AlexNet-based Convolutional Neural Networks for Plant Leaf Disease Classification

Technical Report

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Abstract

An accurate image-based detection of plant disease remains challenging. Previously built CNN models trained on images taken under controlled conditions - as PlantVillage dataset images - often perform poorly on real-world images. Mohanty et al. (2016) achieved 99.27% accuracy training and testing a CNN model on PlantVillage using AlexNet, but the performance dropped to 31.4% on external images. Building upon their approach, we developed an AlexNet-based CNN with transfer learning and fine-tuning to detect plant diseases in PlantVillage images and in external datasets, including PlantDoc and FieldPlantVillage. The baseline model trained only on PlantVillage achieved 97.77% accuracy on PlantVillage, but 19.49% and 29.17% on PlantDoc and FieldPlantVillage, respectively. Including PlantDoc images in training improved accuracy to 44.92% on PlantDoc and 49.63% on FieldPlantVillage, while fine-tuning provided no significant further improvement.

Keywords Plant Disease Detection · CNN · AlexNet

1 Introduction

Plant and crop diseases represent a major threat to global food security and agricultural productivity, causing an estimated annual loss of $220 billion (Ristaino et al., 2021). Climate change further increases disease risk, endangering both food supply and plant biodiversity (Dolatabadian et al., 2024). Detecting and classifying plant diseases is therefore essential for effective management. Traditional approaches to disease detection involve labor-intense field surveys and manual inspections, which are slow and prone to errors (Dolatabadian et al., 2024). This has led to the development of machine-learning approaches. Earliest methods were based on conventional image processing techniques or hand-engineered design features (e.g. SIFT (Lowe, 2004); SURF (Bay et al., 2006)), and several systems were developed based on extracting shapes and colours from images (Sladojevic et al., 2016; Wang et al., 2012; Samanta et al., 2012). However, this approach has important limitations: 1) Feature engineering is laborious and complex, and sensitive to changes on the dataset; 2) The performance relies heavily on the underlying predefined features (Mohanty et al, 2016).

The rapid development of computer vision and artificial intelligence has enabled the application of deep learning methods, such as Convolutional Neural Networks (CNNs), across multiple domains, offering a promising solution for plant disease detection. Mohanty et al. (2016) trained CNNs on the PlantVillage dataset (53,306 images taken under controlled conditions) and achieved up to 99.35% accuracy using GoogLeNet (Szegedy et al., 2015) architecture and 99.27% with AlexNet (Krizhevsky et al., 2012). However, performance dropped to 31.4% when testing on external images from other sources. In this project, we aimed to develop a CNN-based model using the AlexNet architecture to detect and classify plant diseases through image recognition. Our approach builds upon the methods and findings of Mohanty et al. (2016) using their work as a baseline for comparison. Additionally, we aimed to develop a final model that outperforms Mohanty et al.'s (2016) models when evaluated on images collected under non-controlled conditions by including external datasets on training and testing.

2 Related Work

In the past years, the adoption of deep neural network models for automated feature extraction from high-dimensional data has provided significant advantages over traditional, manually designed feature extraction techniques for the development of plant disease detection methods (Jun Liu and Xuewei Wang, 2021). Many studies have relied on different deep neural network frameworks – being CNNs among the most popular architectures – to identify disease patterns on leaf images (Neupane & Baysal-Gurel, 2021), training the model on images taken under controlled conditions.

Lu et al. (2017) developed a CNN based on the AlexNet architecture to classify rice diseases using a dataset of 500 experimental field images. They compared its performance with traditional machine-learning models. The CNN achieved 95.48% accuracy, outperforming the SVM (92.1%) and standard backpropagation model (92%). Mohanty et al. (2016) applied a deep learning approach to develop a plant disease detection system. They developed a CNN model and employed AlexNet and GoogLeNet frameworks. The model was trained on the PlantVillage dataset, using 54306 images taken under controlled conditions. The best performing model achieved a 99.35% when testing on the PlantVillage dataset. Similarly, Brahimi et al. (2017) developed a CNN model for classification of tomato diseases based on PlantVillage images. The fine-tuned GoogLeNet model achieved an accuracy of 99.18%, while the AlexNet model reached 99.66%.

