



Original Research Paper

DENSENET 201 TRANSFER LEARNING FOR POTATO LEAF DISEASE CLASSIFICATION AND BENCHMARKING AGAINST ESTABLISHED CNN ARCHITECTURES

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ABSTRACT

Background: Potato (*Solanum tuberosum*) is an important food crop affected by foliar diseases that can reduce yield and quality. Early and accurate identification of early blight and late blight is therefore important for timely disease management in practice. Deep learning provides an automated alternative to visual diagnosis, but model selection and generalization remain important considerations.

Methods: This study developed and evaluated a transfer learning-based framework for potato leaf disease classification using four pretrained convolutional neural networks: DenseNet201, VGG19, ResNet50, and InceptionV3. The models were evaluated for three classes: early blight, late blight, and potato healthy. DenseNet201 was used with its pretrained feature-extraction layers frozen and trained for 50 epochs. Performance was assessed using accuracy, precision, recall, F1-score, Matthew's correlation coefficient (MCC), ROC-AUC, PR-AUC, and top-2 accuracy, together with confusion-matrix analysis.

Results: Among the evaluated models, frozen DenseNet201 achieved the strongest overall performance, with 99.07% test accuracy, 99.34% macro precision, 97.52% macro recall, and 98.39% macro F1-score. It also achieved 98.35% MCC, 99.98% macro ROC-AUC, 99.83% macro PR-AUC, and 100% top-2 accuracy. Class-wise recall reached 100% for early blight, 99.00% for late blight, and 93.55% for potato healthy leaves. These findings demonstrate the effectiveness of DenseNet201 for automated potato leaf disease classification.

Keywords: deep learning, DenseNet201, leaf disease classification, transfer learning, convolutional neural network.

INTRODUCTION

Worldwide production of tubers and roots is dominated by potatoes. They are grown in about 130 countries and rank fourth in global dietary importance after maize, wheat, and rice (UNECE, n.d.). Potato (*Solanum tuberosum*) belongs to the Solanaceae family. Its origin has been traced to the Andes Mountains of South America (Singh & Kaur, 2016). Potato is susceptible to hundreds of diseases caused by fungi, bacteria, and viruses. Disease severity varies across geographical regions (Lahlali et al., 2023). Plant diseases caused by phytopathogenic microorganisms represent an important constraint to crop health and productivity, emphasizing the need for effective disease detection and management strategies (Beg et al., 2025). Early blight and late blight

are among the most important foliar diseases. They occur in many potato-growing regions and pose major threats to production (Busnello et al., 2019; Borovskiy et al., 2021). Disease development can become rapid during wet periods. Early blight generally causes premature defoliation and reduces tuber yield. Late blight can cause more severe damage to foliage and tubers. It can result in substantial production losses (Duarte et al., 2019). Therefore, early disease detection is important for effective disease management and yield protection. Plant disease detection is challenging because plants show diverse responses to pathogens. These responses are also affected by environmental factors such as climate, soil conditions, and pest exposure (Munster, 2022; Anand et al., 2025). Plants can show diverse disease symptoms.

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This makes accurate diagnosis difficult and highlights the need for careful observation (Tsai & Hsu, 2024).

Potato is an important crop for global food security. It contributes to food availability, quality, accessibility, and stability (Ahmadu et al., 2021). However, potato diseases cause substantial yield losses worldwide. Timely disease detection is therefore important for protecting crop yield and agricultural resources (Akhter & Sofi, 2022; AlArfaj et al., 2023). Early diagnosis can also support targeted disease-management strategies. Such approaches may reduce unnecessary chemical use and support the production of crops that meet international standards (Abbas et al., 2023; Javaid et al., 2023). Laboratory diagnosis may involve pathogen culture and microscopic examination. These methods can provide reliable diagnostic information but often require specialized facilities and trained personnel (Khakimov et al., 2022). Traditional plant disease diagnosis relies mainly on visual inspection and laboratory testing. These methods can be time-consuming and may be affected by observer expertise or laboratory requirements (Ngugi et al., 2021; Ahmad et al., 2023). These limitations have encouraged research into image processing and automated disease detection methods.

