Air journal of Artificial Intelligence

ISSN: 3106-7743 | 3106-7735
Volume 3, Issue 1, 2026

A STUDY OF CNN-BASED METHODS FOR PLANT LEAF DISEASE DETECTION: A COMPARATIVE ANALYSIS

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Keywords
Plant Disease Detection Convolutional Neural Networks (CNNs), Transfer Learning Deep Learning, ResNet50, VGG19, Xception, Precision Agriculture Image Classification, Edge Computing

Article History
Received: 03 January 2026
Accepted: 15 March 2026
Published: 31 March 2026

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Abstract
Automated plant disease detection has emerged as a vital component of precision agriculture, offering the potential to improve crop yield while reducing reliance on manual inspection. This study presents a comparative evaluation of convolutional neural networks (CNNs) for vegetable disease classification. A dataset of over 20,000 images, encompassing 15 disease categories and healthy samples, was employed to assess both a custom CNN model and transfer learning architectures. Four models were analyzed: a custom-designed CNN, VGG19, ResNet50, and Xception. The custom CNN achieved an accuracy of 87.50%, demonstrating the viability of lightweight models for resource-constrained applications. VGG19, leveraging transfer learning, improved performance to 89.52%, while ResNet50 achieved the highest accuracy of 94.86%, alongside strong precision, recall, and F1 scores, confirming its robustness and suitability for real-world deployment. In contrast, Xception underperformed, underscoring the importance of model selection and fine-tuning in plant disease recognition tasks. The findings emphasize the effectiveness of transfer learning, particularly with deep architectures like ResNet50, in delivering accurate and reliable disease detection. At the same time, the custom CNN offers a practical alternative for environments with limited computational resources. This study provides a foundation for future exploration into hybrid and ensemble models, deployment on edge devices, and techniques to address class imbalance for enhanced model robustness and scalability.

INTRODUCTION

Agriculture remains a mainstay for many of the developing economies today [1] and is incredibly important for the food security of global population – which is projected to reach 10 billion by 2050 according to United Nations 2019 report. Many farmers from these developing countries, particularly those working in remote regions, have limited access to reliable information on disease detection and prevention [2]. This forces them to make use of their observation and personal experience alone to identify diseases, without the use of scientific information, which can cause significant crop damage and low crop yield overall – as indicated in the study by [3] of potato farmers in Tanzania.

In today's evolving agricultural landscape, there is an increasing need for quick and precise disease detection information. Rapid changes in climate and weather pattern are causing new variants of plant diseases to emerge [4] which could make traditional methods of disease detection impractical for crop protection. Farmers now require efficient technological instruments, backed by machine learning (ML) and deep learning (DL) algorithms, to quickly detect and treat plant illnesses, since the accuracy of disease categorization and treatment might be compromised by human error in traditional methods of observation [5]

With the rapid evolution of sensing and communication technology, integrating mobile devices, drones, and Internet of Things (IoT) platforms is transforming plant health monitoring by enabling real time data collection and processing directly in the field. Sensor equipped smartphones coupled with lightweight CNN inference engines now allow farmers to receive instantaneous alerts on leaf disease presence, even in remote or resource limited settings. Recent reviews highlight how IoT enabled deep learning architectures streamline disease classification and reduce reliance on manual inspection [6] These systems not only improve disease detection accuracy but also minimise pesticide misuse through precise diagnosis, aligning with sustainability goals in smart agriculture [7].

Despite these advances, a significant gap remains in identifying which CNN architectures deliver optimal performance under varied agricultural constraints such as low quality images, unbalanced datasets, and limited hardware. Ferentinos (2018) demonstrated that basic CNN architectures could reach accuracy levels above 99% on large, curated datasets like PlantVillage; however, their generalisability to real world multi crop scenarios remains questionable. A systematic review by [8] emphasised that performance is highly dependent on model depth, data augmentation, and training configurations, suggesting the need for comparative evaluations across architectures. Motivated by this, the current study investigates the robustness of both custom and pretrained CNNs in detecting diseases in potato, tomato, and pepper crops.