Despite the superior performance CNN models have shown compared to traditional methods when tested on laboratory-acquired images, an accurate identification of plant diseases in uncontrolled field environment remains challenging due to variations in lighting, poses, background, and symptoms variation (Gui et al., 2021; Dolatabadian A. et al., 2024). Several studies have attempted to detect plant diseases in in-the-wild leaf images. Boulent et al. (2019) reviewed 19 studies that relied on CNN-based models, and proposed an intuitive approach to the problem based on adding in-the-wild images to the training set. Sladojevic et al. (2016) followed a similar approach and developed CNN model trained on publicly available leaf images. They used a dataset with 14 disease classes, healthy leaves, and an additional background class to teach the model to distinguish leaves from their surroundings. Using 4,483 original images augmented to reduce overfitting and trained on a modified AlexNet architecture (CaffeNet), their best fine-tuned model achieved 96.3% accuracy. Gui et al. (2021) used a similar methodology, developing a CNN model trained on PlantVillage images with background replacement to improve robustness and leaf resizing to reduce variability in symptom size and position. As a result, accuracy increased from 41.8% to 72.03% when tested on 665 images collected under field conditions.

3 Methods

3.1 Datasets

In the first stage of our project, we built a baseline model using the original PlantVillage dataset with 38 classes, split 80% as a training set and 20% as a test set. The images were 256 x 256 sized RGB pictures of leaves on a plain background. There was a significant class imbalance, with the extremes ranging from 152 to 5507 images per class (Figure 1).

In addition, we used other datasets as external testing sets. The images were taken from various sources, including field photos and processed images. As a preprocessing step, all images were resized by center-cropping to 256 x 256 pixels. In four of five external datasets, there was not full coverage for all classes present in the training set.

In the second stage, after low performance on tests with external datasets, we decided to mix our training set from the previous stage (PlantVillage) with a training set from another source. We chose the PlantDoc dataset (80% of the full dataset split in the source repository), due to sufficient class overlap (28 out of 38 PlantVillage classes) and the number of images per class. In order to avoid bias due to the different nature of PlantDoc images (noisy background, different angles), we limited our training classes to only those present in PlantDoc. An overview of the mixed training set is given in Figure 2. To monitor the training process, we also made a validation set by taking 10% of each existing training set before downsampling (which makes 8% of the data set). Finally, we addressed class imbalance by eliminating PlantVillage images, so that each class had a maximum of 1000 images after mixing. The contents of our datasets are summarized in Table 2.

