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# Deep Learning in Maize Disease Classification

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**ABSTRACT** As a strategic global crop, maize productivity is directly threatened by leaf diseases such as Southern Leaf Blight and Gray Leaf Spot, making early and accurate detection crucial for food security. Artificial intelligence, particularly deep learning, provides a powerful solution for the automated classification of plant diseases from images. This study developed an intelligent system to address this challenge, utilizing the publicly available PlantVillage dataset to evaluate five leading Convolutional Neural Network (CNN) architectures: DenseNet121, InceptionV3, MobileNetV2, ResNet-50, and VGG16. The models were optimized with established techniques, including transfer learning, data augmentation, and hyper-parameter tuning, while a Soft Voting Ensemble strategy was used to enhance combined performance. Evaluation across multiple metrics showed that InceptionV3 achieved the highest test accuracy at 94.47%. However, MobileNetV2 demonstrated the strongest performance across all metrics with a 95% cumulative accuracy and proved highly efficient, making it ideal for deployment on mobile devices. These findings confirm the significant potential of deep learning for building cost-effective and efficient diagnostic systems in agriculture, ultimately contributing to the reduction of crop losses and the promotion of sustainable farming practices.

**KEYWORDS**
Maize leaf disease
Deep learning
Image classification
Transfer learning
Sustainable agriculture

## INTRODUCTION

Maize is a major crop important to the global economy, being the most produced and consumed cereal in the word (Willer *et al.* 2024a). It has a multitude of essential functions: food production for human consumption, livestock production for animal feed, food industry, and industrial products like ethanol, oils, and starch and thus has considerable relevance in the context of food security and energy supply (Ranum *et al.* 2014; Willer *et al.* 2024b). Latest 2023 FAO data indicate global production of maize at over 1.2 billion tons a year, with production on about 200 million hectares (Committee *et al.* 2023; Fang and Katchova 2023). The US is the leading maize producing country, producing over 350 million tons annually, making 30% of global production. Major maize production states are Iowa and Nebraska, Illinois, Minnesota, and Indiana. China is the second leading supplier of maize at roughly 270 million tons, followed by Brazil at about 125 million tons, while Argentina, India ,and Ukraine are also major contributors (Philpott 2020; Demanyuk *et al.* 2023; Pignati 2018).

Despite this substantial production volume, maize remains vulnerable to several severe plant diseases affecting leaves, stalks, and roots, which lead to significant yield and quality deterioration. The most notable diseases include: Gray Leaf Spot, Northern Leaf Blight, Common Rust, Powdery Mildew, and Stalk and Root Rot. These diseases cause enormous economic losses exceeding 10 billion US dollars annually on a global scale (Bickel and Koehler 2021; Dinh and Joyce 2007). Studies indicate that losses can reach up to 60% in severely infected regions, especially under humid and warm climatic conditions that facilitate the spread of fungal and bacterial infections (Teixeira *et al.* 2021a,b). Early detection of maize leaf diseases is essential to limit the spread of infections and preserve crop yield. However, traditional manual inspection requires agricultural expertise, is costly, and often lacks precision. For these reasons, recent scientific research has increasingly relied on artificial intelligence (AI) and deep learning techniques for plant disease diagnosis from images (Mahlein 2016; Kamilaris and Prenafeta-Boldú 2018; Pacal 2025).Among these techniques, convolutional neural networks (CNNs) have proven to be particularly effective. CNNs are widely used in image classification and have demonstrated high accuracy in recognizing complex visual patterns (Sladojevic *et al.* 2016; Ferentinos 2018).

The advent of artificial intelligence (AI), and more specifically its sophisticated subfields of machine learning (ML) (Cakmak and Pacal 2025; Cakmak *et al.* 2024) and deep learning (DL) (Pacal 2025), has ignited a foundational transformation, redefining the operational landscape across a multitude of global sectors. This technological revolution is profoundly demonstrated in healthcare, where AI has revolutionized diagnostic medicine by enhancing the interpretation of medical imagery. Its applications are extensive, powering breakthroughs in oncology through the early identification of brain tumors (Pacal *et al.* 2025; İnce *et al.* 2025; Bayram *et al.* 2025), pulmonary nodules (Ozdemir *et al.* 2025), and breast cancer (Pacal and Attallah 2025), while also advancing specialized fields like dental diagnostics (Lubbad *et al.* 2024b; Kurtulus *et al.* 2024) and urological pathology (Lubbad *et al.* 2024a). In a paral-