To tackle the challenges discussed above, this study will examine and evaluates various DL backed methods under convolutional neural networks (CNNs) for detecting plant diseases. These approaches include some notable pretrained CNN models including VGG19, ResNet50, Xception, and a custom CNN model. We will be testing these models to detect leaf diseases in leaves of Potato, Tomato and Pepper crops only. Our objective here is to demonstrate the robustness and efficiency of CNN models through performance evaluation based on four parameters: accuracy score, F1 score and training time. This evaluation may help us understand the strengths and limitations of these established CNN models in plant disease detection.

Literature Review

CNNs are basically DL algorithms which can be trained on large volume of input datasets holding millions of parameters in the form of 2D data files, such as images, audio and video files etc., and they can be mathematically combined or convolved to generate desired results [9]). As per [10], the architectural design of CNNs allows for automatic and adaptive learning of spatial features with the support of backpropagation that leads to improved model accuracy. This is made possible due to the presence of several building elements which include convolution layers, pooling layers, and fully connected layers (Ibid).

The neural networks of CNN are now among the most widely DL models in the field of computer vision. CNNs holds competitive advantage over traditionally dominant Recurrent Neural Networks (RNNs) in dealing with sequential data (like image and video files) due to their context-sensitive position-awareness mechanism, which includes cross-attention and self-attention [11]. High dimensional image / video data can be efficiently processed by weight sharing mechanism of CNNs, wherein the number of parameters are reduced to enhance generalization and mitigate overfitting [12]. Parallel computation is also possible under CNN architecture that leads to significantly better performance while handling computer vision related tasks [13]. These distinctive features in CNN's architecture have proved to be effective in obtaining high accuracy results in the tasks related to image recognition, detection and classification [14].

CNN models do come with their own set of limitations. One of the chief concerns with CNNs is that they require significantly more computational power and memory allocation compared to RNNs [15]. The high computational cost partly comes with the need of the models to be trained on huge labelled datasets for effective training and better

ISSN: 3106-7743 | 3106-7735
Volume 3, Issue 1, 2026

outcome [16]. Additionally, CNN models have an inherent deficiency rotational and translational invariance, as pointed out by Alzubaidi et al. (2021), which may cause these models to struggle in recognizing objects in different positions and orientation. These challenges, though stern, can be addressed through various mitigating methods – such as deploying pre-trained CNN models (transfer learning), using data augmentation, developing advanced custom built CNN models, and / or incorporating unsupervised or semi-supervised learning for model training (Ibid).

CNNs ability to automatically extract features from images with high accuracy makes them good fit for different image classification tasks, such as disease detection in agricultural plants [17]. They can also be easily integrated with mobile and web applications [18]. Benefitting from these properties, A. A. Ahmed & Reddy (2021), Tembhurne [19], [20] and [21] among several others have developed and tested different plant disease detection mobile apps for farmers.

As discussed above; to overcome the computational cost associated with CNN, most researchers and developers rely on pre-trained CNN models for detecting plant diseases. Popular among them are VGG19, ResNet50 and Xception.

VGG19 model was developed at Oxford University's Department of Engineering Sciences and is widely used for image recognition and classification tasks [22]. It has a deep architecture comprising of a total of 19 layers – 16 convolutional layers and 3 fully connected layers – allowing for capturing of distinctive and complex features of leaves that helps in accurately detecting disease symptoms in plants [23]. Recent research studies on different plant leaves have clearly demonstrated this ability of VGG19. [24] effectively used VGG19 model to successfully detect and classify diseases in Grape leaves with accuracy of 98%. [25] deployed the same model for disease detection in Apple and received a result of 98.71%. Vadivel et al. (2022) obtained an accuracy of 99% in their application of model on Potato leaves. The main limitation of VGG19, however, is that it requires comparatively larger computational power, more memory and longer training time [26].

