AGRISCIENCE AND TECHNOLOGY
Armenian National Agrarian University
ԱԳՐՈԳԻՏՈՒԹՅՈՒՆ ԵՎ ՏԵԽՆՈԼՈԳԻԱ АГРОНАУКА И ТЕХНОЛОГИЯ
International Scientific Journal
ISSN 2579-2822

OPEN ACCESS
UDC 632
doi: 10.52276/25792822-2025.2-105

Crop Disease Detection Using MobileNetV3-Small Convolutional Neural Networks (CNNs) to Support Armenian Agriculture

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ARTICLE INFO

Keywords:
AI,
Armenian agriculture,
challenges,
Convolutional Neural Networks,
crop disease detection

Conflict of Interest
The author declares no conflict of interest concerning the research, authorship, and/or publication of this article.

ABSTRACT

The agricultural sector of Armenia faces many problems, such as low productivity, small landholdings, limited technological machinery, reliance on low-value crops, and inadequate expertise. This article uses Artificial Intelligence (AI), specifically Convolutional Neural Networks (CNNs) based on MobileNetV3-Small architecture, to improve crop disease detection. The model was trained and validated using fruit and berry colored leaf images from the PlantVillage dataset. The final model achieved an accuracy of 99.25% and a macro F1-score of 0.9891 across 13 plant disease and health categories, which indicates the model's strong potential for accurate crop disease detection.

Introduction

Agriculture is one of the important sectors of Armenia and is the branch that ensures the country's food security (Avetisyan, 2010). However, despite its important role, the sector faces a number of significant problems. High production prices, limited technologies, and a shortage of agricultural specialists slow down the growth of the sector (Alaverdyan, et al., 2015). Also, small land areas, the average size of which is 1.4 hectares per household, together with severe land degradation, hinder agricultural production (International Trade Administration, 2018).

Farmers engaged in the cultivation of high-value crops often face climate risks, as a result of which potential outputs and incomes from them become unstable, hindering the ability to invest in new technologies (Alaverdyan and Nijhoff, 2024).

The development of digital technologies, especially the use of Artificial Intelligence (AI), is of great importance for solving the problems of modern agriculture. The latter helps farmers make smarter decisions using robots, sensors, machine learning (ML), and computer vision. Such technologies make it possible to quickly detect and control harmful organisms, as well as estimate crop yields, monitor soil and water quality, and properly organize irrigation (Meshram, et al., 2025).

However, agriculture in Armenia is only at an early stage of implementing AI, and therefore, investments in localized databases and infrastructure are needed to enable the detection of crop pests (IFOAM – Organics International & ICARE Foundation, 2017). Thus, understanding the global potential of AI and the specific context of Armenia is critical for success.

The ML models have already been used to detect the infected crops. In the "Automated Identification of Northern Leaf Blight-Infected Maize Plants from Field Imagery Using Deep Learning" paper by DeChant et al. (2017), CNNs were used to generate heat maps, which a final CNN then processed to classify the entire image of a diseased leaf. The model, as a result, achieved a high accuracy of 96.7% on the test set, as well as 96.8% precision and 97.4% recall.

In another study, "Detection of Plant Diseases with Artificial Intelligence Using the VGG-16 Model" by Alatawi et al. (2022), CNN built on the VGG-16 architecture was developed based on leaf images taken from the PlantVillage (Mohanty, et al., 2016) database. The model was trained on 15,915 mixed images of healthy and diseased leaves (19 types of diseases) of grapes, apples, and corn. The VGG-16 model, using ReLU and Softmax activation functions, achieved 95.2% accuracy and had a test loss of 0.4418.

CNN models can be trained, tested, and validated using datasets like PlantVillage to detect crop diseases as seen in the examples above. Models with high F1-scores, high accuracy, and low loss are considered effective and could be used in local agriculture.

To the best of the Author's knowledge, there have been similar technological attempts to boost productivity among Armenian farmers, yet no documented results were identified in the sources consulted. Hence, this research project has aimed to develop, train, test, and validate a CNN model with high accuracy and reliability to fill this gap as a foundational step, with additional work needed to adapt and implement it to a local system. The research question that guided this study is as follows: "How can AI-based crop disease detection support Armenian farmers in addressing the main productivity challenges in the agricultural sector?"

