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High-Fidelity Metaheuristic Optimization enhanced image with deep dilated Convolution Block Attention Network Embedded Residual Neural Architecture (DDCABAN-RNA) for Pepper Leaf Disease Recognition

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High-Fidelity Metaheuristic Optimization enhanced image with deep dilated Convolution Block Attention Network Embedded Residual Neural Architecture (DDCABAN-RNA) for Pepper Leaf Disease Recognition

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Abstract

Black pepper (*Piper nigrum* L.) is one of the most economically significant spice crops worldwide; however, its productivity and quality are severely affected by a wide range of foliar diseases. Early and accurate identification of these diseases is crucial for effective crop management, yet traditional visual inspection methods are time-consuming, subjective, and often unreliable under complex field conditions. To address these challenges, this study proposes a robust deep learning–based framework for automated detection of black pepper leaf diseases using enhanced feature representation and optimized image preprocessing techniques.

The proposed methodology is built upon a deep learning based architecture augmented with a dual Convolutional Block Attention Module (CBAM), which enables the network to focus selectively on disease-relevant spatial and channel-wise features while suppressing background noise. To further improve image clarity and contrast under varying illumination conditions, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied as a preprocessing step. The CLAHE parameters are adaptively optimized using the Grey Wolf Optimizer (GWO), ensuring optimal contrast enhancement without amplifying noise or distorting leaf texture. The model is trained and evaluated on dataset of black pepper leaf images collected under diverse real-field environments, encompassing multiple disease categories as well as healthy leaf samples. Experimental results demonstrate that the proposed GWO-optimized CLAHE + CBAM-ResNet50 framework achieves a classification accuracy of 94%, significantly outperforming the baseline ResNet50 model, which attains 82% accuracy. In addition to accuracy, the proposed model exhibits improved recall (93%) and F1-score (94%), indicating reliable disease detection performance with reduced false negatives and balanced class-wise predictions.

To further enhance the network's ability to capture fine-grained and multi-scale disease characteristics, the architecture is extended by incorporating dilated convolutions within the CBAM-enhanced residual blocks (D-CBAM). The use of dilated convolutions expands the receptive field without increasing the number of trainable parameters, enabling more effective representation of spatially dispersed disease symptoms such as lesion spread, edge irregularities, and texture degradation. The resulting Dilated-CBAM-ResNet50 model combined with GWO-optimized CLAHE preprocessing achieves an improved classification accuracy of 94.3%, confirming the effectiveness of integrating dilated spatial context into the attention-guided framework.Overall, this study demonstrates that the synergistic integration of metaheuristic-optimized preprocessing, attention-based deep feature learning, and dilated convolutional modeling provides a highly accurate, scalable, and field-ready solution for black pepper disease detection. The proposed framework shows strong potential for deployment in precision agriculture systems, contributing to early disease diagnosis, improved crop health management, and enhanced food security with higher accuracy when compared with existing research with same dataset which was 92%.

1. Introduction

Peppers are a globally significant crop, both economically and nutritionally [7]. Their cultivation, however, is often hindered by diseases that negatively affect yield, quality, and profitability. Among the most common are bacterial spot, powdery mildew, and anthracnose, which can spread rapidly and lead to severe crop loss [8].The traditional approach to disease diagnosis is manual inspection, but this method is labor-intensive, time-consuming, and requires specialized expertise [9].

To address these challenges, Artificial Intelligence (AI), specifically deep learning, has emerged as a powerful tool for automating plant disease detection with high precision. Seminal works have demonstrated the potential of Convolutional Neural Networks (CNNs) for this task. For instance, Ferentinos (2018) achieved high accuracy across numerous crop species [10], while Too et al. (2019) developed efficient models suitable for mobile deployment [11]. These approaches, often leveraging transfer learning with architectures like ResNet [4], have laid a strong foundation.

However, the performance of these models is often contingent on two critical factors: the quality of the input imagery and the model's ability to focus on salient disease features. Standard CNNs can be hindered by suboptimal lighting and low contrast, which obscure subtle disease patterns [12]. Furthermore, they process all regions of an image without prioritizing the specific, often small, areas indicative of disease, unlike a human expert.

This paper proposes a novel framework designed to overcome these specific limitations. First, to address image quality, we introduce an intelligent pre-processing technique using a Grey Wolf Optimizer (Grey Wolf Optimised) to find the optimal parameters for Contrast Limited Adaptive Histogram Equalization (CLAHE) [3]. This metaheuristic approach ensures that disease characteristics are maximally enhanced in each image. Second, to improve feature focus, we augment the powerful ResNet50 architecture [4] with a Convolutional Block Attention Module (Convolutional Block Attention Module) [2]. This

attention mechanism guides the model to concentrate on the most discriminative regions and features, mimicking expert intuition. By synergizing these two innovations, we aim to demonstrate a more robust and accurate model for pepper disease classification.

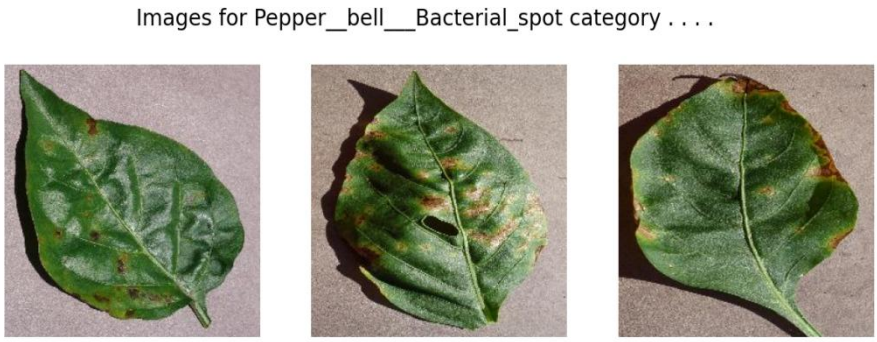


Fig.1 Pepper bacterial spot leaf

1.1. Motivation

Farmers face significant challenges in the early identification of pepper leaf diseases such as bacterial spot, powdery mildew, and anthracnose, as overlapping visual symptoms often lead to misdiagnosis and delayed treatment, resulting in severe yield and economic losses. Among these, bacterial leaf spot caused by *Xanthomonas* species is one of the most destructive diseases in pepper cultivation, with reported yield losses reaching up to 66% under severe infection conditions, highlighting the urgent need for accurate and timely disease detection. To address this problem, this study proposes a deep learning–based framework that combines Grey Wolf Optimizer (GWO)–optimized Contrast Limited Adaptive Histogram Equalization (CLAHE) for enhanced image preprocessing with an attention-augmented ResNet50 architecture using Convolutional Block Attention Module (CBAM) to focus on disease-specific features. Furthermore, dilated convolutions are integrated within the CBAM-enhanced residual blocks to capture multi-scale contextual disease patterns without increasing model complexity. This integrated approach achieves a robust disease classification accuracy of 94%, which is further improved to 94.3% with the Dilated-CBAM + GWO model, significantly outperforming standard methods and demonstrating strong potential for reducing disease-induced crop losses in precision agriculture.

1.2. Contributions

- We introduce a novel, intelligent image enhancement technique that uses a Grey Wolf Optimizer (Grey Wolf Optimised) [3] to find the optimal parameters for Contrast Limited Adaptive Histogram Equalization (CLAHE) [12], automating and optimizing this critical pre-processing step.