ResNet50 is a 50 layered CNN model based on residual learning framework that includes skip or shortcut connections, enabling it to mitigate the vanishing gradient problem in deep networks since gradients are allowed to flow through more fluidly during training of data [27]. One of the main advantages of this model is its pre-trained weights which lessens the need for extensive data training, hence making it more adaptable to new datasets while yielding high results (Ibid). The model has been used in various scientific studies to detect and identify disease symptoms in various plants. One such study by Bharti et al. (2024) on Potato leaves provided an accuracy of 98.36% in correctly identifying diseases in the plant. A similar study for Tomato leaves by Upadhyay & Saxena (2024) achieved an accuracy of over 95%. Hindarto (2024) applied this model to obtain an astonishing 99.16% accuracy in identifying and classifying various diseases in Mango leaves. ResNet50's high performance, however, is dependent on availability of high-quality images and diversity of data set which can limit its applicability in real-time agricultural scenarios where one may not be to ensure these conditions [31].

Xception model of CNN is basically a linear stack of depth-wise separable convolution layers that enables learning with comparatively less parameters than other pre-trained CNN models (Chollet, 2017). Overall, there are 36 convolution layers structured into entry, middle and exit flows (Ibid). These structural characteristics enhance Xception's ability to identify and find intricate features from leaves of a diseased plant [29]. [30] used Xception in their study of health classification of Chili leaves and achieved an accuracy of 91%. A 97.1% accuracy was obtained in research conducted by Sunyoto et al. (2023) on Potato disease classification using Xception model. Another study on Grape leaves by Tanwar & Lamba (2023) was able to demonstrate 99% accuracy while identifying and classifying diseases in Grape plant. While using Xception model such complex image classification tasks, one should be mindful of its high computational cost and, that its performance is sensitive to choice of hyperparameters, and how they are tunned and optimized [29].

While previous studies have successfully applied different CNN models for plant disease detection, there remains a need for comparative research that evaluates these different models under certain conditions. To tackle this gap, the following methodology outlines a comparative analysis of

ISSN: 3106-7743 | 3106-7735
Volume 3, Issue 1, 2026

pretrained CNN models along with a custom CNN model to determine their effectiveness in detecting diseases in potato, tomato, and pepper plants.

A condensed analysis of pertinent reviewed literature for this paper is provided below:

Author(s)	Model / Approach	Dataset / Source	Target Crop(s)	Accuracy / Result	Remarks	Model Limitation
Bj et al. (2024)	VGG19	Grape leaf images	Grape	98%	Used pre trained VGG19 for leaf classification	Dataset used was small and limited to one crop; lacks generalisability
Kumar et al. (2024)	VGG19	Apple leaf dataset	Apple	98.71%	Demonstrated high accuracy using transfer learning	Limited to single-crop classification; no fine tuning performed
Bharti et al. (2024)	ResNet50	Potato leaf dataset	Potato	98.36%	Outperformed other models in potato disease detection	Not tested on multi crop or real time applications
Upadhyay and Saxena (2024)	ResNet50	Tomato leaves	Tomato	>95%	Applied ResNet50 on tomato leaf disease classification	Did not explore regularisation techniques or overfitting prevention
Hindarto (2024)	ResNet50	Mango leaf dataset	Mango	99.16%	Achieved highest accuracy among models for mango classification	Model complexity and size may not be suitable for edge deployment
Wulandari et al. (2024)	Xception	Chili leaf dataset	Chili	91%	Utilised depth wise separable convolutions for lightweight modelling	Lower accuracy compared to other models; sensitive to dataset variations
Sunyoto et al. (2023)	Xception + ReduceLROnPlateau	Potato dataset with callbacks	Potato	97.1%	Learning rate scheduler improved model convergence	Callback techniques improved training, but model still underperformed vs ResNet50
Tanwar and Lamba (2023)	Xception	Grape leaf dataset	Grape	99%	High performance reported with Xception model	Model performance not validated across multiple crops or real world field data