Materials and methods

This study uses innovative structures and algorithmic neural architecture to provide a balance between accuracy and latency. Howard et al. (2019) came up with the architecture, MobileNetV3, which used inverted residuals with SE blocks, optimized by NAS to increase accuracy and efficiency. Additionally, it has Hard-Swish (HS) and Hard-Mish (HM) activation functions, which balance computing efficiency and non-linearity.

The MobileNetV3 has MobileNetV3-Small and MobileNetV3-Large models, where the small one is needed for resource-constrained situations. As the fruits and berries are one of the widely cultivated crops in Armenia (Hofmann, et al., 2022), the model will be trained, tested, and validated on seven types of crops (Table 1) from PlantVillage dataset (Mohanty, et al., 2016): apples, cherries, peaches, blueberries, oranges, raspberries, and strawberries, and therefore, the model introduced in the paper will use the MobileNetV3-Small architecture.

The main parameters used for the model were as follows:

- Validation split: 0.2 (20% of data)
- Image size: 224x224 pixels
- Batch size: 64
- Class weights: balanced
- Base model: MobileNetV3-Small
- Dropout: 0.3 (30% dropout rate used after base model output)
- Dense: 13 units, softmax activation
- Epochs: 100
- Optimizer: Adam – learning rate: 0.0001 (Beta_1: 0.5, Beta_2: 0.99)
- Loss function: Categorical Cross-entropy

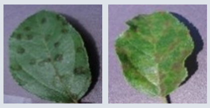
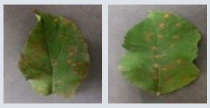
Results and discussions

In this paper, the initial validation accuracy calculated by Equation 1 and loss calculated by Equation 2 of the pre-trained MobileNetV3-Small model were 90.16% and 0.5171, respectively, which improved to achieve a maximum validation accuracy of 99.25% on the 91st epoch and a minimal validation loss of 0.032 on the 95th epoch (Figure 1).

(Eq. 1)

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}.$$

Table 1. Crop and Leaf Types with Training and Testing Images and Counts*

Plant Name	Leaf Label	Examples	Train Images	Test Images
Apple	Scab (AS)		504	126
	Black Rot (ABR)		497	124
	Cedar Apple Rust (ACAR)		220	55
	Healthy (AH)		1316	329
Cherry	Powdery Mildew (CPM)		842	210
	Healthy (CH)		684	170
Peach	Bacterial Spot (PBS)		1838	459
	Healthy (PH)		288	72
Blueberry	Healthy (BH)		1202	300
Orange	Huanglongbing (OH)		4406	1101
Raspberry	Healthy (RH)		297	74
Strawberry	Leaf Scorch (SLS)		888	221
	Healthy (St-H)		365	91

*Source: *PlantVillage dataset.*

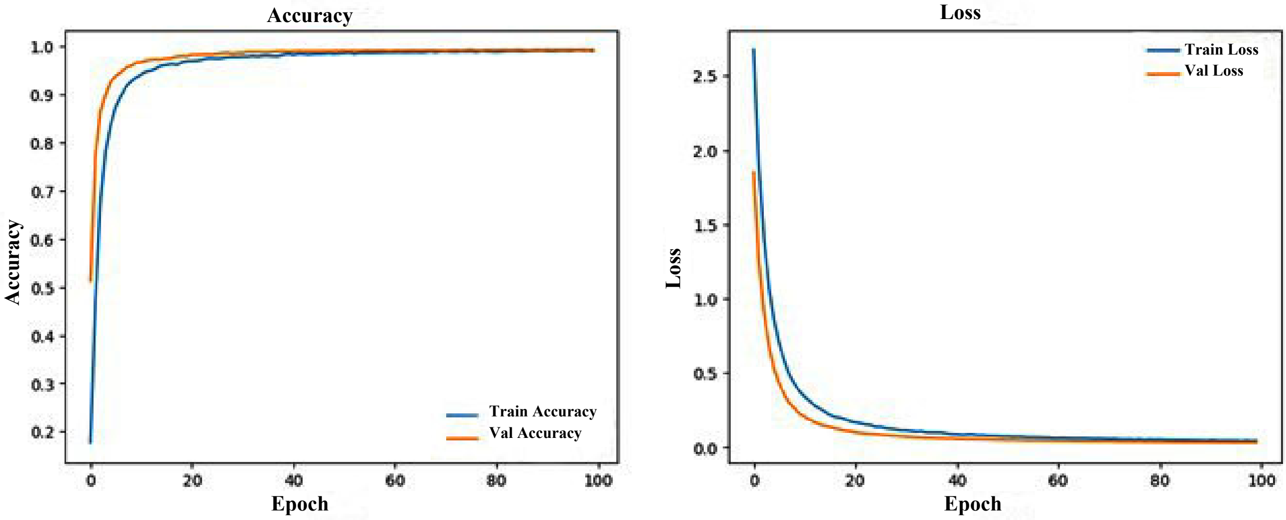


Figure 1. Training and validation loss and accuracy of a model in 100 epochs using Matplotlib (Hunter, 2007) from the Keras training history (Chollet, 2015).

