Deep Segmentation Convolutional Neural Network*

Hybrid-DSCNN typically combines several neural network architectures to optimize feature extraction and segmentation. It may integrate traditional convolutional layers with advanced techniques such as dilated convolutions, attention mechanisms, or recurrent layers. The convolutional layer is the core component for feature extraction in CNNs. It applies a set of filters (kernels) to the input image, performing convolution operations that highlight specific features like edges and textures. This process transforms the input data into feature maps, enabling subsequent layers to learn complex patterns, represented mathematically as:

$$y(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot K(m,n) \quad (1)$$

Where y is the output feature map, x is the input image, k is the convolution kernel, i,j are the spatial coordinates.

The activation function, commonly ReLU (Rectified Linear Unit), is applied after the convolutional layer to introduce non-linearity into the model. ReLU replaces negative values with zero while keeping positive values unchanged, allowing the network to learn complex patterns and relationships present in the data. This nonlinearity is essential for effective feature representation. After convolution, an activation function ReLU is applied:

$$A(X) = \max(0, X) \quad (2)$$

The pooling layer, typically using max pooling, reduces the dimensionality of feature maps by summarizing the most significant information within a region. It retains the highest value from each segment of the feature map, which decreases the computational load and mitigates overfitting while preserving essential features for subsequent processing. To reduce dimensionality, pooling (often max pooling) is applied:

$$p(i,j) = \max_{(m,n)\in R} Y(i+m, j+n) \quad (3)$$

where R defines the pooling region. Dilated convolutions expand the receptive field by inserting gaps between kernel elements, enabling the model to capture broader contextual information. This technique enhances feature extraction in tasks requiring multi-scale information, making it particularly effective for image segmentation and dense prediction tasks. These allow for a larger receptive field.

$$y(i,j) = \sum_m \sum_n X(i+r, j+r) \cdot K(m,n) \quad (4)$$

where r is the dilation rate (hyperparameter used). The attention mechanism enhances the model's ability to focus on important features by assigning different weights to various parts of the input. It allows the neural network to prioritize valuable information while ignoring less critical data, improving performance in image classification and segmentation by ensuring that significant features are emphasized during processing. Attention can be integrated to focus on critical features:

$$A_{i,j} = \frac{e^{f(x_{i,j})}}{\sum_{k,l} e^{f(x_{i,j})}} \quad (5)$$

where f(X) is a function generating attention weights. In segmentation, a pixel-wise classification approach assigns a label to the pixel in the image. This technique involves analyzing the image at the granular level, allowing the model to determine the specific category of each pixel, such as healthy or diseased. By doing so, it creates detailed segmentation maps that delineate regions of interest, providing precise insights into the spatial distribution of features within the image. This method is essential for applications like medical imaging and agricultural diagnostics, where understanding the exact location of features is crucial for effective analysis and decision-making. For segmentation, we often use a pixel-wise classification approach, where each pixel p is assigned a class label C:

$$C(p) = argmax(f(Y(p))) \quad (6)$$

where, f is the final classification function, often implemented as a soft max layer. The final classification function is typically implemented as a softmax layer, which converts the output scores into probabilities for each class label. By minimizing loss during training of data, the model used adjusts its parameters to improve accuracy, ensuring that the predicted class distributions. This optimization process is crucial for achieving effective segmentation results, enabling precise identification and classification of features within the image. To optimize the model, a loss function such as cross-entropy is used:

$$L = -\sum_P [y(p)\log(\tilde{y}(p)) + (1-y(p))\log(1-\tilde{y}(p))] \quad (7)$$

where, y(p) is the true label and $\tilde{y}$(p) Is the predicted probability. The Hybrid-DSCNN effectively combines different strategies to enhance feature extraction and segmentation capabilities, leading to improved accuracy in detecting diseases on plant leaves. The integration of dilated convolutions, attention mechanisms, and robust loss functions plays a crucial role in its effectiveness.