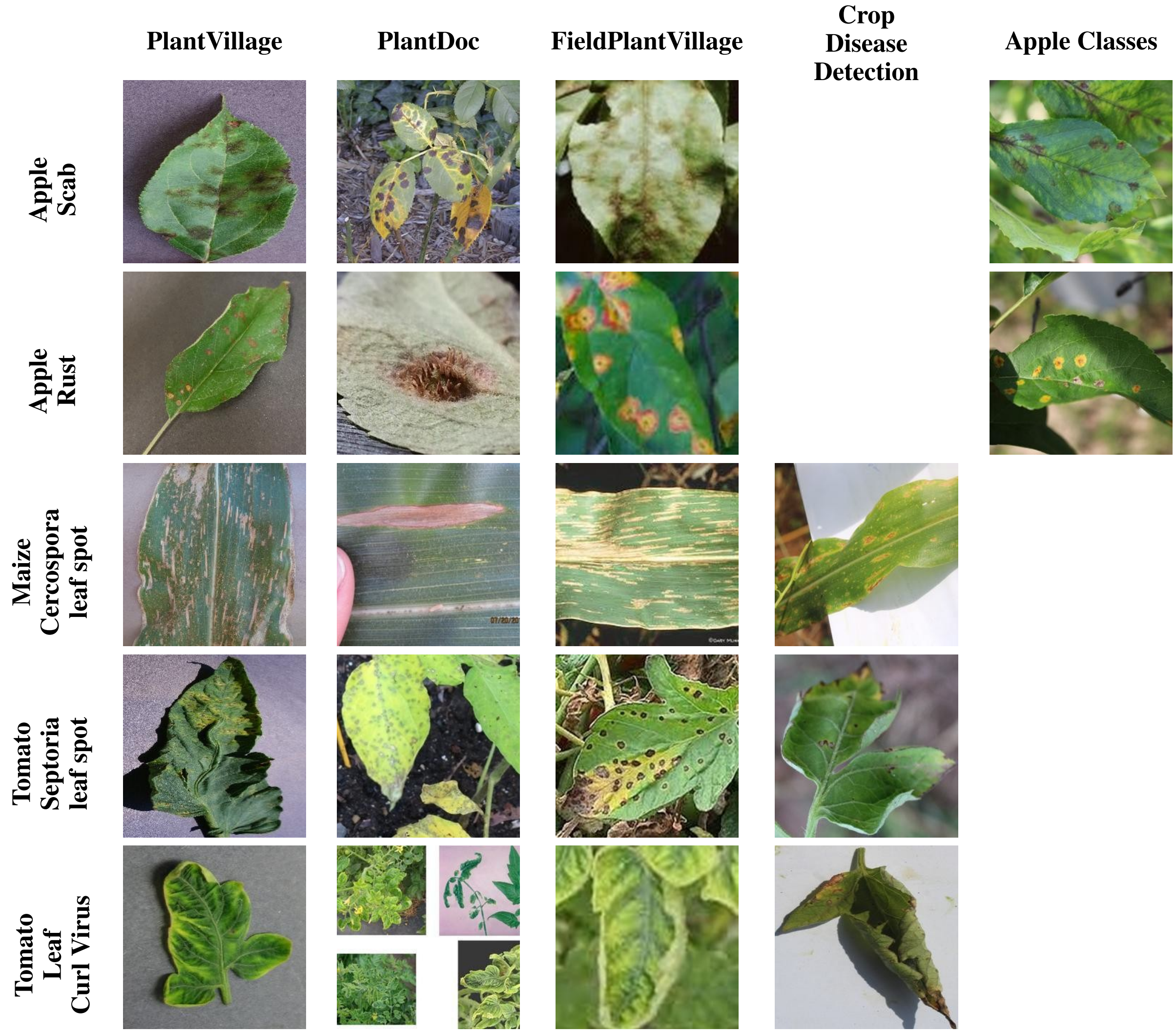


Table 1: Image samples from the different datasets used. The PlantVillage images (first column) have a controlled background, while the images form other sources are heterogenous

