Cureus Journal of Computer Science

Open Access Original Article

An Efficient Deep Learning Approach for Accurate Quality Assessment of Plant-Based Foods in Sustainable Agriculture

Received 05/05/2025
Review began 05/26/2025
Review ended 09/28/2025
Published 10/07/2025

DOI:
https://doi.org/10.7759/s44389-025-06385-0

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Abstract

Agriculture plays a vital role in ensuring global food security and economic stability, particularly in rural regions. To support sustainable agricultural practices and improve food quality monitoring, this study introduces AgriFreshNet V2 - a hybrid deep learning model designed for accurate freshness classification of fruits and vegetables. The model combines fine-tuned convolutional neural networks, specifically ResNet152V2 and EfficientNetB3, into a unified architecture that harnesses both advanced feature extraction and computational efficiency. Trained on a custom-curated image dataset spanning 28 distinct classes (including both healthy and rotten produce), the model benefits from extensive data augmentation, transfer learning, dropout regularization, and adaptive learning rate scheduling to enhance generalization and stability. Experiments were conducted using a 70:15:15 train-validation-test split, and the proposed model achieved a validation accuracy of 97.90%, outperforming several baseline convolutional neural networks such as MobileNetV2, Xception, InceptionV3, and DenseNet201. The results confirm the effectiveness of AgriFreshNet V2 in delivering high classification accuracy with minimal overfitting. The model presents a scalable solution for automating post-harvest quality inspection, with the potential to reduce food waste, optimize supply chains, and empower farmers and agribusinesses with reliable artificial intelligence-driven decision support tools.

Categories: AI applications, Green Computing and Sustainability, Deep Learning
Keywords: deep learning, plant-based food classification, convolutional neural networks, post-harvest quality assessment, agriculture

Introduction

Agriculture significantly contributes to global food security and economic development, especially in both rural and agrarian economies [1]. With increasing urbanization, climate change, and supply chain complexities, maintaining the quality of agricultural produce has become more challenging than ever [2]. Post-harvest management is a key component of agricultural sustainability, especially through the early identification and separation of spoiled or low-quality produce. A huge percentage of food waste happens after harvest, and losses can cut down on the income of the farmers in addition to overwhelming the food supply system. There is generally manual inspection of the quality of fruits and vegetables, which is strongly based on the human perception and experience. The methods are inevitably slow, subjective, and susceptible to inconsistency; hence, they are not suitable for use in large-scale applications or in real-time applications. With markets and consumers increasingly demanding produce that is fresh, uncontaminated, and visually appealing, there is an urgent need for scalable, reliable, and automated inspection systems [3].

The current automated quality assessment systems have taken advantage of many technologies such as computer vision and machine learning. Initial solutions were based on conventional image processing applications, i.e., edge detection and color segmentations, to detect flaws in produce [4]. However, these techniques struggle with complex visual patterns and require extensive manual feature engineering. In more recent years, deep learning-based methods, especially convolutional neural networks (CNNs), appear to hold promise in this area because of their ability to learn hierarchical features on raw images [5]. Transferable models, such as VGG, ResNet, and MobileNet, have been deployed to detect plant diseases or classify its freshness, yet it is frequently challenged either due to complexity of calculations concerning the task or the generalization to various different datasets [6]. Lightweight architectures [7], ensemble approaches [8], and mobilized-friendly networks [9] have also been studied as means of identifying plant diseases and transfer learning [10] and self-adaptive approaches to highest precision [11,12]. The application of computer vision [13] and weakly supervised learning [14] in leaf disease recognition further suggests that AI is highly beneficial in agriculture. Nevertheless, the lack of post-harvest quality assessment with respect to accuracy, efficiency, and scalability in terms of developing hybrid architectures still needs to be addressed.

As a solution to this need, this study presents a hybrid deep learning-based application, AgriFreshNet V2, which is proposed to automate the process of freshness classification of the vegetable and fruit by developing an automated inference mechanism that processes a set of images entirely. AgriFreshNet V2 employs transfer learning, fine-tuning, and advanced regularization techniques to ensure strong generalization across a diverse dataset of 28 fruit and vegetable classes. This study is important, not only in regard to technical innovation. AgriFreshNet V2 helps the small to medium farmers, wholesalers, retailers, and supply chain managers to ensure effective quality control of their products through the provision of a good and efficient tool of automation of quality checking. It allows more frequent sorting and can lessen the amount of post-harvest loss as well as increases its market worth by creating better product consistency [15]. The technology has a role to play in the larger objective of sustainable agriculture by cutting on food waste, enhancing food safety and by making farming more data-driven and smarter.