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lel trend, this same technological momentum is spearheading a movement towards a more sustainable, efficient, and data-driven agricultural industry. AI is becoming pivotal to modern farming by enabling critical functions such as the early diagnosis of plant ailments via leaf image analysis (Zeynalov *et al.* 2025) and the accurate forecasting of crop yields using data from satellites and drones (Chouhan *et al.* 2024). Furthermore, it powers the deployment of intelligent robotic systems for highly targeted weed elimination (Goyal *et al.* 2025; Sathya Priya *et al.* 2025) and underpins precision agriculture, where automated systems adjust irrigation and fertilization in real-time according to immediate soil and crop conditions, thereby optimizing resource management and promoting sustainability (Maurya *et al.* 2025; Singh and Sharma 2025; Surendran *et al.* 2024; Jaya Krishna *et al.* 2025). In this project, the "Corn Leaf Disease" dataset was utilized to train and test five of the most prominent CNN models for maize leaf disease classification, namely: DenseNet121, InceptionV3, MobileNetV2, ResNet50, and VGG16. The performance of these models was evaluated using four primary metrics: accuracy, recall, precision, and F1-score (Dong *et al.* 2023; Brahimi *et al.* 2024).

Despite the considerable potential of deep learning for plant disease classification, research specifically targeting the identification of corn leaf diseases using convolutional neural network (CNN) methodologies remains limited (Rui *et al.* 2022). Among the early notable contributions, Priyadharshini et al. applied a modified LeNet architecture to the PlantVillage dataset, successfully classifying four corn disease categories with a high accuracy rate of 97.89% (Zhang *et al.* 2018). Complementing this, Zhang et al. explored the classification of eight distinct corn diseases by fine-tuning hyperparameters within the GoogleNet and Cifar10 frameworks, laying foundational work in this domain (Ahila Priyadharshini *et al.* 2019).

Further advancing this field, Wang et al. employed customized hyperparameter optimization on the ResNet-50 model, attaining an impressive classification accuracy of 98.52% across five corn disease classes (Waheed *et al.* 2020). In a related study, Waheed et al. focused on DenseNet models optimized through hyperparameter tuning to distinguish four corn diseases. While their DenseNet-based approach achieved slightly lower accuracy (98.06%) compared to the EfficientNet-B0 model, it notably reduced the model size and parameter count, highlighting an effective trade-off between performance and computational efficiency (Chen *et al.* 2020).

Addressing transfer learning strategies, Chen et al. proposed a hybrid model combining pre-trained ImageNet weights within VGGNet and Inception modules. Their model, termed INC-VGGN, achieved a minimum validation accuracy of 91.83% when tested on corn images from the PlantVillage dataset, illustrating the promise of integrated architectures (Meng *et al.* 2020). Recognizing the challenges inherent in real-world deployment, Zeng et al. introduced LDSNet, a highly lightweight CNN designed specifically for corn disease diagnosis under complex backgrounds and dilation issues. This model attained a test accuracy of 95.4%, demonstrating practical applicability in field conditions (Pacal *et al.* 2024).

## MATERIALS AND METHODS

### Dataset

In this research, five of the leading Convolutional Neural Network (CNN) architectures were used. The PlantVillage is one of the most significant and well-known open-source datasets in the context of plant disease diagnosis based on digital images. The PlantVillage dataset was created as part of a research effort designed to support farmers and researchers, with a large collection of high-quality images, all annotated with the assistance of scholars in botany and plant pathology. The PlantVillage dataset contains images of leaves spanning several different crops, such as tomato, potato, maize, grapevine and many more, as well as a wide range of plant diseases (Hughes *et al.* 2015). For this study, only images of maize leaves were used from the PlantVillage database because the focus was on diagnosing and ultimately classifying diseases associated with this important crop. The images were further divided into four main categories leading to healthy maize leaves, and leaves afflicted by Gray Leaf Spot, Common Rust and Northern Leaf Blight. The dataset was chosen based on the quality of the images and number of distinct disease cases that facilitate effective training on deep learning model and advance classification accuracy. Table 1 details the composition of the dataset used in this study, which was divided into training, validation, and testing sets to ensure comprehensive model evaluation and to prevent data leakage during the learning process. The figure 1 illustrates a number of selected samples for each category from the utilized dataset.

