



AI-Powered Corn Disease Classification Using Deep Transfer Learning

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Abstract. Corn, a vital agricultural crop, and essential food source, plays a crucial role in the global food chain and serves as a raw material for various industrial applications like biofuels. Small-scale corn cultivation sustains livelihoods in developing nations, but these crops are highly susceptible to diseases. Extreme weather conditions can exacerbate these diseases, leading to significant declines in agricultural yields.

Advancements in artificial intelligence (AI), particularly deep learning algorithms, offer promising solutions. This study explores the application of deep transfer learning for classifying three distinct corn leaf conditions: rust, northern leaf blight, and healthy plants. By utilizing corn leaf images as input and leveraging convolutional neural networks, the proposed approach eliminates the need for complex pre-processing or manual feature extraction.

Employing well-established deep learning models (VGG19, GoogleNet, and ResNet50) and rigorous evaluation methods with various data splitting scenarios, the study achieved remarkable mean accuracies of 96%, 99%, and 75% in distinguishing the three classes. These results demonstrate the potential for developing practical applications to assist farmers and plant pathologists in accurately and swiftly identifying corn diseases, enabling them to implement appropriate treatment measures.

Keywords: AI · Corn disease Identification · Deep Transfer-Learning · Machine Learning

1 Introduction

Plant diseases are a quiet but persistent enemy, causing billions of dollars in damages to worldwide agriculture annually [1]. Fungi, viruses, and bacteria infiltrate plants causing deformities and weakening them. The \$2 trillion projected cost highlights the pressing need for quicker, more precise methods for detecting, controlling, and treating the issue.

Naked-eye scrutiny is the primary method of defence but has some drawbacks [2]. Misdiagnoses and incorrect treatment approaches often occur due to the limited availability of knowledge. Depending on plant pathologists for analysis may be expensive, time-consuming, and sometimes not feasible in distant locations [3].

We need a more intelligent resolution. An innovative tool that enables farmers to detect and address harmful infections before they devastate their crops [4] quickly and accurately. Innovative technologies such as artificial intelligence and machine learning provide promise for a healthier and more resilient future in agriculture.

This revised version succinctly presents the material, emphasises the pressing nature of the issue, and offers the possibility of AI solutions while retaining the primary ideas of the original article [5, 6].

Corn, a widely grown commodity also called maize in some areas, provides sustenance for millions, and serves as the basis for several goods. Its flexibility is only equaled by its significance, being used for cooking oil and biofuels. However, this essential crop is threatened by a hidden adversary: diseases, especially those that target its leaves as it grows [7, 8].

Corn flourishes in many conditions, showing remarkable genetic variety and productivity potential comparable to rice and wheat [9]. However, its high success rate attracts several diseases, putting crops at risk and affecting global food security.

This study focuses on three very damaging leaf diseases: *Cercospora* leaf spot, common rust, and northern leaf blight [10]. It is essential to comprehend these silent invaders and create efficient strategies to protect the important role of maize in global food supply.

The agricultural landscape is witnessing a transformation driven by technological advancements. One particularly promising area is artificial intelligence (AI), specifically deep learning algorithms which can leverage plant images to inform crucial decision-making [11].

Think of deep learning as a complex neural network with many layers, surpassing the basic input, output, and hidden structures. A specific type, known as convolutional neural networks (CNNs), excels at analysing images. They do this through a series of “convolutions”, “pooling”, and “ReLU” layers, ultimately feeding information to a final, fully connected layer that combines everything learned. This makes CNNs adept at recognizing features even amidst image variations [12].

Building CNN-based systems from scratch offers flexibility, but there’s a clever shortcut: transfer learning [13]. This involves reusing existing, well-established models and their “learned knowledge” for new applications. Imagine using a pre-trained model to recognize basic image features (colours, edges) in its early layers, then fine-tuning the later layers for your specific case, like corn disease detection [14]. This approach offers a significant advantage: leveraging pre-existing knowledge while customizing it for your unique needs. The fight against corn diseases is getting a boost from artificial intelligence (AI). Researchers are exploring various approaches, each with its own strengths and weaknesses. Let’s delve into three recent examples:

1. **Raspberry Pi to the Rescue:** Padilla et al. [15–18] built a portable system using a Raspberry Pi to capture and analyze corn leaf images. Their system, powered by a CNN implemented with OpenMP, achieved an impressive 93% accuracy in detecting leaf blight. However, it fell short with rust and leaf spot diseases, reaching only

89% accuracy. While lacking details about the specific CNN architecture, this study demonstrates the potential of AI for field-based disease detection.

