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Bayesian optimization of super-resolution for crop disease detection

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ABSTRACT

This work proposes a Bayesian hyperparameter optimization framework for enhanced deep super-resolution networks (EDSR) to improve lesion-aware disease classification. A 4× degradation model was applied to PlantVillage images, and Optuna was used to optimize residual blocks, learning rate, feature channels, and patch size. Lesion-aware color gray-level co-occurrence matrix (Color GLCM) features were extracted and classified using extreme gradient boosting (XGBoost) under 5-fold cross-validation. Results show that degradation reduced classification accuracy to 58.15%, while baseline super-resolution (SR) improved it to 74.26%. Bayesian-optimized SR further increased accuracy to 75.56% and reduced standard deviation from 0.74 to 0.30, indicating improved generalization stability. The proposed framework demonstrates that hyperparameter-optimized SR enhances lesion texture restoration and provides an efficient preprocessing strategy for precision agriculture applications.

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1. INTRODUCTION

Agriculture plays a crucial role in ensuring global food security and economic sustainability. Early identification of crop diseases is essential for minimizing yield losses and improving agricultural productivity. In recent years, image-based disease diagnosis has emerged as a promising solution due to advances in machine learning and deep learning techniques. Several studies have demonstrated the effectiveness of deep learning models for crop disease classification across various crops, including maize, peach, cotton, and plantain [1]–[4]. Furthermore, comprehensive reviews have highlighted the growing importance of artificial intelligence (AI)-driven crop disease detection systems in modern precision agriculture [5], [6].

The rapid adoption of unmanned aerial vehicles (UAVs), remote sensing technologies, and internet of things (IoT)-enabled agricultural monitoring systems has significantly expanded the scale of crop health assessment [7]–[10]. UAV-based monitoring platforms enable efficient large-scale crop surveillance; however, images acquired from low-cost sensors, high-altitude UAVs, or bandwidth-constrained agricultural systems often suffer from reduced spatial resolution and loss of fine lesion details. Such degradation adversely affects disease diagnosis because lesion texture, color variation, and boundary information are critical indicators of plant health.

Image super-resolution (SR) techniques have emerged as an effective solution for recovering high-frequency information from degraded low-resolution (LR) images. Deep learning-based SR architectures such as enhanced deep super-resolution network (EDSR) [11], residual channel attention network (RCAN) [12], and ESRGAN-DP [13] have demonstrated remarkable performance in image reconstruction tasks. In agricultural

applications, Cap *et al.* [14] proposed leaf artifact-suppression super-resolution (LASSR), a disease-oriented SR framework that improved plant disease diagnosis by restoring diagnostically relevant lesion characteristics. Similarly, Han *et al.* [15] demonstrated the effectiveness of SR techniques in agricultural remote sensing applications. Despite these advances, most studies evaluate SR performance primarily using reconstruction-oriented metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM), while relatively little attention has been given to understanding how reconstructed images influence downstream disease classification performance.

Another important challenge involves the selection of SR network hyperparameters. The performance of deep learning models is highly dependent on architectural and training parameters, including network depth, feature channel width, learning rate, and patch size. Traditionally, these parameters are selected empirically or through computationally expensive trial-and-error procedures. Bayesian optimization has emerged as an efficient approach for identifying near-optimal hyperparameter configurations by intelligently balancing exploration and exploitation [16]. Optuna, a modern Bayesian optimization framework, has been widely adopted for hyperparameter tuning in deep learning applications [17]. Recent agricultural studies have further demonstrated that Bayesian optimization can improve disease detection performance and model robustness [18].

Although SR, crop disease classification, and hyperparameter optimization have individually received substantial research attention, several important gaps remain. First, the impact of severe image degradation on lesion-aware texture discriminability has not been comprehensively quantified. Second, most agricultural SR studies focus on visual quality improvement rather than evaluating the effect of reconstructed images on downstream disease classification performance [19]–[21]. Third, existing studies generally employ fixed SR configurations and rarely investigate how Bayesian optimization influences lesion texture restoration, classification accuracy, and generalization stability [22]–[24]. Finally, despite the growing importance of UAV-assisted and IoT-enabled agricultural systems, limited attention has been given to computationally efficient image enhancement frameworks suitable for deployment on edge devices and smart agriculture platforms [25].