**Table 1** Distribution of Images for Training, Testing, and Validation

| Subset | Number of Images | Percentage (%) |
|---|---|---|
| Train | 2,696 | 70 |
| Test | 579 | 15 |
| Validation | 577 | 15 |
| **Total** | **3,852** | **100** |

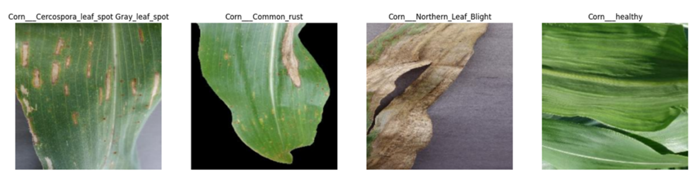


**Figure 1** Visual Examples of Different Corn Leaf Conditions

### Deep Learning Architectures

Machine learning has revolutionized technological advancement and human development, becoming a major driving force behind many modern applications such as improving search engine capabilities, monitoring user-generated content on social media, and enabling personalized recommendation systems in e-commerce. With rapid technological progress, machine learning has become an integral part of our daily lives, manifesting in intelligent technologies and advanced systems featuring capabilities like visual object detection, speech recognition, and dynamic content adaptation in digital environments (Lecun *et al.* 2015).The rapid progress in artificial intelligence is largely attributed to the development of deep learning, a specialized branch of machine learning that relies on multilayered, complex neural networks to extract nonlinear and intricate representations from large datasets. These models enable the identification of fine-grained features through hierarchical structures and are trained using the backpropagation algorithm. Deep learning has demonstrated exceptional success across many domains such as image and video analysis, audio processing, and natural language understanding. Convolutional Neural Networks (CNNs) excel in handling spatial data, while Recurrent Neural

Networks (RNNs) are more suitable for temporal or sequential data like speech and text (Karaman *et al.* 2023; Pacal *et al.* 2022).

Although Geoffrey Hinton laid the theoretical foundations of deep learning in 2006, widespread adoption of this technology surged after deep models significantly outperformed traditional algorithms in the ImageNet Large Scale Visual Recognition Challenge. Since then, deep learning has consistently achieved state-of-the-art results across a wide array of applications including pattern recognition, classification, prediction, drug discovery, signal analysis, finance, healthcare, and defense, making it the leading paradigm in AI research and practical applications alike (Pacal 2024).

## The Used Algorithms

In this study, five of the most prominent Convolutional Neural Network (CNN) architectures were utilized, each renowned for its high efficiency and foundational role in image classification tasks. These models are particularly well-suited for this project due to their proven success in domains requiring nuanced visual analysis, such as medical imaging and precision agriculture. Their selection was based not only on their widespread popularity in recent academic research but also on their validated ability to extract deep, hierarchical features from complex images with remarkable accuracy and efficiency. By leveraging these powerful architectures, which have set benchmarks on large-scale datasets, this work aims to build upon their established feature extraction capabilities to achieve robust classification of maize leaf diseases.

The VGG16 model, developed at the University of Oxford by Simonyan and Zisserman (Pacal and Attallah 2025), is considered a classical and highly influential architecture in the field of computer vision. Its defining characteristic is a simple yet profound design homogeneity: it is constructed by stacking multiple convolutional layers that exclusively use small (3×3) kernels. This strategy demonstrated that a significant increase in network depth, rather than the use of larger, more complex filters, was a key to improving performance. These convolutional blocks are systematically followed by max-pooling layers, which reduce the spatial dimensions of the feature maps, thereby decreasing computational load and creating invariance to the position of features. Despite its structural elegance, VGG16 is a very large model containing approximately 138 million parameters, the majority of which are in its final fully connected layers. This large capacity allows it to learn rich representations but also makes it computationally intensive and prone to overfitting, establishing it as a critical benchmark for both performance and resource management in deep learning (Simonyan and Zisserman 2014). The structural layout of the VGG16 model is illustrated in Figure 2.