2. **Deep Dive with a 9-Layer CNN:** Panigrahi et al. [16–18] took a deeper approach, designing a 9-layer CNN architecture. This model boasted a remarkable 98.78% accuracy and F1-score, suggesting high potential for reliable disease classification. However, concerns remain regarding the lack of information on data splitting methods and potential biases, calling for further research transparency.
3. **Fusion Power:** Pushing the boundaries, Amin et al. [17, 18] experimented with fusing features from two pre-trained CNN models: EfficientNetB0 and DenseNet121. This powerful combination led to a more representative feature map, resulting in superior performance. Their work highlights the potential of combining existing AI models for even more accurate disease detection. These examples showcase the rapid advancements in AI-based corn disease detection. While challenges remain in terms of transparency and robustness, the future looks promising for farmers facing the constant threat of crop disease. We can expect even more sophisticated and reliable AI solutions to emerge in the years to come, safeguarding food security and empowering farmers with powerful tools to protect their crops.

2 Material and Methods

2.1 Datasets

In our research on identifying corn diseases using image analysis, we utilized a dataset containing 2,500 training images and 612 testing images, each categorized into two classes representing distinct diseases: Rust and Northern Leaf Spot. This dataset was carefully curated to incorporate a diverse range of scenarios and image variations, ensuring it comprehensively represents the targeted diseases.

While the initial training data originated from a public Kaggle dataset featuring high-quality JPEG images (5471×3648 pixels), these images required preprocessing. We employed techniques like de-noising and segmentation to resize them to a standard format of 256×256 pixels, as described by Gandhi et al. (2018).

However, we recognized that Kaggle images, typically captured in controlled laboratory settings, might not accurately reflect real-world conditions encountered in fields. To address this gap, we decided to create our own field-specific database. Our testing images were captured using a separate Megapixel camera and stored in a dedicated database.

This approach ensures that our model is trained and tested on representative data, ultimately improving its generalizability and effectiveness in identifying corn diseases in real-world agricultural settings.

While the dataset provides valuable insights, its relatively small size poses limitations to the robustness and generalizability of our results. To mitigate this, we employed data augmentation techniques such as rotation, flipping, scaling, and color adjustments, amongst others to artificially expand the dataset and introduce variability. Additionally, techniques like transfer learning were used to leverage pre-trained models on larger datasets, enhancing the robustness of our results.

2.2 Data Splitting

For robust model evaluation, we randomly split the dataset into 80% training and 20% testing sets. This random split ensures the training set represents the diverse characteristics of the whole data, leading to a more robust and generalizable model. This version emphasizes the importance of random splitting to avoid bias in the training data.

To improve the performance of our machine learning model, we employed several image preprocessing techniques that enhanced the quality and generalizability of the input data.

2.3 Image Processing

To improve the performance of our machine learning model, we employed several image preprocessing techniques that enhanced the quality and generalizability of the input data (Figs. 1 and 2).

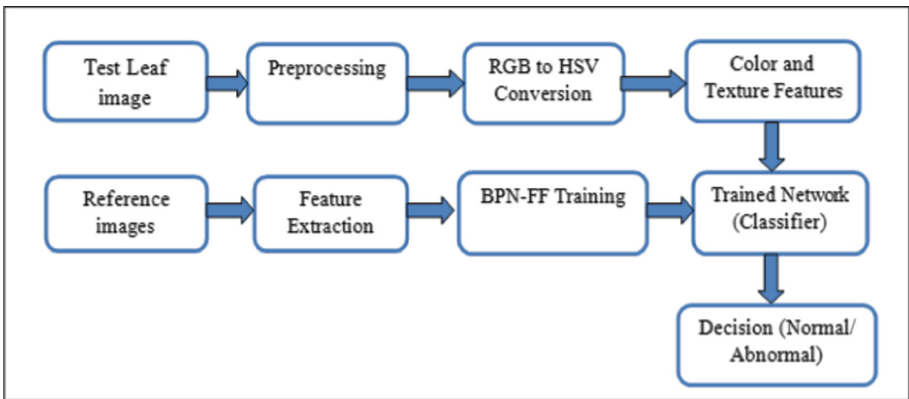


Fig. 1. Leaf Image Processing

2.4 Data Augmentation

Data augmentation plays a vital role in enhancing the performance of machine learning models, especially when limited annotated images are available. This study implements real-time data augmentation during model training using the ImageDataGenerator class. Here's how we diversified the training set:

- **Shear Range:** Controlled deformations mimicked variations in leaf orientation and shape, similar to those encountered in real-world scenarios.
- **Zoom Range:** Random zooming simulated different capture distances, broadening the model's ability to recognize diseases at diverse scales.
- **Horizontal Flip:** By flipping images horizontally, we accounted for potential imbalances in disease distribution across leaves, ensuring the model remains robust to such variations (Fig. 3).

