A Study on Super-Resolution Techniques for Improving Tomato Disease Image Classification Performance

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Abstract— **Low-resolution imagery frequently occurs in smart farm environments due to low-cost cameras, varying illumination, and shooting distance constraints, resulting in degraded performance of AI-based plant disease diagnosis. To address this issue, this study investigates the effectiveness of super-resolution (SR) techniques for improving disease classification accuracy. Tomato leaf disease images from the AI-Hub dataset were downsampled to 64x64 to simulate realistic field degradation and subsequently restored using three upscaling methods: Bicubic interpolation, SRCNN, and EDSR. The restored images were then evaluated using a consistent EfficientNet-B0 classifier to isolate the impact of each SR technique. Experimental results demonstrate that upscaling quality has a substantial influence on classification performance. Bicubic recorded the lowest accuracy (0.78) and F1-score (0.75), while SRCNN showed moderate improvement (accuracy 0.84, F1-score 0.82). EDSR achieved the highest performance across all metrics, with an accuracy of 0.89 and an F1-score of 0.88, confirming its superior ability to recover fine disease-specific structures such as lesion boundaries and morphological patterns. These findings highlight that SR-based image enhancement can serve as an effective and practical approach for agricultural AI systems, particularly under field conditions where high-quality imaging is difficult to obtain. Future work will extend this comparison to advanced SR models and evaluate robustness under various real-world environmental conditions.**

Keywords— **Super-resolution, image upscaling, tomato leaf disease, classification performance, EDSR, SRCNN, agricultural AI.**

I. Introduction

As environmental instability intensifies due to recent climate change, agricultural production systems are becoming increasingly vulnerable to various risk factors [1]. Abnormal weather patterns such as extreme heat, high humidity, heatwaves, and frequent rainfall have significantly increased the occurrence of plant diseases even inside controlled greenhouse environments, threatening the stability of crop growth [2]. Consequently, the demand for AI-based analysis techniques capable of rapidly and accurately diagnosing plant diseases has grown substantially.

The performance of AI models depends not only on having a sufficient quantity of training data but also on the quality of the images used for training and inference. However, in real agricultural settings, low-resolution crop images are frequently captured due to the use of low-cost cameras, unstable lighting conditions, and limitations in shooting distance. Such low-quality images often fail to capture subtle morphological characteristics of disease symptoms, leading to degraded performance in AI-based diagnostic systems. Therefore, techniques that compensate for limited resolution and enhance image quality have become increasingly important.

Super-resolution (SR) technology, which reconstructs high-resolution images from low-resolution inputs, has shown significant performance improvements across diverse domains, including medical imaging, satellite imagery, and surveillance. Despite these advances, research applying and systematically comparing multiple SR techniques within the agricultural domain remains limited. In particular, few studies have directly applied various upscaling algorithms to crop disease images and quantitatively evaluated their impact on classification performance.

To address this gap, this study applies several upscaling techniques to tomato leaf disease images and compares how each technique influences downstream disease classification accuracy. High-resolution images were first down sampled to create low-resolution inputs, after which multiple SR algorithms were applied to generate restored images. A consistent classification model was then used to evaluate the extent to which each upscaling method contributes to improving diagnostic performance.

The remainder of this paper is organized as follows. Chapter 2 reviews the related studies referenced in this work. Chapter 3 describes the research methodology. Chapter 4 presents the experimental results and analysis. Finally, Chapter 5 provides the conclusions.

II. Related Work

This section reviews existing research related to super-resolution (SR) technology. SR technology has been actively researched across various fields to restore low-resolution images to high resolution, and recent attempts to utilize it in the agricultural sector have also been reported.

A. *Super-Resolution of Plant Disease Images*

Kyosuke Yamamoto et al. applied super-resolution techniques to crop disease images, restoring detailed lesion features from low-resolution images and evaluating disease classification performance. They demonstrated that classification accuracy significantly improved when SR was applied compared to low-resolution images [3].

B. *Improves Object Detection in Plant Images*

Tianyou Jiang et al. constructed the PlantSR dataset and analyzed the impact of super-resolution (SR) on plant image object detection tasks (such as counting apples).