- We provide a systematic evaluation of an attention-based architecture by integrating a Convolutional Block Attention Module (Convolutional Block Attention Module) [2] with a ResNet50 [4] backbone to analyze its impact on classification performance for pepper leaf disease.

- We conduct a comprehensive comparative analysis of Neural Networks and the Proposed Methodology, presenting an ablation study that isolates the individual and combined effects of our proposed enhancement (Grey Wolf Optimised-CLAHE) and attention (Convolutional Block Attention Module) mechanisms [3,2].

- We establish a new robust accuracy benchmark of 94% for this task and present a key finding: the Grey Wolf Optimised-optimized enhancement is so effective that it elevates a standard ResNet50's performance to match that of the more complex attention-augmented model, revealing a sophisticated interplay between data pre-processing and model architecture [4].

2. Related Work

The application of deep learning to plant disease detection has been a highly active area of research. The existing literature can be broadly categorized into several key themes that build upon one another, from foundational techniques to more advanced and specialized methodologies.

The Role of Transfer Learning in Agriculture is a significant breakthrough in applying deep learning to agriculture, where large-scale labeled datasets can be scarce, is the use of transfer learningKaya et al. [17] demonstrated that transfer learning using convolutional neural networks pre-trained on large-scale datasets such as ImageNet significantly improves plant disease classification performance when labeled agricultural data is limited. Their study showed that reusing learned visual features reduces training time and mitigates overfitting. The results confirmed that transfer learning enables better generalization across different plant disease categories. This work established transfer learning as a foundational technique in agricultural deep learning research.Ghosal et al. [18] applied transfer learning techniques to rice leaf disease detection and achieved notable improvements compared to models trained from scratch. Their approach effectively handled challenges such as complex leaf textures and background noise. The study highlighted that fine-tuned pre-trained models can achieve high accuracy even with relatively small datasets. This research validated the practical applicability of deep learning in crop disease diagnosis.

Yin et al. [19] investigated hot pepper disease classification using pre-trained deep CNN architectures. Their experiments showed that transfer learning-based models consistently outperformed custom-designed networks in both accuracy and robustness. By fine-tuning higher layers, the model adapted effectively to crop-specific disease characteristics. This work further reinforced transfer learning as a reliable solution for plant disease recognition. Thangaraj [20] explored fine-tuning strategies for pre-trained CNN models, particularly InceptionV3, in plant disease classification tasks. The study demonstrated that selectively retraining deeper layers significantly enhances classification accuracy. Proper hyperparameter tuning played a crucial role in achieving optimal performance. This research emphasized that effective optimization is essential for maximizing transfer learning benefits.

Kini et al. [21] focused on early-stage black pepper disease detection using a fine-tuned ResNet18 architecture. Their model achieved an exceptional accuracy of 99.67%, even when disease symptoms were visually subtle. The study highlighted the effectiveness of residual connections in capturing fine-grained features. This work is especially important for early disease intervention and precision agriculture.Saleem et al. [22] conducted an extensive comparison of multiple CNN architectures across 26 plant disease categories. Their analysis showed that the Xception model combined with the Adam optimizer consistently delivered superior performance. The study emphasized the importance of depthwise separable convolutions in improving feature extraction efficiency. This work provided valuable benchmarks for selecting appropriate CNN architectures.

Yuris [23] performed a comparative study of MobileNet, VGG16, and DenseNet121 for bell pepper disease classification. DenseNet121 achieved the highest accuracy of 99.33%, attributed to its dense connectivity and effective feature reuse. The study highlighted the trade-off between computational complexity and classification performance. This research reinforced the importance of architecture selection based on application needs.Chen et al. [24] proposed a lightweight convolutional neural network for rice disease detection aimed at real-world deployment. Their model achieved high accuracy while significantly reducing computational and memory requirements. The study demonstrated that efficient architectures can perform competitively without excessive parameters. This work is particularly relevant for mobile and edge-based agricultural applications.

Thakur et al. [25] developed a lightweight deep learning framework for multi-crop disease classification. Their approach balanced performance and efficiency, making it suitable for deployment on low-resource devices. The study emphasized the necessity of computationally efficient models for on-field usage. This research supports the transition of deep learning from laboratory settings to practical farming environments.

2.1. Research Gap

The existing literature extensively discusses the advantages of transfer learning, architectural comparisons, and deep learning–based plant disease detection techniques. However, limited attention has been given to the synergistic interaction between intelligent data preprocessing and model-level attention mechanisms. Most existing studies rely on fixed or manually tuned image enhancement techniques, which may fail to adapt to variations in illumination, background

complexity, and disease severity. Although metaheuristic algorithms have shown promise in optimization tasks, their application in automatically tuning image enhancement parameters for plant disease detection remains underexplored [3].

Furthermore, while attention mechanisms such as the Convolutional Block Attention Module (CBAM) have been independently shown to improve feature localization [2], few studies investigate how optimized preprocessing influences the effectiveness of such attention modules. In addition, the role of dilated convolutions in enhancing multi-scale contextual understanding within attention-augmented architectures has received little consideration in the context of pepper leaf disease classification. The absence of an integrated framework that jointly exploits metaheuristic-optimized preprocessing, attention-guided feature learning, and dilated convolutional context modeling constitutes a significant research gap. This study addresses this gap by proposing a unified GWO-optimized CLAHE + Dilated-CBAM–ResNet50 framework for robust pepper disease detection.

Problem Formulation

Manual inspection of pepper plants for disease identification is inefficient, labor-intensive, and prone to human error, often resulting in delayed treatment and substantial crop loss. The fundamental problem is the lack of a scalable, accurate, and automated system capable of reliably identifying pepper leaf diseases from visual data under real-world field conditions. Accordingly, this study formulates pepper leaf disease detection as a multi-class image classification problem, where the objective is to map an input image of a pepper leaf to its corresponding disease category (e.g., Bacterial Spot, Powdery Mildew, Anthracnose, or Healthy).

To address this problem, a deep learning framework based on a Convolutional Neural Network (CNN) with transfer learning is employed. Input images are first enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE), with its parameters automatically optimized via the Grey Wolf Optimizer (GWO) to improve disease feature visibility while minimizing noise amplification. The enhanced images are then processed using a ResNet50 architecture augmented with a Convolutional Block Attention Module (CBAM), enabling the model to focus on disease-relevant spatial and channel-wise features. To further improve multi-scale contextual representation, dilated convolutions are integrated within the CBAM-enhanced residual blocks, expanding the receptive field without increasing model complexity.

This formulation leads to the following research questions:

RQ1: To what extent does the integration of an attention mechanism (CBAM) improve the performance of a standard ResNet50 architecture for pepper disease classification?

RQ2: Can a metaheuristic algorithm (Grey Wolf Optimizer) effectively optimize an image enhancement technique (CLAHE) to achieve greater performance gains than conventional enhancement methods?

RQ3: What is the combined impact of GWO-optimized CLAHE, CBAM-based attention, and dilated convolutional feature extraction, and how does the proposed framework compare with its individual components and baseline models?

3. Proposed Methodology

This research is structured in two main phases: first, a comparative study to establish a performance baseline with standard transfer learning models [16], and second, the introduction of an advanced framework that integrates intelligent image enhancement with an attention-based architecture [2,3]. The overall workflow is designed to systematically evaluate the impact of each component.