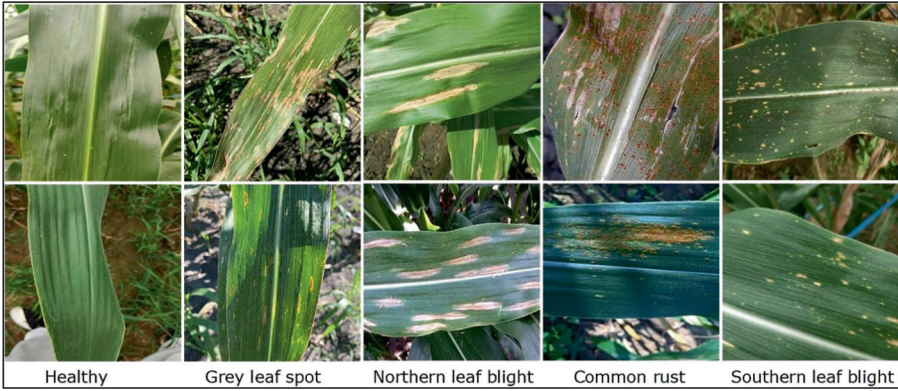


Fig. 2. Image dataset classification

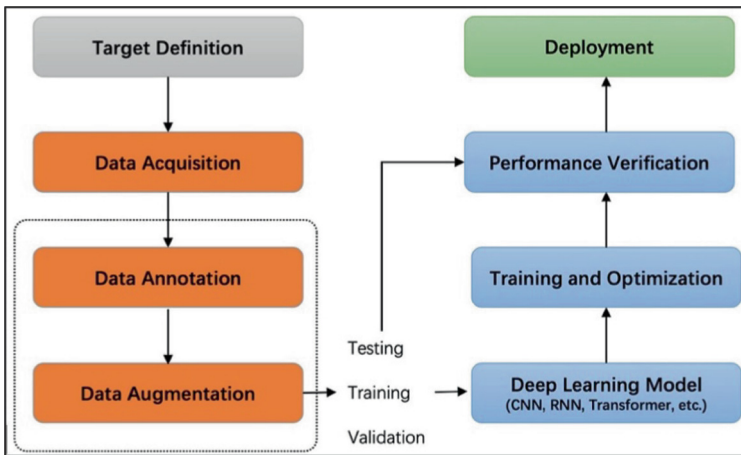


Fig. 3. Data augmentation process

2.5 Image Resizing and Noise Reduction

Leveraging pre-trained models like VGG19, ResNet50, and GoogLeNet for efficient image classification, all images were resized to a standard resolution of 224×224 pixels, matching the input requirements of these models.

To minimize the impact of noise on our dataset and ensure accurate disease identification, we employed two key noise reduction techniques while carefully preserving essential disease-related features:

- Gaussian Blur: This technique smooths out high-frequency noise while maintaining the overall image structure. We used it to reduce minor variations that might not be relevant to disease identification.
- Median Filtering: This non-linear method effectively suppresses salt-and-pepper noise, which often arises during image acquisition. It does so by replacing each pixel

with the median value of its neighbors, effectively removing isolated noise points without blurring important image details.

2.6 VGG19 Model

VGG19, which stands for “Visual Geometry Group 19-layer deep convolutional neural network”, is a type of artificial intelligence model specifically designed for image recognition and classification. It is a convolutional neural network (CNN), meaning it uses a series of filters and pooling layers to automatically extract features from images. These features are then used to make predictions about the content of the image (Fig. 4).

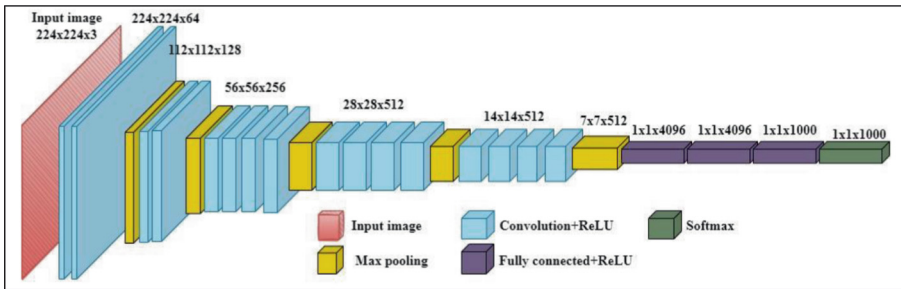


Fig. 4. VGG-19 Architecture

2.7 ResNet50 Model

ResNet50, short for Residual Network 50, is a powerful convolutional neural network (CNN) architecture widely used for image recognition tasks. It stands out for its innovative use of residual connections, which helped overcome challenges faced by earlier deep CNNs like vanishing gradients.

