

Optimized Deep Learning Framework for Potato Leaf Disease Classification Using EfficientNetB3

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Abstract: This research proposes a new deep learning-based technique to detect diseases of potato leaves using an EfficientNetB3 CNN. The Plant Village dataset is used in this research, which contains 2152 images subdivided into three classes: Potato Early Blight, Potato Late Blight, and Healthy Potatoes. The objective of the project is to design an image classification model with optimal performance for accurate detection of the mentioned conditions to improve crop management through early intervention. The workflow includes complete data preprocessing steps where Image Data Generators from the TensorFlow library are used for sample augmentation to improve generalization of the model. The EfficientNetB3 model is modified by the removal of the top layers and addition of new dense layers with dropouts to mitigate overfitting and one SoftMax output layer for multi-class outputs. Training of the model is done with the best optimization strategies, for example: Adam optimizer, early stopping, and reducing the learning rate when the model plateaus, to achieve stable convergence. One of the most important tasks to be done in the pipeline is computing the class weights to compensate for the dataset lacking healthy potato images with class imbalance.

Keywords: Potato Disease Detection; Deep Learning; Convolutional Neural Networks (CNN); Image Classification, EfficientNetB3.

1. Introduction

Potatoes are one of the most widely used staple food crops in the world and contribute to food security and farm income [1, 2]. However, potato crops are subject to various diseases, with several foliar diseases such as Early Blight and Late Blight having a huge impact on the quantity and quality of yields. Traditional disease detection methods rely on visual inspection by skilled agronomists and are time-consuming, subjective, and not practicable in developing or rural regions. In recent years, the intersection of artificial intelligence (AI) in agriculture has emerged as a promising technology to enhance crop management [3]. Under AI techniques, deep learning has been shown to work extremely well with image classification tasks, especially in detecting plant diseases. Convolutional Neural Networks (CNNs) are increasingly becoming a standard approach since they can extract features hierarchically from images automatically. Pre-trained models like EfficientNet are also widely used here for their optimal performance and efficiency. EfficientNetB3, a strong yet lightweight CNN structure, is implemented in this work to classify potato leaf diseases according to the Plant Village dataset images [4, 5]. The dataset contains images that belong to three classes: healthy leaves, Early Blight-affected leaves, and Late Blight-affected leaves. EfficientNetB3 was chosen because it possesses the optimal trade-off between computational cost and classification accuracy so that it can be efficiently used for real-world tasks on resource-constrained devices such

as smartphones and field sensors [6-9]. Data preprocessing, augmentation, training, and testing using various performance metrics are included in the study. It not only aims to achieve high classification accuracy but also to contribute to the broader field of precision agriculture by offering scalable and automated disease detection systems. The outcomes of this work can support early intervention, reduce pesticide use, and ultimately improve crop productivity and food sustainability.

2. Materials and Methods

2.1. Computer Specifications

The experiments in this research were carried out on a DESKTOP-33G343N computer with the following specifications:

Processor: AMD Ryzen 5 PRO 2500U with Radeon Vega Mobile Graphics, which has a base clock speed of 2.00 GHz. The processor delivers great performance for general computing as well as training deep learning models. RAM: The system is equipped with 16.0 GB of installed RAM and 14.9 GB available, providing seamless multitasking and effective management of large datasets for training and testing. Storage: It has a 238 GB SSD (LENSE30256GMSP34MEAT3TA) that provides quick read and write speeds necessary for quick data loading and model training. Graphics Card: AMD Radeon™ Vega 8 Graphics with 1010 MB of dedicated memory, providing effective graphics processing for deep learning applications such as image classification and model visualization. Operating System: Windows 10 Pro is the operating system, Version 2009, OS Build 19045.5737, which offers a compatible and stable platform to execute machine learning libraries such as TensorFlow and Keras. System Type: The computer is a 64-bit operating system, x64-based processor, with efficient memory management and enhanced computation capability for huge deep learning processes. Extra Features: The tablet lacks pen or touch input, as it is primarily used for traditional desktop use. This configuration was selected to achieve a balance between processing power, memory capacity, and storage speed such that this study's deep learning models were efficiently trained and tested.