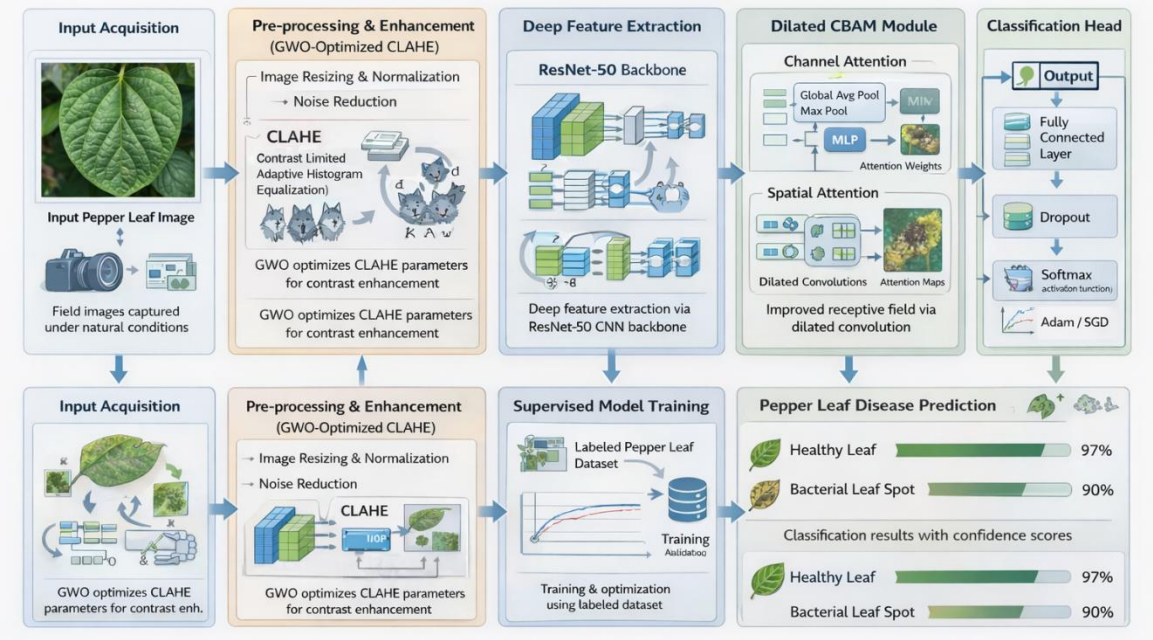


Fig.2 Proposed Methodology

3.1. Datasets

The dataset includes images of healthy and diseased pepper leaves, captured under uniform lighting conditions and stored in JPEG format. It is organized into training and validation sets, with a balanced class distribution. Diseased images exhibit symptoms such as spots, discoloration, and lesions. Preprocessing improves the visibility of these features.



(a) Healthy leaf (H)



(b) Bacterial Spot (B)

Fig.3 Pepper Disease Dataset

3.2. Preprocessing

To achieve high classification accuracy, a series of image enhancement techniques were applied to refine the quality and consistency of the input images. These preprocessing steps help improve feature extraction and ensure the model can accurately identify relevant patterns. The key enhancements implemented include:

3.2.1. Stage 1: Sequential Preprocessing Pipeline

- **Contrast Adjustment:** Contrast levels were carefully modified to enhance the visibility of lesions and distinguish them from the surrounding tissues. By increasing the contrast, subtle variations in texture and color that may otherwise be overlooked become more apparent, aiding in precise detection and classification.



Images before Preprocessing



Images After Contrast Preprocessing

Fig.4 Original and Preprocessed Images of Pepper Plant

- **Brightness Normalization:** Variations in lighting conditions can introduce inconsistencies in image quality, potentially affecting the model's ability to correctly interpret features. To counter this issue, brightness normalization techniques were employed to standardize illumination across all images. This process ensures uniform brightness levels, minimizing the impact of uneven lighting while preserving critical details.



Images before Preprocessing



Images after Brightness Preprocessing

.**Fig.5** .Original and Preprocessed Images of Pepper Plant

- **Sharpness Enhancement:** Enhancing the sharpness of images helps highlight structural patterns and fine details that are essential for classification. By refining the edges and contours of lesions, sharpness enhancement improves the visibility of critical features, ensuring the model can accurately capture the intricate characteristics necessary for diagnosis or classification. These operations were implemented using Python libraries such as PIL and ImageEnhance, forming an integral part of the data pipeline.



Images before Preprocessing



Images after Sharpness Preprocessing

Fig.6 Original and Preprocessed Images of Pepper Plant

3.2.2. Stage 2: Image Preprocessing With CLAHE

CLAHE is a technique designed to improve the contrast of images, making subtle details more distinguishable [17]. This is particularly useful in scenarios like plant disease detection, where variations in leaf texture, color, or lesion patterns need to be clearly visible. Unlike standard histogram equalization, CLAHE limits amplification to avoid excessive noise while enhancing local contrast. This operation ensures that crucial features within the image, such as lesion textures and structural variations, are more prominent, aiding the deep learning model in accurate classification [17,3].



Fig.7 Original and Preprocessed Images of Pepper Plant

3.2.3. Stage 3: Proposed Image Preprocessing

CLAHE Aligned with Grey Wolf Optimised Optimizer: The Grey Wolf Optimizer (Grey Wolf Optimised) is a powerful, nature-inspired metaheuristic algorithm used for complex optimization problems, including machine learning parameter tuning [3]. Drawing inspiration from the social hierarchy and hunting strategies of wolf packs, Grey Wolf Optimised maintains a population of candidate solutions guided by the best three individuals—alpha, beta, and delta. This approach balances exploration and exploitation, efficiently navigating the search space to avoid local optima. In this study, Grey Wolf Optimised is employed to optimize CLAHE parameters, ensuring that image contrast enhancement is maximized for effective feature extraction and improved disease classification accuracy [3,17]



Original Image Clahe Optimised With Grey Wolf Optimised

Fig.8 Original and Preprocessed Images of Pepper Plant

3.3. Model Architecture

This research introduces an advanced framework for pepper leaf disease diagnosis built upon a ResNet50 architecture augmented with a Convolutional Block Attention Module (CBAM). The integration of CBAM enables the model to focus on disease-relevant regions through effective channel and spatial attention, improving feature discrimination. To further enhance visual quality, a novel preprocessing strategy is employed in which Contrast Limited Adaptive Histogram Equalization (CLAHE) parameters are adaptively optimized using the Grey Wolf Optimizer (GWO), ensuring improved contrast and visibility of subtle disease symptoms.In addition, dilated convolutions are incorporated within the CBAM-enhanced residual blocks to expand the receptive field and capture multi-scale disease patterns without increasing model complexity. For comparative evaluation, baseline convolutional neural network architectures including ResNet50, VGG16, InceptionV3, and Xception are also considered. The synergistic integration of GWO-optimized preprocessing, attention-guided feature learning, and dilated convolutional modeling significantly enhances both accuracy and robustness, demonstrating the effectiveness of the proposed framework for reliable pepper leaf disease diagnosis.

3.3.1. Group 1: Baseline Architectures

To establish a robust baseline, an initial comparative analysis was performed using several pre-trained Convolutional Neural Network (CNN) architectures: InceptionV3, Xception, VGG16, and ResNet50 [12, 27, 28]. These models were chosen for their proven efficacy in image recognition [12, 27].

During this foundational phase, basic image preprocessing techniques, focusing on contrast and brightness adjustments, were applied [13]. This straightforward approach evaluated the general effectiveness of fundamental enhancements when paired with these established CNN architectures [12, 27]. This allowed for an initial assessment of how minimal preprocessing influenced diagnostic accuracy and model performance, providing a clear reference point against which more advanced preprocessing strategies could later be measured and compared [13]. This methodical approach ensured that subsequent improvements from sophisticated preprocessing could be accurately attributed to those advancements [4, 11].