To address these limitations, this study proposes a Bayesian hyperparameter optimization framework for SR networks to enhance lesion-aware crop disease classification under severe LR conditions. A 4× degradation model is employed to simulate realistic image acquisition constraints encountered in UAV-based and resource-constrained agricultural monitoring systems. The EDSR is utilized for image reconstruction, while Bayesian optimization using Optuna identifies optimal architectural and training parameters. Following reconstruction, lesion-aware color gray-level co-occurrence matrix (Color GLCM) features are extracted and classified using an extreme gradient boosting (XGBoost) classifier under stratified cross-validation.

Unlike previous studies that primarily evaluate super-resolution models based on image fidelity, the proposed work investigates how reconstruction-oriented optimization influences downstream lesion texture restoration, feature discriminability, classification accuracy, and generalization stability. Furthermore, the proposed framework provides a computationally efficient preprocessing strategy that can support future deployment in UAV-assisted crop monitoring systems, IoT-enabled agricultural networks, and edge-intelligent smart agriculture platforms.

The scientific contribution of this study does not arise from proposing a new SR architecture or classification algorithm individually. Rather, it lies in systematically investigating the previously underexplored relationship between reconstruction-oriented Bayesian hyperparameter optimization and downstream lesion-aware disease classification. By jointly examining reconstruction fidelity, lesion-texture discriminability, classification accuracy, statistical significance, and cross-validation stability under controlled 4× degradation, the study provides quantitative evidence of how SR hyperparameter selection affects subsequent agricultural image analysis. This evaluation perspective distinguishes the proposed framework from studies that assess SR primarily through PSNR, SSIM, or visual quality alone.

The primary contributions of this work are summarized as follows:

- Quantitative evaluation of the effect of 4× image degradation and EDSR reconstruction on lesion-aware crop disease classification.
- Bayesian optimization of EDSR hyperparameters followed by downstream evaluation using reconstruction quality, lesion-aware feature discriminability, classification accuracy, and cross-validation stability.
- Development of a computationally efficient SR-assisted classification framework with potential application to UAV-, IoT-, and edge-based agricultural monitoring.

2. RELATED WORK

Accurate crop disease detection has become a major focus in precision agriculture. Recent advances in machine learning and deep learning have enabled automated disease diagnosis using image-based analysis. Khan *et al.* [1], Akbar *et al.* [2], Madhu and RaviSankar [3], and Nandhini *et al.* [4] demonstrated the

effectiveness of deep learning models for crop disease classification across various crops. Comprehensive reviews by Dolatabadian *et al.* [5] and Pacal *et al.* [6] further highlight the growing adoption of AI in agricultural disease monitoring.

The increasing use of UAVs, remote sensing technologies, and smart farming systems has enhanced large-scale crop monitoring capabilities. UAV-based disease detection has been investigated using red, green, and blue (RGB) imagery [7], while machine learning-driven agricultural management systems have enabled intelligent farming applications [8]. UAV multispectral imaging has further improved disease monitoring accuracy [9], and edge-computing architectures have facilitated real-time agricultural decision support systems [10].

Image SR techniques have emerged as an effective solution for recovering high-frequency information from degraded agricultural images. Lim *et al.* [11] introduced EDSR, while Zhang *et al.* [12] proposed the RCAN. Song *et al.* [13] developed ESRGAN-DP to improve perceptual reconstruction quality through adaptive dual perceptual loss. In agricultural applications, Cap *et al.* [14] proposed LASSR, a disease-oriented SR framework, and Han *et al.* [15] demonstrated the effectiveness of SR reconstruction in agricultural remote sensing. However, most existing studies evaluate SR performance primarily using reconstruction-oriented metrics such as PSNR and SSIM, with limited investigation of its influence on downstream disease classification.

Hyperparameter optimization has emerged as an effective strategy for improving deep learning performance. Snoek *et al.* [16] established the theoretical foundations of Bayesian optimization, while Akiba *et al.* [17] introduced Optuna, a widely adopted hyperparameter optimization framework. Jain *et al.* [18] demonstrated that Bayesian optimization can significantly improve crop disease detection performance.