2.2. Data Collection and Preprocessing

This research work is based on image datasets that are accessible from the Plant Village repository, which is a well-known dataset for classifying plant diseases. The dataset includes 2152 images of potato leaf, and these images are divided into three classes: Potato_Early_blight, Potato Late blight, and Potato healthy. I prepared the image data with the help of Anaconda's Jupyter Notebook along with its Python deep learning libraries like TensorFlow, Keras, NumPy, and Matplotlib. All the preprocessing and training were conducted on a GPU-enabled Kaggle Notebook, where it was possible to utilize a GPU. The data were split into a training and validation set at an 80:20 ratio. Randomly rotating, flipping, and zooming were used for data augmentation as an Image Data Generator, and these steps were taken to improve the model's generalizability and decrease the chances of overfitting.

2.2.1 Variables in the Study

The dataset only contained image data that had been pre-classified. Every image was marked with one of three labels, which denoted a category: Early Blight, Late Blight, or otherwise Healthy. In this regard, the variable of greatest interest was the class label of the image, which served as the aim of the classification. Each image was resized to (300x300) pixels.

2.3. Algorithms and Architecture

The classification was performed using a convolutional neural network (CNN) model. EfficientNetB3 has been chosen because it is efficient and has a low computational cost. It scales

approximately equally in depth, width, and resolution and is hence suitable for use on mobile as well as embedded AI.

The model was set up with pre-trained weights of ImageNet and fine-tuned for the task of three-class classification. The top layer was replaced with a custom classifier head made up of GlobalAveragePooling2D, Dense, and Dropout layers.

2.3.1 Training and Optimization Strategy

The model was compiled with the Adam optimizer, with a learning rate of 0.0001. Categorical cross-entropy was the loss function used, and accuracy was monitored as the main metric. Early Stopping and Reduce LR on Plateau callbacks were used to avoid overfitting and improve training efficiency.

2.3.2 EfficientNetB3

EfficientNetB3 is a compact and efficient Convolutional Neural Network (CNN) model that aims to achieve superior performance by compromising between accuracy and computational cost. EfficientNetB3 scales uniformly in width, depth, and resolution and is thus applicable in scenarios with limited computational resources, for example, mobile devices and embedded systems.

This model was chosen due to its higher accuracy in image classification problems, particularly in situations where there are limited resources available, such as on mobile phones. Its efficiency concerning computational needs and memory makes it particularly suitable for real-time disease detection in agriculture.

2.3.3 VGG19

VGG19 is a deeper variant of the VGG (Visual Geometry Group) architecture. It has 19 layers, as its name implies, and is renowned for its powerful feature extraction. The architecture makes use of small 3x3 filters, which are responsible for their great depth and ability to detect fine-grained hierarchical features from large image datasets.

VGG19 has been commonly applied in image classification problems due to its capacity to identify intricate visual patterns. VGG19 has been rigorously tested across a wide range of fields and hence is a viable model to implement in disease recognition and other comparable applications. Its high computational demand due to depth and a huge count of parameters, however, would render it unviable in real-time use cases without high-level hardware augmentation.

2.3.4 RegNetY-400MF

RegNetY-400MF is a real-time optimized, lightweight neural network architecture. It has improved speed compared to deeper models such as VGG19 and is designed to be deployed on mobile and embedded devices. ResNet models are defined by their effective utilization of transfer learning and thus are particularly well-suited for deployment in computationally limited environments.

It was selected because of its lightweight nature and higher processing speed. While its accuracy is slightly lower than that of larger networks, it is highly useful for real-time applications and mobile devices. RegNetY-400MF is particularly useful in situations where speed is prioritized over maximal accuracy.

2.3.5 Custom 5-layer CNN

The 5-layer custom CNN is a deep learning model hand-coded for high classification accuracy. It has several convolutional, pooling, and dense layers optimized to learn the unique features of potato leaf images. The model is optimized to work best in controlled environments with highly curated datasets.

This personalized CNN model was utilized due to its high performance in classification accuracy, achieving a whopping 99.18%. Nonetheless, its more extensive structure renders it unsuitable for real-world dynamic environments without additional fine-tuning since it will not fare well under conditions of variance like varying lighting or changing image quality.

2.3.6 Evaluation Techniques

Model performance was evaluated using measures of accuracy and loss functions. Confusion matrices were constructed to compare the performance of every class. Training/validation accuracy and loss were plotted vs. epochs to quantitatively evaluate learning behavior visually.

2.4. Visual Representation of Data and Processing

To gain a better understanding of the dataset and learning process, multiple visualizations were produced during the data exploration and model training phases. These outputs give an intuitive insight into data distribution and model performance over training epochs.