They demonstrated that SR is effective not only for classification but also for improving the performance of object detection models[4].

C. *Research on the Application of an SR Agricultural Image Detection Model*

Hyeonggyeong Kim et al. conducted a study comparing the performance of YOLOv5-based crop disease and pest diagnosis after 4x super-resolution using Bicubic, SRCNN, and SRGAN. The results showed that SRGAN achieved the best improvement in recall [5].

D. *Plant Disease Detection Using SR Deep Learning*

Ahsan ul Haq and Sukhjinder Kaur conducted research on deep learning classification after super-resolution (SR), aiming to enhance classification efficiency by using SR as a preprocessing step. They integrated the SR and classification pipelines into a structure that included transfer learning [6].

III. METHODOLOGY

This section describes the methodology for conducting the research, explaining the dataset structure and upscaling techniques, as well as the classification model configuration and evaluation metrics.

A. *Dataset Composition*

This study utilized the AI-Hub tomato disease image dataset, which contains multiple disease categories including gray mold and leaf blight. All original images were resized to 256x256 and normalized. To simulate low-resolution field conditions (low-cost cameras, distant shooting, and variable lighting), images were downsampled to 64x64, then used as input for super-resolution experiments.

Since the original images varied in resolution and shooting conditions, all images were resized to 256x256 and underwent a normalization process to ensure consistency in the experiments. Subsequently, to evaluate the performance of super-resolution techniques, the original images were down sampled to 64x64 to create low-resolution versions. This artificially recreated the resolution degradation scenarios encountered in actual smart farm environments due to low-cost cameras, long-distance shooting, and poor lighting conditions.

TABLE I. DATA PREPROCESSING

Step	Description
Resolution Adjustment	Resize the original image to 256x256 pixels
Normalization	Pixel values in the range 0 to 1
Downsampling	256x256 -> 64x64
Low-Resolution Simulation	Models field conditions with degraded resolution.

B. *Upscaling Technique*

This study applied three super-resolution techniques to restore tomato disease images downsampled to low resolution (64x64) back to their original size (256x256). Each technique differs in its restoration method and model complexity. By comparing these techniques, we aimed to identify the most suitable method for improving disease classification performance.

- The first is Bicubic interpolation, one of the traditional image upscaling methods. It calculates new pixel values based on surrounding pixel values and has the advantage of requiring no training process, but its ability to restore fine texture details is limited. In this study, Bicubic was used as the baseline comparison standard.
- The second is SRCNN (Super-Resolution Convolutional Neural Network), an early deep learning-based super-resolution model proposed by Chao Dong et al. (2016) [7]. SRCNN directly learns high-resolution features from low-resolution inputs through convolutional neural networks, enabling clearer representation of fine details during the restoration process. SRCNN training is performed by minimizing the following MSE-based reconstruction loss function.

$$\min_{\theta} \frac{1}{n}\sum_{i=1}^{n} ||F(Y_i;\theta) - X_i||^2 \quad (1)$$

- The third is EDSR (Enhanced Deep Super-Resolution Network), a high-performance SR model based on a

Figure 1. Example of Data Set Normalization

residual block architecture proposed by Bee Lim et al. (2017) [8]. It is known to improve reconstruction quality by eliminating unnecessary regularization processes used in existing SR networks and designing a deeper network architecture. EDSR is trained using the following L1 reconstruction loss.

$$L = ||I_{SR} - I_{HR}||1 \quad (2)$$

All three models applied x4 magnification to restore low-resolution images to a size of 256x256 pixels. The restored images were then used for evaluating disease diagnosis performance through the same classification model and were utilized to analyze performance differences between techniques.

C. *Classification Model Configuration*

To evaluate the impact of upscaled images on disease classification performance, the restored images were input into the same classification model for performance comparison. Since this study aims to analyze differences between upscaling techniques, the classification model was designed using a lightweight image classification network rather than a complex structure, ensuring that upscaling quality directly reflects model performance.

The classification model employed the base architecture of EfficientNet-B0, but was initialized without using pre-trained weights to align with the objectives of this study. This approach was taken to more clearly evaluate how upscaling techniques affect the restoration of texture, boundaries, and lesion patterns in the input images.