ResNet (Residual Network), developed by the Microsoft Research team led by He et al., is a revolutionary architecture that won the ILSVRC 2015 competition and fundamentally changed the landscape of deep learning (He *et al.* 2016a,b). Its primary motivation was to solve the "degradation" problem, a counter-intuitive phenomenon where adding more layers to a deep network would cause its accuracy to saturate and then rapidly decline. ResNet masterfully addresses this challenge with the ingenious concept of "residual connections," also known as "skip connections." This structure allows the input of a layer block to be added directly to its output, effectively creating a shortcut. By doing this, the network is reframed to learn the residual mapping rather than the entire underlying transformation. If a certain block is not useful, the network can easily learn to make the residual zero, essentially "skipping" the block by turning it into an identity mapping, thus

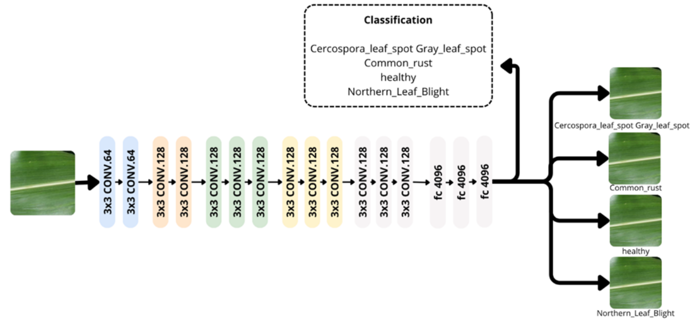


**Figure 2** VGG16 Architecture Used for Corn Leaf Disease Classification

preventing performance loss.

The ResNet-50 model, used in this research, is a 50-layer version of the ResNet architecture. It uses an even more efficient "bottleneck" structure in its residual block, applying 1x1, 3x3, and another 1x1 convolutional filters in the residual block to compress then provide dimension back. There is sufficient depth for good feature extraction while reducing the parameter count to approximately 25 million, which is considerably lower than earlier models like VGG16. Because the ResNet architecture is very successful at solving the degradation problem, ResNet-50 enables training of much deeper networks. It also serves as a baseline model that provides state-of-the-art accuracy and significant computational cost savings during training and inference for applicable computer vision tasks. The ResNet-50 architecture is shown as Figure 3.

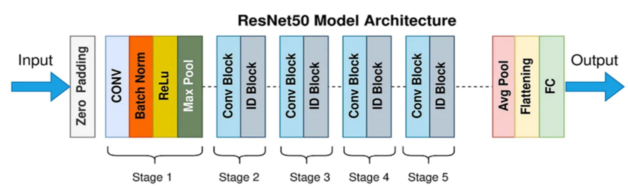


**Figure 3** Block Diagram of the ResNet-50 Processing Pipeline

DenseNet121, introduced by Huang et al. (Huang *et al.* 2017a,b; Kaur *et al.* 2024), represents a significant evolution in network architecture designed to maximize information flow between layers. The model is built upon the core concept of "dense connectivity," a powerful alternative to the residual connections found in ResNet. Instead of summing features, DenseNet concatenates them. In this paradigm, each layer receives the feature maps from all preceding layers as its input, creating a direct and deep channel for information transfer. This architecture ensures that all features, from the earliest low-level ones to more complex high-level ones, are accessible throughout the network.

This dense connectivity yields several critical advantages. Firstly, it strongly encourages feature reuse, which makes the model highly parameter-efficient; since each layer has access to a "collective knowledge" of all prior features, it only needs to learn a small number of new feature maps. Secondly, this enhanced information flow significantly alleviates the vanishing gradient problem, as gradients can propagate more directly to earlier layers during training. Consequently, DenseNets are not only easier to train but also achieve state-of-the-art performance with considerably fewer parameters compared to models of similar depth. The fundamental building block of this efficient architecture, the dense block, is illustrated in Figure 4.