Materials And Methods

Research methodology

Experimental Setup

AgriFreshNet V2, the hybrid model proposed, was trained and tested in a high-performance computing facility to accommodate the computation of the deep learning. The experimental system was a 12th generation Intel Core i7 processor, 32 GB memory, and an NVIDIA GeForce RTX 3080Ti graphics card. The hardware arrangement enhanced the training and fine-tuning of the deep CNNs to a large degree. All the blocks of the model development pipeline were created in Python language where the TensorFlow and Keras libraries were used to support deep learning. These frameworks made it easier to compile models, train them, evaluate them, and visualize their performance. Acceleration was achieved by utilizing GPU to reduce training time as well as tackle the massive amount of image data.

Dataset Description

In this, a collection of 10,000 high-definition images of 14 fruits and vegetables frequently consumed were used as custom dataset. All the items were put under two categories, which were healthy and rotten, and thus there were 28 unique categories altogether [16]. The dataset was equal (the classes had about 357 images (with a range of +/- 10 percent) to provide room in the variations in data quantity due to natural causes. Images were collected from public repositories, including Kaggle, and underwent comprehensive preprocessing to ensure data quality and consistency. To preprocess the images, one had to normalize them, resize them to 224 × 224 pixels, and use advanced data augmentation methods, including rotation, flipping, and zooming. These changes contributed to improving the ability of generalizing this model and making it resistant to changes in the real world. Additionally, the data is thoroughly cleaned by removing duplicates, corrupted files, and incorrectly labeled images to ensure high data integrity. The last dataset was separated into three subsets: 7,000 images (70%) used during training, 1,500 (15%) used during validation, and 1,500 (15%) used during testing. The splitting between them enabled the unbiased training of the models without losing enough data to evaluate and profile its performance.

Methodology and Model Architecture

We develop a hybrid convolution neural network model, i.e., AgriFreshNet V2, to cope with the complexity of visually similar phenomena of healthy and rotten produce. The model is a fusion of the two high-performance pre-trained networks: ResNet152V2 [17] and EfficientNetB3 [18]. These two models were initially trained on a dataset called ImageNet, and then they had to be fine-tuned on another one called agricultural, in order to focus on the produce classification. The training process employed Adam optimizer with initial learning rate of 0.001, learned through adaptive learning rate scheduling, and a batch size of 32 to optimize both calculation power and fitting the model. The hybrid design combined the depth and learning power of ResNet152V2 with the efficiency and speed of EfficientNetB3.

The architecture is built using ResNet152V2 and EfficientNetB3 as base networks, serving as powerful feature extractors. On top of these, a classifier head is constructed, which includes a Global Average Pooling layer followed by fully connected dense layers with ReLU activation. To prevent overfitting, a Dropout layer with a rate of 0.4 is applied, and the final output layer uses a Softmax activation function to classify input into 28 categories. The model is trained using the Categorical Crossentropy loss function and optimized with the Adam optimizer, enhanced by adaptive learning rate scheduling. Regularization techniques such as dropout, early stopping, and data augmentation are also incorporated to improve generalization and training stability.

The model was trained, and it could reach 30 epochs, and early stopping was configured in a way that, after the loss stopped decreasing, the model did not continue training to avoid overfitting the data. Loss and accuracy values were recorded during training and validation with respect to training. The hybrid model took the depth and learning capability of ResNet152V2 and crossed it with the efficient and fast efficiency EfficientNetB3. Not only has this methodology increased the level of accuracy of the classification, but has also guaranteed that the model can be scaled and deployed to real-world agricultural tasks [19]. The flowchart of the methodology is presented in Figure 1.