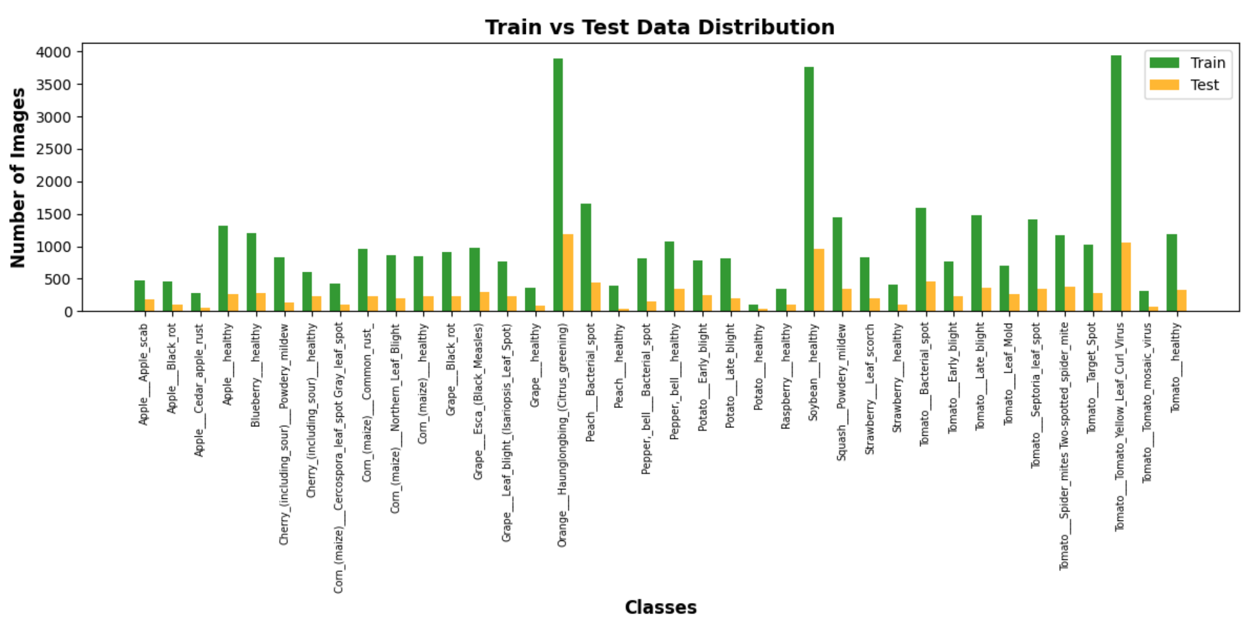


Figure 1: Data Distribution in PlantVillage Dataset

Table 2: Dataset Compositions on the different stages of the project

Dataset	First Stage			Second Stage			
	Classes	Train Set	Test Set	Classes	Train Set	Validation Set	Test Set
PlantVillage	38	43381	10937	**28**	19088	2078	7818
PlantDoc	28	-	236	28	2114	222	236
Crop Disease Detection	5	-	5176	**4**	-	-	4970
Apple Classes	3	-	1730	3	-	-	1730
Field Plant Village	38	-	665	**28**	-	-	405