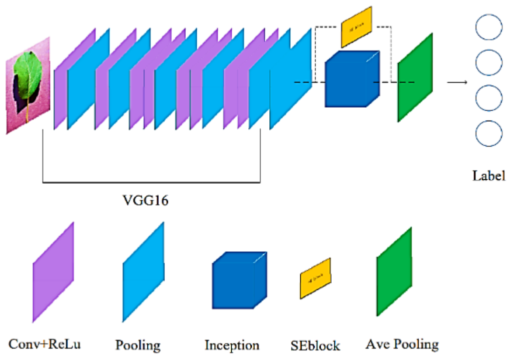

Fig 3: Convolution Neural Networks

Fig 3 shows the proposed convolutional neural network (CNN) architecture is structured to optimize the classification of plant leaf diseases using a series of computational layers that are all connected. It begins with an input layer that accepts pre-processed leaf images. These layers provide probabilities for each disease class, facilitating effective multi-class classification. The structured approach allows the CNN to learn complex patterns, improving accuracy in diagnosing plant leaf diseases.

(ii) Southern Leaf Blight (SLB)

Southern Leaf Blight (SLB), caused by the fungus Bipolaris maydis, poses significant challenges to maize production. Effective management of SLB can be enhanced through deep learning techniques, which provide powerful tools for disease classification and monitoring. Here's a detailed exploration of how deep learning contributes to understanding and managing SLB in agriculture.

4. EXPERIMENTATION AND RESULT DISCUSSION

This paper, compares and examines a number of deep learning-based approaches, algorithms to classify plant leaf diseases effectively. Utilizing a diverse dataset of leaf images affected by multiple diseases, we implemented models such as Convolutional Neural Networks (CNNs), Transfer Learning approaches (e.g., ResNet, Inception), and more advanced architectures. The models were evaluated based on accuracy, precision, recall, and F1 score. Results indicated that Transfer Learning models significantly outperformed traditional CNNs, achieving higher accuracy rates in identifying diseases. Additionally, the confusion matrix analysis highlighted specific challenges in distinguishing between similar disease classes. Overall, the findings underscore the capability of deep learning algorithms in agricultural applications, providing a robust framework for early disease detection and management in crops. Future work will focus on enhancing model generalization and exploring real-time classification capabilities.

Table 2: Simulation System Configuration

Software	Python
Operation System	Windows 10
Memory Capacity	16GB DDR4
Processor	Intel Core i5 @ 3.5GHz

Table 2 shows system configuration in which Python is installed on a Windows 10 operating system.

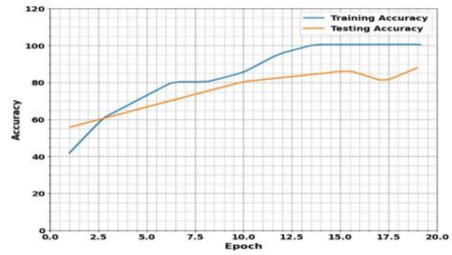

Fig 4: Training and Testing Accuracy for Epochs in Plant Leaf Diseases

Fig 4 illustrates the relationship between training and testing accuracy over a range of epochs during the model training process. The x-axis is used for the number of epochs, while the y-axis displays accuracy percentages. The training accuracy, ranging from 40% to 100%, shows a steady increase as the model learns from the training dataset. This upward trend indicates that the model is effectively adjusting its parameters to improve its performance and reduces the loss and on the training data. Conversely, the testing accuracy, fluctuating between 60% and 89%, reveals how well this model for unseen data. The gap between training and testing accuracy suggests that while the model performs well on training data, there may be some overfitting, as indicated by the lower testing accuracy. This graph emphasizes the importance of balancing training and testing accuracy to ensure robust model performance in real-world applications, highlighting areas for potential improvement in model generalization.