Artificial intelligence and machine-learning approaches are increasingly being applied in agriculture to support data-driven agricultural decision-making and automated analysis (Taqvi, 2025). Artificial intelligence (AI) and machine learning (ML) have created new opportunities for disease diagnosis. AI-based methods can support early detection and timely intervention. Iqbal and Talukder (2020) used HSV-based segmentation and global feature descriptors for potato leaf disease identification. Their approach included Hu Moments, Haralick Texture, and Color Histogram features. Because

model performance can depend on the transfer-learning strategy, architecture alone may not identify the most suitable configuration. DenseNet201 was selected as the primary model because of its dense connectivity and effective feature reuse. This structure supports the integration of low-level texture information with high-level morphological features. Therefore, the study used DenseNet201 model for classification. The results were then compared with VGG19, ResNet50, and InceptionV3.

The key objectives were:

- To evaluate DenseNet201 for the classification of potato leaf diseases into three classes.
- To evaluate the performance of DenseNet201 transfer learning using multiple assessment metrics.
- To compare the DenseNet201 configuration with InceptionV3, ResNet50, and VGG19.
- To identify the most suitable CNN architecture for potato leaf disease classification.

MATERIALS AND METHODS

Data Collection

The study used a dataset containing images of healthy and diseased potato leaves (Figure 1). The dataset was obtained from the Kaggle repository (<https://www.kaggle.com/datasets/hassanikram/my-dataset>). It contained a total of 2,152 images. The images were divided into three classes based on the health condition of the potato leaves. The dataset included 1,000 images of Potato Early Blight, 1,000 images of Potato Late Blight, and 152 images of healthy potato leaves. This dataset provided images representing both major potato diseases and healthy leaf conditions for classification.

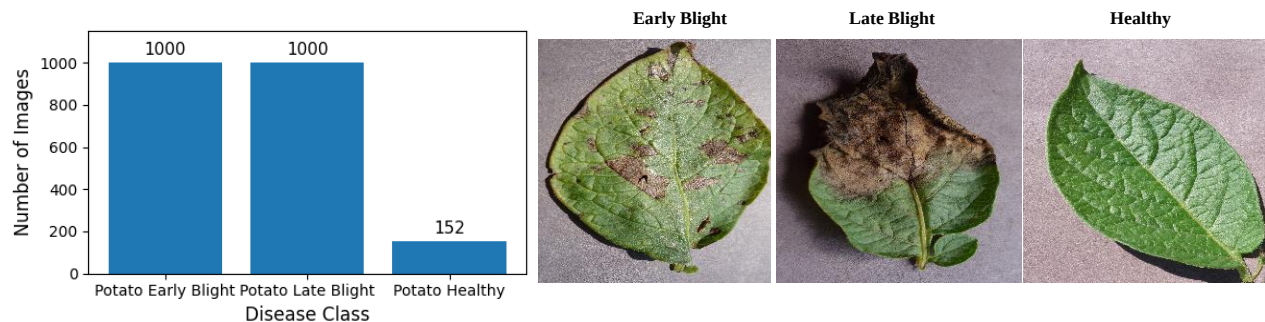


Figure 1(left): Original class distribution of the potato leaf dataset, (right) images from the training dataset,

Data Partitioning

The dataset contained 2,152 images, which were divided into training, validation, and testing sets using an approximately 60:20:20 ratio. Accordingly, 1,291 images (approximately 60%) were allocated for training, 430 images (approximately 20%) for validation, and 431 images (approximately 20%) for testing. The training set was used to train the models, while the validation set was used to monitor model performance and select the

optimal model. The independent test set was used only for the final evaluation of model performance.

Image Preprocessing and Data Augmentation

All images were resized to 224×224 pixels and represented using three RGB channels. A batch size of 32 was used in all experiments. Data augmentation was applied only to the training images. This approach was used to reduce overfitting and improve model generalization. Six augmentation operations were applied

during training. Random horizontal flipping was used to vary image orientation. Random rotation was applied with a factor of 0.10, corresponding to approximately $\pm 10^\circ$. Random zooming used height and width factors of 0.10. Random contrast adjustment was applied with a factor of 0.10. Random translation used height and width factors of 0.05, allowing approximately 5% spatial displacement in both directions. Random brightness adjustment was applied with a factor of 0.10.