ResNet50 is a powerful and versatile tool for image recognition, known for its efficient learning capabilities and pre-trained versions. However, it’s crucial to consider its computational demands and explore newer models depending on your specific needs and resources (Fig. 5).

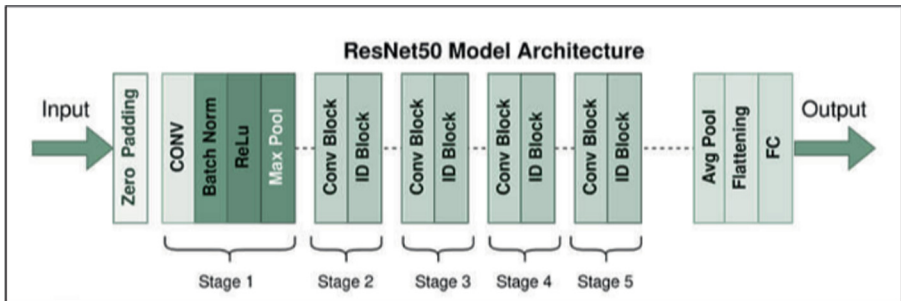


Fig. 5. ResNet50 Architecture

2.8 GoogLeNet Model

GoogLeNet, also known as InceptionV1, is a convolutional neural network (CNN) architecture developed by Google in 2014. It achieved groundbreaking results in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) that year, winning both the classification and detection tasks (Fig. 6).

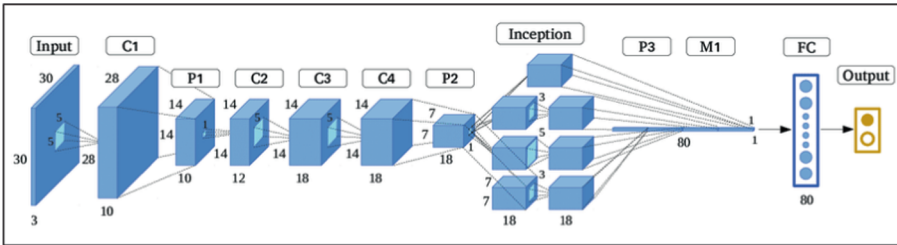


Fig. 6. GoogLeNet Architecture

2.9 Evaluation Index

While accuracy is a common evaluation metric, it can be misleading in situations with imbalanced datasets. This research addresses this issue by employing a combination of metrics:

- **Accuracy:** Measures the overall proportion of correct classifications, but can be skewed by dominant classes in imbalanced data.

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

- **Precision:** Represents the model’s ability to correctly identify positive samples (e.g., diseased corn leaves) among all predicted positives.

$$\text{Precision} = \frac{TP}{TP + FP'}$$

- **Recall:** Reflects the model’s ability to capture all positive samples within the dataset, even if it produces some false positives.

$$\text{Recall} = \frac{TP}{TP + FN'}$$

- **F1-score:** Combines precision and recall into a single metric, providing a balanced measure of model performance in both identifying true positives and avoiding false positives.

$$F1 = \frac{2Precision * Recall}{Precision + Recall'}$$

where TP is the True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

2.10 Architecture Comparison

We implemented several deep learning architectures, including VGG19, ResNet50, and GoogleNet. Each architecture has its strengths and weaknesses, which influence their potential in relation to our corn disease classification data (Table 1).