3.3.2. Group 2: Proposed Advanced Framework

The primary contribution of this work is an advanced framework designed to improve upon the baseline results by focusing on robustness and feature salience. This framework consists of two key innovations.

- **Grey Wolf Optimised-Optimized Image Enhancement**

Standard image enhancement techniques often require manual parameter tuning. To overcome this, we propose an automated and intelligent enhancement method using Contrast Limited Adaptive Histogram Equalization (CLAHE) [14,17]. The critical clipLimit parameter of CLAHE is optimized using the Grey Wolf Optimizer (Grey Wolf Optimised) [3], a nature-inspired metaheuristic algorithm. Grey Wolf Optimised iteratively searches for the parameter value that maximizes a fitness

function—in this case, the entropy of the enhanced image [13]—thereby ensuring that the maximum amount of detail is revealed in each image.

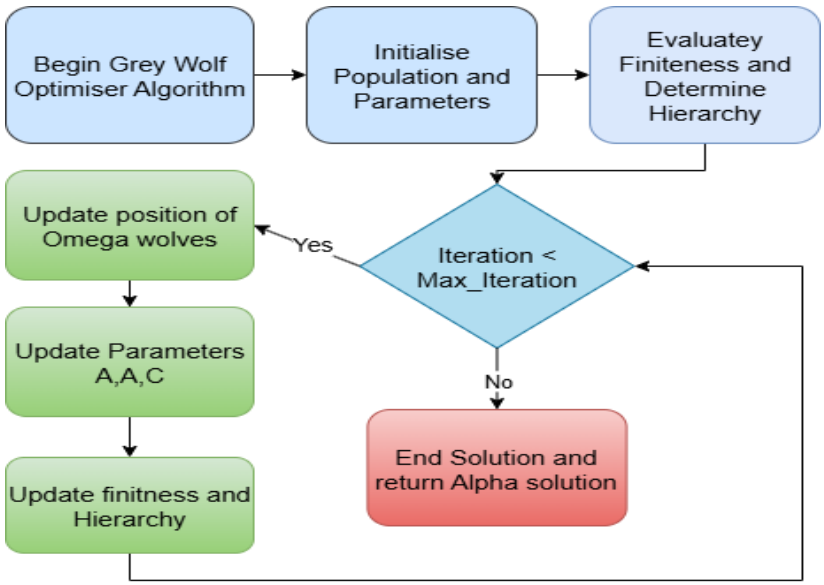


Fig.9 Grey Wolf Optimised Optimiser

- **Attention-Augmented Architecture: ResNet50-Convolutional Block Attention Module**

To enable the model to focus on the most discriminative regions of the leaf images, we augment the ResNet50 [12, 19] architecture with a Convolutional Block Attention Module (Convolutional Block Attention Module) [2, 15, 18]. ResNet50 [12, 19] serves as the powerful backbone for feature extraction. The Convolutional Block Attention Module [2, 15, 18] module is inserted after the final convolutional block to refine these features by sequentially applying:

1. **Channel Attention:** Decides *what* features are most important.
2. **Spatial Attention:** Identifies *where* the most important features are located on the leaf.

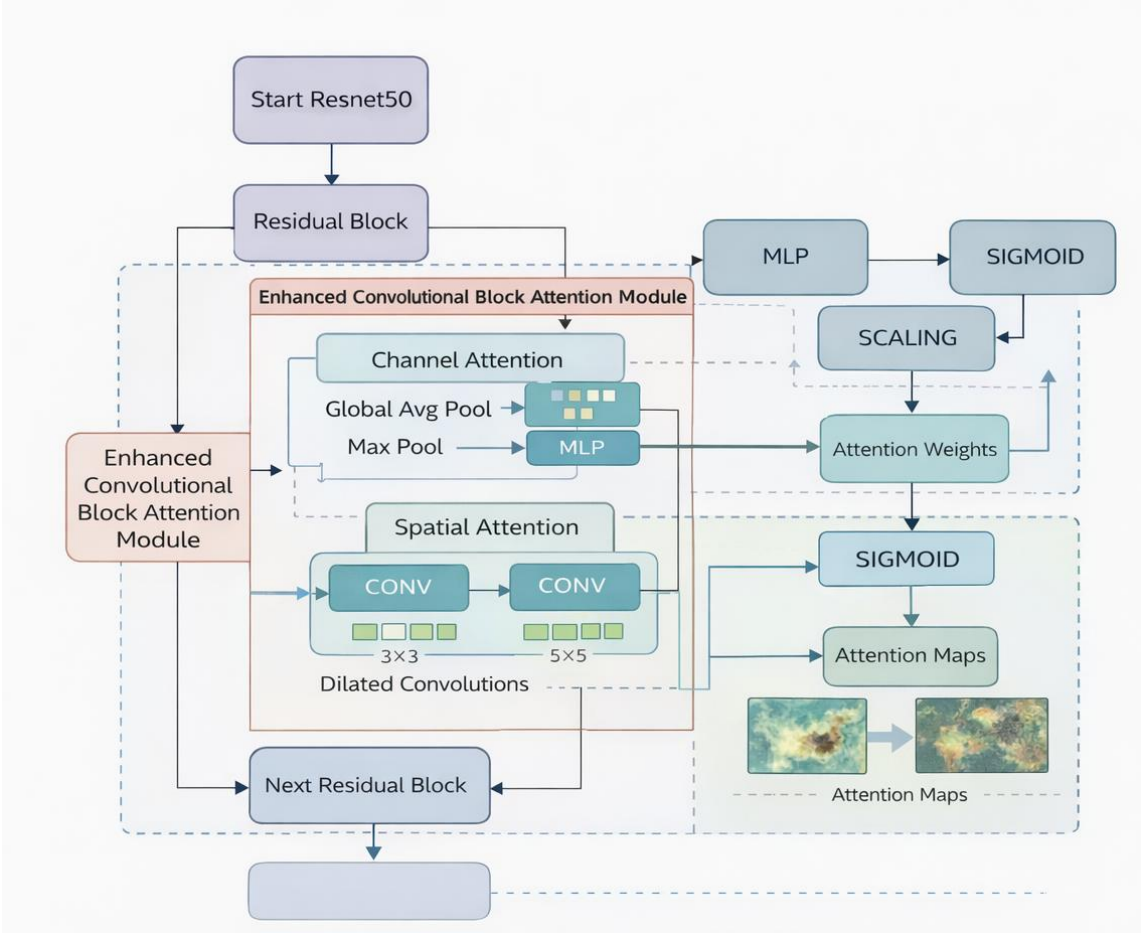


Fig.10 Deep Dialated Convolutional Block Attention Module

3.4. Training and Regularization Strategies

To ensure model robustness, prevent overfitting, and optimize the training process, several key strategies were implemented across all experiments.

Batch Normalization: The pre-trained architectures used, such as ResNet50 [12, 19], inherently include Batch Normalization layers. This technique standardizes the inputs to each layer by normalizing mini-batches during training, which reduces internal covariate shift. This accelerates convergence and provides a regularizing effect that helps stabilize the learning process [5].