(Eq. 2)

$$Loss = -\sum_{i=1}^{C} y_i \log\left(\hat{y}_i\right),$$

where C is the number of classes; y_i is the true label (1 if correct, 0 otherwise); $\hat{y}_i$ is the predicted probability for class i.

As seen in Figure 1, there are no significant fluctuating patterns in both accuracy and loss graphs, which means that the model learned effectively without overfitting.

To evaluate the performance of the MobileNetV3-Small-based model, Table 2 was created using three main classification metrics: precision (Eq. 3), recall (Eq. 4), and F1-score (Eq. 5).

(Eq. 3)

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP) + False Positives (FP)}}\ .$$

(Eq. 4)

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP) + False Negatives (FN)}}\ .$$

(Eq. 5)

$$\text{F1} = 2 \cdot \frac{\text{Precision (Eq. 3)} \cdot \text{Recall (Eq. 4)}}{\text{Precision (Eq. 3) + Recall (Eq. 4)}}\ .$$

Table 2. Precision, recall, and F1-scores for both individual and summary of classes*

Class	Precision	Recall	F1-score
Apple Scab	0.9449	0.9524	0.9486
Apple Black Rot	0.9920	1.0000	0.9960
Cedar Apple Rust	1.0000	1.0000	1.0000
Apple Healthy	0.9759	0.9848	0.9803
Blueberry Healthy	1.0000	1.0000	1.0000
Cherry Powdery Mildew	0.9952	0.9905	0.9928
Cherry Healthy	0.9940	0.9824	0.9882
Orange Huanglongbing	0.9991	0.9991	0.9991
Peach Bacterial Spot	0.9978	0.9847	0.9912
Peach Healthy	0.9595	0.9861	0.9726
Raspberry Healthy	1.0000	1.0000	1.0000
Strawberry Leaf Scorch	1.0000	1.0000	1.0000
Summary Metrics			
Accuracy	—	—	0.9925
Macro Average	0.9875	0.9908	0.9891
Weighted Average	0.9926	0.9925	0.9925

*Composed by the author.

The table 2 provides an understanding of the model's ability to identify 13 different classes of plant health and disease accurately.

The results of the analysis show that the model works effectively on all 13 classes. For many classes, the F1-score exceeds 0.98, and for some classes, such as Cedar Apple Rust, Blueberry Healthy, Raspberry Healthy, and Strawberry Leaf Scorch, it reaches the maximum value of 1.0000. The 0.9891 macro and 0.9925 weighted F1-scores, as well as 99.25% accuracy, show that the model is not only reliable but also performs well when the classes are imbalanced.

The normalized confusion matrix shown in Figure 2 helps to analyze the model's classification behavior further and understand which classes the model distinguished correctly and which classes it mislabeled.

The Y-axis shows the real classes of the crop leaf images, and the X-axis shows the classes predicted by the CNN model. Each cell tells how often a real class was expected as a particular class. The blue cells on the diagonal are correct predictions — darker color means higher accuracy. The normalized values from 0 to 1 inside the cells show the proportion of predictions for each class.

t-SNE visualization (Figure 3) applied to high-dimensional feature vectors extracted by the final layers of the model additionally helps to understand how the model internally organizes the learned patterns. It is a nonlinear dimensional reeducation technique that projects high-dimensional data onto a 2D space while preserving local structures.

The visualization shows the clusters, which are either well-separated and compact or scattered and partially mixed with others. Blueberry Healthy, Cherry Powdery Mildew, Cherry Healthy, Orange, Cedar Apple Rust, Raspberry Healthy, Strawberry Leaf Scorch, and Strawberry Healthy show isolated clusters. While Apple Black Rot, Peach Bacterial Spot, Peach healthy, and the rest have slight overlaps with each other and feature separation is more challenging, the model showed promising results in these classes.

