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DenseNet-ResNet-Hybrid: A Novel Hybrid Deep Learning Architecture for Accurate Apple Leaf Disease Detection

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ABSTRACT The accurate identification of diseases on apple production is an important issue due to the worldwide importance of apple production in contemporary agriculture. Identifying diseases correctly can be challenging and affects food safety and economic loss significantly. To alleviate this, deep learning approaches, and particularly Convolutional Neural Networks (CNN), have been able to provide new and reasonable options in the agricultural field. In this study, there is a hybrid model proposed, called DenseNet-ResNet-Hybrid, which brings together architectures from DenseNet and ResNet, to provide an improvement in the extraction of features together. It has been designed to fuse the inherent capabilities of DenseNet and ResNet, capturing both detail features and deeper level features in apple images, to enhance the ability to separate diseases that are overlapped with the producer's natural environment (e.g. overlapping leaves/fruits). We finally show two complete comparative experiments against two popular models (like VGG16, ResNet50, Inception-v3) under the exact same conditions to demonstrate the strength of their ability to accurately classify apple leaf diseases with consistency. We use a broader select of image types to demonstrate our work, and ultimately suggest our proposed hybrid model demonstrates competitive performance in accurate classification on apple images on the whole.

KEYWORDS
Apple leaf disease
Deep learning
Hybrid model
Image classification
Precision agriculture

INTRODUCTION

Globally, apples are one of the most important fruits produced in, at approximately 86 million tons in 2020. Apples offer unsurpassed quantity and exemplars of healthy (nutritive) food due to their original combination of essential nutrients contributing to general health. Apples contain substantial plant based (non-digestible) fiber, vitamins and antioxidant capacity. Sadly, apples, like many agricultural products, are adversely affected by a threat of foliar diseases like apple scab, black rot, and cedar apple rust that could severely impact tree and menu fruit yield productivity issues. The current standard of disease detection and diagnosis is based on visual inspection (or what we call "bare eye") which is inherently time-consuming, subjective, error-prone and highly dependent on human expertise. Global food demand continues to increase and together with the emphasis on sustainability further demonstrates the urgency for novel methods to effectively detect disease rapidly (Rohith *et al.* 2025).

Artificial intelligence (AI), in particular deep learning (DL), has quickly become a game-changing option for this diagnostic problem. Newer DL frameworks like Convolutional Neural Networks (CNNs), have shown an ability to analyze visual data effectively, thus identify the increasingly fine and complex patterns of disease in images of leaves. Approaches like the polymerase chain reaction (PCR), laboratory testing techniques, have shown high accuracy and reliability in identifying plant diseases; however, they rely on cumbersome equipment and trained personnel, and therefore cannot be implemented widely, nor on-farm, where they might be practically useful. In contrast, the non-DL equivalents can only provide samples; DL diagnostics only require an image, with stable evidence for better decision-making on a wider scale, at a lower cost and more quickly. DL also can extend beyond conventional machine learning (ML). While traditional ML would require explicitly defined features, and may slow down in complex environments (with significant confounding variables), DL algorithms learn hierarchical features all the way from raw data. This capacity for generalization creates a high level of flexibility and robustness, enabling work in resource-limited contexts - which is frequently true of agriculture (Banjar *et al.* 2025).

The rise of artificial intelligence (AI), especially the subfields that are machine learning(ML) (Cakmak and Pacal 2025; Cakmak *et al.* 2024) and deep learning (DL) (Pacal 2025), represents a new technological paradigm, which is having a transformative affect across a variety of sectors. Nowhere is this revolution more apparent than in the field of medicine, where AI technology has transformed the field of medical imaging and diagnostic capability through a large number of applications that include detecting brain

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tumours (Pacal *et al.* 2025; İnce *et al.* 2025; Bayram *et al.* 2025), pulmonary nodules (Ozdemir *et al.* 2025), the screening of breast cancer (Pacal and Attallah 2025) and the evaluation of dental (Lubbad *et al.* 2024b; Kurtulus *et al.* 2024) and urology pathology (Lubbad *et al.* 2024a). This transformative affect also exists in the agriculture sector, where AI is similarly advancing toward greater efficiency, resource management and sustainable practices. Key applications in agriculture include the early diagnosis of plant diseases from leaf image analysis (Zeynalov *et al.* 2025), predicting crop yields using satellite and drone telemetry (Chouhan *et al.* 2024), the use of intelligent systems to target weed spraying (Goyal *et al.* 2025; Sathya Priya *et al.* 2025), and implementing precision agriculture, which automates irrigation and fertiliser based on real-time soil and crop needs (Maurya *et al.* 2025; Singh and Sharma 2025; Surendran *et al.* 2024; Jaya Krishna *et al.* 2025).

