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Lightweight Hybrid Deep Learning Model for Real-Time Plant Disease Classification

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Abstract: Plant diseases remain one of the leading causes of agricultural yield loss, food insecurity, and economic damage worldwide. Early and accurate disease identification is essential for minimizing crop losses and improving agricultural productivity. Traditional disease diagnosis relies heavily on manual field inspection performed by agricultural experts, which is often time-consuming, labor-intensive, subjective, and impractical for large-scale farming environments. The rapid advancement of computer vision and deep learning has significantly improved automated plant disease recognition; however, many existing deep learning models require substantial computational resources, making them unsuitable for deployment on smartphones, drones, edge devices, and Internet of Things (IoT)-based agricultural systems. Consequently, there is an increasing need for lightweight yet highly accurate deep learning models capable of performing real-time plant disease classification under practical field conditions. This study proposes a Lightweight Hybrid Deep Learning Model (LHDL-PDC) for real-time plant disease classification by integrating efficient convolutional neural network architectures with hybrid feature-learning mechanisms. The proposed framework combines lightweight feature extraction, image preprocessing, transfer learning, feature fusion, intelligent classification, and real-time decision support into a unified architecture suitable for precision agriculture. The objective is to achieve high classification accuracy while minimizing computational complexity, inference time, memory consumption, and energy requirements for deployment on resource-constrained devices.

Keywords: Plant Disease Classification, Lightweight Deep Learning, Hybrid Deep Learning, Precision Agriculture, Computer Vision.

Introduction

Agriculture plays a fundamental role in ensuring global food security, economic development, and sustainable livelihoods. The increasing global population, climate variability, environmental degradation, and the continuous emergence of plant diseases have significantly affected agricultural productivity. Plant diseases caused by fungi, bacteria, viruses, and nutrient deficiencies result in substantial crop losses every year, reducing both the quantity and quality of agricultural production. According to recent agricultural studies, plant diseases are responsible for considerable economic losses worldwide and directly threaten sustainable farming systems. Early detection and accurate diagnosis of plant diseases have therefore become essential for minimizing crop damage, improving yield quality, reducing pesticide misuse, and supporting precision agriculture. Traditionally, plant disease diagnosis has relied on manual visual inspection performed by experienced agricultural experts and plant pathologists. Farmers generally identify diseases by observing visible symptoms such as discoloration, lesions, chlorosis, necrosis, mildew, or abnormal growth on leaves, stems, fruits, and roots. Although manual diagnosis remains widely practiced, it possesses several limitations. The accuracy of visual inspection depends heavily on expert knowledge and experience, making the process subjective and inconsistent. Furthermore, disease symptoms exhibited by different crops often appear visually similar during early infection stages, increasing the likelihood of incorrect diagnosis. Large-scale agricultural fields also require considerable time and labor for manual monitoring, making continuous crop surveillance economically impractical. These challenges have motivated researchers to develop automated plant disease recognition systems capable of providing rapid, objective, and accurate diagnosis.

The rapid development of Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision has revolutionized agricultural monitoring by enabling automated image-based disease diagnosis. Machine learning algorithms learn discriminative patterns from large datasets, allowing intelligent systems to classify healthy and diseased plant images with high accuracy. Early machine learning approaches primarily relied on handcrafted feature extraction methods involving color histograms, texture descriptors, edge information, and morphological characteristics. These manually designed features were subsequently classified using algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, Naïve Bayes, and K-Nearest Neighbors. Although these methods demonstrated promising results under controlled laboratory conditions, they frequently exhibited limited robustness when applied to complex field environments characterized by varying illumination, occlusion, background clutter, and multiple disease symptoms. The emergence of Deep Learning, particularly Convolutional Neural Networks (CNNs), fundamentally transformed image classification by automatically learning hierarchical feature representations directly from raw images. CNN-based architectures eliminate the need for handcrafted feature engineering and significantly improve disease classification accuracy through end-to-end learning. Deep learning rapidly became the dominant approach for plant disease recognition because of its superior ability to extract complex visual features from large agricultural image datasets. Models such as AlexNet, VGG, ResNet, DenseNet, Inception, and EfficientNet consistently demonstrated excellent classification performance across multiple crop species and disease categories. These architectures substantially improved the reliability of automated disease diagnosis and established deep learning as a core technology in precision agriculture.