Overall, this visualization confirms that the model has developed to a stage where it can clearly distinguish between plant leaf conditions.

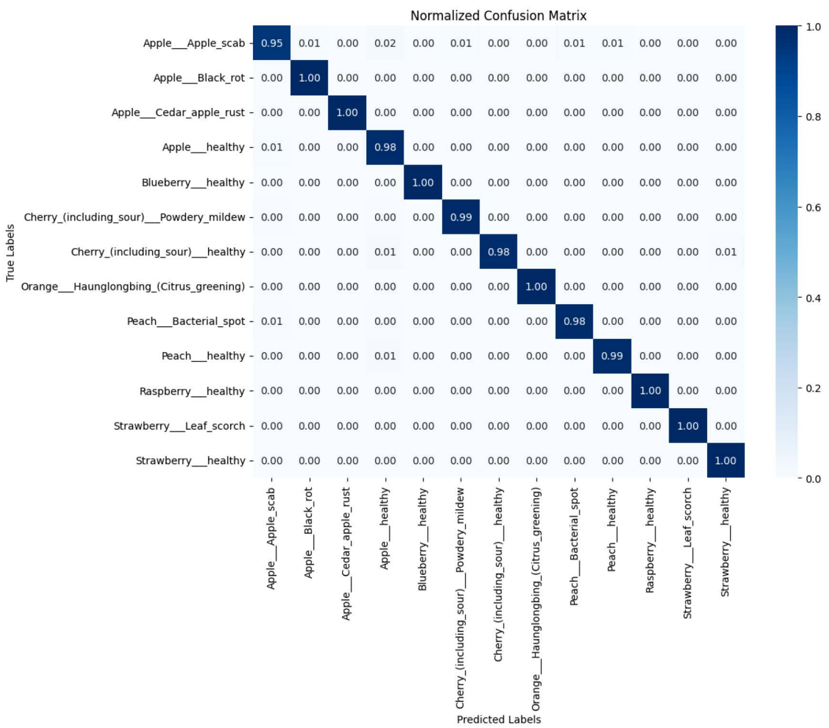


Figure 2. Confusion matrix showing proportions of predictions for each class (*generated using scikit-learn (Pedregosa et al., 2011) for confusion matrix computation and Matplotlib (Hunter, 2007) for visualization*).

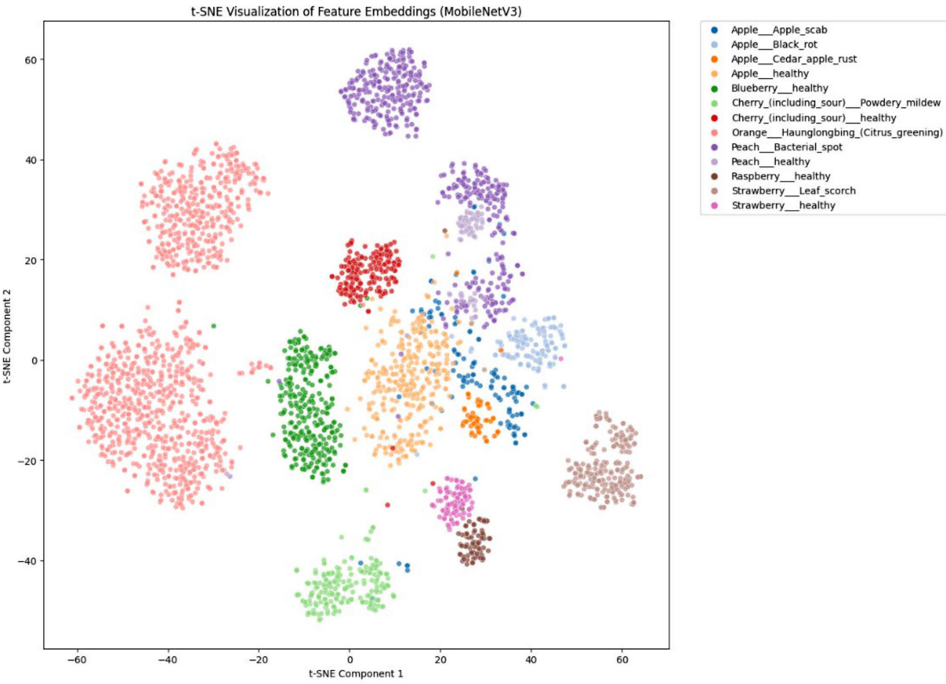


Figure 3. t-SNE Visualization (*van der Maaten & Hinton, 2008*) of Feature Embeddings from the model.