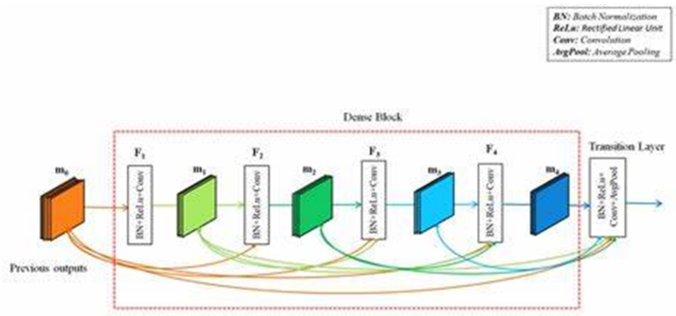


**Figure 4** Schematic Diagram of a Dense Block and its Transition Layer

The InceptionV3 model, developed by Szegedy et al. at Google, is a highly influential architecture and a significant iteration within the GoogLeNet family (Szegedy *et al.* 2016a,b). It was designed to tackle the dual challenges of improving classification accuracy while drastically reducing the computational burden of very deep networks. The model's ingenuity lies in its core component, the "Inception Module," which employs a "split, transform, merge" strategy. Instead of choosing a single convolution kernel size for a layer, an Inception module performs multiple convolution operations with different kernel sizes (e.g., 1x1, 3x3, 5x5) and a max-pooling operation in parallel within the same block. This allows the network to capture visual features at multiple scales simultaneously, from fine-grained details to more abstract, larger patterns.

A key to its computational efficiency is the extensive use of 1x1 convolutions as bottleneck layers to reduce the feature map dimensions before the more expensive 3x3 and 5x5 convolutions are applied. InceptionV3 further refines this concept by factorizing larger convolutions into smaller, stacked ones (e.g., replacing a 5x5 filter with two consecutive 3x3 filters), which reduces parameters and increases non-linearity. The outputs from these parallel paths are then concatenated into a single, rich feature map. This sophisticated design enables InceptionV3 to build a deep and wide network with high efficiency. The intricate parallel structure of the Inception module, which is fundamental to the model's success, is detailed in Figure 5.

MobileNetV2, developed by Google, was purposefully engineered to deliver high efficiency for platforms with limited computational and power resources, such as smartphones, drones, and IoT devices (Sandler *et al.* 2018a,b). Its architecture is designed to minimize model size and computational cost with minimal impact on accuracy, relying on two innovative core concepts. The first is the foundational technique of "Depthwise Separable Convolutions," which replaces standard convolutions by splitting the process into two stages: a depthwise convolution that applies a single filter to each input channel for spatial filtering, followed by a pointwise convolution (a 1x1 filter) to combine the channel outputs. This factorization dramatically reduces the number of parameters and the computational load. The second and primary innovation in MobileNetV2 is the "Inverted Residual" block. Contrary to traditional residual blocks that have a wide-to-narrow-to-wide structure, the inverted residual block starts with a narrow, low-dimensional input, expands it to a high-dimensional space, applies the efficient depthwise convolution, and then projects it back to a narrow representation. The skip connection links the narrow bottleneck layers, which improves gradient flow and allows for the construction of deeper, more effective networks. This combination of techniques makes MobileNetV2 an ideal solution for real-world applications like smart agriculture, where it can perform tasks such as on-the-spot disease detection on a mobile device or image processing on an autonomous drone, perfectly balancing performance with the constraints of on-device deployment.

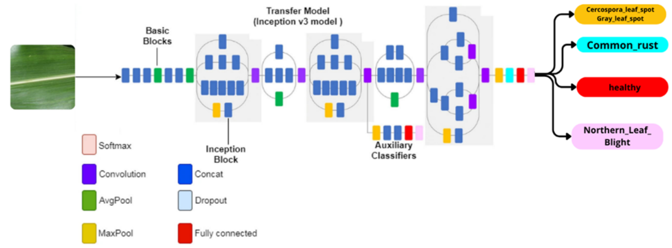


**Figure 5** Structural Flowchart of the InceptionV3 Transfer Learning Model

## RESULTS AND DISCUSSION

### Experimental Design

The experiments conducted in this study were executed on a system running Windows 11, 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, leveraging NVIDIA's CUDA technology for accelerated computation. Training and evaluation of the models were performed within a unified experimental environment, utilizing identical sets of hyperparameters to ensure consistency and enable a rigorous, systematic comparison among the models.