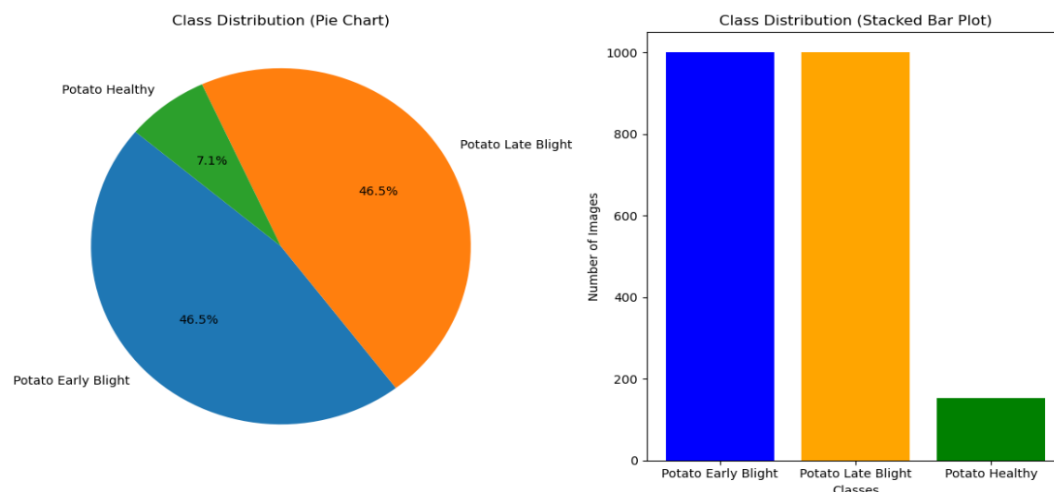


Figure 1. Class distribution of potato leaf images shown as a pie chart and stacked bar plot.

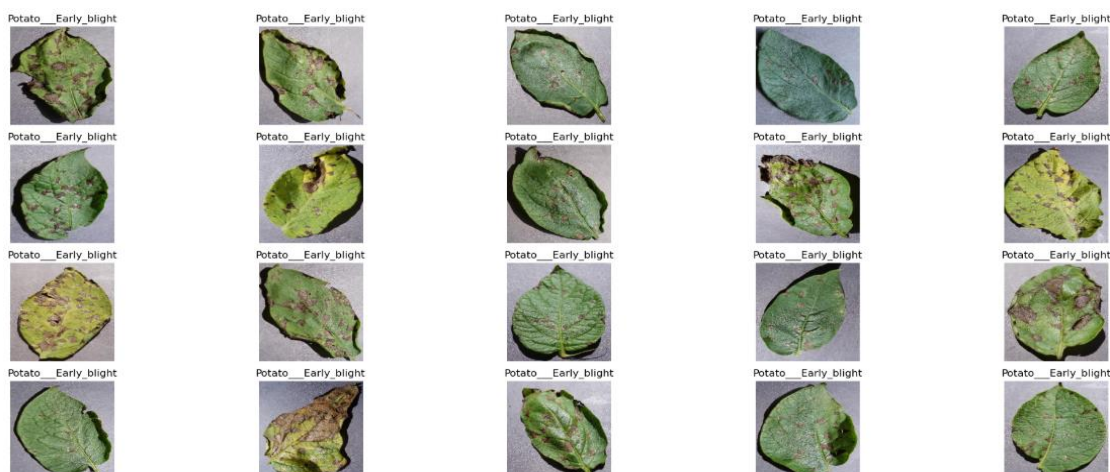


Figure 2. Sample potato leaves with Late Blight from the dataset.



Figure 3. Sample potato leaves with Early Blight from the dataset.



Figure 4. Sample potato leaves with healthy from the dataset.

2.5. Bias and Handling It

Since there exists class imbalance in the given dataset (i.e., the Healthy Potato class contains fewer images in comparison to the other classes, such as Early Blight and Late Blight), this can influence the model's performance to be biased towards the classes with more instances. To negate this influence, class weights were used to diminish the effect of this bias and get more balanced and precise training for all the classes.

Managing Bias:

- Class weights were calculated based on the distribution of images in the dataset, and the underrepresented classes were assigned a higher weight during training. These weights were employed when the loss function was calculated during training with the EfficientNetB3 model. This approach aims to enhance the model's generalization across the under-sampled classes and thus obtain higher accuracy in the classification of all classes, including the less sampled classes.