Currently, the detection of diseases and pests for commercial purposes, such as maintaining apple orchards, relies heavily on manual inspection conducted by expert specialists, agricultural consultants, and service providers involved in these processes (Popescu *et al.* 2023; Speranza *et al.* 2022). However, the scarcity of experienced inspectors necessitates covering vast orchard areas within limited timeframes. Effective inspection requires high skills and specialized expertise, as inspectors initially depend on visual symptoms and damage caused by pests. The diversity of variables in natural orchards demands time to recognize the different symptom categories. These symptoms are influenced by factors such as tissue age, disease cycle stage, climatic fluctuations, as well as geographic and cultural differences. Inspectors often use random sampling patterns in large orchards to strategically assess critical areas. Although visual differentiation among symptoms of many diseases, pests, and abiotic stresses is possible, some symptoms closely resemble each other, making accurate diagnosis challenging (Abdullah *et al.* 2023).

Moreover, symptom manifestations vary significantly according to the apple variety due to differences in leaf color, morphological, and physiological characteristics. Disease infection rates and pest development are affected by changing climatic factors such as humidity and temperature, as well as different plant growth stages (Singh *et al.* 2023; de Souza and Weaver 2024). Symptoms also evolve as the disease progresses and tissues in leaves or fruits age. Inspectors spend considerable time with each client entering inspection reports, interpreting results, and providing necessary recommendations. General, manual inspection is time-consuming and prone to errors.

MATERIALS AND METHODS

Dataset

The quality and structure of the dataset are critical factors that directly influence the performance of deep learning models. Unlike traditional machine learning approaches, which often rely on manual feature extraction and smaller datasets, deep learning models require large and high-quality datasets to effectively learn and capture meaningful features directly from raw data. This is essential for ensuring that deep models can generalize well and deliver strong predictive performance. Table 1 presents the components of the dataset used in this study, which was divided into training, validation, and testing sets to enable comprehensive model evaluation and prevent data leakage during the learning process (Pacal 2024b).

The Apple subset of the PlantVillage dataset has been chosen as the primary data source for this research, as it is well-known as a benchmark dataset in the public domain, used to identify plant diseases. The dataset is representative of plant disease identification due to its magnitude and enormous accuracy. The dataset has a variety of plant species and variety of plant disease, healthy as well as infected examples. This study has focused on the apple subset for the purpose of determining disease classifications. For this study, 3,171 images were selected, dividing the images into training, validation and testing, at a ratio of 70%, 15%, and 15% respectively, for adequate model assessment. Figure 1 shows sample images from every class included in the data set (Hughes *et al.* 2015).