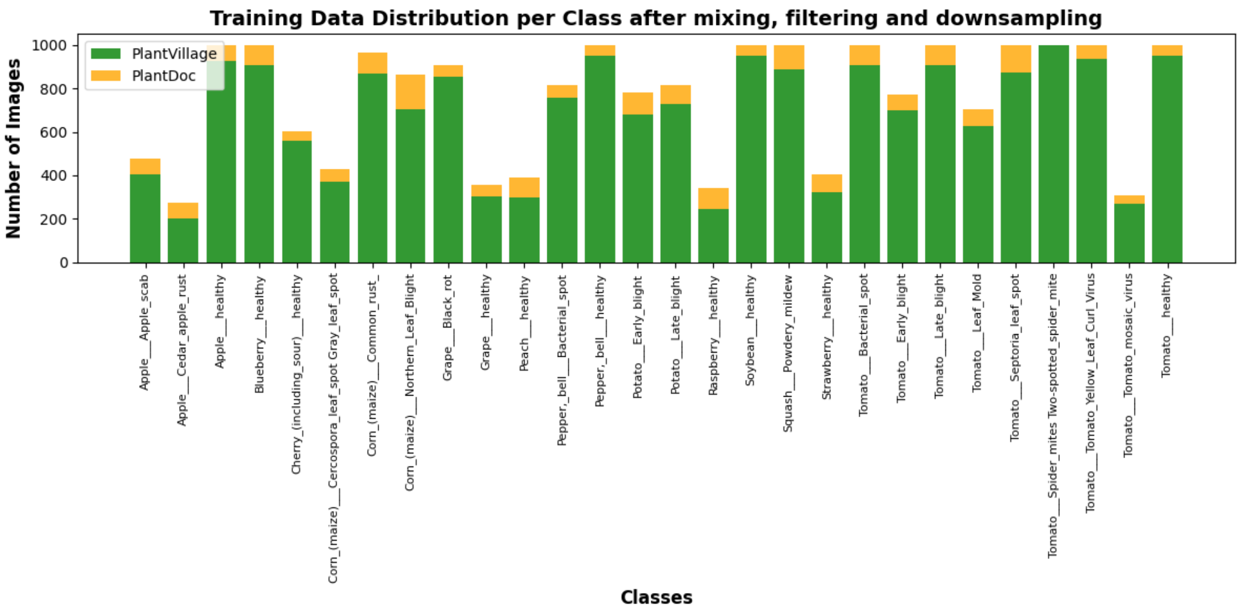


Figure 2: Data Distribution in Training Set of second stage

3.2 Network Architecture and training parameters

Following the methods of Mohanty et al. (2016), our initial setup for the baseline model included the Pytorch implementation of the pretrained AlexNet on ImageNet-1K, on which we performed transfer learning using the original PlantVillage dataset.

We applied the same hyperparameters as in Mohanty et al. (2016):

Solver Type: Stochastic Gradient Descent, Base learning rate: 0.005, Learning Rate Policy: Step(decreases by a factor of 10 every 30/3 epochs), Momentum: 0.9, Weight Decay: 0.0005, Gamma: 0.1, Batch size:100.

After filtering, mixing, and downsizing our training set, we repeated the transfer learning process on the pretrained AlexNet (ImageNet-1K), using our new training set and the same hyperparameters. We used the validation accuracy and loss in order to monitor the training process and saved intermediate versions of the model every five epochs.

Finally, building upon the optimal version of our last model, we tried fine tuning by unfreezing the last two convolutional blocks. We added early stopping with patience of five epochs and saved the model with the optimal validation performance.

3.3 Experiments

We performed tests on five different test sets, originating both from the datasets used for training and from external datasets. We calculated the accuracy (number of correctly classified test images / total number of test images %) over all training classes (38 in case of our initial model, 28 in case of the models of the next stages) but also the "restricted accuracy", for test sets that contain only a subset of the classes of the model. For restricted accuracy the predictions were made based on the highest probability among only the classes present in the test set.

4 Results

Our baseline model, trained on 80% of the PlantVillage dataset, achieved 97.77% accuracy when tested on the 20% of the same dataset. The overall accuracy on external testing sets was lower than 30%, while the restricted accuracy ranged from 22.03% to 57.69%.

While training our second model, the highest validation accuracy was achieved on epoch 20, therefore we chose that version for the test and the next training stage. Our chosen model showed 96.76% accuracy on the PlantVillage test set, 1% lower than that of the baseline model. For the rest of the testing sets, the overall accuracy increased by at least 20%, except for Crop Disease Detection, for which it dropped by 1.2%. However, for the same dataset, the restricted accuracy increased by 17%. For the other restricted test set (Apple Classes), the restricted accuracy increased by 15%.