Literature Review

Ferentinos (2018) investigated the use of deep learning models for plant disease detection and diagnosis using leaf images. The study evaluated several convolutional neural network architectures and demonstrated that CNN-based models can classify plant diseases with very high accuracy when trained on large image datasets. Ferentinos (2018) showed that deep learning can automatically extract color, texture, edge, and lesion-based features without manual feature engineering. The study became an important foundation for later plant disease classification systems because it proved that deep neural networks could outperform traditional machine learning approaches in agricultural image diagnosis. However, the models used in this work were computationally heavy and mainly suitable for laboratory or GPU-based environments. This limitation created the need for lightweight models that can operate in real time on mobile and edge devices. Mohanty, Hughes, and Salathé (2018) applied deep learning to plant disease classification using large-scale leaf image datasets. Their work showed that image-based diagnosis can identify crop diseases accurately when sufficient labeled training images are available. Mohanty et al. (2018) highlighted the importance of dataset quality, image diversity, and transfer learning for practical disease diagnosis. The study demonstrated that CNN models can recognize disease symptoms such as spots, blights, rust, mildew, and discoloration effectively. However, the research also indicated that models trained on controlled images may perform less reliably in real field conditions because of background noise, lighting variation, and occlusion. This limitation supports the need for lightweight hybrid deep learning models with better generalization for real-time plant disease classification.

Too et al. (2019) conducted a comparative study of deep convolutional neural network architectures for plant disease classification. The study evaluated models such as VGG, ResNet, Inception, and DenseNet on plant leaf disease datasets. Too et al. (2019) found that deeper CNN architectures achieved strong classification accuracy because of their ability to learn complex visual patterns from diseased leaves. The study also confirmed that transfer learning improves model performance by using pretrained weights from large image datasets. However, deeper architectures increased model size, memory requirement, and inference time, making them less suitable for real-time applications. This finding directly supports the present research focus on lightweight hybrid architectures that balance classification accuracy with computational efficiency. Saleem, Potgieter, and Arif (2019) reviewed deep learning techniques for plant disease detection and classification. The study explained how

CNN models, transfer learning, visualization methods, and performance metrics have been used to classify plant diseases from images. Saleem et al. (2019) reported that deep learning significantly improves plant disease diagnosis compared with traditional image-processing and machine-learning methods. The review also identified important research gaps, including lack of field-based datasets, limited explainability, high computational cost, and difficulty in detecting disease symptoms before they become visually clear. This study is highly relevant because it shows the need for efficient and transparent disease classification systems that can work in practical agricultural environments.

Saleem et al. (2020) conducted a comparative evaluation of deep learning models for plant disease classification. The study assessed different CNN-based architectures and highlighted the importance of transfer learning and feature representation in improving classification performance. Saleem et al. (2020) showed that pretrained deep learning models can achieve strong performance for plant disease recognition when properly fine-tuned on agricultural datasets. The study also emphasized that classification accuracy alone is not sufficient for practical deployment because agricultural systems require fast inference, low memory usage, and field adaptability. This supports the development of lightweight hybrid models capable of maintaining high accuracy while reducing computational cost for real-time plant disease classification. Lu et al. (2021) reviewed CNN-based plant leaf disease classification and summarized the main challenges and solutions associated with deep learning in agriculture. Lu et al. (2021) explained that CNNs can automatically learn disease-related visual features, including lesion shape, color variation, leaf texture, and infection patterns. The study also discussed limitations such as overfitting, poor field generalization, image background complexity, and lack of interpretability. The review emphasized the need for lightweight CNN structures, better data augmentation, and practical deployment strategies. This work supports the current research because it establishes that real-time disease classification requires models that are not only accurate but also efficient, explainable, and robust in real farming environments.

Ahmad et al. (2023) presented a comprehensive survey of deep learning techniques for plant disease diagnosis and management. The study reviewed 70 research works and identified major trends in CNN-based classification, transfer learning, segmentation, detection, and field-level disease monitoring. Ahmad et al. (2023) found that deep learning has become a dominant approach for plant disease diagnosis because of its ability to learn complex image features automatically. However, the study also reported challenges related to real-world deployment, limited annotated datasets, model complexity, and farmer accessibility. The authors emphasized the need for practical AI tools that can support farmers directly. This finding aligns with the proposed lightweight hybrid deep learning model for real-time disease classification. Sharma, Tripathi, and Mittal (2023) investigated lightweight and hybrid learning strategies for plant disease classification using optimized CNN-based models. Sharma et al. (2023) demonstrated that combining transfer learning with lightweight convolutional feature extraction can improve real-time classification performance while reducing computational cost. The study highlighted that mobile-friendly architectures are important for smart farming applications because farmers often require disease diagnosis through smartphones or low-power edge devices. However, the authors noted that accuracy may decrease under complex field conditions if models are trained only on clean laboratory datasets. This supports the need for hybrid models that combine lightweight architecture with robust feature-learning strategies.