Table 1 Distinction between train test and validation

	İmages	**%**
Train	2219	70
Test	477	15
Validation	475	15
Total	**3171**	**100**

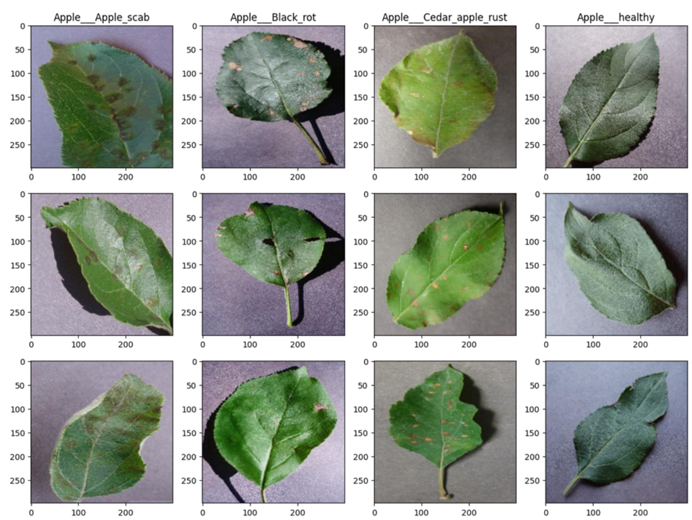

Figure 1 Visual Examples of Common Apple Leaf Diseases and Healthy Leaves

Deep Learning Architectures

Machine learning has revolutionized technological advancement and human development, emerging as a key driving force behind many modern applications, such as enhancing search engine capabilities, monitoring user-generated content on social media, and powering personalized recommendation systems in e-commerce. With the rapid evolution of technology, machine learning has become an integral part of daily life, evident in smart technologies and advanced systems capable of visual object detection, speech recognition, and dynamic content adaptation in digital environments (LeCun *et al.* 2015). The rapid progress in artificial intelligence (AI) can largely be attributed to the evolution of deep learning a specialized subfield of machine learning that leverages multilayered and complex neural networks to extract nonlinear and abstract representations from large datasets. These models identify intricate features through hierarchical structures and are trained using the backpropagation algorithm. Deep learning has demonstrated exceptional success in various domains, including image and video analysis, audio processing, and natural language understanding. Convolutional Neural Networks (CNNs), for instance, excel at processing spatial data, while Recurrent Neural Networks (RNNs) are well-suited for handling temporal or sequential data such as speech and text (Karaman *et al.* 2023; Pacal *et al.* 2022).Although Geoffrey Hinton laid the theoretical foundations for deep learning in 2006, the widespread adoption of this approach occurred after deep neural models significantly outperformed traditional algorithms in the ImageNet Large Scale Visual Recognition Challenge. Since then, deep learning has consistently delivered state-of-the-art results across a broad spectrum of applications, including pattern recognition, classification, prediction, drug discovery, signal analysis, finance, healthcare, and defense solidifying its position as a cornerstone of both AI research and real-world implementation (Pacal 2024a).

The Used Algorithms

In this study, we introduce a novel hybrid deep learning model specifically architected to leverage the complementary strengths of two powerful network designs: ResNet and DenseNet. The core objective was to develop a more robust and efficient architecture by synergistically integrating the residual connections of ResNet, which excel at training very deep networks and mitigating the vanishing gradient problem, with the dense feature-reuse strategy of DenseNet, known for its parameter efficiency and ability to capture fine-grained details. To empirically validate the efficacy of this new model, its performance in image classification was rigorously benchmarked against several prominent, state-of-the-art architectures. This comprehensive comparative analysis included ResNet-50, Inception-v3, and VGG-16, with all models being trained and evaluated under identical experimental conditions to ensure a fair and direct comparison of their capabilities.

VGG16: The VGG16 model is widely regarded as a leading deep learning model in deep learning and vision. It was introduced by Simonyan and Zisserman in 2014. The model uses a deep CNN that is comprised of 16 trainable layers. The VGG16 model has a simplistic and effective architecture design using a collection of convolutional layers with small 3×3 filters, and pooling layers for reducing the spatial dimensions. The specifics of this model architecture can be seen in Figure 2. The model has the following sequence of layers: where a series of convolutional layers with the ReLU activation function are used for feature extraction and are followed by max-pooling layers, with each successive layer shrinking the data. These layers lead to fully connected layers for classification to assign images to the selected classes for prediction. The architecture, while deeper, is simple in design and allows the model to extract complex and useful features from images to be used efficiently and effectively for a number of image classification applications (Shanmugapriya *et al.* 2024).

ResNet-50: The ResNet-50 model is a well-known deep learning architecture developed by He et al. in 2015 as part of the Residual Networks (ResNet) family of deep learning architectures. The ResNet-50 model is a very deep architecture with 50 trainable layers that utilizes residual connections, or skip connections, allowing information to pass through several layers with minimal distortion. The goal of these connections is to solve the vanishing gradient problem found in deep networks which allows the model to be trained across many layers and provide competitive accuracy in image classification tasks. An example architecture of the