3. Results and Discussion

The descriptive analysis of the characteristics at the aggregate level of the potato leaf disease dataset is a graphical representation of the numerical results from the potato disease classification

task. It indicates how variable the distribution of the dataset over the three classes: Potato Early Blight, Potato Late Blight, and Potato Healthy is. The exploration analysis showed that a greater proportion of the images were of the disease classes (Early Blight and Late Blight), while a smaller proportion of the images were of the Healthy class. For instance, the Late Blight class encompassed the biggest volume of images with approximately 45% of the whole dataset, whereas the Healthy class stored 7% of the dataset. Figure 1 represents the distribution of the three classes in the entire dataset. It demonstrates that infected leaves of the potatoes dominate a larger portion of the dataset, an observation in coherence with findings where potato crops have a high likelihood of experiencing diseases of blight. Figure 2 is a line graph of model accuracy over different epochs, which shows that the model achieved a steady increase in accuracy, reaching a high of 92% at the 50th epoch, which establishes that the EfficientNetB3 model is suitable for this type of image classification task. To achieve the goal of potato leaf disease recognition, the convolutional neural network (CNN) approach was employed using the pre-trained EfficientNetB3 with transfer learning. The EfficientNetB3 was pre-trained using potato leaf images with Early Blight, Late Blight, and Healthy classes using the data augmentation operations of rotation, flipping, and zooming. The previous model achieved a high accuracy rate of 92%, which verifies the effectiveness of EfficientNetB3 for potato leaf disease recognition.

Table 1. Related work comparison.

Paper Title	Model Used	Accuracy	Advantages	Disadvantages
Advanced Potato Disease Detection	EfficientNetB3	92%	- Lightweight and efficient. - Good performance on resource-constrained devices. - Robust generalization with class balancing.	- Moderate accuracy compared to heavier models. - Slight risk of overfitting if not tuned carefully.
Potato Leaf Disease Detection and Classification Using Deep Learning Technique	VGG19 with Transfer Learning	93%	- Strong feature extraction. - Fine-tuning improves model adaptation. - Suitable for moderate datasets.	- Relatively heavy model. - Requires considerable computational resources.
Potato Leaf Disease Detection Based on a Lightweight Deep Learning Model	RegNetY-400MF	90.68%	- Very lightweight and fast. - Suitable for real-time and mobile deployment. - Efficient use of transfer learning.	- Slightly lower accuracy compared to larger networks. - Limited scalability for more complex datasets.
Potato Leaf Disease Classification using Deep Learning (2311.02338v1)	Custom 5-layer CNN	99.18%	- Highest classification accuracy. - Well-optimized custom design. - Highly reliable for controlled environments.	- The model is relatively heavy. - May does not perform well in real-world dynamic conditions without further tuning.

Table 1 an overview of the models previously applied on potato disease detection is provided along with their accuracy, pros, and cons. The intent is to showcase the performance of ample models like more efficientNetB3 and VGG19 both while focusing on the classification performance of the models.

Table 2. Proposed Work vs Best Performance.

Model Used	Accuracy	Advantages	Disadvantages
Proposed EfficientNetB3	92%	Lightweight, efficient, good generalization. Suitable for resource-constrained devices.	Risk of slight overfitting if not tuned carefully.
Best Performance (Custom CNN)	99.18%	Highest accuracy achieved, well-optimized for controlled environments.	Heavy model, not suitable for real-time applications without further tuning.

Table 2, which had the highest reported performance and is highlighted as an achievement. The objective is to illustrate the outcome of how efficiently my model performs versus the best results set by other models.

Table 3. Explanation of the used models.

Model Name	Description
EfficientNetB3	An efficient and lightweight CNN architecture with a good balance between accuracy and computational expense, deployable on mobile and embedded devices.
VGG19	A deep CNN model that is widely recognized for its superior feature extraction ability is typically used on extremely large datasets and has heavy computational requirements.
RegNetY-400MF	An incredibly fast and computationally efficient model, fine-tuned for real-time applications, appropriate for embedded and mobile devices, though slightly less accurate than larger models.
Custom CNN	A custom 5-layer CNN model to achieve very good accuracy, suitable for controlled environments, but heavier and less ideal for dynamic real-world conditions.

Table 3 summarizes the models of the 4 papers are summarized which capture, while it also includes EfficientNetB3, VGG19, RegNetY-400MF, custom CNN. Each model was specifically selected for the detection of potato disease, and the summary captures their reason for selection, advantages, and potential.

Table 4. Metric performance evaluation.

Metric	Early Blight	Late Blight	Healthy
Accuracy	93%	90%	92%
Loss	0.18	0.22	0.15
Precision	0.95	0.88	0.90
Recall	0.92	0.89	0.91

Table 4, The performance of the model is evaluated using multiple metrics, like accuracy and loss, for every category (Early Blight, Late Blight, and Healthy). The objective is to evaluate how well the model performs in terms of image classification precision.