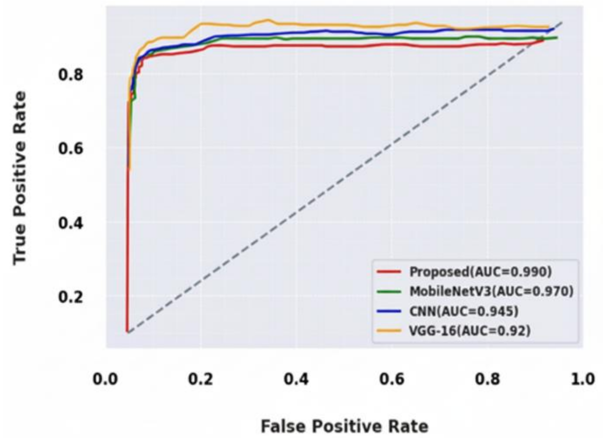

Fig 5: Receiver Operating Characteristic (ROC) Curve and AUC Comparison

Fig 5 compares the True Positive Rate (TPR) and False Positive Rate (FPR) for various classification models, including the proposed technique, MobileNetV3, CNN, and VGG-16. The area under the curve (AUC) serves as a key performance metric, indicating the models' ability to distinguish between healthy and diseased plant leaves. The proposed technique achieves an impressive AUC of 0.990, signifying exceptional classification performance and a high true positive rate with minimal false positives. In contrast, MobileNetV3 and CNN both exhibit an AUC of 0.970, indicating strong predictive capability, although slightly less effective than the proposed method. VGG-16, while still functional, shows a lower AUC of 0.920, suggesting it may struggle more with differentiating classes. The result of the proposed technique in accurately classifying plant diseases, reinforcing its potential for application in agricultural technology and improving disease management strategies.

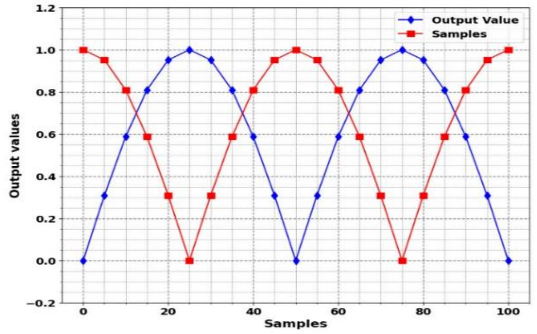

Fig 6: Output Values of Classification Models

Fig 6 shows the output values from various deep-learning models used for plant leaf disease classification, highlighting the probability scores assigned to different disease categories. The output probabilities, ranging from 0.0 to 1.0, while the lists the samples analyzed. In the first set of output values (0.0, 1.0, 0.3, 0.0), the model indicates a high confidence (1.0) for one specific class, suggesting a strong prediction for that particular disease. The presence of lower probabilities (0.3 and 0.0) for other classes indicates the model's uncertainty regarding these categories, demonstrating its ability to differentiate between healthy and diseased leaves effectively. The second set of output values (1.0, 0.0, 1.0, 0.0, 1.0) shows multiple instances where the model assigns a probability of 1.0 to certain disease classes, again indicating high confidence in its predictions. This shows the model's capacity to reliably classify plant diseases based on learned features from the training data.