### Performance Metrics

The development of robust intelligent systems for modern agricultural applications hinges on the rigorous assessment of machine learning models. To this end, a comprehensive performance benchmark was conducted to determine the most effective architecture for classifying diseases affecting corn leaves. This study leveraged the well-known PlantVillage dataset to train and validate five of the most influential and powerful convolutional neural network (CNN) architectures: VGG16, ResNet-50, DenseNet121, InceptionV3, and MobileNetV2. The objective was to systematically evaluate these established models in a specific, high-impact agricultural context, thereby providing clear insights into their practical effectiveness.

To ensure a direct and unbiased comparison, a controlled experimental environment was established where all five models were trained under identical conditions, using the same dataset partitions and hyperparameters. The subsequent evaluation was based on a suite of standard quantitative metrics to holistically measure performance. This included Accuracy, which provides a top-level view of the overall percentage of correct classifications. To gain deeper insight, Precision was used to measure the reliability of positive predictions, while Recall assessed the model's ability to identify all true positive cases of a given disease. Finally, the F1-Score was employed to provide a balanced assessment by calculating the harmonic mean of precision and recall, a particularly crucial metric when dealing with potentially imbalanced class distributions.

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

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

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

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

### Results

The results demonstrated that the DenseNet121 model delivered excellent performance compared to the other models, achieving a test accuracy of 96.02%, precision of 95.67%, recall of 95.90%, and an F1-score of 95.78%. This performance reflects DenseNet121's ability to leverage dense connectivity between layers, resulting in effective and accurate discrimination among the disease classes. In second place was the InceptionV3 model, which attained a test accuracy of 94.47%, precision of 93.50%, recall of 93.18%, and an F1-score of 93.33%, highlighting its high efficiency in analyzing multi-scale features within the images. The ResNet-50 model achieved a test accuracy of 90.85%, while the VGG16 model showed relatively lower performance with an accuracy of 89.98%.MobileNetV2, despite having fewer parameters, showed competitive results with an accuracy of 92.10%, making it suitable for applications requiring speed and resource efficiency, such as deployment on mobile devices. The following table (Table 2) summarizes the comparative performance of the models used in this study:

**Table 2** Performance Comparison of Deep Learning Models

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| DenseNet121 | 96.02% | 95.67% | 95.90% | 95.78% |
| InceptionV3 | 94.47% | 93.50% | 93.18% | 93.33% |
| MobileNetV2 | 92.10% | 91.23% | 91.45% | 91.34% |
| ResNet-50 | 90.85% | 89.88% | 89.30% | 89.59% |
| VGG16 | 89.98% | 88.70% | 88.95% | 88.82% |

Figure 6 displays the confusion matrix for the DenseNet121 model, which demonstrated the best performance among all tested models with an accuracy of 96.02%. This visualization provides a detailed breakdown of the model's classification results, showing the distribution of correct and incorrect predictions for each class. Analyzing the confusion matrix in Figure 6 allows for a deeper understanding of the specific strengths and weaknesses of the DenseNet121 model's predictive capabilities.