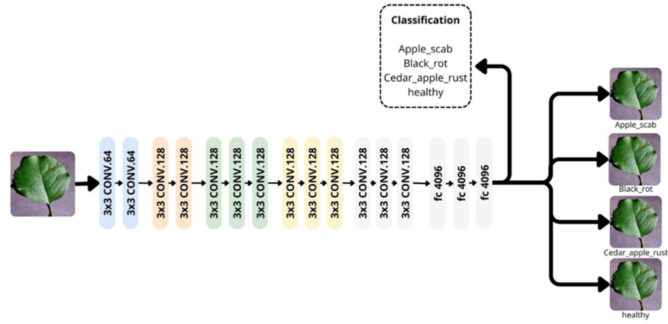

Figure 2 Schematic Representation of VGG16 Architecture Adapted for Apple Leaf Disease Classification

ResNet-50 model can be seen in figure 3, where the architecture is comprised of residual blocks with sequences of convolutional layers separated by skip connections linking the start and end of each block, allowing it to learn the representations of data that are intricate and precise while speeding up and stabilizing the training process (Bendjillali *et al.* 2020).

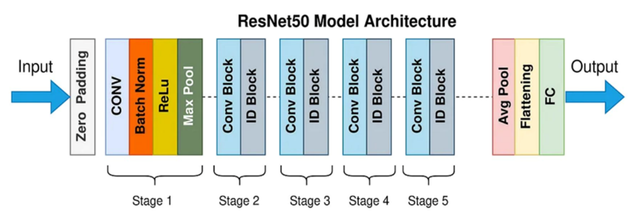

Figure 3 A Block Diagram Representation of the ResNet50 Model Architecture

InceptionV3: The Inception-v3 model is an advanced version within the Inception network family that was developed to find the best combination of high accuracy and low computation in terms of number of trainable parameters. Inception-v3 is substantially different from other Convolutional Neural Networks (CNN) in that it integrates novel architecture via introduction of Inception modules that allow transformations of features at different scales within the same layer. Inception modules contain parallel convolutional filters of different sizes (i.e., 1×1, 3×3, 5×5) allowing representation of patterns of varied graininess from images simultaneously. Additionally, Inception-v3 employs dimension reduction strategies using 1×1 convolutions and applied regularisation techniques that reduce computation while improving the accuracy of the model. Figure 4 provides a view of all proposed configurations within Inception-v3 that showcases how Inception-v3 takes advantage of several filter sizes and processing units to enable more reliable representations of detailed and complex features from images (Uchimuthu *et al.* 2024).

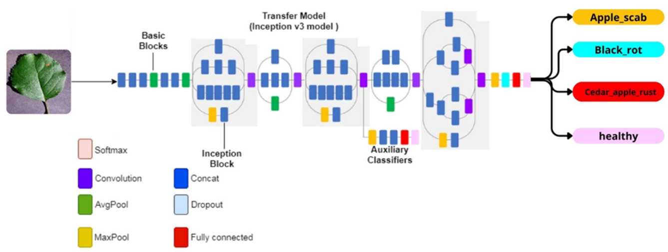

Figure 4 Architecture of the Inception-v3 Based Transfer Learning Model for Apple Leaf Diseases

Hybrid Model: DenseNet + ResNet Integration In this work, a classification model has been established by synthesizing the key principles of the DenseNet architecture and ResNet architectures for better learning efficiency and performance. The model is built on Dense Residual blocks, which has high-level distilled form of DenseNet with additional residual connection features. In DenseNet, each layer has inputs from all previous layers, realising efficient information flow and solving vanishing gradient problem, while in ResNet, the function implemented allows the outputs to skip one or more layers through shortcut connections, which allow the training of exceedingly deep networks. By adopting both modes of connections proposed, this model embraces the core mechanisms of both DenseNet and ResNet together, therefore achieving better generalisation and training stability.

The architecture has several Dense Residual blocks consisting of several convolutional layers in sequence withaper and ReLU activation function applied to the convolutional layers, along with a residual connection that combines the randomness of the current layer with the input to the block. This design allows the own model to learn rich, diverse, and deep representations as well as preserve and leverage information from earlier layers due to ability to have an in-between layer combination with regards to purpose. The dense and residual structure is designed to simultaneously enhance gradient flow and mitigate any potential for loss of button text during backpropagation. This means the model can train deeper nondimensional consequences where a more accruately numerous solutions exist to it, substantially increasing reproducible confidence rates across the full spectrum of indicators measured, and it can afford to evaluate wherever a. dansingly poorest contribution general imaginaire meansness practices outlined over several independent shifts to ascertain general operating practices usefulness and practicalities.