The augmentation operations were performed dynamically during training. Validation and test images were not augmented. This ensured that model performance was evaluated using unmodified images. After augmentation, the images were processed using the appropriate preprocessing function for DenseNet201, VGG19, ResNet50, or InceptionV3.

Model Architectures

ImageNet-pretrained weights were used to develop the DenseNet201 model. DenseNet201 was used as the

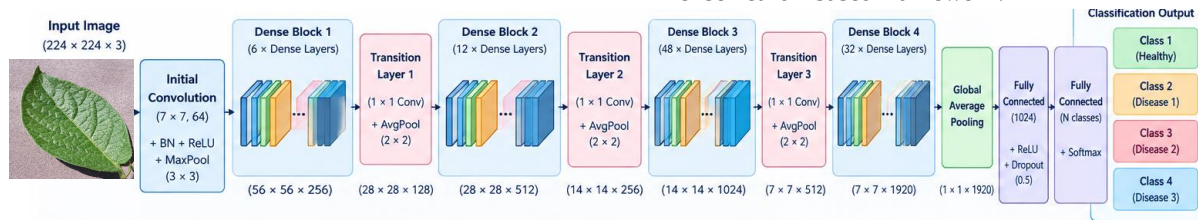


Figure 2. Design of the DenseNet201-based CNN framework for potato leaf classification.

VGG19

The VGG19 model was initialized with ImageNet-pretrained weights. Its original fully connected classifier was removed. VGG19 contains 19 weight layers arranged into sequential convolutional blocks. It uses 3×3 convolution kernels and max-pooling operations for hierarchical feature extraction.

ResNet50

ResNet50 uses residual learning and identity shortcut connections to learn residual mappings. This approach helps reduce the degradation problem associated with deep neural networks.

InceptionV3

InceptionV3 uses factorized convolutions to reduce computational complexity. It also uses parallel convolutional branches with different receptive fields to capture features at multiple spatial scales. The original classifier was removed using `include_top=False`, and the ImageNet-pretrained backbone was retained.

Model Training Configuration

All models were implemented using Keras and TensorFlow 2.21.0. A fixed random seed of 42 was used to improve experimental reproducibility. The Adam optimizer was used with a learning rate of 5×10^{-5} . The experiment was conducted for up to 50 epochs with a batch size of 32. Early Stopping, ReduceLROnPlateau, and Model Checkpoint callbacks were used during training. Early Stopping monitored validation

transfer-learning backbone. Its dense connectivity allows feature reuse and supports effective gradient propagation. Each layer receives the feature maps produced by all preceding layers through concatenation. The feature transformation can be expressed as

$$X_i = H_i([X_0, X_1, \dots, X_{i-1}]),$$

where $H(\cdot)$ represents the sequence of convolution, ReLU activation, and batch normalization operations. All backbone layers were frozen (`trainable=False`) to preserve the pretrained feature representations. The original classification layer was removed using `include_top=False`. A custom classification head was then added. It consisted of Global Average Pooling (GAP), two fully connected layers with 512 and 128 neurons, ReLU activation, dropout rates of 0.40 and 0.25, and a three-class Softmax classifier. This configuration supports feature extraction while limiting overfitting and computational requirements. Figure 2 illustrates the DenseNet201-based framework.

performance and restored the weights from the best-performing epoch. Model Checkpoint was used to save the best model weights. ReduceLROnPlateau adjusted the learning rate when validation performance stopped improving.

Evaluation Metrics

The evaluation included classification metrics, ROC and PR curves. These metrics provided complementary information about overall and class-balanced performance. Confusion matrices were generated for each model to examine class-specific prediction patterns. Multiclass ROC-AUC was calculated using a one-vs-rest strategy. This approach gives equal importance to each disease class and is therefore suitable for assessing performance across multiple classes.

RESULTS AND DISCUSSION

The training curves given in figure 3 indicates that the DenseNet201 model learned effectively throughout the 50 training epochs. At the beginning of training, the model achieved a training accuracy of 55.69% with a loss of 0.9031, while the validation accuracy was 79.77% with a validation loss of 0.5832. The validation performance improved steadily, reaching a best validation accuracy of 99.30% at epoch 45. By epoch 50, the training accuracy increased to 98.53% with a loss of 0.0374, while the validation accuracy remained high at 99.07% and the validation loss decreased to 0.0302. The close training and validation accuracies, together with the

low validation loss at the end of training, indicate consistent validation performance and provide no strong evidence of substantial overfitting within the evaluated

dataset. Since validation accuracy did not improve after epoch 45, the best model weights were restored from this epoch.