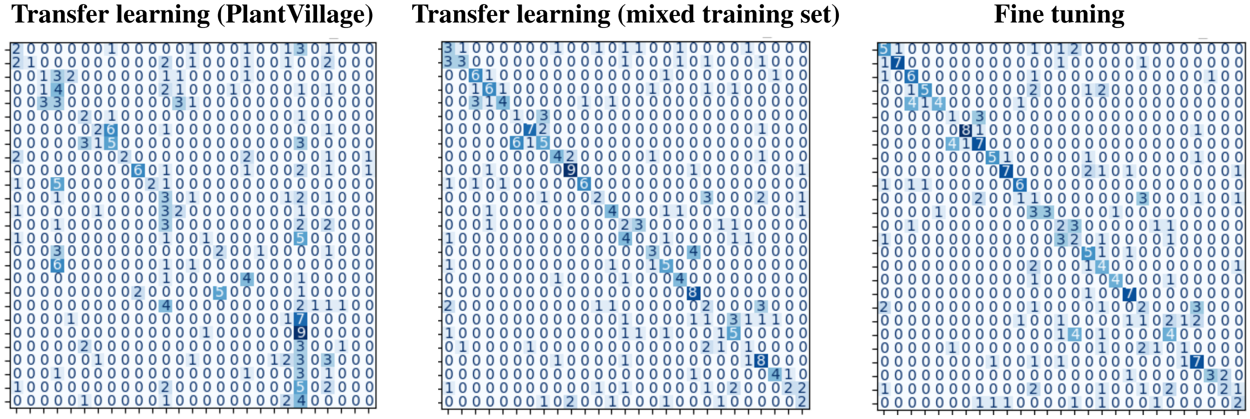
Our fine tuned model, which was trained for 10 epochs before early stopping, showed a slight increase of up to 1.14% in accuracy when tested with PlantVillage, PlantDoc and Apple Classes test sets. However, there was a decrease in accuracy, of around 2-3% for Crop Disease detection and FieldPlantVillage sets. Our detailed results are summarized in Table 3.

Table 3: Overall and Restricted Accuracy per Model and Test Set

Testing set	Transfer Learning PlantVillage (38 classes)		Transfer Learning Mixed Dataset (28 classes)		Fine Tuning Mixed Dataset	
	Overall Acc.	Restricted Acc.	Overall Acc.	Restricted Acc.	Overall Acc.	Restricted Acc.
PlantVillage	97.77% (10693/10937)	-	96.76% (7565/7818)	-	96.98% (7582/7818)	-
PlantDoc	19.49% (46/236)	22.03% (52/236)	44.92% (106/236)	-	46.61% (110/236)	-
Crop Disease Detection	15.13% (783/5176)	57.69% (2986/5176)	13.92% (692/4970)	74.67% (3711/4970)	10.26% (510/4970)	73.78% (3667/4970)
Apple Classes	10.69% (185/1730)	53.99% (934/1730)	49.65% (859/1730)	69.42% (1201/1730)	51.79% (896/1730)	70.58% (1221/1730)
FieldPlantVillage	29.17% (194/665)	-	49.63% (201/405)	-	47.16% (191/405)	-

Table 4: Confusion matrices on PlantDoc test set in the three stages of our project

Transfer learning (PlantVillage) **Transfer learning (mixed training set)** **Fine tuning**



Confusion matrices on PlantDoc test set in the three stages of our project

5 Discussion

Our baseline model's performance is similar to that reported by Mohanty et al. (2016). The poor generalization power on external datasets seems to be reasoned on the uniform and controlled background of PlantVillage images in contrast to the noisy and heterogenous images of the external datasets. This is strongly indicated by the significant improvement in accuracy (both overall and restricted) when even a relatively small set of images with these characteristics is added to the training data. The slight drop of performance on the PlantVillage test set could be explained by the reduction of variety in the training set caused by downsampling and by the model optimizing for a broader domain than PlantVillage - like images.

Fine tuning did not substantially improve the performance of our model. This might mean that the current state might be near the limit of what this model and dataset configuration can provide. Alteration of more convolutional blocks is not expected to improve accuracy, as early layers are trained to generalize well on a variety of features. This seems to also be the case for Mohanty et al (2016)., in which transfer learning outperforms training from scratch for both architectures and all the different dataset divisions and image versions (colored, grayscale, segmented). Further training steps could include data augmentation and artificial field background addition, as suggested by Gui et al., (2021).

Although our method seems to improve performance on field images, the reported accuracies are still not high enough for confident predictions on such data. In addition, as Mohanty et al. (2016) state, the model has the double task of predicting both the plant species and the disease, which complicates its applicability in real world settings.