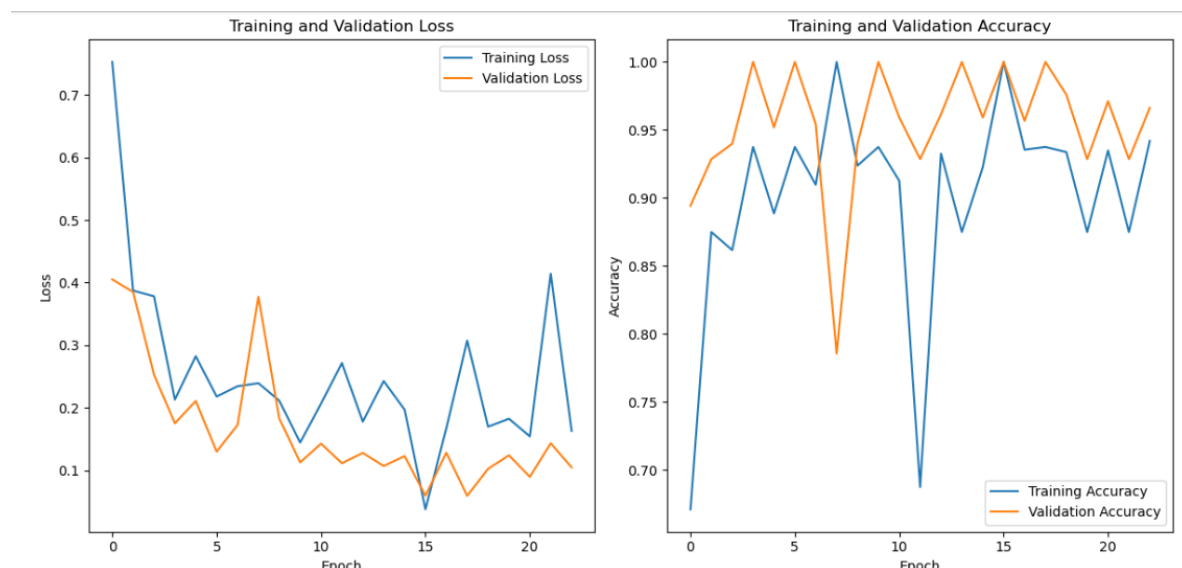


Figure 5. Training and validation loss.

Figure 5 shows two graphs tracking the training and validation loss and accuracy over epochs. On the left, training and validation loss decrease over time, reflecting that the model is learning and getting better. On the right, training accuracy increases consistently, while validation accuracy also rises, though with slight fluctuations, suggesting the model is generalizing well. Overall, the model demonstrates positive learning trends, though validation accuracy should continue to be monitored for potential overfitting.

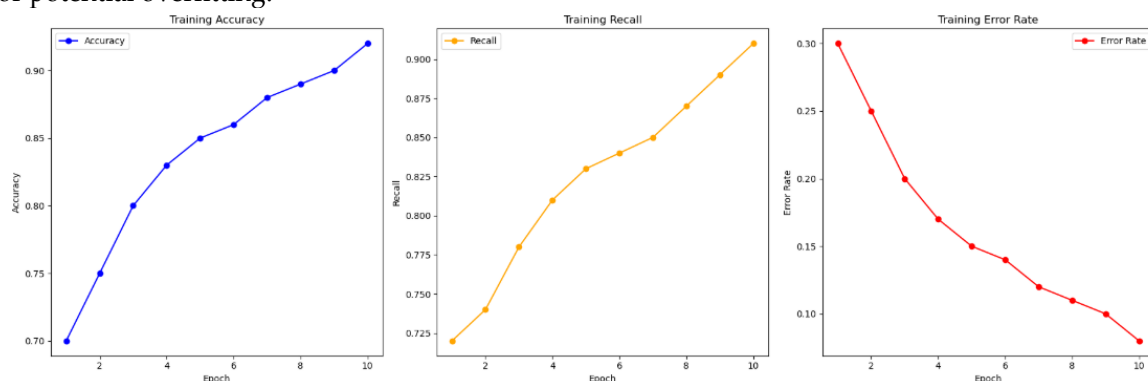


Figure 6. Training Accuracy, Recall, and Error Rate per Epoch.