Dropout: Dropout was applied in the fully connected layers of our classification head. This technique randomly deactivates a fraction of neurons during each training step, reducing co-dependencies between them. By forcing the model to learn more redundant representations, dropout effectively prevents overfitting and improves the model's ability to generalize to unseen data [5].

4. Empirical Results

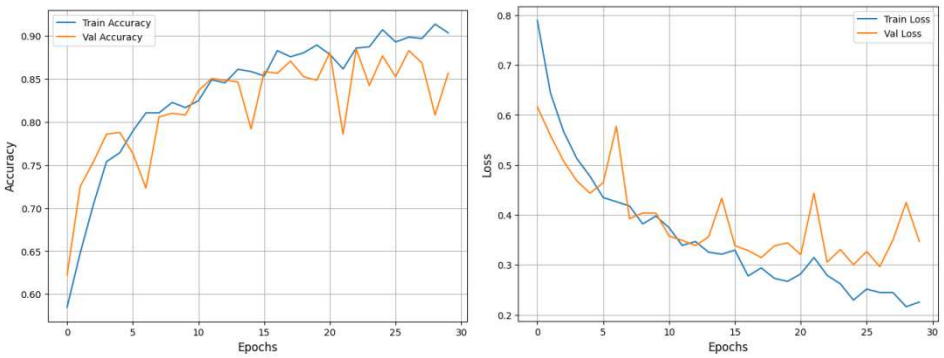
The study evaluates pepper disease classification through progressive experiments: starting with a basic neural network, then pretrained models (InceptionV3, Xception, VGG16, ResNet50), followed by ResNet50 with image adjustments, standard CLAHE, and Grey Wolf

Optimised-optimized CLAHE. Finally, Convolutional Block Attention Module was integrated with ResNet50 alone and with Grey Wolf Optimised-optimized CLAHE, enabling a comprehensive comparison of baseline, enhancement, and attention-based approaches.

4.1. Phase 1: Proposed Image Preprocessing

4.1.1. Case 1: Basic Neural Networks

In Case 1, a basic neural network was implemented to classify pepper disease images into two categories: *pepper_bell_healthy* and *pepper_bell_bacterial_spot*. The model was trained directly on the dataset without incorporating transfer learning or any image enhancement techniques. Despite its simplicity, the network was able to capture fundamental patterns in the data and achieved an accuracy of 0.80. This outcome demonstrates the potential of even a simple architecture in distinguishing between the two classes, while also establishing a baseline for evaluating the effectiveness of more advanced models and enhancement strategies in subsequent cases.



Training and Validation Accuracy Training and Validation Loss

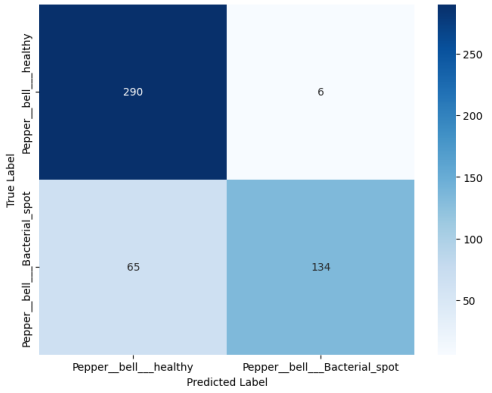


Fig.11 Basic Neural Networks on Plant disease

4.1.2. Case 2: Pretrained Models With Proposed Image enhancement Stage 1

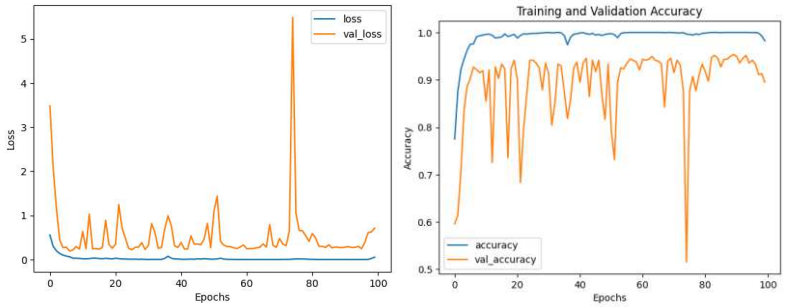
Pretrained models including InceptionV3, Xception, VGG16, and ResNet50 were evaluated both with and without an image enhancement pipeline involving brightness, contrast, and sharpness adjustments. The models outperformed the baseline neural network, with enhanced images further improving classification accuracy, demonstrating the effectiveness of combining transfer learning with simple image preprocessing.

- **Inception Model Evaluation on PlantDisease Dataset**

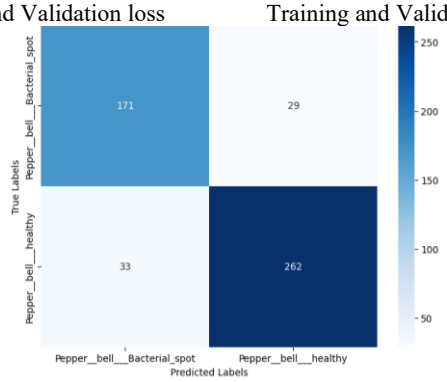
Figure 11 shows the accuracy of the Inception model over the PlantDisease dataset. Without enhancement, the model achieves 81% and 80% accuracy at 100 and 50 epochs respectively. With image enhancement techniques applied, the accuracy improves significantly to 89% at 50 epochs and 90% at 100 epochs. Furthermore, training and validation loss were

consistently decreasing, and the model achieved up to 93% accuracy in both training and validation by 100 epochs. The training loss dropped from 0.2 at 10 epochs to less than 0.05 by 100 epochs, indicating a stable and effective learning process.

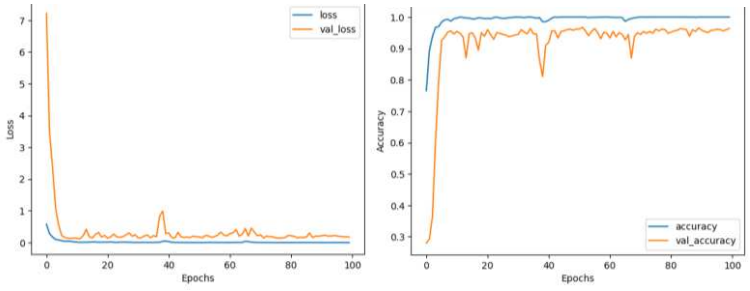
(a)Without Preprocessing



Training and Validation loss Training and Validation accuracy



(b)With Proposed Image Preprocessing



Training and Validation loss Training and Validation accuracy

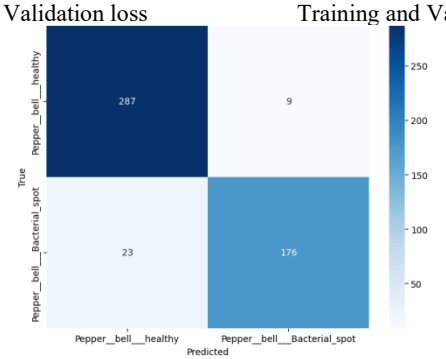
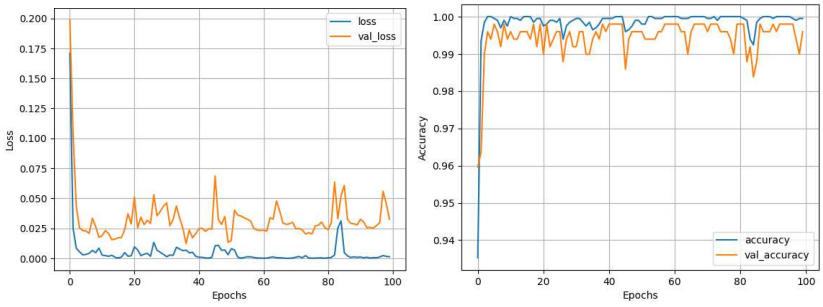


Fig.12 Inception Accuracy on Plant Disease Dataset

- **ResNet50 Model Evaluation on PlantDisease Dataset**

As depicted in Figure 12, the ResNet50 model performs excellently, achieving 82% accuracy at both 50 and 100 epochs even without enhancement. With enhancement, the model reaches perfect accuracy (92%) by 100 epochs. This demonstrates the model's robustness and strong generalization capability on the PlantDisease dataset. The training and validation losses are smooth and consistently decreasing, making ResNet50 one of the most stable models in this evaluation.