Methodology

This study involves the comparative evaluation of multiple CNN models for the classification of diseases in three crops: Potato, Tomato, and Pepper. Four models were selected for this task. Three of these models are pretrained CNN models and the

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ISSN: 3106-7743 | 3106-7735
Volume 3, Issue 1, 2026

last one is our custom CNN model. The model looks at the pictures of the leaves of these crops and determines if they are healthy or have some kind of disease. The dataset used in this paper is taken from 'Plant Village' database on Kaggle, uploaded in 2018, and it consists of labeled images of diseased and healthy leaves for the selected crops. In the table below is the complete description of the dataset. It contains the classes and the total data for each class for training.

Class	**Images**
Tomato_healthy	1591
Tomato__Tomato_mosaic_virus	373
Tomato__Tomato_YellowLeaf__Curl_Virus	3209
Tomato__Target_Spot	1404
Tomato_Spider_mites_Two_spotted_spider_mite	1676
Tomato_Septoria_leaf_spot	1771
Tomato_Leaf_Mold	952
Tomato_Late_blight	1909
Tomato_Early_blight	1000
Tomato_Bacterial_spot	2127
Potato___healthy	152
Potato___Late_blight	1000
Potato___Early_blight	1000
Pepper__bell___healthy	1478
Pepper__bell___Bacterial_spot	997
Total	20,638

The dataset was preprocessed before training to ensure consistency. The images were first resized to a uniform size, then the pixel values were normalized between 0 and 1. After that we applied augmentation techniques on the dataset by rotating, flipping, and zooming to artificially expand the dataset and help prevent overfitting.

To understand the performance of each CNN based approach, it is essential to briefly describe the design and configuration of each model used in the study. Four models were evaluated: one custom-designed CNN built from scratch and three pre-trained transfer learning models (VGG19, ResNet50, and Xception) adapted using the ImageNet weights. All models were compiled using the Adam optimizer with a learning rate of 0.001 (default setting), sparse categorical cross entropy as the loss function, and accuracy as the evaluation metric. Training was conducted for 20 epochs with a batch size of 32. The dataset was split into 80-10-10 split with 80% training data, 10% validation and testing data.

1. Custom CNN

The custom CNN model was constructed using four convolutional layers with filter sizes of 32, 32, 64, and 64 respectively, each followed by max pooling layers for dimensionality reduction. The convolutional layers used a kernel size of 3x3 and ReLU activation. After flattening, a fully connected dense layer with 64 neurons (ReLU activation) and an output softmax layer with 15 neurons (for 15 classes) was added. In total, the model had approximately 869,423 trainable parameters.

2. VGG19

For the VGG19 model, the convolutional base was imported from Keras applications with ImageNet pre trained weights, excluding the top classification layer. The base was frozen to preserve learned features, and a new classification head was added comprising a global average pooling layer, a 128 neuron dense layer with ReLU activation, a dropout layer with 0.5 rate to prevent overfitting, and a final dense layer with 15 neurons using softmax activation.

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Volume 3, Issue 1, 2026

3. ResNet50

ResNet50 was also applied using transfer learning with its convolutional base frozen. Its architecture, based on residual learning with 50 layers, included skip connections that mitigated the vanishing gradient problem during training. Similar to VGG19, a new top classifier was appended with a global average pooling layer, followed by a dense layer with 128 units, a dropout layer (rate 0.5), and a 15 unit output layer.

4. Xception

The Xception model, built with depth wise separable convolutions, was also adapted using pre-trained ImageNet weights and a custom top classifier. The classifier followed the same architecture as other transfer models: a global average pooling layer, 128 unit dense layer (ReLU), dropout layer (0.5), and a 15 class output layer.

We evaluated the models by comparing the accuracy, time taken, and F1 score. Accuracy measured the overall correctness of the model predictions whereas the F1 score provided us with a balanced measure of precision and recall, especially useful for our dataset as it had an imbalance of classes. Training time was also recorded for each model to assess the computational efficiency of the models. After training these metrics were compared to determine the best model for plant disease detection in the selected crops.