Table 1. Strength and Weakness Table of Implemented Architectures

Model	Strength	Drawback	Potential for our data
VGG-19	Straightforward, sequential architecture Effective Feature Extraction	Computationally Intensive Large Training Time	Beneficial for identifying subtle disease symptoms in corn images due to effective feature extraction
GoogLeNet	Captures multi-scale features Computationally efficient	Harder to implement Memory intensive	Efficient for limited training epochs Advantageous for detecting diseases manifesting at various scales and locations on corn leave
ResNet-50	Mitigates vanishing gradient problem Converges faster, better performance with fewer epochs	Complexity: Requires careful tuning of hyperparameters	Highly suitable due to efficiency and deeper representations

3 Result and Discussion

3.1 Model Training

This study explored the effectiveness of VGG19, ResNet50, and GoogLeNet models in classifying corn diseases, specifically rust and northern leaf spot. To ensure robust performance and generalizability, we employed a comprehensive preprocessing pipeline involving:

- **Data augmentation:** Artificially increasing data diversity through techniques like flipping, rotation, and zooming, addressing potential limitations of a real-world dataset.
- **Noise reduction:** Smoothing out unwanted noise while preserving disease-relevant features, leading to cleaner images for model training.
- **Contrast correction:** Enhancing image clarity and highlighting key features for easier disease identification.

By applying these preprocessing steps, we aimed to create a more reliable and broadly applicable corn disease classification model. The diverse pre-trained models, each with its own strengths and learning capabilities, were then trained on the enhanced dataset.

3.2 Fine-Tune Strategy

This section details the fine-tuning strategy employed to optimize pre-trained models for corn disease classification.

– **Leveraging Transfer Learning:**

- We utilized pre-trained models like VGG19, ResNet50, and GoogLeNet, leveraging their knowledge from millions of images (e.g., ImageNet) as a starting point.
- To adapt these models to our specific corn disease dataset, we employed fine-tuning, focusing on optimizing the top layers for the classification task.

– **Key Strategies:**

- **Freezing Convolutional Layers:** We “froze” the pre-trained convolutional layers by setting their trainable parameters to False. This preserved the valuable features learned on diverse images while allowing the final layers to adapt to the new dataset.
- **Dense Layers and Activation Functions:** We added a dense layer with 256 ReLU units, followed by a 50% dropout layer to prevent overfitting. Finally, a 2-unit dense layer with softmax activation performed the final classification (one unit per disease class).

– **Training and Optimization:**

- **Adam Optimizer and Categorical Crossentropy Loss:** These were chosen for efficient optimization and suitability with multi-class classification.
- **Accuracy Metric:** We tracked accuracy as the primary evaluation metric.
- **10 Epochs and Batch Size of 32:** This configuration balanced convergence with computational efficiency.

The model was trained for 10 epochs. To achieve more robust results, we undertook a comprehensive parameter optimization process, including adjustments to learning rates, batch sizes, and dropout rates. To address the limitations of training with only 10 epochs, we employed transfer learning techniques. By leveraging pre-trained models on larger and more diverse datasets, we were able to achieve significant performance improvements. Transfer learning allowed us to utilize the feature extraction capabilities of models, which have been trained on extensive image datasets. Additionally, we implemented data augmentation techniques to artificially expand the dataset and introduce variability. This combination of transfer learning and data augmentation ensured that our models achieved robust performance even with a limited number of training epochs. Comparative analysis was performed among the top-performing models, evaluating them based on accuracy, precision, recall, and F1-score to ensure a thorough assessment of their performance.

Overall, this fine-tuning approach aimed to harness the power of pre-trained models while adapting them specifically to the corn disease classification task, potentially leading to a more accurate and robust model (Fig. 7, 8, 9 and Table 2).