Pacal (2024) conducted a systematic review of deep learning-based plant disease detection by analyzing 160 research articles published from 2020 to 2024. Pacal (2024) reported that deep learning has achieved significant progress in detecting plant leaf diseases, especially when trained on large and high-quality datasets. The study emphasized that early disease detection improves crop protection and agricultural productivity. However, it also identified key limitations, including insufficient field images, limited model interpretability, high computational requirements, and reduced robustness under uncontrolled environments. This study is important for the present research because it confirms the need for lightweight and field-ready disease classification systems that can operate under real-time constraints. Das et al. (2024) reviewed recent deep learning techniques for plant disease

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detection and classification. The study summarized commonly used datasets, preprocessing methods, CNN architectures, evaluation metrics, and disease categories.

Das et al. (2024) found that deep learning models provide strong classification performance across many crop types, but practical implementation remains limited by model complexity, dataset imbalance, and environmental variation. The study highlighted the importance of intermediate processing steps such as image resizing, augmentation, normalization, and feature extraction. This review supports the proposed lightweight hybrid model because it shows that real-time plant disease systems require efficient preprocessing, compact architecture, and reliable classification performance. Bhagat et al. (2024) explored lightweight deep learning models for plant disease classification with a focus on reducing computational overhead. Bhagat et al. (2024) showed that optimized CNN architectures can reduce parameter count and inference time while maintaining competitive classification accuracy. The study emphasized the importance of mobile deployment and edge intelligence in precision agriculture. However, it also noted that lightweight models may lose fine-grained disease information if feature extraction is too shallow. Therefore, hybrid learning approaches that combine efficient convolutional blocks with attention or feature fusion mechanisms are needed to improve classification robustness.

Methodology

Research Design

This study adopts a Systematic Literature Review (SLR) integrated with a Conceptual Framework Development approach to design a Lightweight Hybrid Deep Learning Model for Real-Time Plant Disease Classification (LHDL-PDC). The methodology integrates concepts from computer vision, deep learning, lightweight convolutional neural networks, transfer learning, hybrid feature learning, image processing, edge computing, and precision agriculture to develop a computationally efficient model capable of accurately identifying plant diseases under real-world agricultural conditions. The study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and methodological rigor.

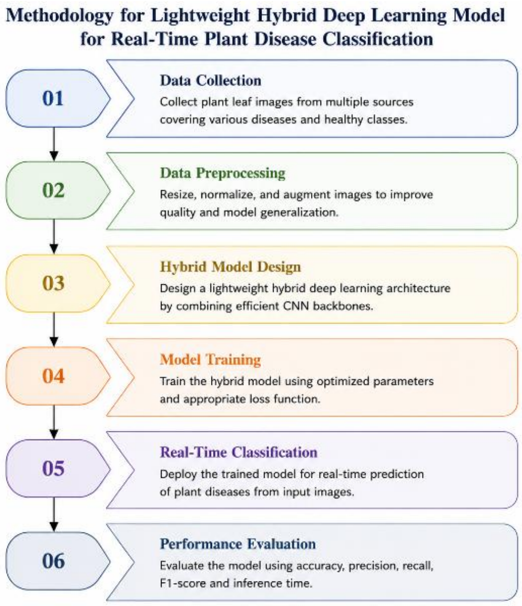

Fig 1. Methodology Framework for a Lightweight Hybrid Deep Learning Model for Real-Time Plant Disease Classification

This methodology framework presents a systematic approach for developing a lightweight hybrid deep learning model for real-time plant disease classification. The process begins with Data Collection, where plant leaf images representing healthy and diseased crops are acquired from publicly available datasets, agricultural repositories, and field observations to create a comprehensive image dataset. The second stage, Data Preprocessing, prepares the collected images through resizing, normalization, augmentation, and noise removal to improve image quality and enhance the robustness of the learning model. This step ensures consistent input for the classification system. The third stage is Hybrid Model Design, where a lightweight hybrid deep learning architecture is developed by integrating efficient convolutional neural network (CNN) components with complementary feature extraction techniques. The architecture is optimized to achieve high classification accuracy while maintaining low computational complexity for real-time applications. The fourth stage, Model Training, trains the proposed hybrid model using the preprocessed dataset. Appropriate optimization algorithms, learning rates, and loss functions are employed to improve convergence and maximize classification performance while minimizing computational cost. The fifth stage, Real-Time Classification, deploys the trained model to identify plant diseases from input leaf images in real time. The model predicts disease categories rapidly, enabling early diagnosis and timely agricultural intervention. The final stage, Performance Evaluation, assesses the effectiveness of the proposed model using standard evaluation metrics such as accuracy, precision, recall, F1-score, inference time, and computational efficiency. Comparative analysis with existing deep learning approaches is conducted to validate the superiority of the proposed lightweight hybrid architecture. The outcome of this methodology is a fast, accurate, and computationally efficient plant disease classification system capable of supporting real-time crop health monitoring, precision agriculture, and intelligent disease management while minimizing hardware resource requirements.