Conclusion

The model's accuracy reached 99.25% with a macro-F1 score of 0.9891. It shows a strong potential, primarily when the study was conducted using sparse and unbalanced materials from the PlantVillage dataset.

Class imbalance in the dataset might've skewed the performance; however, the model didn't have any fluctuating results and achieved high outcomes. Nevertheless, the study has some limitations as it didn't consider Armenia-specific factors such as soil conditions or local pests, and did not include field testing and Decision Support Systems (DSS), which limits how useful it is in real farming.

Future research could support Armenian farmers by creating a local dataset (fruits, berries, grains, vegetables), validating the model in the fields, and integrating CNNs with a Decision Support System (DSS) for actionable recommendations. These steps would help reduce crop losses, improve disease monitoring, and boost AI-based disease detection, automation, and adoption in Armenia.

References

1. Alatawi, A. A., Alomani, S. M., Alhawiti, N. I., & Ayaz, M. (2022). Plant disease detection using AI based VGG-16 model. International Journal of Advanced Computer Science and Applications, 13(4). https://doi.org/10.14569/IJACSA.2022.0130484.
2. Alaverdyan, D., Kehende, O., & Panosyan, I. (2015). Analysis of Agricultural Production and Programs in Armenia. International Journal of Innovation and Scientific Research, 17(2). https://ijisr.issr-journals.org/abstract.php?article=IJISR-15-113-06.
3. Avetisyan, S. (2010). Agriculture and food processing in Armenia, 135 p. https://library.asue.am/open/4941.pdf.
4. Chollet, F. (2015). Github. https://github.com/fchollet/keras.
5. DeChant, C., Wiesner-Hanks, T., Chen, S., Stewart, E. L., Yosinski, J., Gore, M. A., ... & Lipson, H. (2017). Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning. Phytopathology, 107(11), 1426-1432. https://doi.org/10.1094/phyto-11-16-0417-r.
6. Hofmann, M., Schierhorn, F., Müller, D., Egamberdiev, B., & Bobojonov, I. "Development of an MSE Multi-Peril Risk Management Concept" Report-Work Package 5. - Armenia. https://lsg.iamo.de/microsites/lsg.iamo.de/fileadmin/Dokumente/TR_Armenia.pdf.
7. Howard, A., Sandler, M., Chu, G., Chen, L. C., Chen, B., Tan, M., ... & Adam, H. (2019). Searching

for mobilenetv3. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 1314-1324). https://doi.org/10.48550/arXiv.1905.02244.

8. Hunter, J. D. (2007). Matplotlib: A 2D Graphics Environment. Computing in Science & Engineering, 9(3). https://doi.org/10.1109/MCSE.2007.55.

9. IFOAM – Organics International, & ICARE Foundation (2017). Capacity Development Strategy and Plan for the Organic Agriculture Sector in Armenia. https://www.entwicklung.at/fileadmin/user_upload/Dokumente/Publikationen/Downloads_Laender_DivBerichte/Armenien/Armenia_Organic_Capacity_final_EN.PDF.

10. International Trade Administration. (2018). Armenia Country Commercial Guide - Agricultural Sector | Privacy Shield. https://www.privacyshield.gov/ps/article?id=Armenia-agribusiness.

11. Maaten, L. van der, & Hinton, G. (2008). Visualizing Data using t-SNE. Journal of Machine Learning Research, 9(86). https://www.jmlr.org/papers/v9/vandermaaten08a.html.

12. Meshram, K., Mishra, U., & Rathnayake, U. (2025). Application of Artificial Intelligence in Agri-Tech, Environmental and Biodiversity Conservation. Array, 100412. https://doi.org/10.1016/j.array.2025.100412.

13. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 215-232. https://doi.org/10.3389/fpls.2016.01419.

14. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12(85). https://www.jmlr.org/papers/v12/pedregosa11a.html.

15. The World Bank. (2024). Armenia Firms' Adoption of Digital Technologies. https://openknowledge.worldbank.org/entities/publication/ff590e28-c0ba-4bbb-8918-05f8b185ff90.

Received on 30.04.2025
Revised on 02.06.2025
Accepted on 30.06.2025