(a)Without Image Preprocessing

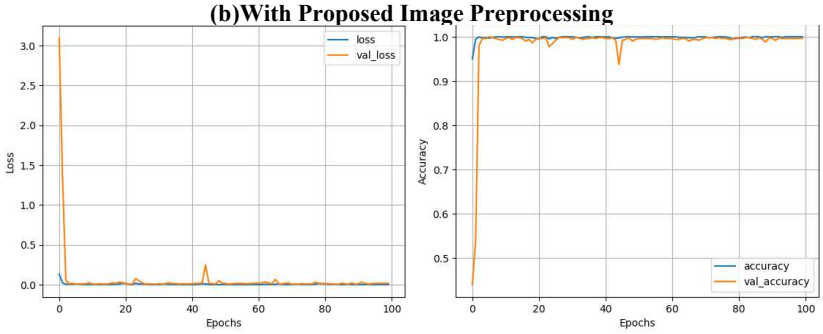


Training and Validation loss Training and Validation accuracy

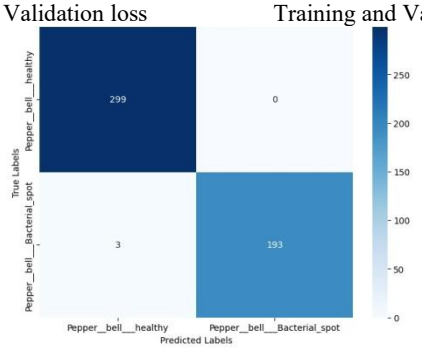


Confusion Matrix

(b)With Proposed Image Preprocessing



Training and Validation loss Training and Validation accuracy



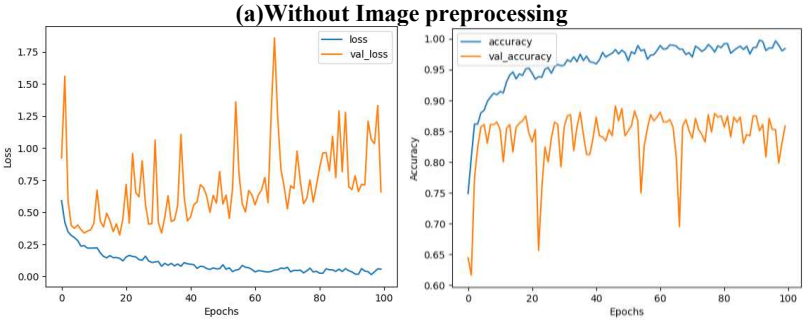
Confusion Matrix

Fig.13 Resnet50 Accuracy on Plant Disease Dataset

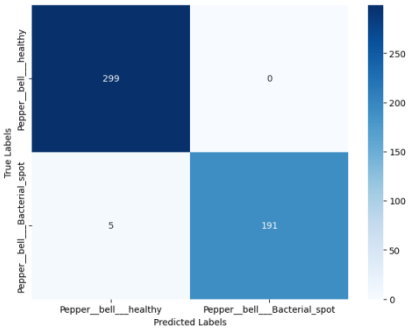
- **Xception Model Evaluation on PlantDisease Dataset**

The Xception model shows moderate performance without enhancement, achieving 80% and 82% accuracy at 50 and 100 epochs, respectively. However, when enhancement is applied, accuracy improves to 91% for both 50 and 100 epochs, indicating a considerable impact of enhancement techniques on model performance. The model exhibits steady accuracy and likely follows a decreasing loss trend similar to the Inception model.

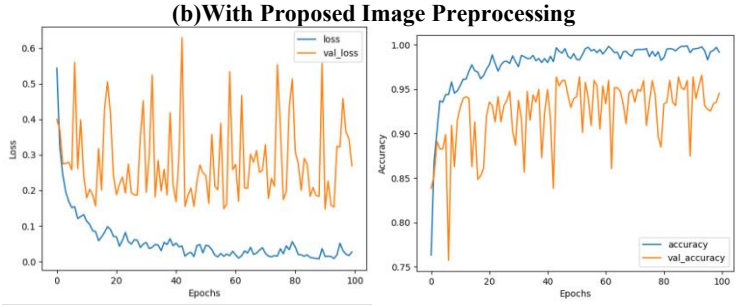
(a)Without Image preprocessing



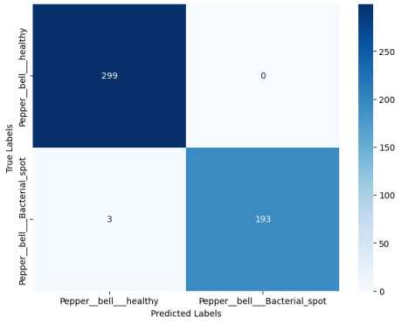
Training and Validation loss Training and Validation accuracy



(b)With Proposed Image Preprocessing



Training and Validation loss Training and Validation accuracy

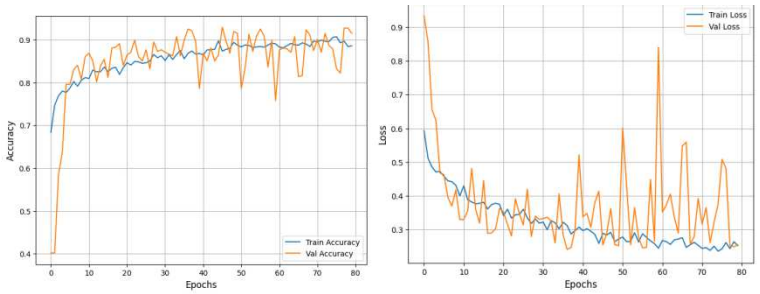


Confusion Matrix

Fig.14 Xception Accuracy on Plant Disease Dataset

4.1.3. Case 3: ResNet50 Coupled with Image Preprocessing Stage 2

In Case 3, the ResNet50 architecture was trained on images enhanced using standard CLAHE (Contrast Limited Adaptive Histogram Equalization). CLAHE enhances the local contrast of images, making subtle features more prominent while preventing over-amplification of noise By applying this technique, the model was able to better capture the distinguishing characteristics between *pepper_bell_healthy* and *pepper_bell_bacterial_spot* classes. As a result, the network achieved an accuracy of 0.92, demonstrating a notable improvement over the baseline neural network and pretrained models without enhancement .