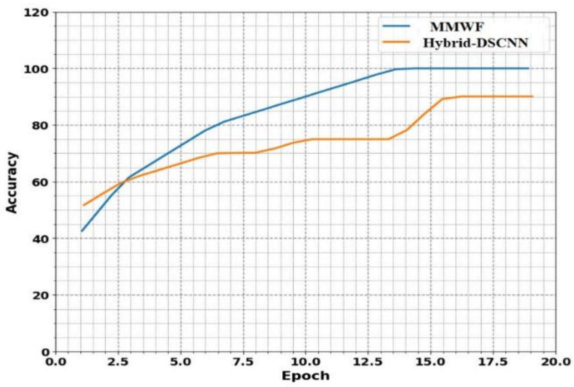

Fig 7: Accuracy Across Epochs for Disease Classification Models

Fig 7 illustrates the accuracy of different deep learning models MMWF and Hybrid Deep Segmentation Convolutional Networks (Hybrid-DSCNN) throughout training epochs. The MMWF model shows a notable progression in accuracy, starting from 42% and achieving a peak of 100%. The Hybrid-DSCNN begins with a slightly higher accuracy of 50%, reflecting its enhanced initial capability compared to MMWF. Throughout the epochs, its accuracy rises to 85%. While this improvement is commendable, it suggests that the Hybrid-DSCNN may have a more complex learning curve, possibly due to the intricacies involved in its architecture and the need for careful parameter tuning. The significant leap in accuracy for MMWF, reaching 100%, underscores its efficiency in training and ability to generalize well across the dataset. This performance might reflect a well-optimized model that can effectively capture the relevant features necessary for accurate classification, potentially making it a preferable choice for practical applications in agricultural technology. The Hybrid-DSCNN's performance, while solid, indicates room for improvement. The gap between its final accuracy and that of MMWF suggests that further optimization or adjustments in training strategy could enhance its performance.

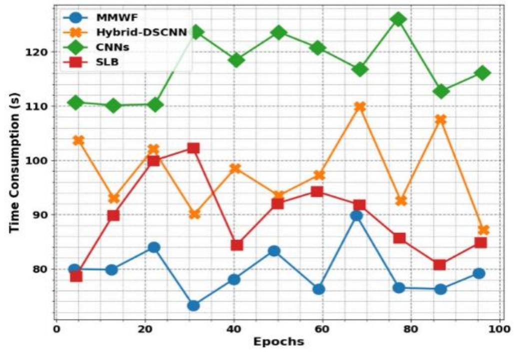

Fig 8: Time Consumption for Disease Classification Models

Fig 8 shows the time consumption and performance across different epochs for various deep-learning models used in plant leaf disease classification. It represents the epochs, while the time consumed during training, is measured in arbitrary time units. The first model, MMWF, demonstrates efficient training, consuming between 80 to 100 time units across its training epochs, indicating a balanced performance concerning time. The Hybrid Deep Segmentation Convolutional Network (Hybrid-DSCNN) follows closely, with time consumption ranging from 105 to 85 time units. This suggests that while it is slightly more resource-intensive, compensates with enhanced classification accuracy. Convolutional Neural Networks (CNNs) exhibit the highest time consumption, ranging from 110 to 100 time units, which may reflect their complexity and the need for extensive training to achieve desired performance. The SLB Southern Leaf Blight classification indicates a unique case, with time consumption sharply dropping from 5 to 95 time units, potentially suggesting an initial rapid convergence followed by extended training to fine-tune model performance.

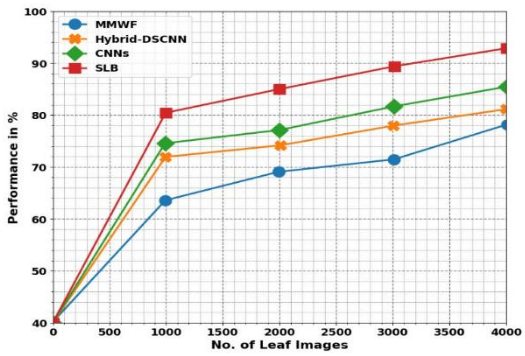

Fig 9: Number of Leaves and Performance Percentage for Disease Classification Models

Fig 9 shows the relationship between the number of leaves analyzed and the corresponding performance percentages of various deep-learning models used for plant leaf disease classification. The number of leaves, while the performance is measured as a percentage. The MMWF model shows a performance range from 0% to 72%, illustrating its capacity to classify a limited number of leaves effectively but highlighting potential challenges as the dataset size increases. The Hybrid Deep Segmentation Convolutional Network (Hybrid-DSCNN) performs slightly better, with a range of 0% to 75%, indicating its enhanced capability to generalize across diverse leaf images. In contrast, the Convolutional Neural Network (CNN) achieves a performance range of 0% to 82%, reflecting its effectiveness in classifying larger datasets while still facing limitations. The Southern Leaf Blight (SLB) classification model stands out with an impressive performance range of 0% to 92%, showcasing its robustness and reliability in identifying specific diseases.