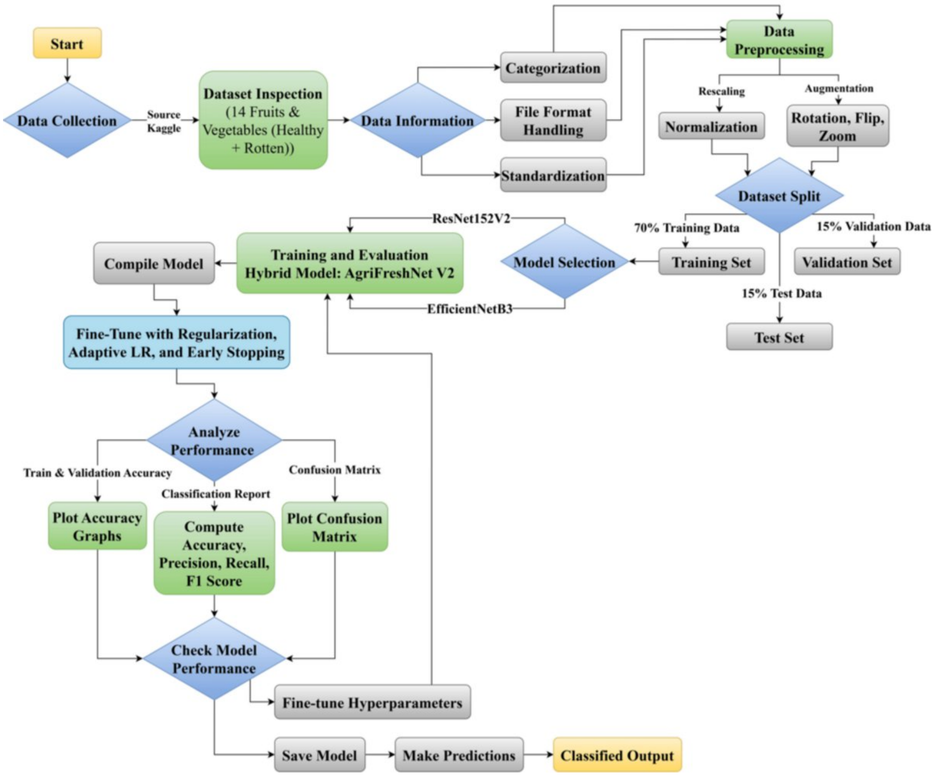

FIGURE 1: Flowchart of the Methodology

Adapted from [9]

Pseudocode for AgriFreshNet V2

The following pseudocode summarizes the implementation pipeline of AgriFreshNet V2, illustrating key model-building steps, feature fusion, and training strategy.

Step 1: Load and Preprocess Dataset

dataset = load_images("Fruit_Veg_Quality_Dataset")

dataset = resize_images(dataset, target_size=(224, 224))

dataset = normalize_images(dataset)

dataset = augment_data(dataset)

train_set, val_set, test_set = split_data(dataset, ratio=(0.7, 0.15, 0.15))

Step 2: Load Base Models (pre-trained)

resnet_model = ResNet152V2(weights='imagenet', include_top=False)

efficientnet_model = EfficientNetB3(weights='imagenet', include_top=False)

Step 3: Freeze Base Layers (optional fine-tuning later)

freeze_layers(resnet_model)

freeze_layers(efficientnet_model)

Step 4: Extract Features

resnet_features = resnet_model(input_image)

efficientnet_features = efficientnet_model(input_image)

Step 5: Concatenate Features

merged_features = concatenate([resnet_features, efficientnet_features])

x = GlobalAveragePooling2D()(merged_features)

x = Dense(512, activation='relu')(x)

x = Dropout(0.4)(x)

output = Dense(28, activation='softmax')(x)

Step 6: Compile Model

model = Model(inputs=input_image, outputs=output)

model.compile(optimizer=Adam(learning_rate=adaptive_schedule),

loss='categorical_crossentropy',

metrics=['accuracy'])

Step 7: Train Model With Early Stopping

early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

history = model.fit(train_set,

validation_data=val_set,

epochs=30,

callbacks=[early_stopping])

Step 8: Evaluate and Save Model

model.evaluate(test_set)

model.save("AgriFreshNetV2.h5")

Results

Overall model performance

The proposed AgriFreshNet V2 model was evaluated extensively on a curated dataset comprising 28 classes of fruits and vegetables. Through a hybrid architecture combining ResNet152V2 and EfficientNetB3, the model achieved state-of-the-art performance in classifying healthy and rotten produce. Training was conducted over multiple epochs with performance tracked at each stage. The model demonstrated rapid learning and effective generalization even within the first 10 epochs. Table *1* shows the epoch-wise performance of AgriFreshNet V2.