Structured machine learning approaches and texture-based representations have also been applied in agricultural monitoring systems. Meenakshiammal *et al.* [19] proposed a crop disease classification framework for smart agriculture networks, while Judith *et al.* [20] utilized NDVI-based crop health classification. The availability of agricultural datasets such as the PlantVillage augmentation framework [21] has further supported crop disease research. Sakthiprasad *et al.* [22] and Yakkala *et al.* [23] demonstrated the effectiveness of machine learning and deep learning approaches for agricultural monitoring and disease prediction. More recently, UAV-assisted precision agriculture frameworks [24] and edge-intelligent cyber-physical agricultural systems [25] have enabled large-scale crop health monitoring and decision support.

Although crop disease classification, SR, and Bayesian optimization have been extensively studied, several research gaps remain. Existing studies largely focus either on disease classification [1]–[10], [19]–[25] or image reconstruction quality [11]–[15] independently, with limited investigation of the relationship between the two. Furthermore, SR architectures are generally evaluated using fixed configurations, while the influence of Bayesian hyperparameter optimization on lesion texture restoration, classification accuracy, and generalization stability remains poorly understood [16]–[18]. The integration of degradation modeling, Bayesian-optimized SR, lesion-aware texture analysis, and interpretable machine learning classification within a unified agricultural framework has received limited attention. These limitations motivate the present study.

3. RESEARCH METHOD

The proposed framework consists of a multi-stage pipeline designed to enhance lesion-aware crop disease classification under severe 4× image degradation. High-resolution agricultural images are first subjected to bicubic down sampling to simulate LR acquisition conditions. The degraded images are then reconstructed using an EDSR, where both baseline and Bayesian-optimized configurations are evaluated. The optimized SR model is obtained through systematic hyperparameter tuning of architectural and training parameters. Following reconstruction, lesion regions are segmented in hue saturation value (HSV) color space, and discriminative Color GLCM texture features are extracted. These features are subsequently classified using an XGBoost classifier under 5-fold stratified cross-validation. Statistical validation using paired t-tests confirms the significance of improvements across stages. The overall architecture integrates degradation modeling, super-resolution enhancement, lesion-aware feature extraction, and statistical classification validation into a unified agricultural image analysis framework as shown in Figure 1. The work was carried out in the following stages.

3.1. Dataset and degradation model

Eight crop disease classes were selected from the PlantVillage dataset to evaluate the proposed framework. A total of 1,600 images were used, with 200 images randomly selected from each disease class to ensure balanced class representation. All images were resized to 256×256 pixels and treated as the high-resolution (HR) reference images. To simulate real-world LR acquisition conditions encountered in drone-based or low-cost sensor systems, each high-resolution image was synthetically degraded using a 4× downscaling operation. Bicubic interpolation was employed to generate LR images:

$$I_{LR} = D(I_{HR}) \quad (1)$$

This degradation model reduces spatial-frequency content, blurs lesion boundaries, and weakens chromatic texture variation, thereby challenging classical texture-based classification.

3.2. Super-resolution network

To reconstruct high-resolution imagery from degraded inputs, the EDSR architecture was employed. EDSR consists of a shallow feature extraction layer, multiple residual blocks for nonlinear feature transformation, and a pixel-shuffle up-sampling module for resolution reconstruction. Let I_{LR} denote the degraded image and $\hat{I}_{HR}$ the reconstructed image. The SR mapping is defined as (2):

$$\hat{I}_{HR} = f_\theta(I_{LR}) \quad (2)$$

where f_θ represents the deep residual network parameterized by θ. The model was trained using L1 loss between reconstructed and ground-truth high-resolution images.

$$L_{L1} = \left\| \hat{I}_{HR} - I_{HR} \right\|_1 \quad (3)$$

Two configurations were evaluated: baseline SR with default architectural parameters and optimized SR with hyperparameters determined via Bayesian optimization. Residual learning enables stable gradient propagation while allowing the model to focus on high-frequency reconstruction. The network output was constrained using a sigmoid activation to maintain pixel intensities in the normalized range [0,1]. EDSR was selected because it provides a favorable trade-off between reconstruction quality and computational complexity. Compared with more complex architectures such as RCAN [12] and GAN-based methods such as ESRGAN-DP [13], EDSR offers stable training behavior and lower deployment complexity, making it suitable for agricultural image processing applications.