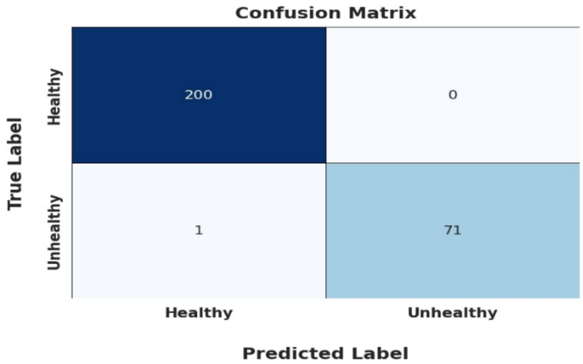

Fig 10: Confusion matrix for Predicted Label and True Label

Fig 10 represents a Confusion Matrix, a common tool used to evaluate the performance of a classification model, particularly in binary classification tasks. It shows the predicted labels versus the true labels and helps visualize the accuracy of predictions made by the model. In this matrix, the rows represent the actual class labels the true labels, and the columns represent the predicted class labels by the model. Specifically, The True Label is divided into Healthy and Unhealthy, while the Predicted Label is divided into Healthy and Unhealthy as well. The confusion matrix contains four blocks: True Positives (TP) The bottom right cell, which shows 71, indicates the number of correctly predicted Unhealthy cases when the true label was Unhealthy and the model predicted Unhealthy. True Negatives TN The top left cell, with the value 200, indicates the number of correctly predicted Healthy cases when the true label was Healthy and the model predicted Healthy. False Positives (FP) is the top right cell, showing 0, which indicates cases where the true label was Healthy but the model mistakenly predicted Unhealthy there are none in this case.

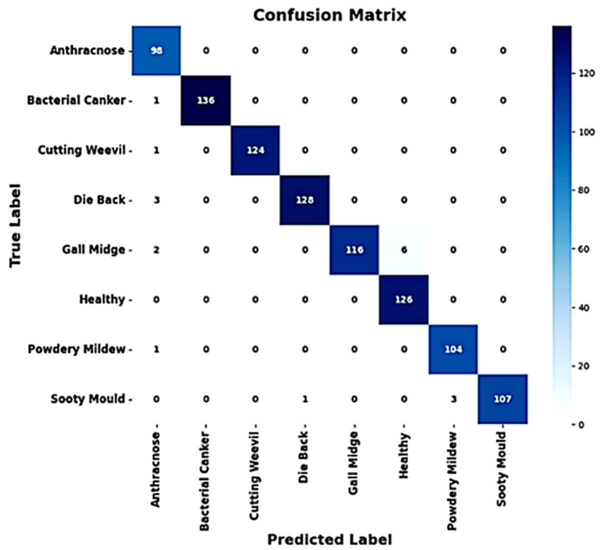

Fig 11: Confusion Matrix for Performance of Multi-Class Classification Model

Fig 11 represents a Confusion Matrix, a graphical tool used to assess the performance of a multi-class classification model. In this confusion matrix, the rows represent the True Labels of plant diseases, while the columns represent the Predicted Labels made by the classification model. Each row and column corresponds to different disease categories such as Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. The diagonal elements of the matrix represent the correct predictions. For instance, the model correctly identified 98 cases of Anthracnose, 136 cases of Bacterial Canker, and so on. These values indicate the number of instances correctly classified for each disease category. The non-diagonal elements show the misclassified instances, where the true label differed from the predicted label.