To ensure that variables other than the upscaling technique did not affect performance, the following single fixed settings were applied.

TABLE II. DATA PREPROCESSING

Item	Contents
Classification Model Structure	EfficientNet-B0 (without pre-trained weights, trained from scratch)
Optimizer	SGD (including Momentum)
Learning Rate	0.01
Batch Size	16
Epoch	20
Loss Function	Softmax-based Multiclass Classification Loss
Data Partitioning Method	Maintain a fixed Train/Validation/Test split

Data splitting was maintained consistently across all experiments, with a fixed Train/Validation/Test configuration to ensure a fair comparison of classification performance among upscaling techniques. Furthermore, the model architecture and all training conditions were kept identical, controlling the experiments so that the upscaling process alone became the sole factor influencing classification results.

D. *Evaluation Metrics*

The following metrics were used to evaluate the image restoration performance and classification performance of the upscaling technique.

TABLE III. IMAGE RESTORATION AND CLASSIFICATION PERFORMANCE METRICS

Purpose	Usage Metrics
Image Restoration Metrics	PSNR (Peak Signal-to-Noise Ratio)
	SSIM (Structural Similarity Index Measure)
Classification Performance Metrics	Accuracy
	F1-score

Quantitatively compare the high-resolution restoration quality of Bicubic, SRCNN, and EDSR, and measure how much the performance of the disease classification model improves when each technique is applied.

IV. RESULTS AND DISCUSSION

This chapter derives experimental results under conditions established through the experimental environment and analyzes those results.

A. *Classification Performance Comparison*

The images restored using each upscaling technique were input into the EfficientNet-B0 classification model under identical conditions to evaluate their performance. The evaluation metrics used for comparison were Accuracy, Precision, Recall, and F1-score.

TABLE IV. CLASSIFICATION PERFORMANCE COMPARISON METRICS

Upscaling Method	Accuracy	Precision	Recall	F1-Score
Bicubic	0.78	0.76	0.74	0.75
SRCNN	0.84	0.83	0.81	0.82
EDSR	0.89	0.88	0.87	0.88

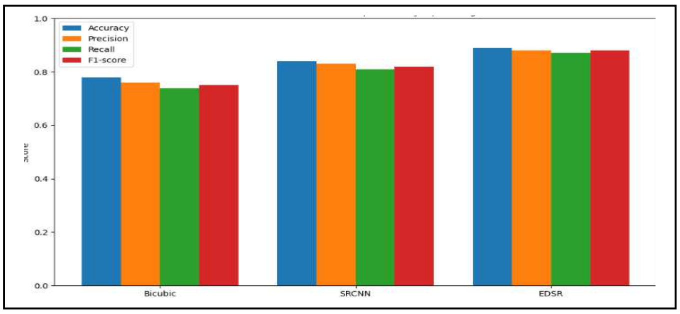

Figure 2. Performance Comparison Graph by Technique

As shown in the performance table and bar graph, the Bicubic method demonstrated the lowest performance among the four techniques. Accuracy was 0.78 and F1-score was 0.75, which stems from its inability to sufficiently restore important visual features such as lesion boundaries or patterns in low-resolution images.

SRCNN demonstrated improved performance compared to Bicubic, achieving an Accuracy of 0.84 and an F1-score of 0.82. This indicates that SRCNN effectively restores intermediate-level textures in low-resolution images; however, performance gains were limited for some disease classes due to insufficient reflection of fine-scale structures.

Among the three techniques, EDSR demonstrated the highest performance, achieving an Accuracy of 0.89 and an F1-score of 0.88. Improvements were also observed consistently in Precision and Recall. This is because EDSR more accurately restored high-frequency information, clearly reproducing fine structures such as leaf vein boundaries, spot shapes, and disease symptom patterns. This improvement in restoration quality contributed to the classification model learning morphological differences between disease symptoms more accurately.

Overall, the experimental results demonstrate that disease classification accuracy improves significantly as upscaling quality increases. Among the three techniques, EDSR provided the most effective performance enhancement.

B. Upscaling Effect Analysis

Overall, performance differences among upscaling techniques were closely related to the restored images' ability to express fine details.