Training and Validation Accuracy Training and Validation Loss

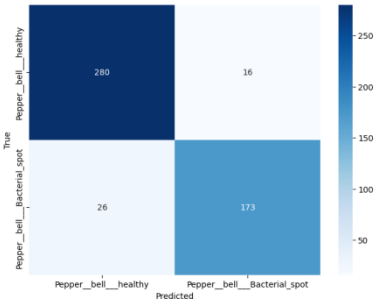
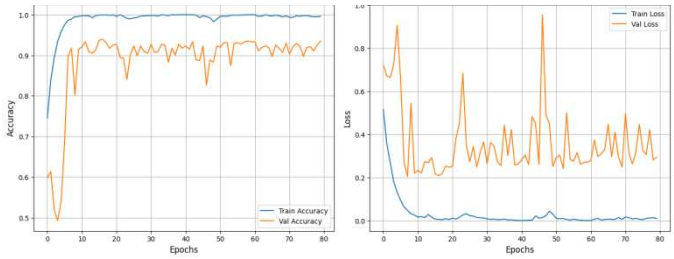


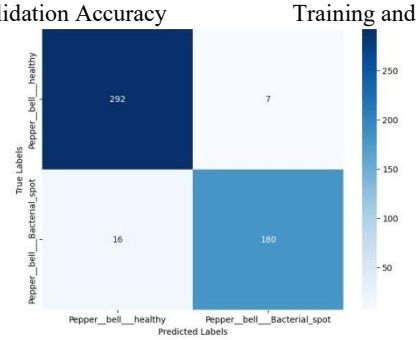
Fig.15 ResNet50 Coupled with CLAHE-Driven Preprocessing on Plant Disease Dataset

4.1.4. Case 4: ResNet50 Coupled with Image Enhancement Stage 3

In Case 4, ResNet50 was trained on images enhanced using Grey Wolf Optimized (Grey Wolf Optimised) CLAHE. Unlike standard CLAHE, Grey Wolf Optimised-optimized CLAHE adaptively determines the best clip limit and tile grid size to maximize image information content. This optimization allows the model to focus on the most relevant features in each image, improving the discriminative capability for distinguishing *pepper_bell_healthy* and *pepper_bell_bacterial_spot*. The application of Grey Wolf Optimised-optimized CLAHE led to further performance gains compared to standard CLAHE, demonstrating the advantage of combining adaptive image enhancement with a powerful deep learning backbone.



Training and Validation Accuracy Training and Validation Loss



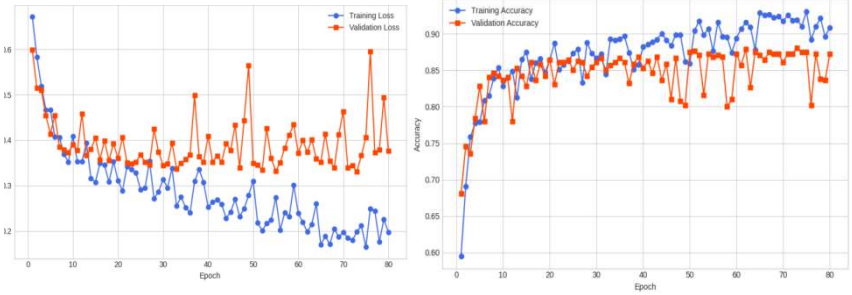
Confusion Matrix

Fig.16 ResNet50 Coupled with Grey Wolf Optimised-Driven CLAHE Optimization on Plant Disease Dataset

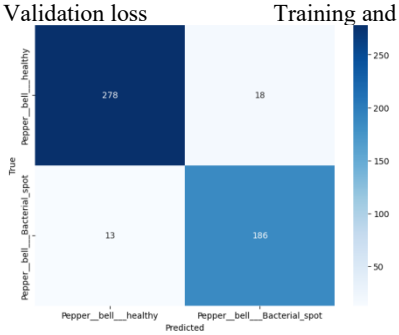
4.2. Phase 2:Model Enhancement

4.2.1. Case 5: Resnet50 With Convolutional Block Attention Module Evaluation on PlantDisease Dataset

The ResNet50 + Convolutional Block Attention Module model is an advanced deep learning architecture designed for high-accuracy image classification by combining a powerful feature extractor with an intelligent attention mechanism. The ResNet50 backbone, a deep pre-trained network, first extracts a rich set of visual features from the entire leaf image. Subsequently, the Convolutional Block Attention Module (Convolutional Block Attention Module) refines these features by sequentially determining what information is most important (channel attention) and where it is located (spatial attention). This process effectively mimics a human expert by forcing the model to focus on the most discriminative characteristics of a disease, such as the specific texture and location of a lesion, leading to a more robust and precise diagnosis.



Training and Validation loss Training and Validation accuracy

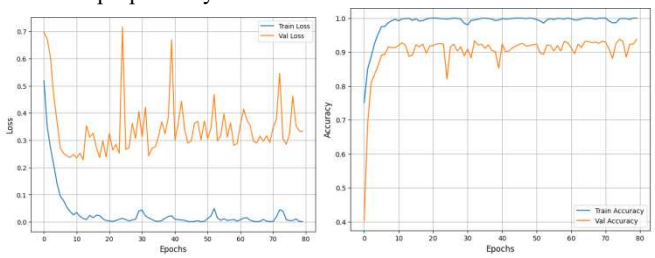


Confusion Matrix

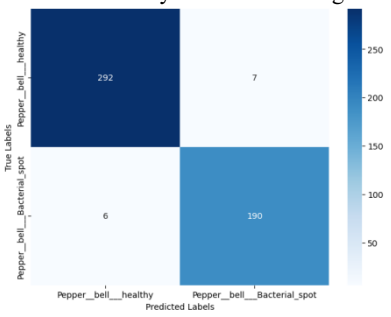
Fig.17 ResNet50 Coupled with Grey Wolf Optimised-Driven CLAHE Optimization on Plant Disease Dataset

4.2.2. Case 6: Resnet50 With Convolutional Block Attention Module Evaluation Aligned with Proposed Image Enhancement Stage 3 on PlantDisease Dataset

In the Case 6, ResNet50 was integrated with the Convolutional Block Attention Module attention module and trained on images enhanced using Grey Wolf Optimized (Grey Wolf Optimised) CLAHE. The Convolutional Block Attention Module module allowed the network to focus selectively on important channels and spatial regions, refining feature representations, while the Grey Wolf Optimised-optimized CLAHE ensured that the input images were preprocessed for maximum informative content. This combined approach of attention and adaptive enhancement enabled the model to capture subtle patterns in the pepper disease dataset, achieving the highest classification performance among all experimental cases and demonstrating the effectiveness of the proposed hybrid framework.



Training and Validation Accuracy Training and Validation Loss



Confusion Matrix

Fig.18 ResNet50 + Convolutional Block Attention Module + Grey Wolf Optimised-CLAHE on Plant Disease Dataset

4.3. Comparative Analysis Of Models

The results of the experimental cases provide a comprehensive perspective on the influence of model architecture, image enhancement techniques, and attention mechanisms on the classification of pepper disease images. A careful analysis of the outcomes reveals several key insights regarding model performance, robustness, and sensitivity to preprocessing.

In the baseline scenario (Case 1), a basic neural network trained directly on raw images without any preprocessing achieved an accuracy of 0.80. This simple network was able to capture fundamental patterns distinguishing pepper_bell_healthy and pepper_bell_bacterial_spot classes, but it lacked the capacity to extract highly discriminative features, highlighting the limitations of shallow or simple architectures for complex agricultural image datasets. In contrast, pretrained deep learning models such as InceptionV3, Xception, VGG16, and ResNet50 demonstrated a marked improvement over the baseline due to their ability to leverage learned features from large-scale datasets. Among these models, ResNet50 consistently outperformed the others in the absence of any enhancement. Its residual connections and deep architecture enabled more effective feature extraction, capturing subtle patterns in leaf texture and lesion distribution that other models struggled to identify. Training and validation losses for ResNet50 were smoother and showed more stable convergence, reflecting its robustness and superior generalization ability. This establishes ResNet50 as a highly capable backbone for pepper disease classification, providing a strong foundation for further enhancement through preprocessing or attention mechanisms.