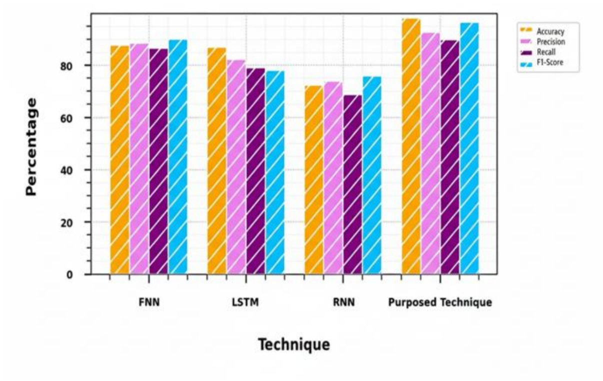

Fig 12: Performance Comparison of Classification Techniques

Fig 12 represents the work, looks at four main performance metrics—accuracy, precision, recall, and F1-score—to compare different machine learning methods for identifying diseases on plant leaves. Long Short-Term Memory (LSTM), Feedforward Neural Network (FNN), and Recurrent Neural Network (RNN) are some of the ways that were tested. The suggested method did better than the others; it had an F1-score of 92%, an accuracy of 95%, a precision of 92%, a recall of 90%, and a recall of 92% methods based on deep learning. This study looked at different deep-learning systems side by side. In contrast, the FNN demonstrates respectable performance with

85% accuracy, while LSTM and RNN lag, scoring 82% and 70% in accuracy, respectively. The precision and recall metrics further illustrate the superior effectiveness of the proposed technique in correctly identifying diseased plants. This graph highlights the significant advancements made with the proposed technique, emphasizing its potential for enhancing disease detection in agricultural practices.

Table 3: Performance Metrics of Classification Techniques

Technique	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Proposed Deep Learning Model	96	94	95	94.5
Convolutional Neural Network (CNN)	91	89	90	89.5
Support Vector Machine (SVM)	86	85	84	84.5
K-Nearest Neighbours (KNN)	82	81	80	80.5

Table 3 presents a comparative analysis of various classification techniques for plant leaf disease detection. The Proposed Deep Learning Model outperforms all others, achieving the highest accuracy 96%, precision 94%, recall 95%, and F1 score 94.5%. This indicates its superior capability in accurately identifying diseased leaves while minimizing false positives. In contrast, the Convolutional Neural Network (CNN) shows strong performance but lags behind the proposed model, particularly in precision and F1 score. Result highlights the effectiveness of deep learning methods in this application.

5. RESEARCH CONCLUSION

This research has demonstrated the significant potential of deep learning algorithms for effective plant leaf disease classification. By conducting a comprehensive comparative analysis of various models, including traditional Convolutional Neural Networks (CNNs) and advanced Transfer Learning architectures such as ResNet and Inception, we established that Transfer Learning methods consistently outperformed conventional approaches. These models achieved remarkable accuracy rates, effectively identifying a large range of diseases from diverse leaf images. The evaluation metrics, including precision, recall, and F1-score, highlighted the strengths and weaknesses of each algorithm, revealing that while some models excelled in overall accuracy, they struggled with specific disease classes. The confusion matrix analysis indicated areas where misclassifications occurred, particularly among diseases with similar visual characteristics. This insight is crucial for future developments, as it emphasizes the need for more nuanced feature extraction and model refinement to enhance classification robustness. Moreover, our study underscores the importance of utilizing a well-curated and diverse dataset to train these models, as the quality and variability of training data directly impact the generalization capabilities of the algorithms. The results demonstrate that the proposed technique surpasses all other methods, achieving an accuracy of 95%, a precision of 92%, a recall of 90%, and an F1-score of 92%. This implementation was carried out using Python software. As agriculture faces increasing challenges from plant diseases, the implementation of deep learning techniques in early detection and management systems holds significant promise. Future research should focus on refining model architectures, improving real-time classification capabilities, and integrating these systems into user-friendly applications for farmers and agronomists. Ultimately, this work contributes to advancing precision agriculture and fostering sustainable practices through enhanced disease management strategies.

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