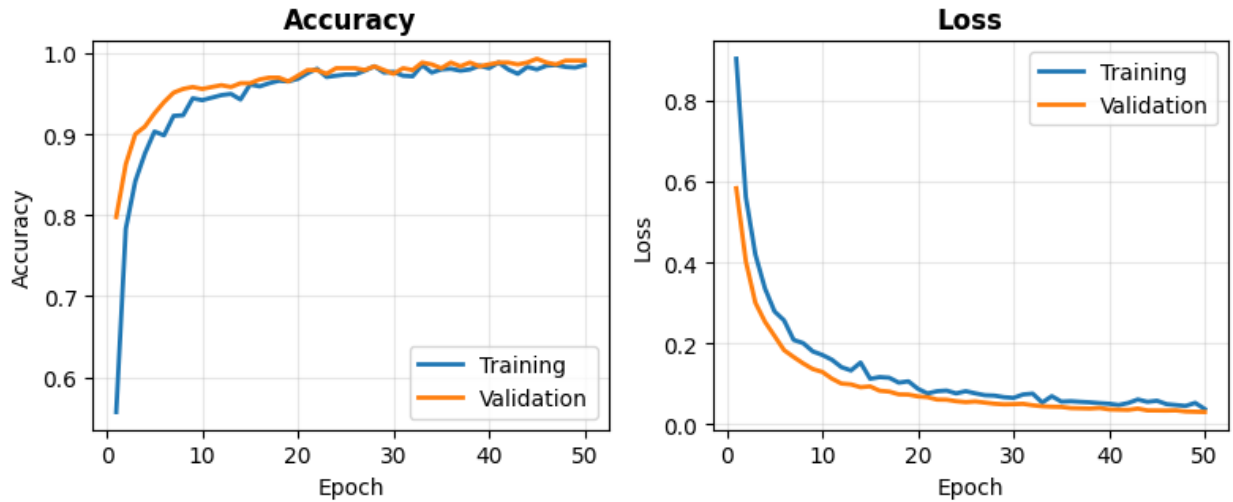


Figure 3. Training and validation accuracy and loss curves of the DenseNet201 model over 50 epochs.

The confusion matrix shows that the DenseNet201 model classified the three potato leaf classes (Figure 4). All 200 Early blight images were correctly classified, with no misclassification. Among the 200 Late blight images, 198 were correctly identified, while 2 were incorrectly classified as Early blight. For the 31 Potato healthy images, 29 were correctly classified, while 2 were

predicted as Late blight. Overall, 427 of 431 test images were correctly classified, corresponding to approximately 99.07% accuracy. The results indicate that the model effectively distinguished diseased and healthy potato leaves, with only minor confusion between Late blight and the other classes.