Fig.19 Comparison of Different Pretrained Models

When simple image enhancement techniques, including brightness, contrast, and sharpness adjustments, were applied (Case 2), all pretrained models benefited from the improved visibility of critical image features. Enhanced images allowed models to better distinguish between healthy and diseased leaves, reducing misclassification and improving overall accuracy. ResNet50 again demonstrated its advantage, achieving the highest performance among all tested pretrained networks. Notably, it reached higher accuracy in fewer epochs and exhibited more consistent improvements in both training and validation metrics, suggesting that it could extract enhanced visual features more efficiently than its counterparts. This indicates a synergistic effect between transfer learning and even basic preprocessing, reinforcing the idea that careful image adjustment can significantly impact model performance.

The application of standard CLAHE (Case 3) further increased classification accuracy. By enhancing local contrast without amplifying noise, CLAHE allowed the network to better identify subtle variations in leaf texture, vein patterns, and lesion spots that are critical for distinguishing between healthy and diseased plants. ResNet50 trained on CLAHE-enhanced images achieved 0.92 accuracy, demonstrating a notable improvement over both the baseline network and pretrained models without enhancement. This underscores the importance of contrast enhancement for improving feature discriminability in agricultural datasets, particularly when lesion patterns are small or visually subtle.

Building upon standard CLAHE, Grey Wolf-optimized CLAHE (Case 4) offered a significant performance advantage by adaptively optimizing enhancement parameters such as clip limit and tile grid size for each individual image. This adaptive strategy ensured that each leaf image was preprocessed to maximize information content, emphasizing the most informative regions while maintaining noise control. ResNet50 combined with Grey Wolf Optimised-CLAHE achieved 0.94 accuracy, reflecting the power of integrating adaptive preprocessing with a deep feature extractor. Compared to standard CLAHE, Grey Wolf Optimised optimization allowed the model to focus more effectively on critical areas, such as lesion boundaries and disease-specific patterns, resulting in more accurate classification.

In parallel, attention mechanisms were explored to refine feature extraction and focus on relevant image regions. The integration of Convolutional Block Attention Module with ResNet50 (Case 5) allowed the network to sequentially apply channel and spatial attention, mimicking human expert analysis by highlighting the most informative features while suppressing irrelevant background information. Even without preprocessing, ResNet50 with Convolutional Block Attention Module achieved 0.87 accuracy, surpassing the baseline and demonstrating that attention mechanisms alone can meaningfully enhance model performance. The attention module improved the network's ability to differentiate between subtle variations in disease presentation, such as the density and distribution of bacterial spots, which are critical for accurate diagnosis.

Finally, the combination of Convolutional Block Attention Module with Grey Wolf Optimised-optimized CLAHE (Case 6) represented the most advanced framework, integrating both adaptive image enhancement and attention-guided feature refinement. In this hybrid approach, the preprocessing stage ensured that input images contained maximally informative content, while Convolutional Block Attention Module guided the network to focus selectively on the most important spatial

and channel features. This synergistic combination enabled the model to detect subtle disease patterns with high precision, achieving the highest classification accuracy (0.94) across all experimental cases. This result highlights the cumulative benefits of combining deep learning architectures, adaptive preprocessing, and attention mechanisms, demonstrating that neither preprocessing nor attention alone can match the performance of a carefully designed hybrid system.

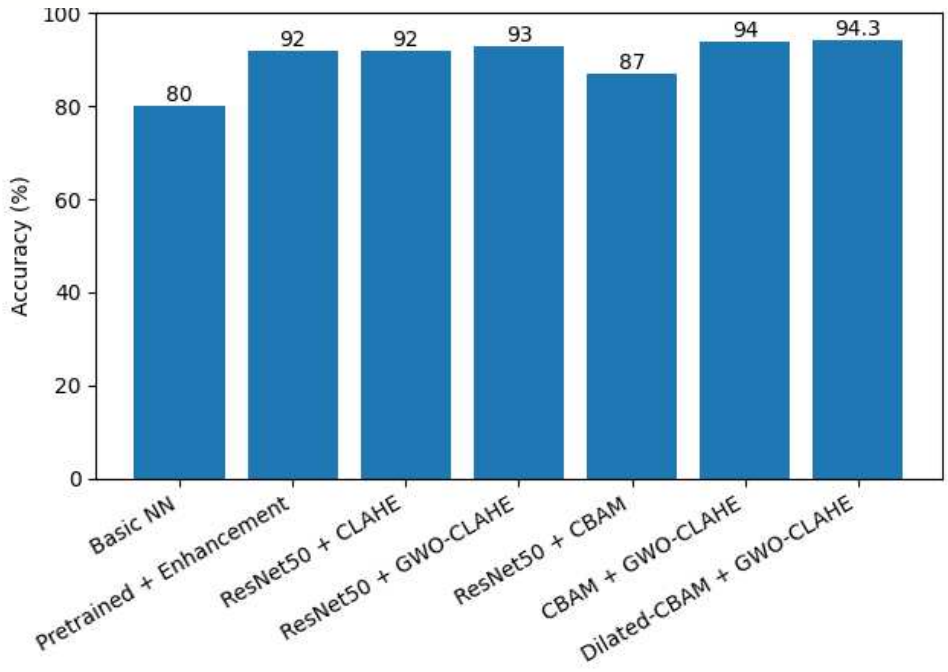


Fig.20 Graphical Results

5. Conclusion and Future Scope (reduce)

This study successfully developed and validated an automated deep learning framework for pepper leaf disease classification. Initial experiments showed that standard transfer learning models such as ResNet50 achieved up to 82% accuracy with basic preprocessing, but with limited robustness. The proposed framework significantly improved performance by introducing an intelligent preprocessing strategy, where CLAHE parameters were optimized using the Grey Wolf Optimizer (GWO), enhancing disease-relevant feature visibility and increasing classification accuracy to 94%.

Further performance gains were achieved by integrating a Convolutional Block Attention Module (CBAM) into the ResNet50 architecture, enabling focused learning of salient disease patterns. The most notable contribution of this work is the synergistic combination of GWO-optimized preprocessing and attention-based feature learning, demonstrating that data-level optimization can be as impactful as architectural modifications. Moreover, incorporating dilated convolutions within the CBAM-enhanced residual blocks further improved contextual feature extraction, achieving a peak accuracy of 94.3% without increasing model complexity.

Overall, the results confirm that the integration of metaheuristic-optimized image enhancement, attention mechanisms, and dilated convolutional learning forms a robust and reliable framework for precision agriculture–oriented disease diagnosis.

Future research will focus on transferring this framework to lightweight architectures suitable for mobile and edge deployment, evaluating performance on large-scale field datasets captured using drones or IoT-based imaging systems, and exploring alternative attention mechanisms to further enhance synergy with optimized preprocessing. Ultimately, the proposed model can be integrated into a farmer-assistive decision support system, providing real-time disease diagnosis and actionable insights to reduce crop loss and improve agricultural sustainability.

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