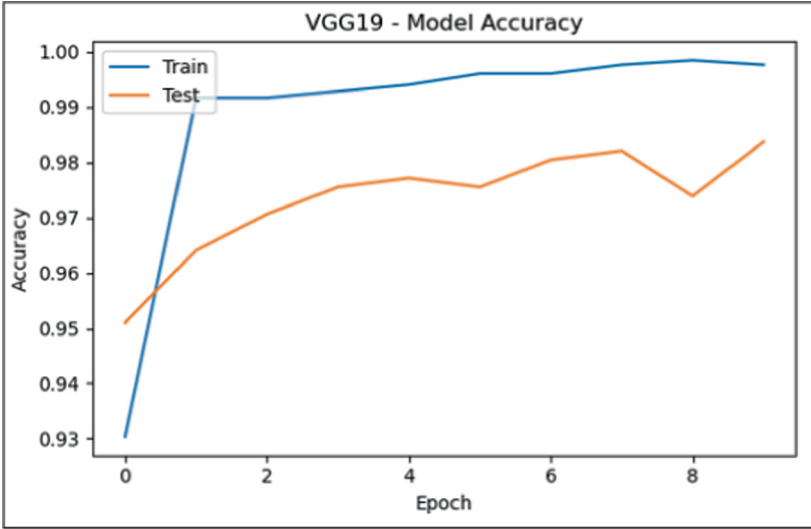


Fig. 7. VGG19 Accuracy Graph

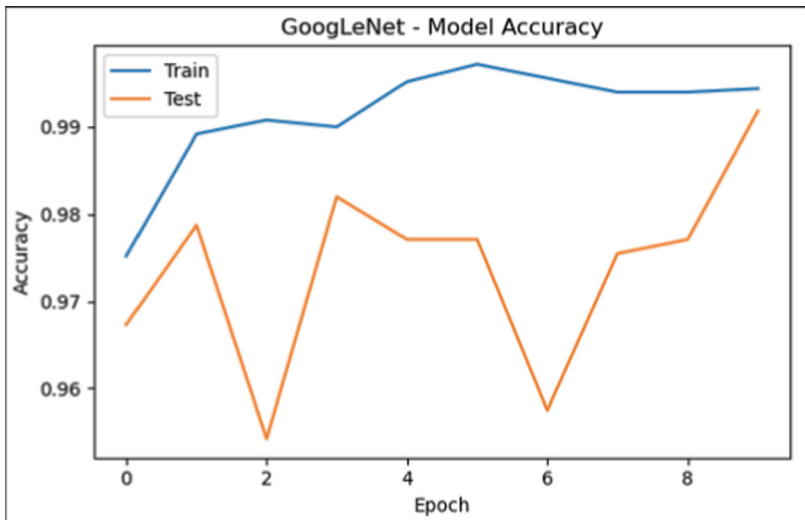


Fig. 8. GoogleNet Accuracy Graph

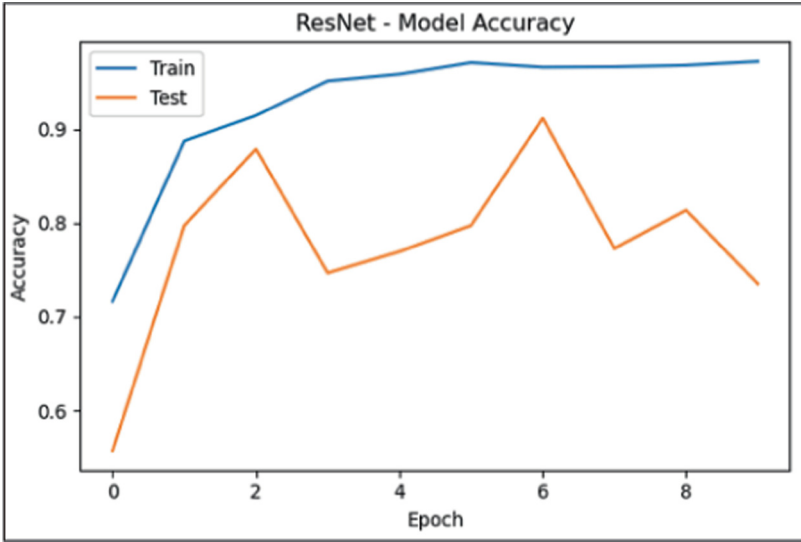


Fig. 9. ResNet-50 Accuracy Graph

Table 2. Metrics table

Model	Accuracy	Recall	Precision	F-1
VGG-19	0.96	0.93	0.97	0.95
GoogLeNet	0.99	0.98	0.99	0.99
ResNet-50	0.75	0.74	0.75	0.75

3.3 Confusion Matrix

A confusion matrix is a performance measurement technique used in machine learning to evaluate the accuracy of a classification model. It is a table with four different combinations of predicted and actual values: true positives, true negatives, false positives (Type I error), and false negatives (Type II error). Each of these combinations can provide insights into the performance of the model in terms of precision, recall, accuracy, and various other metrics.

The following is the confusion matrix of the three models of transfer learning algorithms (Fig. 10):

3.4 Generalizability

To address the generalizability of our models, we evaluated their performance under different environmental conditions and on an external dataset not seen during training. We decided to create our own field-specific database. Our testing images were captured using a separate Megapixel camera and stored in a dedicated database. This step is crucial