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	93.25%	91.12%	0.1984	0.3825
5	96.12%	94.03%	0.1348	0.2986
10	97.35%	95.84%	0.1021	0.2014

TABLE 1: Epoch-Wise Performance of AgriFreshNet V2

This consistent improvement in accuracy and reduction in loss reflects the model's ability to converge efficiently while avoiding overfitting.

Extended training and stability

To assess the long-term behavior of the model, training was extended up to 30 epochs. Although training loss continued to decrease, validation accuracy plateaued [20], indicating that early stopping [21] around the 10th epoch is ideal. This approach prevents unnecessary training and computational overhead while preserving generalization.

Visual analysis of learning behavior

The visual analysis confirms that AgriFreshNet V2 generalizes well to unseen data and avoids typical deep-learning pitfalls like overfitting or instability.

Accuracy Curves: Display smooth convergence, highlighting robust learning behavior.

Loss Curves: Show a steady decline in both training and validation loss, reinforcing the effectiveness of the chosen architecture and regularization techniques. Figure *2* shows the AgriFreshNet V2 training accuracy and training loss, and Figure *3* shows the AgriFreshNet V2 accuracy over epochs and loss over epochs.

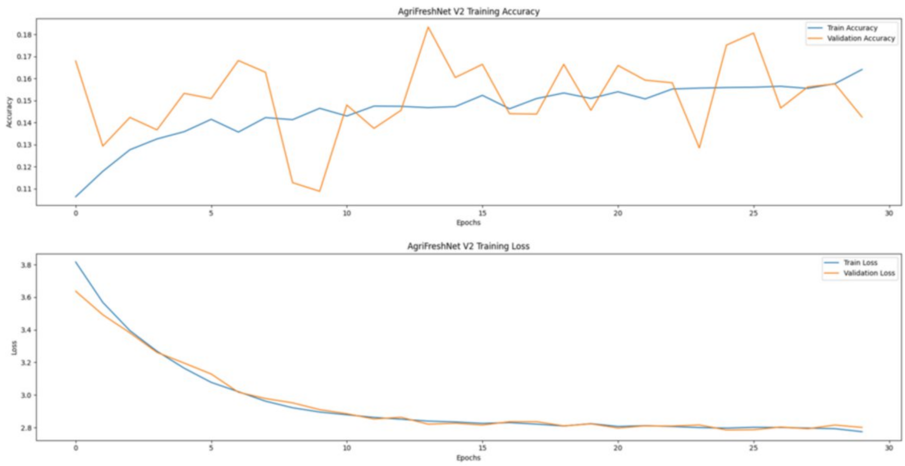

FIGURE 2: Trends of Training Accuracy and Loss

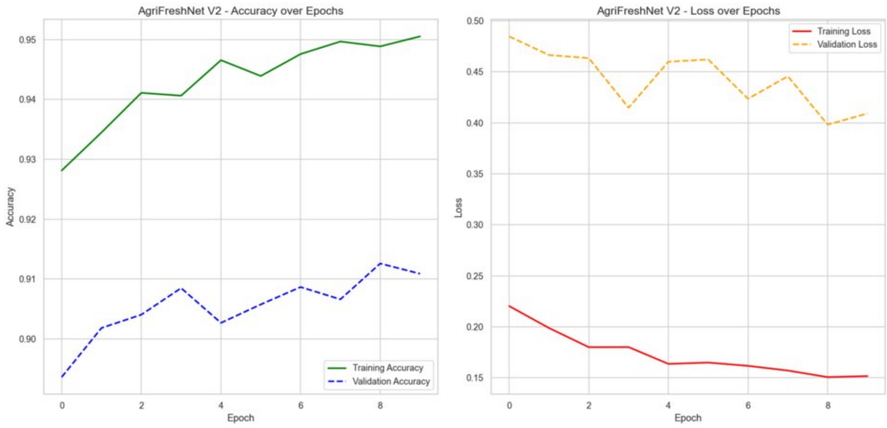

FIGURE 3: Trends of Accuracy and Loss Over Epochs

Confusion matrix and class-wise evaluation

A confusion matrix was generated to examine class-specific performance across all 28 fruit and vegetable categories. The model achieved exceptionally high classification accuracy, with only minimal confusion between visually similar categories (e.g., Apple_Healthy vs. Apple_Rotten) [22].