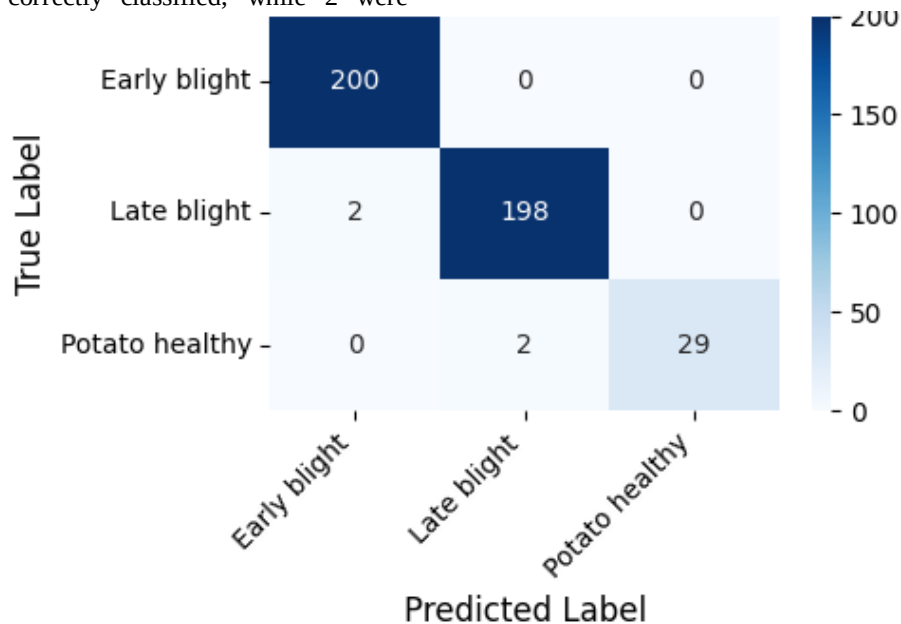


Figure 4. Confusion matrix of the DenseNet201 model

The ROC curves demonstrate excellent class discrimination by the DenseNet201 model (Figure 5). The model achieved an AUC of 1.0000 for Early blight, 0.9997 for Late blight, and 0.9996 for Potato healthy, indicating near-perfect separation among the three classes. The precision-recall curves also remained close to the upper-right region, with average precision values of 1.0000, 0.9996, and 0.9951 for Early blight, Late

blight, and Potato healthy, respectively. These results show that the model maintained both high precision and high recall across the classes. The slightly lower performance for the healthy class is consistent with the minor confusion observed in the confusion matrix. Overall, the curves confirm the strong classification capability and reliable class discrimination of the DenseNet201 model.

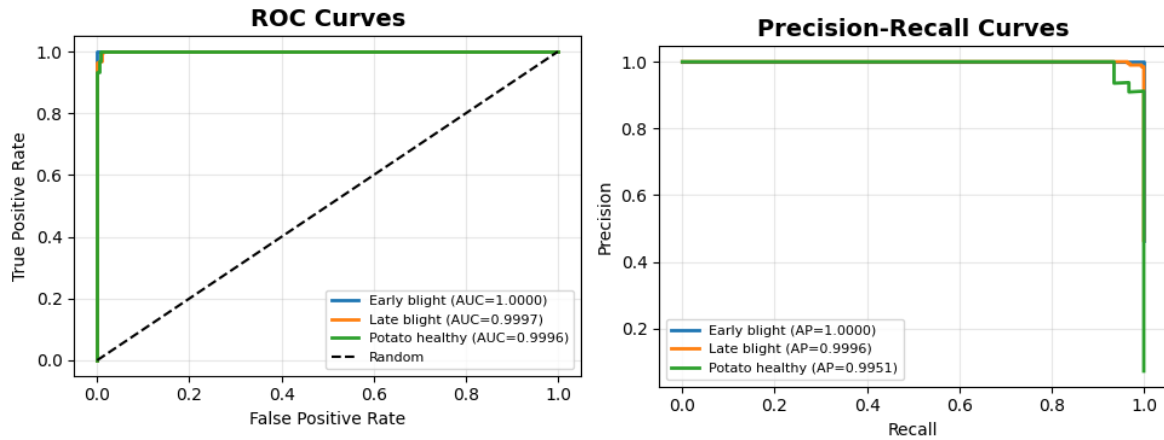


Figure 5. ROC and precision–recall curves of the DenseNet201 model.

Table 1 presents the class-wise classification performance of DenseNet201 for Early blight, Late blight, and Potato healthy classes. The model achieved 100% recall for Early blight, correctly identifying all 200 images, while Late blight achieved 99.00% precision, recall, and F1-score. The Potato healthy class obtained

100% precision, although its recall was comparatively lower at 93.55%, indicating that a small number of healthy images were misclassified as diseased. Overall, the macro F1-score of 98.39% and weighted F1-score of 99.07% demonstrate consistently strong classification performance across the three classes.

Table 1. Class-wise classification performance of the DenseNet201 model

Class	Precision	Recall	F1-score	Support
Early blight	99.01%	100.00%	99.50%	200
Late blight	99.00%	99.00%	99.00%	200
Potato healthy	100.00%	93.55%	96.67%	31
Macro average	99.34%	97.52%	98.39%	431
Weighted average	99.08%	99.07%	99.07%	431

Table 2 summarizes the overall performance of the DenseNet201 model. The model achieved an accuracy of 99.07%, with macro-precision, macro-recall, and macro F1-score of 99.34%, 97.52%, and 98.39%, respectively. The high MCC of 98.35% indicates strong agreement between the predicted and actual classes. Furthermore,

the model obtained an excellent macro ROC-AUC of 99.98% and macro PR-AUC of 99.83%, demonstrating strong class discrimination and precision-recall performance. The 100% Top-2 accuracy indicates that the correct class was included among the model's top two predictions for all test images.