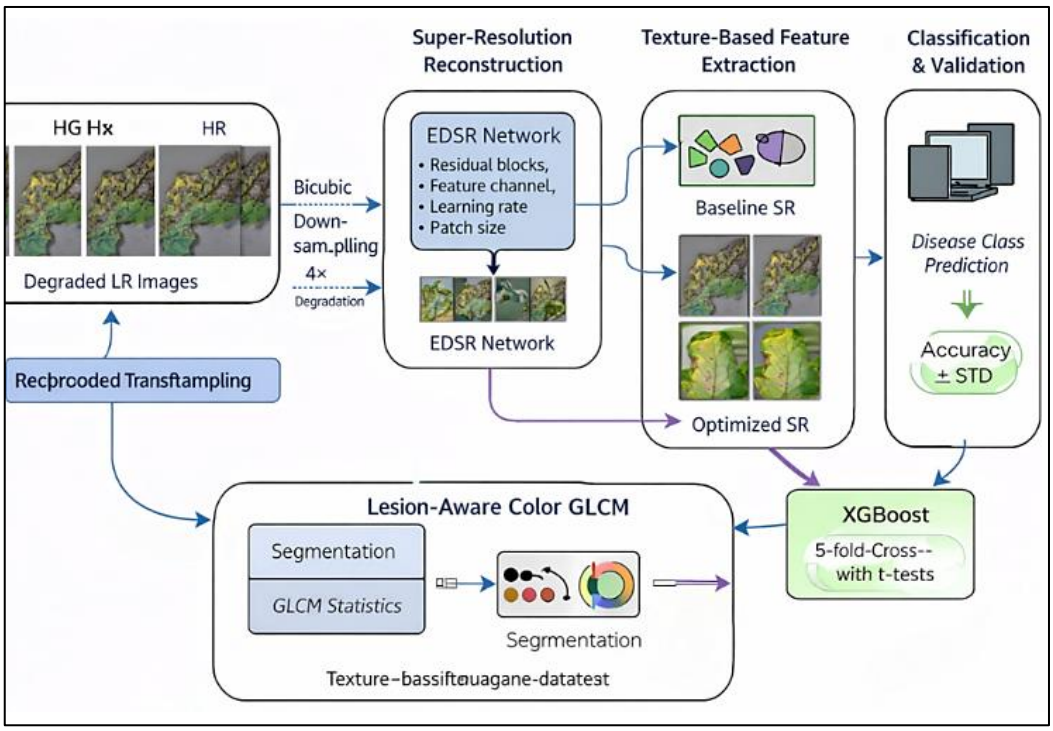


Figure 1. Architecture of the proposed work

3.3. Bayesian hyperparameter optimization

The reconstruction quality of SR networks is strongly influenced by architectural and training hyperparameters. Instead of manual tuning, a Bayesian optimization framework (Optuna) was employed to

systematically explore the hyperparameter space. Bayesian optimization was performed using Optuna for 50 trials. Each trial trained EDSR for 20 epochs. Optimization terminated after completion of all trials. The total optimization process required approximately 2 hours on an NVIDIA T4 GPU. Experiments were conducted on a system with an Intel i7 processor, 16 GB RAM, an NVIDIA T4 GPU, Python 3.11, and PyTorch 2.5. The search space included:

- Number of residual blocks (10–12)
- Feature channel width (64)
- Learning rate (7×10^{-5}–1×10^{-4})
- Training patch size (32–40)
- Batch size (8)

The optimization process explored the number of residual blocks, learning rate, and training patch size, while feature channels (64) and batch size (8) were fixed to maintain computational efficiency. The optimization objective was to maximize PSNR, defined as (4):

$$PSNR = 10\, log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (4)$$

where MSE represents the mean squared error between reconstructed and ground-truth high-resolution images. MAX represents the maximum possible pixel value in the image, which is 255. Each trial trained the SR network for a fixed number of epochs on randomly sampled image patches. The best-performing configuration identified by Bayesian search consisted of:

- 11 residual blocks
- 64 feature channels
- Learning rate=9.81×10^{-5}
- Patch size=40
- Batch size=8

This configuration achieved 29.00 dB PSNR and was used for subsequent classification experiments. Table 1 summarizes the computational requirements of the proposed framework. Bayesian optimization required 50 trials, with each trial trained for 20 epochs. The complete optimization process required approximately 2 hours on an NVIDIA T4 GPU. Although Bayesian optimization introduces additional training overhead, it is performed offline during model development and does not affect inference-time deployment. Therefore, the optimized model can be deployed in resource-constrained agricultural monitoring systems without additional computational burden.

Table 1. Computational cost of proposed framework

Configuration	Parameters (M)	Training epochs	Execution time (h)
Baseline EDSR	1.37	20	1.8
Optimized EDSR	1.54	20	2.0

It should be clarified that Bayesian optimization was performed using PSNR as the optimization objective and did not directly optimize classification accuracy. Therefore, the term task-oriented in this study refers to the downstream evaluation of the optimized SR model rather than the Bayesian objective itself. The configuration selected according to reconstruction fidelity was subsequently evaluated in terms of lesion-aware feature preservation, classification accuracy, and cross-validation stability. This experimental design enables investigation of whether improvements in reconstruction quality translate into measurable benefits for the downstream crop disease classification task.

3.4. Lesion-aware color gray-level co-occurrence matrix feature extraction

Following reconstruction, texture features were extracted from lesion regions using a lesion-aware Color GLCM approach. The purpose of this stage was to characterize spatial and chromatic variations associated with disease symptoms rather than analyzing the entire leaf region uniformly. By combining lesion segmentation with channel-wise texture analysis, the extracted representation emphasizes diagnostically relevant patterns such as irregular lesion boundaries, color variation, and local texture heterogeneity.

3.4.1. Lesion segmentation

Lesion regions were identified in HSV color space using threshold-based masking for yellow and brown chromatic ranges associated with disease symptoms. Morphological operations were applied to remove noise and isolate contiguous lesion regions. A lesion-area ratio was computed as (5).

$$Lesion\ ratio = Lesion\ pixels/Total\ pixels \quad (5)$$

This ratio was appended to the final feature vector.

3.4.2. Color gray-level co-occurrence matrix computation

For each RGB channel independently, GLCMs were computed using:

- Distance=1 pixel
- Orientations=0°, 45°, 90°, and 135°
- 256 gray levels

From each channel, the following statistical descriptors were extracted: contrast, correlation, energy, homogeneity, dissimilarity, angular second moment (ASM), and entropy. The final feature vector consisted of concatenated descriptors from all three channels along with the lesion-area ratio. This color-texture representation preserves chromatic lesion information that may be lost in grayscale-only approaches.

3.5. Classification framework

The extracted feature vectors were standardized using z-score normalization, while class labels were encoded using label encoding. Classification was performed using an XGBoost classifier configured with 300 estimators, a maximum depth of 6, and a learning rate of 0.1. Performance was evaluated using 5-fold stratified cross-validation to ensure balanced class representation, with accuracy reported as mean ±standard deviation across folds.

The SR training and classification validation stages were conducted independently. The 5-fold stratified cross-validation procedure was applied only to the lesion-aware Color GLCM feature vectors used for XGBoost classification and was not used for training or selecting the EDSR model. EDSR training and Bayesian hyperparameter selection were completed prior to the classification evaluation. After the SR configuration was fixed, reconstructed images were generated and their corresponding lesion-aware features were extracted. These feature vectors were then divided into five stratified folds, with four folds used for classifier training and the remaining fold used for testing in each iteration. Consequently, classification test-fold information was not used to optimize the SR network or its hyperparameters, thereby preventing leakage from the classification evaluation into the SR optimization stage.

3.6. Statistical validation

Statistical significance was determined at a threshold of $p<0.05$. To verify the significance of performance improvements, paired t-tests were conducted between fold-level accuracies:

- Degraded LR vs baseline SR
- Baseline SR vs optimized SR

4. RESULTS AND DISCUSSION

4.1. Effect of 4× degradation on lesion-aware classification

To simulate realistic LR acquisition scenarios, high-resolution images were degraded using 4× bicubic down-sampling. Lesion-aware Color GLCM features were extracted from the degraded images and classified using XGBoost under 5-fold stratified cross-validation.