Results and Comparative Analysis

As discussed in the methodology, we have deployed four convolutional neural network (CNN) models for this research to perform multi-class classification on vegetable disease images: a custom-designed CNN, VGG19, ResNet50, and Xception. The dataset utilised for this task comprised 20,638 images spanning 15 distinct classes, covering a variety of vegetable diseases as well as healthy plant conditions. The dataset was split into training, validation, and testing sets in the ratio of 80:10:10, and models were evaluated based on accuracy, precision, recall, and F1 score. The results of our study are discussed below in detail.

The custom CNN architecture, built from scratch, consisted of multiple convolutional layers interspersed with max-pooling layers, followed by dense layers culminating in a softmax output layer. After 20 epochs, the model achieved a test accuracy of 87.50%, with a precision of 0.8400, recall of 0.8503, and an F1 score of 0.8339. The learning curves indicate that the model progressively improved over epochs, reducing both training and validation loss substantially, although minor fluctuations in validation loss were observed in the mid-epochs. These could be attributed to the model overfitting slightly on certain classes or inherent class imbalance in the dataset. The strong performance of the custom model validates the design choices, particularly the balance between depth and complexity which allowed it to generalise effectively without pre-trained weights.

The VGG19 model, adapted via transfer learning, demonstrated a test accuracy of 89.52%, precision of 0.8956, recall of 0.8691, and F1 score of 0.8759. These results surpass those of the custom CNN, highlighting the advantage of leveraging pre-trained weights on large-scale datasets like ImageNet. The validation accuracy of the VGG19 model consistently improved with each epoch, and the gap between training and validation loss remained minimal, suggesting good generalisation capability. The model's superior precision indicates it was better at avoiding false positives compared to the custom model, which is particularly useful in agricultural applications where misclassifying a healthy plant as diseased (or vice versa) could have significant implications for farm management.

Among all tested architectures, the ResNet50 model emerged as the best performer, achieving 94.86% test accuracy, precision of 0.9453, recall of 0.9443, and an F1 score of 0.9438. The model's depth and use of residual connections appear to have played a crucial role in effectively learning complex feature hierarchies without falling prey to vanishing gradient issues. The training and validation loss curves for ResNet50 displayed stable convergence with minimal overfitting. The high and balanced precision and recall underscore its robustness across all disease categories, including those with subtle visual differences. Notably, the ResNet50 model consistently outperformed the others from the early epochs, reflecting the strength of its architecture in transfer learning scenarios for fine-grained image classification.

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ISSN: 3106-7743 | 3106-7735
Volume 3, Issue 1, 2026