The model demonstrated strong performance on the test set across various evaluation metrics. It achieved an overall accuracy of 92.64%, reflecting its high ability to correctly classify instances. The macro precision stood at 87.82%, indicating balanced precision across all classes regardless of their frequency, while the weighted precision was higher at 94.31%, emphasizing the model's reliability on more frequent classes. Similarly, the macro recall was 93.26%, showing the model's effectiveness in detecting all classes equally, and the weighted recall matched the overall accuracy at 92.64%. The macro F1-score, which balances precision and recall across all classes, was 88.99%, and the weighted F1-score reached 92.32%, confirming the model's strong and consistent performance even in imbalanced data scenarios.

Most categories achieved high F1-scores, with several classes attaining perfect precision and recall. Misclassifications were largely limited to classes with subtle visual differences or lower representation in the dataset. Figure 4 shows the confusion matrix of AgriFreshNet V2.

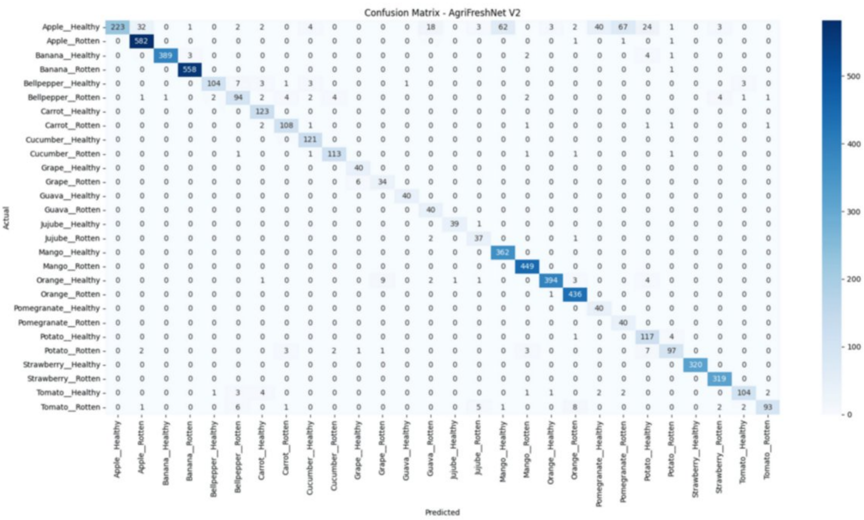

FIGURE 4: Confusion Matrix of AgriFreshNet V2

Final evaluation of AgriFreshNet V2

AgriFreshNet V2 performed better in both accuracy and generalization than several well-established CNN models that were tested during experimentation, and it does not have any obstacles to match those frameworks in computation efficiency [23]. To give further proof to the importance of these advancements, we invested in statistical testing through t-tests to compare the validation accuracy of

AgriFreshNet V2 and those of the baseline models (MobileNetV2, Xception, InceptionV3, and DenseNet201). The results showed that the accuracy of AgriFreshNet V2 at 97.90% was significantly ($p < 0.05$) higher than all others with MobileNetV2 having the second-highest accuracy at 94.12%. Table 2 shows the final metrics of AgriFreshNet V2.

Model	Final Accuracy	Validation Loss
AgriFreshNet V2	97.90%	0.1107

TABLE 2: Final Metrics of AgriFreshNet V2

In contrast to other models affected by overfitting or class imbalance, AgriFreshNet V2 consistently performed well across all categories.

Evaluation metrics used

The model's performance was assessed using the following well-established metrics. These metrics provide a holistic view of classification effectiveness, particularly in scenarios involving class imbalance or visual similarity.