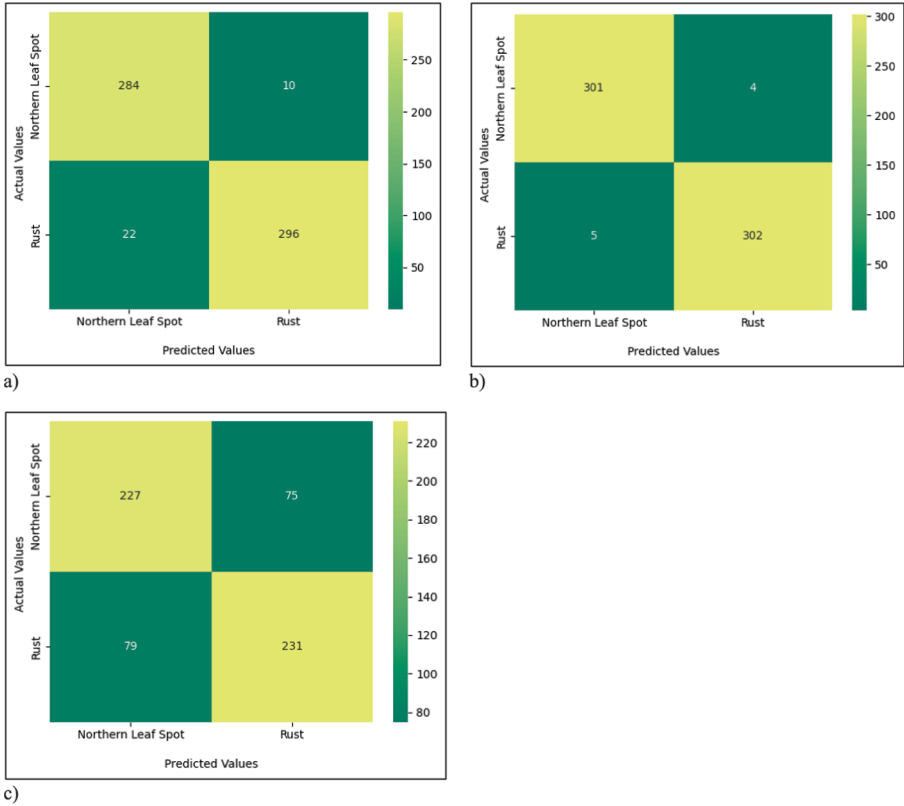


Fig. 10. Confusion matrix for: a) VGG19, b) GoogLeNet and c) ResNet-50

to ensure the models' applicability in various real-world scenarios, including different geographic regions, climatic conditions, and stages of corn growth (Fig. 11).

3.5 Practical Implementations

Deploying AI-powered corn disease classification models in agriculture entails overcoming several practical challenges. Integration with existing farm systems requires developing compatible interfaces and APIs. Ensuring robust performance across varying environmental conditions necessitates extensive testing and dataset diversity. Managing computational resources on edge devices like smartphones and drones requires optimizing model efficiency. User acceptance hinges on providing intuitive interfaces and clear insights. Continuous maintenance and updates are crucial for enhancing model accuracy and applicability. Addressing these challenges collaboratively ensures AI technology supports sustainable agriculture by optimizing yield and minimizing crop damage.