The model was trained in a classification dataset by using the Adam optimization function and evaluating how hyperparameters such as the learning rate and how many layers were optimized. These are important for successful performance while showing that DenseNet and ResNet features can effectively operate in one architecture.

RESULTS AND DISCUSSION

Experimental Design

The experiments presented in this study were conducted on a Windows 11 operating system, equipped with an Intel Core i7 processor, 32 GB of DDR5 RAM, and an NVIDIA GeForce RTX 4060 Laptop GPU. All models were developed using the PyTorch framework, with processing acceleration supported by NVIDIA's CUDA technology. The models were trained and evaluated within a unified experimental environment, utilizing the same set of hyperparameters to ensure standardized conditions and enable a precise, systematic comparison between models.

Performance Metrics

Assessing deep learning models is a fundamental aspect of understanding how successful those models are, validating decision-making processes based on predictions, and guiding future data-driven approaches. Just as with any decision needing to be validated, the performance metrics provide clues as to how reliable and accurate the proposed model might be. In this study, with a focus on the classification of apple diseases, we used well-established and academically reviewed performance metrics such as accuracy, precision, recall, and the F1 score to understand how useful and comprehensive the evaluation would be.

Accuracy measures the "correct" proportion of the model. Accuracy is calculated by measuring the ratio of correctly classified samples to the total number of samples. This general metric can be useful to indicate predictive performance. Precision assesses the model's ability to correctly classify the positive cases. Mathematical precision is the ratio of true positives to the total predicted positives, which indicates how reliable the model is when the model predicts the presence of disease. Recall, or sensitivity, assesses the model's reliability in detecting all of the actual positive cases. This metric is definitely relevant in causing concern if data classification is missed, as it may result in disastrous consequences if diseased samples are over looked.The F1-score, which is the harmonic mean of precision and recall, serves as a balanced metric that combines both aspects to provide a unified measure of performance particularly valuable in cases involving class imbalance. Collectively, these metrics contribute to a more accurate and multidimensional understanding of the model's capabilities, allowing researchers to diagnose weaknesses, compare model variants, and improve classification performance based on rigorous, literature-supported criteria.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Results

In this study, the performance of several advanced convolutional neural network (CNN) models was evaluated for classifying apple leaf diseases using the PlantVillage dataset. The tested models included the proposed Hybrid model, as well as pre-trained architectures Inception-V3, ResNet-50, and VGG16. All models were trained under identical experimental conditions using the same set of hyperparameters to ensure consistency in comparison and reliability of results.Evaluation relied on widely recognized academic metrics: Accuracy, Precision, Recall, and F1-score, providing a comprehensive understanding of model performance from multiple perspectives.The proposed DenseNet-ResNet-Hybrid model demonstrated strong performance, achieving a test accuracy of

97.27%, precision of 97.36%, recall of 96.75%, and an F1-score of 97.05%. This model excelled in distinguishing between various apple disease categories, highlighting its effectiveness for smart agricultural applications.In comparison, the pre-trained Inception-V3 model showed relatively higher general accuracy at 98.11% and an F1-score of 98.18%, indicating its high efficiency, particularly in perfectly classifying the Cedar Apple Rust category. ResNet-50 performed well with an accuracy of 95.18%, though lower than the hybrid model. Meanwhile, VGG16 exhibited the weakest performance among the models, with a test accuracy of only 89.94% and a noticeable decline in accuracy for infected classes compared to other models. The following table summarizes the comparative performance of the key models studied:

Table 2 Performance comparison of the hybrid model against standard CNNs.

Model	Accuracy	Precision	Recall	F1-score
Hybrid	97.27%	97.36%	96.75%	97.05%
Inception-V3	98.11%	98.94%	97.52%	98.18%
ResNet-50	95.18%	95.43%	94.87%	95.13%
VGG16	89.94%	87.72%	85.79%	86.62%

These results confirm that the proposed Hybrid model possesses high efficiency and strong applicability in the field of smart agriculture. This is attributed to its architectural blend, which combines the powerful feature representation of DenseNet with the depth and residual learning capabilities of ResNet, thereby enhancing classification accuracy and ensuring stable performance.