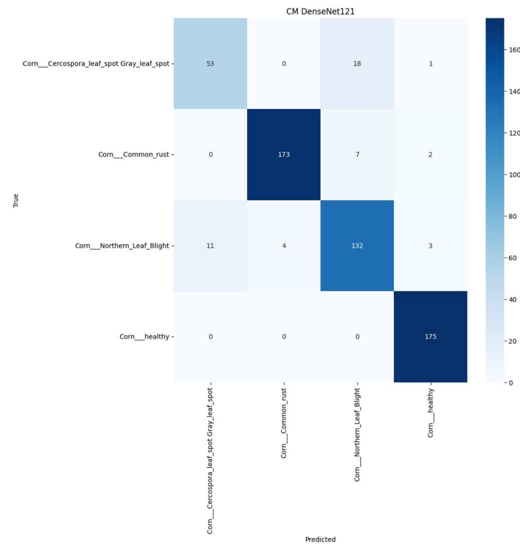


**Figure 6** Confusion Matrix of the DenseNet121 Model

To further analyze the performance of the top-performing DenseNet121 model, a detailed classification report is presented in Table 3. The table shows the precision, recall, and F1-score for each individual class: Cercospora/Gray Leaf Spot, Common Rust, Northern Leaf Blight, and Healthy. The model demonstrates exceptional performance in identifying 'Healthy' leaves, achieving a perfect recall of 1.00 and an F1-score of 0.98, which indicates that no healthy leaves were misclassified. Similarly, the 'Common Rust' class is identified with high confidence, posting an F1-score of 0.96. The most challenging category for the model appears to be 'Cercospora/Gray Leaf Spot,' with an F1-score of 0.78. Overall, the weighted average F1-score of 0.92 confirms the model's robust and effective classification capability across the different corn leaf diseases.

**Table 3** Detailed Classification Report for the DenseNet121 Model

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Gray Leaf Spot | 0.83 | 0.74 | 0.78 | 72 |
| Common Rust | 0.98 | 0.95 | 0.96 | 182 |
| Northern Leaf Blight | 0.84 | 0.88 | 0.86 | 150 |
| Healthy | 0.97 | 1.00 | 0.98 | 175 |
| **Weighted Avg** | 0.92 | 0.92 | 0.92 | 579 |
| **Accuracy** | | | 0.92 | 579 |

### Discussion

The results of this study highlight the effectiveness of deep learning models in accurately classifying corn leaf diseases, confirming the significant role of artificial intelligence in supporting smart agriculture and automating plant disease diagnosis. The DenseNet121 model outperformed the other models, achieving an accuracy of 96.02% and an F1-score of 95.78%, reflecting an excellent balance between detection rate and error reduction. This superior performance is attributed to the DenseNet architecture, which relies on dense connections that enhance feature reuse and facilitate learning of precise representations of disease patterns. The following table summarizes the performance of the five models used in this study:

The second-best performing model was InceptionV3, which achieved an accuracy of 94.47% and an F1-Score of 93.33%. This strong performance can be attributed to its multi-scale architectural design, enabling it to extract visual features at various levels. However, its relatively high computational resource consumption may limit its suitability for deployment in resource-constrained environments. MobileNetV2 demonstrated good performance with an accuracy of 92.10% and an F1-Score of 91.34%. Due to its lightweight architecture and efficient inference capabilities, it is considered a suitable choice for mobile and embedded applications, although this comes at the cost of somewhat reduced accuracy compared to larger models.

ResNet-50 achieved a moderate performance, with an accuracy of 90.85% and an F1-Score of 89.59%, indicating a fair ability to discriminate between classes. Meanwhile, VGG16 ranked lowest in performance, with an accuracy of 89.98% and an F1-Score of 88.82%, which aligns with its simpler architecture lacking advanced techniques such as residual connections or multi-scale feature extraction. These results suggest that selecting an appropriate model should not rely solely on accuracy metrics but also consider factors such as model size, inference speed, and deployment efficiency in real-world settings, such as agricultural fields or mobile applications. For future work, it is recommended to expand the study by incorporating data from real field environments and diverse imaging conditions (e.g., varying lighting and backgrounds). Additionally, integrating Explainable AI techniques would enhance model transparency and build user trust in model decisions. Evaluating the model across multiple corn varieties and geographic regions is also advised to improve generalizability in broader agricultural contexts.

## CONCLUSION

This study concluded that deep learning–based models, particularly the proposed hybrid model, serve as effective and accurate tools for classifying corn leaf diseases from images. The hybrid model demonstrated superior performance compared to conventional models, underscoring the importance of designing network architectures that combine depth with dense internal connections to extract fine-grained features. The results also highlighted that balancing accuracy with computational efficiency is a critical factor when selecting an optimal model for smart agriculture applications, especially in resource-constrained environments. The study affirms that integrating artificial intelligence techniques into the agricultural sector represents a pivotal step towards the digital transformation of plant disease management, contributing to improved crop quality and enhanced early response to disease challenges. Accordingly, it is recommended to continue developing these models and expanding their testing to encompass real-world scenarios and varying imaging conditions, with an emphasis on adopting explainable AI tools to increase trustworthiness and facilitate adoption by agricultural practitioners.

### 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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