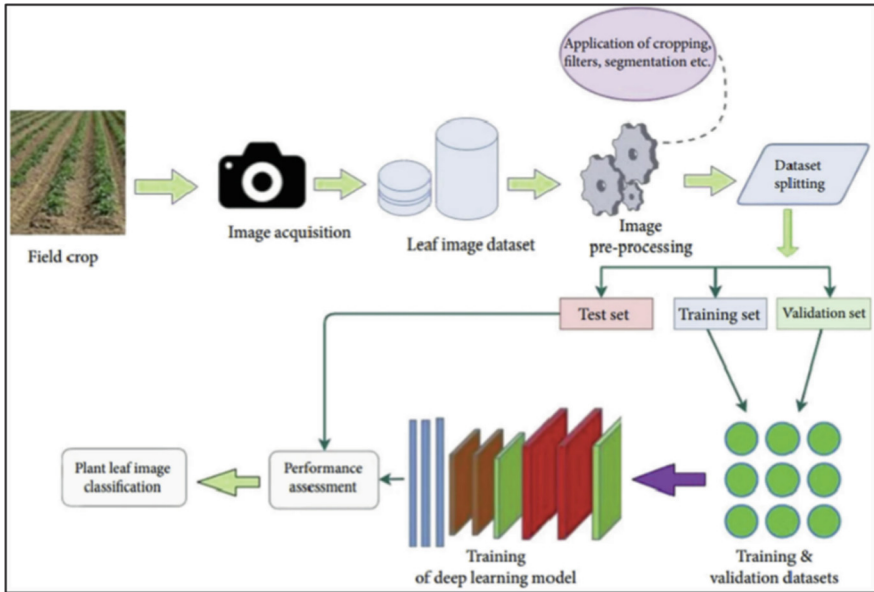


Fig. 11. General Architecture of the Model

References

1. Storey, G., Meng, Q., Li, B.: Leaf disease segmentation and detection in apple orchards for precise smart spraying in sustainable agriculture. *Sustainability* **14**(3), 1458 (2022). <https://doi.org/10.3390/su14031458>
2. Rahman, C.R., et al.: Identification and recognition of rice diseases and pests using convolutional neural networks. *Biosys. Eng.* **194**, 112–120 (2020). <https://doi.org/10.1016/j.biosys.2020.03.020>
3. Xie, X., Ma, Y., Liu, B., He, J., Li, S., Wang, H.: A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. *Front. Plant Sci.* **11** (2020). <https://doi.org/10.3389/fpls.2020.00751>
4. Singh, D., Rana, A., Gupta, A., Sharma, R., Kukreja, V.: An enhanced CNN-LSTM based hybrid deep learning model for corn leaf eye spot disease classification (2023). <https://doi.org/10.1109/csnt57126.2023.10134732>
5. Srivastava, P., Singh, S.P., Vishnoi, A., Sapra, V.: Classification of corn leaf diseases using various pre-trained deep learning networks and performance comparison (2022). <https://doi.org/10.1109/icacm56405.2022.10009476>
6. Singh, S., Verma, A., Guleria, V., Yadav, S., Singh, N.P.: Deep learning-based networks to detect leaf disease in maize and corn (2023). <https://doi.org/10.1109/icicat57735.2023.10263746>
7. Amin, H., Darwish, A., Hassanien, A.E., Soliman, M.: End-to-end deep learning model for corn leaf disease classification. *IEEE Access* **10**, 31103–31115 (2022). <https://doi.org/10.1109/access.2022.3159678>
8. Tanwar, V., Lamba, S.: Classification of multiple maize leaf diseases using a blended convolutional neural network (2023). <https://doi.org/10.1109/conit59222.2023.10205797>
9. Shobana, G., Vignesh, K., Sree Dharshan, S.: Plant disease detection using deep neural network (2023). <https://doi.org/10.1109/icaeca56562.2023.10199940>

10. Wang, R., Wu, L.: Drought-tolerant crop disease identification based on attention mechanism (2023). <https://doi.org/10.1109/itnec56291.2023.10082310>
11. Zhou, C., Zhou, S., Xing, J., Song, J.: Tomato leaf disease identification by restructured deep residual dense network. *IEEE Access* **9**, 28822–28831 (2021). <https://doi.org/10.1109/access.2021.3058947>
12. Wu, W., et al.: Detection and enumeration of wheat grains based on a deep learning method under various scenarios and scales. *J. Integr. Agric.* **19**(8), 1998–2008 (2020). [https://doi.org/10.1016/s2095-3119\(19\)62803-0](https://doi.org/10.1016/s2095-3119(19)62803-0)
13. Nevavuori, P., Narra, N., Lipping, T.: Crop yield prediction with deep convolutional neural networks. *Comput. Electron. Agric.* **163**, 104859 (2019). <https://doi.org/10.1016/j.compag.2019.104859>
14. Mahamat, A.A., Boukar, M.M.: On the use of machine learning technique to appraise thermal properties of novel earthen composite for sustainable housing in Sub-Saharan Africa, pp. 161–170 (2024). https://doi.org/10.1007/978-3-031-51849-2_11
15. Boukar, M.M., Mahamat, A.A., Djibrine, O.H.: The impact of artificial intelligence (AI) on content management systems (CMS): a deep dive. *Int. J. Intell. Syst. Appl. Eng.* **12**(1), 552–560 (2024). <https://ijisae.org/index.php/IJISAE/article/view/3953>
16. Djibrine, O.H., Ahmat, D., Boukar, M.M., Bello, U.A., Ali, A.Y.: Transfer learning for animal species identification from CCTV image: case study Zakouma National Park. *Int. J. Intell. Syst. Appl. Eng.* **12**(1), 28–40 (2024). <https://ijisae.org/index.php/IJISAE/article/view/3673>
17. Wright, P., Parker, M., Van Tilburg, R., Hedderley, D.: Effect of planting dates and azoxystrobin fungicide application regimes on common rust of maize. *N. Z. J. Crop. Hortic. Sci.* **42**(2), 99–110 (2014). <https://doi.org/10.1080/01140671.2013.860040>
18. De Rossi, R.L., et al.: Crop damage, economic losses, and the economic damage threshold for northern corn leaf blight. *Crop Prot.* **154**, 105901 (2022). <https://doi.org/10.1016/j.cropro.2021.105901>