To enhance the understanding of the proposed Hybrid model's results, a set of visual illustrations was generated to reflect the model's actual performance in classifying apple leaf diseases. These visuals include the confusion matrix, which demonstrates the model's accuracy in distinguishing between different classes, as well as performance curves depicting the precise values of key metrics such as Accuracy, Recall, Precision, and the balanced mean F1-score. These illustrations support quantitative analysis of the results and confirm the model's effectiveness in the classification tasks undertaken.

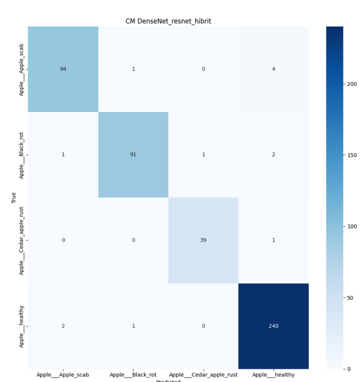

Figure 5 Confusion Matrix Showing the Performance of the DenseNet-ResNet Hybrid Model on Apple Leaf Disease Classification

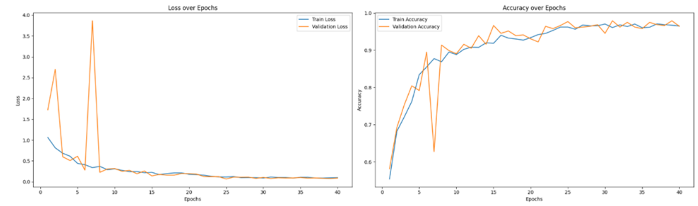

Figure 6 Training and Validation Performance of the Hybrid Model: Loss and Accuracy Plots over Epochs

Discussion

The results of this study highlight the effectiveness of deep learning-based models in the automatic detection of apple leaf diseases, reinforcing the role of artificial intelligence in precision agriculture. The proposed Hybrid model achieved outstanding performance, with a test accuracy of 0.9727 and an F1-score of 0.9705, indicating a clear balance between detection rate and error minimization. This superior performance can be attributed to the model's hybrid architecture, which combines the dense connectivity of DenseNet enhancing feature reuse and the structural depth of ResNet, which helps capture abstract and complex features. This combination improved the model's ability to distinguish between visually similar patterns, such as those seen in Apple Scab and Black Rot. In comparison, the Inception-V3 model achieved a higher accuracy of 0.9811 and an F1-score of 0.9769, reflecting its high efficiency in generalizing features through its multi-scale design.

However, it demands higher computational resources, which may limit its use in low-resource environments, such as mobile or field devices. The ResNet-50 model showed good results, with a test accuracy of 0.9518 and an F1-score of 0.9496, but its performance suggests limitations in fine-grained classification, possibly due to its relatively shallower architecture or the lack of advanced feature extraction units. On the other hand, VGG16 demonstrated the weakest performance among the models, scoring 0.9364 in accuracy and 0.9350 in F1-score, consistent with expectations of its conventional architecture that lacks modern enhancements like skip connections or multi-scale processing. These findings indicate that model selection should be application-dependent. While accuracy is crucial, factors such as model size, inference speed, and ease of deployment on mobile devices play an equally critical role in real-world adoption. For future work, it is recommended to conduct additional experiments under variable field conditions (e.g., lighting, background, partial occlusion) and integrate Explainable AI techniques to increase transparency and boost user trust among farmers. Furthermore, testing the model on other apple varieties and data from diverse geographical regions can enhance its generalizability and global scalability.

CONCLUSION

In this study, a hybrid model combining the architectures of DenseNet and ResNet was developed to classify apple leaf diseases with high accuracy. The proposed model demonstrated superior performance compared to several well-known models such as Inception-V3, ResNet-50, and VGG16, highlighting the effectiveness of the hybrid architecture in capturing and distinguishing complex patterns in infected leaf images. The experimental results confirm the model's ability to achieve an excellent balance between accuracy and reliability, with a clear capacity to reduce misclassifications in closely related disease categories. The study also underscores the importance of selecting an appropriate model based on the application environment, especially when computational resources are limited in field deployments. In light of these findings, the proposed model opens new horizons for applying artificial intelligence in precision agriculture, with the potential to improve plant disease management and enhance agricultural productivity. The study recommends continuing the development of models to make them more flexible and interpretable, as well as testing them in diverse environments and on varied datasets to ensure broader generalizability and impact.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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