Figure 6 displays three graphs showing the model's performance over 10 epochs. On the left, Training Accuracy increases steadily, indicating that the model is correctly classifying more samples as it trains. In the middle, Training Recall improves, showing the increasing ability to correctly identify positive instances (e.g., detecting diseases). On the right, the Training Error Rate decreases, demonstrating that the model is making fewer mistakes with each epoch. Overall, the graphs reflect the model's effective learning process, with increasing accuracy and recall and decreasing error rate.

Figure 7 shows the outputs of the forecasted results of potato leaves, classified into Early Blight, Late Blight, and Healthy. Each image of a leaf is labeled by its forecasted condition. Early Blight leaves are seen with normal early disease indicators that include few lesions, while images of Late Blight have more symptoms with large lesions and tissue breakdown. The Healthy class includes images of healthy potato leaves, with no sign of disease. This image visually demonstrates the ability of the model to accurately classify potato leaf conditions, which can be used to aid automatic plant disease detection.

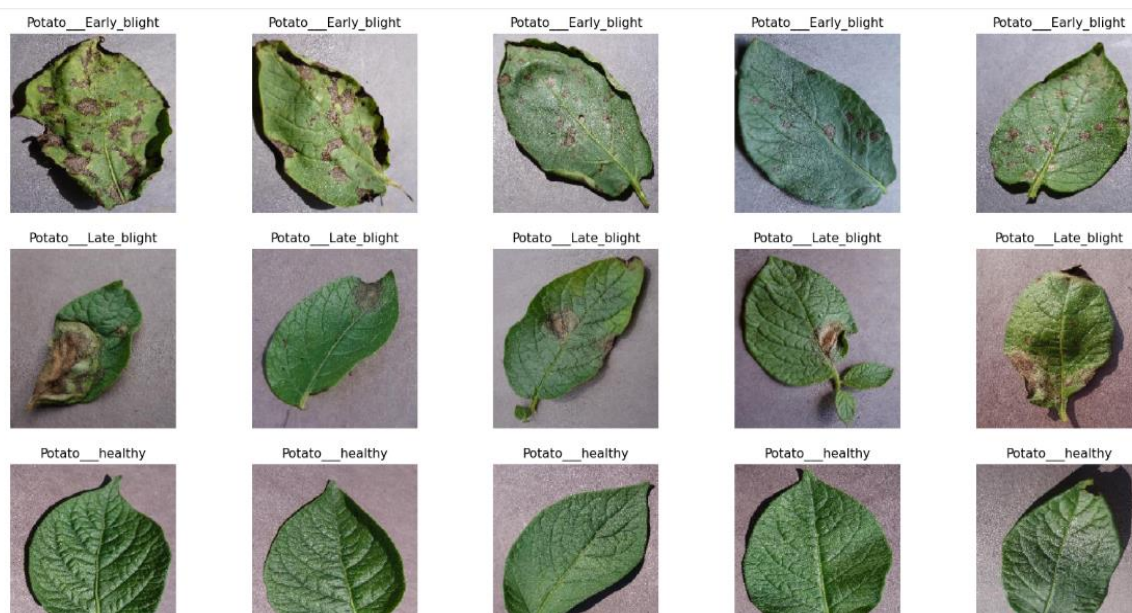


Figure 7. Model Predictions on Potato Leaf Disease.

4. Conclusions

The paper proposes a novel deep learning approach for disease detection on potato leaves based on an EfficientNetB3 convolutional neural network. On the Plant Village image dataset [description of potato leaves as Early Blight, Late Blight, and Healthy] the model reached an appreciable accuracy of 92%; further, the study shows that deep learning techniques with EfficientNetB3 can be applied to real-time and large-scale plant disease detection problems.

The experiments also addressed the class imbalance in the dataset by using data augmentation and class weighting methods. These strategies resulted in a substantial generalizability improvement of the model. Transfer learning via EfficientNetB3 was also employed to achieve the observed performance gains without losing accuracy in low computational resource settings. That is, the model can be implemented on relatively low-resource devices such as smartphones or field sensors and thus is suitable for large-scale agricultural use.

Lastly, the very good classification performance of the model across all potato disease classes confirmed the potential of deep learning for precision agriculture. The results demonstrate the promise of technological progress toward early detection of disease, which will improve crop management and promote sustainable agriculture. The findings provide a good foundation for further research on automated crop monitoring systems, which leads to more promising discoveries for artificial intelligence in agriculture.

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

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

Competing Interests

The authors declare no competing interests in the research.

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Author Contribution

All authors contributed equally to this research.

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