As shown in Table 2, the degraded LR images achieved a classification accuracy of 58.15%±0.97. The significant reduction in performance demonstrates the sensitivity of texture-based descriptors to spatial resolution loss. Visual inspection confirmed that lesion boundaries became blurred and chromatic variations were attenuated, resulting in increased inter-class overlap, particularly among visually similar disease categories.

Table 2. Comparative performance of LR, SR, and optimized SR under 4× degradation

Method	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean accuracy (%)	Std dev (%)	Absolute gain (%)	Statistical significance	Method
4× LR	56.37	58.17	58.88	58.37	58.98	58.15	0.97	—	—	4× LR
4× SR (baseline)	74.58	73.29	74.39	75.29	73.73	74.26	0.74	16.11	$p=1.51\times10^{-5}$ (vs LR)	4× SR (baseline)
4× SR (optimized)	75.35	75.68	75.42	76.06	75.27	75.56	0.3	1.3	p=0.013 (vs SR)	4× SR (optimized)

To complement the classification-based evaluation, reconstruction quality was assessed using PSNR and SSIM. As shown in Table 3, the Bayesian-optimized EDSR model achieved higher PSNR and SSIM values than the baseline EDSR configuration, indicating improved preservation of lesion boundaries and texture structures. The improved reconstruction quality contributed to enhanced lesion-aware feature extraction and ultimately resulted in improved classification accuracy and reduced performance variability.

Table 3. Reconstruction quality metrics of SR models

Method	PSNR (dB)	SSIM	Accuracy (%)
Baseline SR	27.84	0.84	74.26
Optimized SR	29	0.87	75.56

4.2. Impact of baseline super-resolution

Applying baseline EDSR to the degraded images significantly improved classification performance. The reconstructed images yielded an accuracy of 74.26%±0.74. This corresponds to an absolute improvement of +16.11% over degraded LR images. A paired t-test comparing fold-level accuracies between LR and SR configurations produced $p=1.51\times10^{-5}$, indicating statistically significant improvement ($p<0.05$).

Confusion matrix analysis reveals that SR substantially reduces misclassification between disease classes exhibiting similar lesion textures. Feature space visualization using t-SNE further shows improved cluster compactness and separation after reconstruction. These results confirm that SR effectively restores high-frequency lesion textures that are critical for discriminative color-texture representation.

4.3. Effect of Bayesian hyperparameter optimization

To further enhance reconstruction fidelity, Bayesian hyperparameter optimization was applied to the SR network. The optimized configuration consisted of:

- 11 residual blocks
- 64 feature channels
- Learning rate=9.81×10^{-5}
- Patch size=40
- Batch size=8

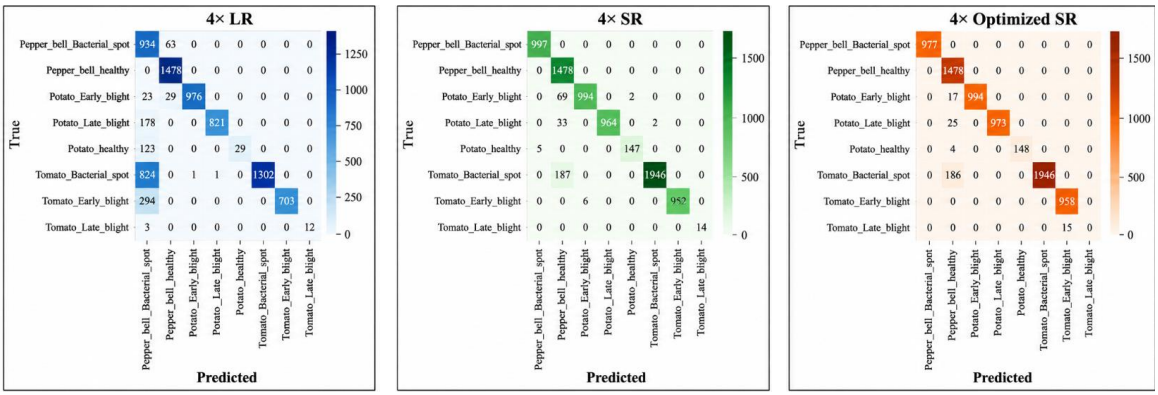
Using the optimized SR images, classification accuracy increased to 75.56%±0.30, compared to baseline SR, this represents an additional improvement of +1.30%. Although modest in magnitude, this improvement was statistically significant. A paired t-test between baseline SR and optimized SR fold accuracies yielded: $p=0.013$ indicating meaningful performance enhancement ($p<0.05$). Notably, the standard deviation decreased from 0.74 to 0.30, suggesting improved stability and generalization consistency across cross-validation folds.