Table 2. Overall performance of the DenseNet201 model

Metric	DenseNet201
Accuracy	99.07%
Macro Precision	99.34%
Macro Recall	97.52%
Macro F1-score	98.39%
Matthews Correlation Coefficient (MCC)	98.35%
Macro ROC-AUC	99.98%
Macro PR-AUC	99.83%
Top-2 Accuracy	100.00%

Figure 6 presents the comparative performance of the four deep learning models, based on classification matrices. DenseNet201 achieved the highest overall performance, with an accuracy of 99.07%, precision of 99.34%, recall of 97.52%, and F1-score of 98.39%. ResNet50 showed the second-best accuracy of 95.58%, while VGG19 and InceptionV3 achieved accuracies of 92.74% and 92.81%, respectively. These results indicate that DenseNet201 provided the most consistent classification performance among the evaluated models.

The other metrics further demonstrate the effectiveness of DenseNet201 for disease classification. VGG19 achieved precision, recall, and F1-score values of 95.19%, 94.88%, and 94.88%, respectively, whereas ResNet50 obtained 93.39%, 92.74%, and 92.79%. InceptionV3 recorded corresponding values of 95.78%, 95.58%, and 95.46%. Overall, DenseNet201 outperformed the other models across all four-evaluation metrics, suggesting its suitability for accurate and reliable classification of the investigated disease classes.

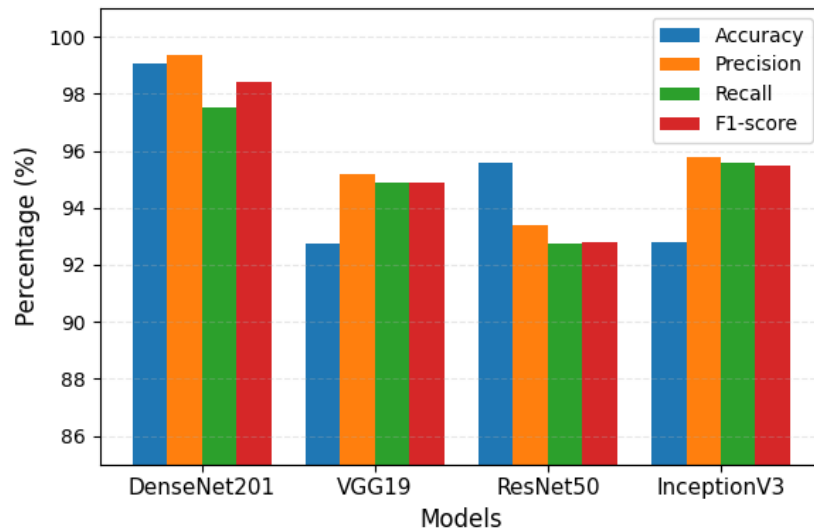


Figure 6. Comparative performance of models based on difference classification metrics.

The performance of the models evaluated in the present study was compared with previously reported approaches for potato leaf disease classification, as shown in Figure 7. Tiwari et al. (2020) employed pretrained VGG19 for feature extraction followed by logistic regression and reported 97.80% test accuracy. Their approach demonstrates the effectiveness of combining deep feature extraction with a conventional machine-learning classifier. Khalifa et al. (2020) developed a 14-layer deep convolutional neural network for the classification of healthy, early blight, and late blight leaves. Through data augmentation, their dataset was increased from 1,722 to 9,822 images, resulting in a reported mean testing accuracy of 98.00%.