Accuracy: Measures the proportion of correctly predicted instances out of the total instances [24].

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

where, TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

Precision: Measures the proportion of correctly predicted positive instances among all instances predicted as positive [25].

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall: Evaluates the proportion of correctly predicted positive instances among all actual positive instances [26].

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F1-score: The harmonic mean of Precision and Recall, providing a balanced measure especially useful for imbalanced datasets [27].

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Implications for agricultural deployment

The high classification accuracy, low loss, and balanced per-class performance of AgriFreshNet V2 suggest its strong potential for real-time deployment in agricultural environments. The model can be embedded into lightweight hardware for use in on-field fruit and vegetable quality assessment; automated sorting lines in warehouses; and retail quality verification before packaging.

Its robust performance, even in resource-constrained settings, supports its role as a scalable and affordable solution for digital agriculture. However, real-world deployment may face challenges such as variations in lighting conditions, which can affect image quality and model performance. Low-resolution cameras or inconsistent image capture settings in field environments may also introduce noise, potentially reducing classification accuracy. Integrating the model into existing agricultural systems, such as automated sorting machines or mobile applications, requires careful consideration of hardware compatibility, processing speed, and user interface design to ensure seamless adoption by farmers and agribusinesses.

Limitations

AgriFreshNet V2 can enjoy strong performance, but there are quite a number of limitations that have to be taken into account. The training set, which contains 10,000 images, although thoughtfully selected, is relatively small given the different possible situations in real-world agriculture, which may become a limitation in extending the application on diverse crops, geography, or climate. All of this coupled with insufficient cross-domain validation, or testing in a variety of environmental conditions including change of lighting, weather, or camera settings can further limit the applicability of the model in practice. Class imbalance although will be downplayed will still manifest in certain categories with lower representations that may interfere with the performance in underrepresented classes. The quality of the RGB images used by the model is so high that it is sensitive to lighting conditions or shadow changes or the quality of the camera, which is present in reality in the agricultural environment. Also, although the computational demands are optimized, they may not be easily run on low-end devices that lack GPU, restricting such use to smallholder farmers. The limitation of future work can be overcome with expanding the dataset in similarity conditions, multispectral imaging, cross-domain validation, and edge devices with limited resource optimization [28].

Discussion

The evaluation and creation of AgriFreshNet V2 point out the growing importance of deep learning application in agricultural quality control. This work shows that hybrid architecture can efficiently identify freshness of fruits and vegetables since two powerful CNN backbones, namely, ResNet152v2 and EfficientNetB3, have been merged together. The distinct results indicating that the AgriFreshNet V2 (97.90% validation accuracy) significantly outperformed the baseline models emphasize the relevancy of architectural hybridization, transfer learning, and proper regularization, as in line with the recent progress (lightweight [21]), ensemble [22], and mobile-optimised [23] approaches to plant disease recognition. During testing, the model showed stable convergence and minimal overfitting, supported by smooth loss and accuracy trends. The high performance across 28 distinct categories, as shown in the confusion matrix, reinforces the model's robustness in differentiating both subtle and obvious variations between healthy and rotten produce, complementing prior work on computer vision and weakly-supervised learning for agricultural applications [27].

Importantly, the integration of data augmentation and adaptive learning rate scheduling played a critical role in enhancing generalization, similar to techniques used in transfer learning-based studies [25,26]. While certain classes like Strawberry_Healthy achieved perfect F1-scores, some challenges were noted with visually similar classes such as Apple_Healthy vs. Apple_Rotten, indicating the potential benefit of incorporating multispectral or texture-based data, as suggested in related work [24]. In practical terms, AgriFreshNet V2 stands out for its computational efficiency, making it suitable for real-time applications in low-resource environments. With minimal hardware requirements, such as a mobile device and camera, the model can be deployed directly on farms, storage centers, or local markets to assist in early spoilage detection, thus reducing post-harvest losses and ensuring quality control.