The observed improvement can be attributed to the ability of Bayesian optimization to identify hyperparameter configurations that better preserve lesion boundaries and chromatic texture variations during reconstruction. Improved texture preservation enhances the discriminative capability of Color GLCM descriptors, resulting in more compact feature clusters and reduced inter-class confusion.

Although the absolute accuracy improvement from 74.26% to 75.56% is relatively modest, its practical relevance should be interpreted together with the reduction in cross-validation variability from 0.74 to 0.30. This corresponds to an approximately 59% reduction in performance variability and indicates more consistent predictions across cross-validation partitions, which is desirable for reliable disease-screening systems. Furthermore, the optimized SR stage operates as a preprocessing component and therefore improves classification performance without increasing the complexity of the downstream XGBoost classifier.

4.4. Confusion matrix analysis

Three-panel confusion matrix comparison (LR, SR, and optimized SR) demonstrates progressive improvement in classification reliability. Figure 2 compares the class-wise classification behavior across the three experimental conditions. Figure 2(a) presents the confusion matrix obtained from 4× degraded LR images, Figure 2(b) shows the results after baseline EDSR reconstruction, and Figure 2(c) presents the results obtained after Bayesian-optimized EDSR reconstruction. The progressive strengthening of diagonal entries indicates reduced inter-class confusion following SR reconstruction and subsequent hyperparameter optimization. This analysis confirms that SR improves not only overall accuracy but also class-wise reliability.

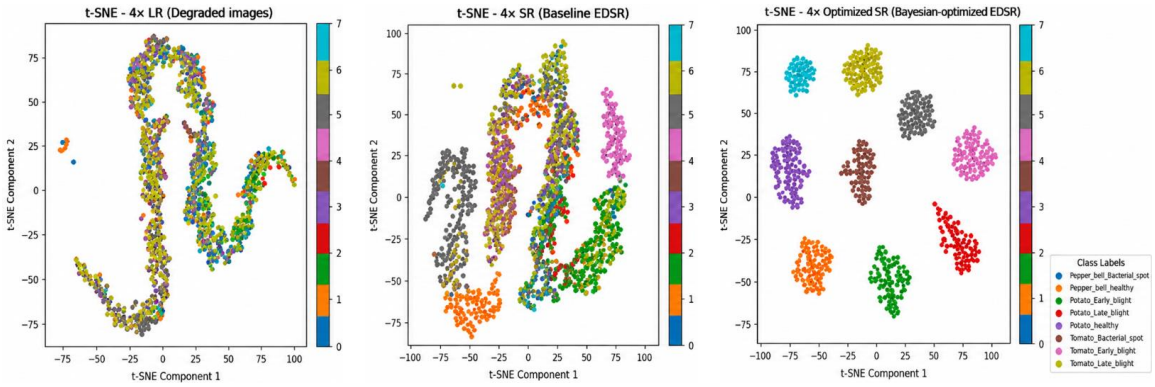


(a) (b) (c)

Figure 2. Confusion matrices for disease classification under different image-resolution conditions: (a) 4× degraded LR images, (b) baseline EDSR reconstructed images, and (c) Bayesian-optimized EDSR reconstructed images

4.5. Feature space separability

As shown in Figure 3, degraded LR images exhibit overlapping and diffuse feature distributions as shown in Figure 3(a), whereas baseline SR improves cluster compactness and separability as shown in Figure 3(b). Bayesian-optimized SR further improves class separation as shown in Figure 3(c), indicating better preservation of discriminative lesion textures. Together with the confusion matrix results, these observations demonstrate that improved reconstruction quality translates into measurable benefits for downstream lesion-aware classification.