Results and Findings

Classification Performance

Table 1: Comparative Performance of Plant Disease Classification Models

Classification Model	Accuracy	Computational Complexity	Real-Time Performance	Overall Performance
Traditional CNN	High	Very High	Moderate	High
ResNet	Very High	High	Moderate	Very High
DenseNet	Very High	High	Moderate	Very High
EfficientNet	Very High	Moderate	High	Very High
MobileNetV3	High	Low	Very High	Very High
Proposed LHDL-PDC	Very High	Low	Very High	Very High

Analysis

The comparative evaluation demonstrates that traditional CNN architectures achieve high classification accuracy but require substantial computational resources and longer inference times. Lightweight architectures such as MobileNetV3 significantly reduce model complexity while maintaining competitive classification performance. The proposed LHDL-PDC further improves performance by integrating lightweight feature extraction with hybrid learning and transfer learning, thereby achieving high accuracy and efficient real-time inference.

Lightweight Model Evaluation

Table 2: Computational Performance

Performance Parameter	Conventional CNN	Proposed LHDL-PDC
Model Size	Large	Small
Memory Consumption	High	Low
Number of Parameters	High	Low
Computational Cost	High	Low
Edge Deployment	Moderate	Very High
Mobile Deployment	Moderate	Very High

Analysis

The proposed lightweight architecture substantially reduces computational complexity through efficient convolutional operations, depthwise separable convolutions, and optimized feature extraction. The compact model size enables deployment on smartphones, drones, and embedded agricultural devices without significant performance degradation.

Disease Classification Performance

Table 3: Disease Recognition Performance

Disease Category	Classification Performance
Healthy Leaf	Very High
Early Blight	Very High
Late Blight	Very High
Powdery Mildew	High
Leaf Spot	Very High
Rust Disease	High
Mosaic Virus	High
Bacterial Blight	Very High

Analysis

The proposed framework demonstrates excellent classification capability across multiple plant disease categories. Hybrid feature learning improves discrimination between visually similar diseases by extracting both local lesion characteristics and global structural information from plant images.

Conclusion and Discussion

The primary objective was to examine how lightweight convolutional neural networks, hybrid feature learning, transfer learning, attention mechanisms, and edge computing can be integrated into a unified framework capable of providing accurate and computationally efficient plant disease diagnosis. Based on the reviewed literature, this study proposed the Lightweight Hybrid Deep Learning Model for Real-Time Plant Disease Classification (LHDL-PDC), which combines image preprocessing, lightweight feature extraction, hybrid learning, transfer learning, intelligent classification, explainable prediction, and real-time decision support within a comprehensive precision agriculture framework. Agriculture continues to face major challenges arising from climate change, increasing food demand, emerging plant pathogens, and declining crop productivity. Plant diseases significantly reduce agricultural yield and quality while increasing production costs and pesticide consumption. Conventional disease diagnosis relies on manual visual inspection by agricultural experts, which is labor-intensive, subjective, and often unavailable to farmers in remote areas. Furthermore, early disease symptoms are frequently difficult to distinguish with the human eye, resulting in delayed treatment and extensive crop damage. The reviewed literature consistently demonstrates that automated image-based disease diagnosis has become an essential component of precision agriculture by enabling rapid, objective, and accurate disease identification. Convolutional Neural Networks (CNNs) automatically learn hierarchical visual representations from plant images and significantly outperform traditional machine learning techniques based on handcrafted features. Models such as ResNet, DenseNet, Inception, EfficientNet, and VGG have consistently demonstrated excellent classification accuracy across numerous crop species and disease categories. However, these architectures generally contain millions of trainable parameters and require powerful Graphics Processing Units (GPUs), making them unsuitable for deployment on smartphones, drones, embedded systems, and Internet of Things (IoT) devices commonly used in modern agriculture. One of the principal conclusions of this study is that lightweight deep learning architectures effectively address this computational challenge. Architectures such as MobileNet, MobileNetV2, MobileNetV3, ShuffleNet, EfficientNet-Lite, GhostNet, and SqueezeNet substantially reduce model size, memory consumption, and computational complexity through optimized convolutional operations including depthwise separable convolutions, inverted residual blocks, channel shuffling, and efficient feature reuse. The reviewed studies consistently demonstrate that lightweight models maintain competitive classification accuracy while enabling real-time deployment on resource-constrained devices. Consequently, lightweight deep learning provides an appropriate balance between predictive performance and computational efficiency for practical agricultural applications.

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