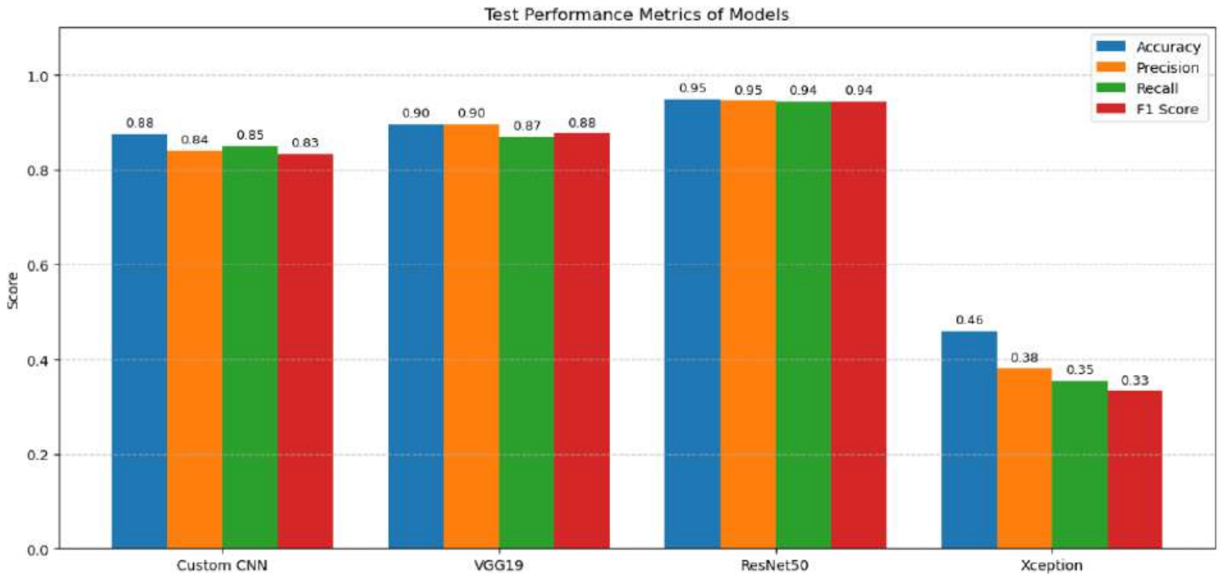
In contrast, the Xception model lagged behind, registering a test accuracy of 45.96%, precision of 0.3805, recall of 0.3545, and an F1 score of 0.3322. This underperformance may stem from a combination of factors: first, the model's reliance on depth wise separable convolutions might have limited its capacity to effectively capture the nuanced features of the plant disease dataset, particularly in the absence of fine-tuning. Additionally, the training logs revealed slower convergence and higher variance between training and validation metrics, indicative of poor generalisation. The Xception model's lower recall suggests it failed to detect many positive instances of diseases, which is concerning in a real-world deployment context where missing a diseased plant could allow the spread of infection.

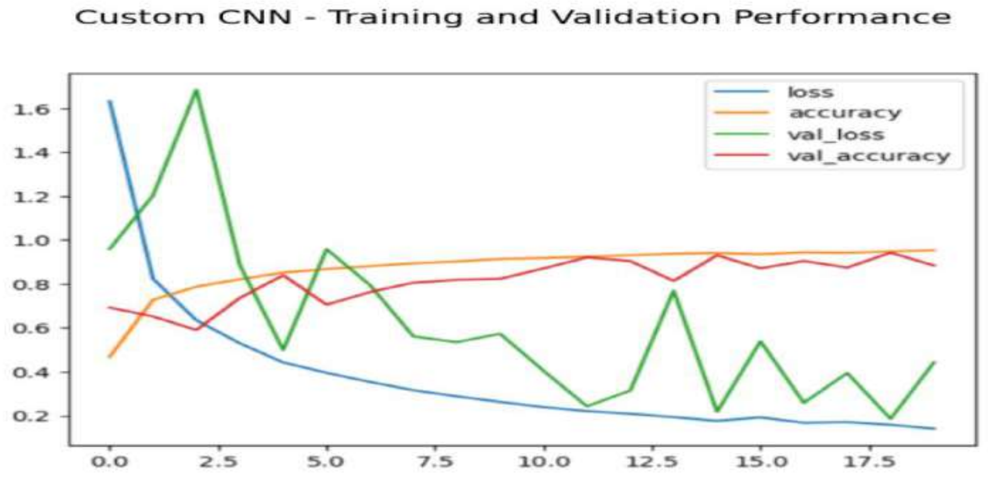
A comparative overview of the models shows that transfer learning significantly enhances classification performance for this task. Both VGG19 and ResNet50 outperformed the custom CNN in all metrics, with ResNet50 demonstrating a clear edge. This aligns with expectations, as deeper models with residual connections can better exploit feature representations learned on diverse datasets. Interestingly, while VGG19 achieved competitive precision, its recall was slightly lower than ResNet50, suggesting that it might be more conservative in classifying positive cases.