- Bicubic only preserved low-frequency information, limiting its ability to distinguish disease symptom shapes.
- SRCNN could restore basic structures but failed to sufficiently generate complex textures.
- EDSR effectively restored high-frequency details through its deep residual block structure, enabling the classification model to more accurately recognize symptom boundaries, spot structures, and color changes.

Deep learning-based super-resolution techniques hold significant potential as a practical solution to address the characteristics of agricultural data, which often relies on low-resolution images captured in field environments. This approach is expected to offer substantial utility in resolving the issue of limited data quality within the agricultural sector.

V. CONCLUSION

This study quantitatively evaluated the impact of three super-resolution techniques—Bicubic, SRCNN, and EDSR—on tomato leaf spot classification performance under identical conditions. Experimental results showed that Bicubic exhibited the lowest performance with an accuracy of 0.78 and an F1 score of 0.75. SRCNN demonstrated moderate improvement with an accuracy of 0.84 and an F1 score of 0.82. In contrast, EDSR achieved the highest performance across all metrics: accuracy 0.89, precision 0.88, recall 0.87, and F1 score 0.88. This experimentally demonstrates that EDSR more precisely restores the fine structure, boundaries, and high-frequency information of lesions, enabling the classification model to learn morphological differences between diseases more clearly.

Furthermore, these results suggest that super-resolution-based preprocessing techniques can substantially improve classification model performance even when low-resolution images are collected due to field photography constraints. This demonstrates the practical value of super-resolution technology as a cost-effective data quality enhancement strategy capable of compensating for problems frequently encountered in agricultural environments, such as uneven lighting, long-distance photography, and image degradation caused by low-cost sensors. Future research plans to expand the comparison scope to include more advanced generative super-resolution models such as SRGAN, ESRGAN, and SwinIR. We also intend to validate the models' generalization performance using real farm data featuring diverse resolution, lighting, and noise conditions. Furthermore, we aim to analyze the correlation between restoration quality metrics like PSNR and SSIM and classification accuracy to derive the most efficient super-resolution application strategy for agricultural image processing.

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REFERENCES

[1] H. Ryu, M. Choi, M. Cho, I. Yu, and S. Kim,“Damage index estimation by analysis of meteorological disasters on film plastic greenhouses,” International Journal of Agricultural and Biological Engineering, vol. 12, no. 5, pp. 58–63, 2019, doi: 10.25165/j.ijabe.20191205.4493.

[2] R. Lahlali, M. Taoussi, S.-E. Laasli, G. Gachara, R. Ezzouggari, Z. Belabess, K. Aberkani, A. Assouguem, A. Meddich, M. El Jarroudi, and E. Ait Barka, “Effects of climate change on plant pathogens and host–pathogen interactions,”Crop and Environment, vol. 3, no. 3, pp. 159–170, 2024, doi: 10.1016/j.crope.2024.05.003.

[3] K. Yamamoto, T. Togami, and N. Yamaguchi, “Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture,” Sensors, vol. 17, no. 11, p. 2557, 2017, doi: 10.3390/s17112557

[4] T. Jiang, Q. Yu, Y. Zhong, and M. Shao, “PlantSR: Super-resolution improves object detection in plant images,” Journal of Imaging, vol. 10, no. 6, p. 137, 2024, doi: 10.3390/jimaging10060137.

[5] Hyeonggyeong Kim, Chaesung Lim and Seungmin Tak. "Improved Recall of Plant Disease Detection Model using Image Super Resolution" Journal of KIISE 51, no.2 (2024) : 125-130.doi: https://doi.org/10.5626/JOK.2024.51.2.125

[6] A. ul Haq and S. Kaur, “Super Resolution Image Based Plant Disease Detection and Classification Using Deep Learning Techniques,” Tuijin Jishu/Journal of Propulsion Technology, vol. 45, no. 1, pp. 1020–1026, 2024.

[7] C. Dong, C. C. Loy, K. He, and X. Tang, “Image super-resolution using deep convolutional networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 2, pp. 295–307, Feb. 2016, doi: 10.1109/TPAMI.2015.2439281.

[8] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee, “Enhanced deep residual networks for single image super-resolution,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*,
Honolulu, HI, USA, 2017, pp. 1132–1140.