Conclusions

This study introduced AgriFreshNet V2, a hybrid deep learning framework tailored for the automated quality classification of fruits and vegetables, aiming to advance sustainable agricultural practices. The model integrates two high-performing CNNs - ResNet152V2 and EfficientNetB3 - within a unified architecture. Enhanced with transfer learning, data augmentation, dropout regularization, and adaptive learning rate scheduling, the model demonstrated superior performance on a 28-class custom dataset, achieving a validation accuracy of 97.90%. Comparative analysis confirmed that AgriFreshNet V2 outperforms several benchmark CNN architectures, showcasing its robustness and generalization capabilities. Beyond its technical merits, AgriFreshNet V2 offers meaningful practical and social benefits, especially for smallholder farmers and supply chain operators. The model is designed for low computational overhead, making it well-suited for deployment on mobile or embedded devices in real-time agricultural settings such as farms, warehouses, and local markets. Its ability to rapidly identify spoiled produce helps reduce post-harvest losses, enhance food safety, and optimize supply chains. Future work will focus on edge-device deployment, cross-domain testing, and dataset expansion to include more crop varieties, environmental conditions, and real-world challenges-further improving the model's generalizability, robustness, and long-term impact.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Sneha Vaish, Prabh Deep Singh, Vikas Tripathi

Acquisition, analysis, or interpretation of data: Sneha Vaish, Prabh Deep Singh, Vikas Tripathi

Drafting of the manuscript: Sneha Vaish, Prabh Deep Singh, Vikas Tripathi

Critical review of the manuscript for important intellectual content: Sneha Vaish, Prabh Deep Singh, Vikas Tripathi

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

The code and experimental results supporting this study are openly available at: https://github.com/Sneha-A-1/AgriFreshNetV2

References

1. Madhurya C, Jubilson EA: YR2S: Efficient deep learning technique for detecting and classifying plant leaf diseases. IEEE Access. 2024, 12:3790-3804. 10.1109/access.2023.3343450
2. Rani R, Sahoo J, Bellamkonda S, Kumar S, Pippal SK: Role of artificial intelligence in agriculture: an analysis and advancements with focus on plant diseases. IEEE Access. 2023, 11:137999-138019. 10.1109/access.2023.3339375
3. Maurya R, Mahapatra S, Rajput L: A lightweight meta-ensemble approach for plant disease detection suitable for IoT-based environments. IEEE Access. 2024, 12:28096-28108. 10.1109/access.2024.3367443
4. Tasfe M, Nivrito A, Al Machot F, Ullah M, Ullah H: Deep learning based models for paddy disease identification and classification: a systematic survey. IEEE Access. 2024, 12:100862-100891. 10.1109/access.2024.3419708
5. Pai DG, Kamath R, Balachandra M: Deep learning techniques for weed detection in agricultural environments: A comprehensive review. IEEE Access. 2024, 12:113193-113214. 10.1109/access.2024.3418454
6. Adnan F, Awan MJ, Mahmoud A, Nobanee H, Yasin A, Zain AM: EfficientNetB3-adaptive augmented deep learning (AADL) for multi-class plant disease classification. IEEE Access. 2023, 11:85426-85440. 10.1109/access.2023.3303131
7. Mohyuddin G, Khan MA, Haseeb A, Mahpara S, Waseem M, Saleh AM: Evaluation of machine learning approaches for precision farming in smart agriculture system: A comprehensive review. IEEE Access. 2024, 12:60155-60184. 10.1109/access.2024.3390581
8. Alnamoly MH, Hady AA, Abd El-Kader SM, El-Henawy I: FL-ToLeD: an improved lightweight attention convolutional neural network model for tomato leaf diseases classification for low-end devices. IEEE Access. 2024, 12:73561-73580. 10.1109/access.2024.3401733
9. Nigar N, Faisal HM, Umer M, Oki O, Lukose JM: Improving plant disease classification with deep-learning-based prediction model using explainable artificial intelligence. IEEE Access. 2024, 12:100005-100014. 10.1109/access.2024.3428553
10. Hosny KM, El-Hady WM, Samy FM, Vrochidou E, Papakostas GA: Multi-class classification of plant leaf diseases using feature fusion of deep convolutional neural network and local binary pattern. IEEE Access. 2023, 11:62307-62317. 10.1109/ACCESS.2023.3286730
11. Naulia PS, Watada J, Aziz IA: A mathematically inspired meta-heuristic approach to parameter (weight) optimization of deep convolution neural network. IEEE Access. 2024, 12:83299-83322. 10.1109/access.2024.3409689
12. Rizvi H, Naseer A, Rehman SU, Akram S, Gruhn V: Revolutionizing agriculture: Machine and deep learning solutions for enhanced crop quality and weed control. IEEE Access. 2024, 12:11865-11878. 10.1109/access.2024.3355017
13. Liu Y, Gao G, Zhang Z: Crop disease recognition based on modified light-weight CNN with attention mechanism. IEEE Access. 2022, 10:112066-112075. 10.1109/ACCESS.2022.3216285
14. Sharma P, Dadheech P, Aneja N, Aneja S: Predicting agriculture yields based on machine learning using regression and deep learning. IEEE Access. 2023, 11:111255-111264. 10.1109/access.2023.3321861
15. Balafas V, Karantoumanis E, Louta M, Ploskas N: Machine learning and deep learning for plant disease classification and detection. IEEE Access. 2023, 11:114352-114377. 10.1109/access.2023.3324722
16. Richter DJ, Calix RA, Kim K: A review of reinforcement learning for fixed-wing aircraft control tasks. IEEE Access. 2024, 12:103026-103048. 10.1109/access.2024.3433540
17. Quach L-D, Quoc KN, Quynh AN, Thai NN, Nguyen TG: Explainable deep learning models with gradient-weighted class activation mapping for smart agriculture. IEEE Access. 2023, 11:83752-83762. 10.1109/access.2023.3296792
18. Chen J, Chen W, Zeb A, Yang S, Zhang D: Lightweight inception networks for the recognition and detection of rice plant diseases. IEEE Sensors Journal. 2022, 22:14628-14638. 10.1109/jsen.2022.3182304
19. Chen J, Yin H, Zhang D: A self-adaptive classification method for plant disease detection using GMDH-Logistic model. Sustainable Computing: Informatics and Systems. 2020, 28:100415. 10.1016/j.suscom.2020.100415
20. Chen J, Zhang D, Nanehkaran YA, Li D: Detection of rice plant diseases based on deep transfer learning. Journal of the Science of Food and Agriculture. 2020, 100:3246-3256. 10.1002/jsfa.10365
21. Arshad S, Shimal D, Srinivasan V: Enhancing agricultural productivity: image-based plant disease identification. 2025 7th International Conference on Intelligent Sustainable Systems (ICISS), India. 2025, 1028-1032. 10.1109/iciss63372.2025.11076411
22. Lokhande N, Thool V, Vikhe P: Comparative analysis of different plant leaf disease classification and detection