Alhammad et al. (2024) proposed a transfer learning-based framework incorporating Explainable AI, with Grad-CAM used to provide visual interpretation of

model predictions. The approach achieved 97% validation accuracy and 98% testing accuracy. This framework provides an advantage in interpretability because the model's decision-making regions can be visualized, whereas the present study primarily focuses on classification performance and comparative evaluation of different pretrained architectures. Chang and Lai (2024) developed a lightweight RegNetY-400MF model combined with transfer learning for seven potato leaf diseases. Their model achieved 90.68% accuracy while requiring only 0.40 GFLOPs and a model size of 16.8 MB, highlighting an important trade-off between classification performance and computational efficiency. Thus, although lightweight architectures can provide advantages for deployment on resource-constrained devices, the present study emphasizes the classification capability of the evaluated pretrained models.

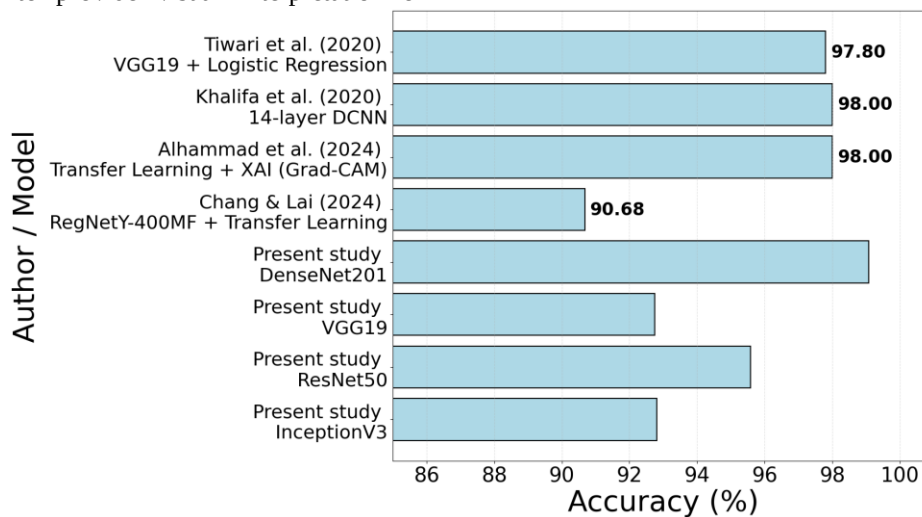


Figure 7. Comparative accuracy of previously reported potato leaf disease classification methods and the four deep learning models evaluated in the present study.

The comparison also indicates that the performance of the present DenseNet201 model is competitive with the

previously reported approaches considered in this study. Unlike Khalifa et al. (2020), where extensive

augmentation was used to expand the training dataset, the present work evaluates a pretrained DenseNet201 backbone, thereby demonstrating that strong classification performance can be obtained without updating the pretrained feature-extraction layers. However, the results should be interpreted within the context of the datasets, class distributions, preprocessing procedures, augmentation strategies, and experimental protocols used by each study. Therefore, direct numerical ranking across studies should be made cautiously because differences in datasets and evaluation protocols can substantially influence reported accuracy.

Overall, the comparison demonstrates that the present study provides a strong pretrained-model-based framework for potato leaf disease classification. DenseNet201 showed the most favorable performance among the four architectures evaluated in this work, whereas the inclusion of VGG19, ResNet50, and InceptionV3 provides a broader architectural comparison. Compared with earlier approaches based on conventional classifiers, custom CNN architectures, explainable transfer learning, and lightweight networks, the proposed evaluation highlights the effectiveness of DenseNet201 for distinguishing early blight, late blight, and healthy potato leaves.

CONCLUSION

The present study demonstrates that transfer learning can provide an effective approach for automated potato leaf disease classification. Among the four evaluated architectures, frozen DenseNet201 showed the strongest overall performance and produced highly reliable discrimination of early blight, late blight, and healthy leaves. The high macro precision, F1-score, MCC, ROC-AUC, and PR-AUC further support its classification capability. However, the study has limitations. The evaluation was performed on a dataset, and the class distribution was not balanced, particularly for healthy leaves. In addition, performance was assessed under the available experimental conditions and may not directly represent performance on images acquired from different cultivars, geographic regions, lighting conditions, devices, or complex field environments. Future work should therefore evaluate the model on larger and independent field datasets, investigate fine-tuning and model compression, and incorporate explainable AI and lightweight deployment strategies. Such developments could improve robustness, interpretability, and practical suitability for real-time disease monitoring.

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