As Gui et al. (2021) reported, further efforts are needed to enhance deep learning algorithms to achieve more accurate plant disease detection models. Currently, there are important limitations that need to be addressed. Liu et al. (2021) noted that no publicly accessible, comprehensive dataset exists to enable consistent comparison of algorithms. Dolatabadian et al. (2024) also suggested incorporating contextual field data to improve machine learning and deep learning algorithms.

6 Dataset Sources

PlantVillage: https://github.com/spMohanty/PlantVillage-Dataset

PlantDoc: https://github.com/pratikkayal/PlantDoc-Dataset

Apple Classes: https://www.kaggle.com/competitions/plant-pathology-2020-fgvc7/data

Crop Disease Detection: https://www.kaggle.com/datasets/nirmalsankalana/crop-pest-and-disease-detection/data

FieldPlantVillage: https://github.com/PatrickGui/FPDR/tree/master/data/Field-PlantVillage

References

Bay, H., Ess, A., Tuytelaars, T., and Van Gool, L. (2008). Speeded-up robust features (SURF). *Comput. Vis. Image Underst.*, 110(3):346–359.

Boulent, J., Foucher, S., Théau, J., and St-Charles, P.-L. (2019). Convolutional neural networks for the automatic identification of plant diseases. *Front. Plant Sci.*, 10:941.

Brahimi, M., Arsenovic, M., Laraba, S., Sladojevic, S., Boukhalfa, K., and Moussaoui, A. (2018). Deep learning for plant diseases: Detection and saliency map visualisation. In *Human and Machine Learning*, pages 93–117. Springer International Publishing, Cham.

Brahimi, M., Boukhalfa, K., and Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. *Appl. Artif. Intell.*, 31(4):299–315.

Dolatabadian, A., Neik, T. X., Danilevicz, M. F., Upadhyaya, S. R., Batley, J., and Edwards, D. (2025). Image-based crop disease detection using machine learning. *Plant Pathol.*, 74(1):18–38.

Gui, P., Dang, W., Zhu, F., and Zhao, Q. (2021). Towards automatic field plant disease recognition. *Comput. Electron. Agric.*, 191(106523):106523.

Hughes, D. P. and Salathe, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Commun. ACM*, 60(6):84–90.

Liu, J. and Wang, X. (2021). Plant diseases and pests detection based on deep learning: a review. *Plant Methods*, 17(1):22.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vis.*, 60(2):91–110.

Lu, Y., Yi, S., Zeng, N., Liu, Y., and Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, 267:378–384.

Mohanty, S. P., Hughes, D. P., and Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Front. Plant Sci.*, 7:1419.

Ristaino, J. B., Anderson, P. K., Bebber, D. P., Brauman, K. A., Cunniffe, N. J., Fedoroff, N. V., Finegold, C., Garrett, K. A., Gilligan, C. A., Jones, C. M., Martin, M. D., MacDonald, G. K., Neenan, P., Records, A., Schmale, D. G., Tateosian, L., and Wei, Q. (2021). The persistent threat of emerging plant disease pandemics to global food security. *Proc. Natl. Acad. Sci. U. S. A.*, 118(23):e2022239118.

Samanta, D., Chaudhury, P. P., and Ghosh, A. (2012). Scab diseases detection of potato using image processing. *International Journal of Computer Trends and Technology*, 3(1):109–113.

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., and Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Comput. Intell. Neurosci.*, 2016:3289801.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., and Rabinovich, A. (2015). Going deeper with convolutions. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE.

Too, E. C., Yujian, L., Njuki, S., and Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Comput. Electron. Agric.*, 161:272–279.

Wang, H., Li, G., Ma, Z., and Li, X. (2012). Application of neural networks to image recognition of plant diseases. In *2012 International Conference on Systems and Informatics (ICSAI2012)*. IEEE.