using CNN. 2024 International Conference on Recent Innovation in Smart and Sustainable Technology (ICRISST), Bengaluru, India. 2024, 1-4. 10.1109/icrisst59181.2024.10921975

23. Kaur A, Randhawa GS, Abbas F, Ali M, Esau TJ, Farooque AA, Singh R: Artificial intelligence driven smart farming for accurate detection of potato diseases: a systematic review. IEEE Access. 2024, 12:193902-193922. 10.1109/access.2024.3510456
24. Shorewala S, Ashfaque A, Sidharth R, Verma U: Weed density and distribution estimation for precision agriculture using semi-supervised learning. IEEE Access. 2021, 9:27971-27986. 10.1109/access.2021.3057912
25. Bijoy MH, Hasan N, Biswas M, et al.: Towards sustainable agriculture: a novel approach for rice leaf disease detection using dCNN and enhanced dataset. IEEE Access. 2024, 12:34174-34191. 10.1109/access.2024.3371511
26. Elavarasan D, Vincent PMD: Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. IEEE Access. 2020, 8:86886-86901. 10.1109/access.2020.2992480
27. Jalal S, Kamarulzaman SF, Rahman MA, Uddin M: A comprehensive review on deep learning assisted computer vision techniques for smart greenhouse agriculture. IEEE Access. 2024, 12:4485-4522. 10.1109/access.2024.3349418
28. Fujdiak R, Mikhaylov K, Pospisil J, Povalac A, Misurec J: Insights into the issue of deploying a private LoRaWAN. Sensors. 2022, 22:2042. 10.3390/s22052042