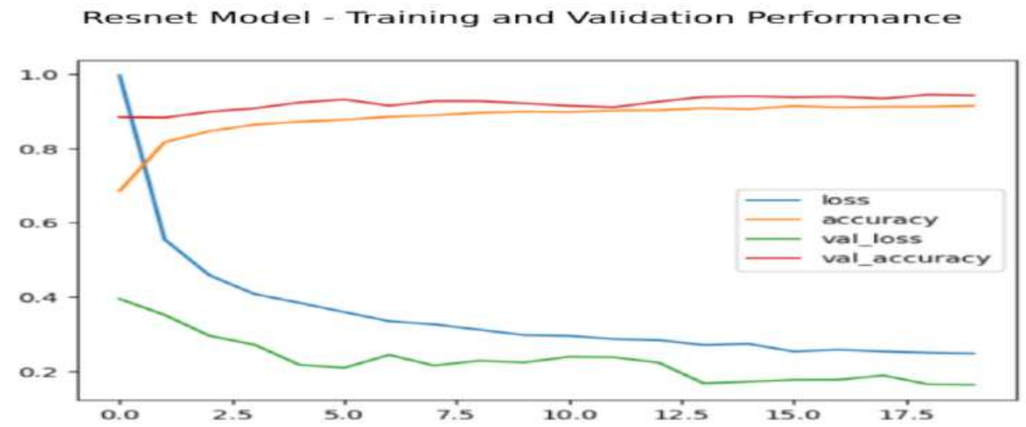
Table 1: Comparative Performance of CNN Models on Test Data

Model	Test Accuracy	Precision	Recall	F1 Score	Time
Custom CNN	0.8750	0.8400	0.8503	0.8339	34 min
VGG19	0.8952	0.8956	0.8691	0.8759	51 min
ResNet50	0.9486	0.9453	0.9443	0.9438	36 min
Xception	0.4596	0.3805	0.3545	0.3322	41 min

(Source: Model evaluation results)




Custom CNN - Training and Validation Performance
loss
accuracy
val_loss
val_accuracy


Resnet Model - Training and Validation Performance
loss
accuracy
val_loss
val_accuracy


VGG19 Model - Training and Validation Performance
loss
accuracy
val_loss
val_accuracy

(Source: Model evaluation results)

The custom CNN, despite not being pre-trained, proved to be a strong baseline model, reinforcing the idea that domain-specific architectures tailored to the task can be highly effective. Its performance was close to VGG19, which is noteworthy given the resource efficiency of training a lighter, custom-designed model versus a heavyweight pre-trained one.

On the other hand, Xception's unexpectedly poor results underscore the importance of model selection and hyperparameter tuning in transfer learning applications. The architecture, while theoretically powerful, appears to have been ill-suited to this specific classification task without additional tuning or possibly unfreezing some layers for fine-tuning.

Practical Implications and Conclusion

From a practical standpoint, the results indicate that ResNet50 would be the most appropriate model for deployment in an agricultural decision support system for early plant disease detection. Its high accuracy, coupled with balanced precision and recall, would help minimise both false positives and false negatives, supporting timely and accurate interventions. However, it is important to consider the computational requirements associated with such models, particularly in low-resource settings where edge devices might be used for inference. In these cases, the custom CNN could offer a trade-off between accuracy and computational efficiency, especially given its relatively strong performance.

Furthermore, the variability in model performance points to the potential benefits of exploring ensemble methods or hybrid approaches, combining the strengths of multiple architectures to further enhance robustness. Future work could also focus on class-specific analysis to identify which diseases were most prone to misclassification and why, as well as investigate the impact of augmenting the dataset with more diverse samples to address potential class imbalance issues.

In summary, the comparative evaluation clearly shows that transfer learning with ResNet50 provides superior performance for vegetable disease classification, with VGG19 also delivering strong results. The custom CNN offers a viable lightweight alternative, while Xception, in its current configuration, did not meet the requirements for accurate classification. These insights provide a solid foundation for further refinement and deployment of automated plant disease detection systems in precision agriculture.

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