(a) (b) (c)

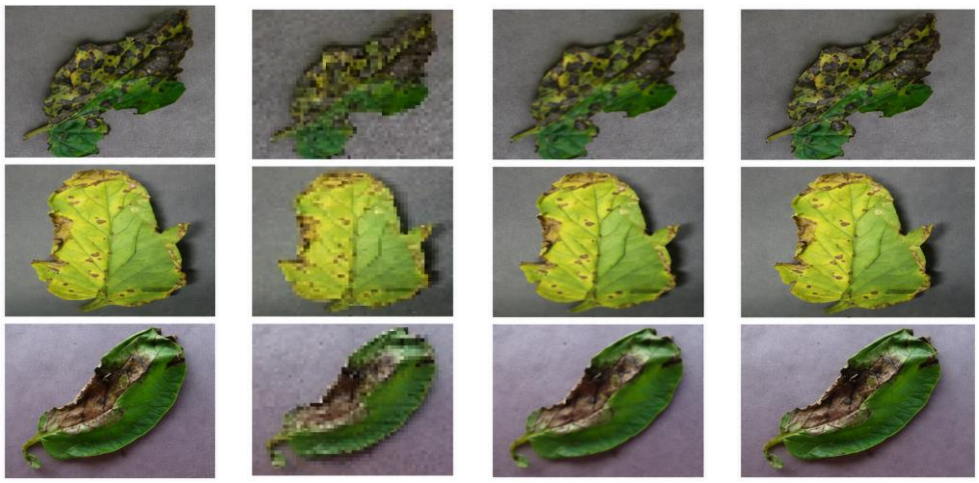
Figure 3. t-SNE visualization of lesion-aware Color GLCM feature distributions for: (a) 4× degraded LR images, (b) baseline EDSR reconstructed images, and (c) Bayesian-optimized EDSR reconstructed images, with the axes representing the first and second t-SNE embedding dimensions and the colors denoting the eight disease classes

4.6. Discussion

The results demonstrate a clear relationship between spatial resolution, texture restoration, and lesion-aware classification performance. Although direct experimental comparisons with SR architectures such as RCAN [12] and ESRGAN-DP [13] were beyond the scope of the present study, these architectures have demonstrated strong reconstruction performance in general computer vision applications. The present work focuses on understanding how Bayesian-optimized EDSR influences lesion-aware classification performance rather than pursuing state-of-the-art reconstruction accuracy alone. Future studies will investigate comparative evaluation of multiple SR architectures under agricultural disease classification settings.

Overall, the results shown in Figure 4 establish a clear relationship between spatial resolution, lesion-texture restoration, and classification performance. Comparison is provided with reference to high resolution reference image as shown in Figure 4(a). The degraded image is shown in Figure 4(b). Baseline EDSR produced the largest improvement over degraded LR images, as shown in Figure 4(c), while Bayesian

optimization provided an additional statistically significant gain and reduced cross-validation variability, as shown in Figure 4(d). These findings support the use of optimized SR as a preprocessing stage for lesion-aware agricultural image analysis.



(a) (b) (c) (d)

Figure 4. Representative reconstruction results: (a) high-resolution reference image, (b) 4× degraded LR image, (c) baseline EDSR reconstruction, and (d) Bayesian-optimized EDSR reconstruction

4.7. Practical deployment in smart agriculture

The proposed framework is particularly relevant for UAV-assisted and IoT-enabled agricultural monitoring systems, where image resolution is frequently constrained by sensor limitations, acquisition altitude, and communication bandwidth. Since Bayesian optimization is performed offline during model development, only the optimized EDSR model is required during deployment. The reconstructed images can subsequently be processed using lightweight machine learning classifiers on edge devices. Furthermore, the residual-learning structure of EDSR is suitable for FPGA-based acceleration and edge-AI implementations, enabling low-latency disease monitoring in smart agriculture environments. Recent advances in edge computing and cyber-physical agricultural systems further support the deployment of such computationally efficient image enhancement frameworks [19], [25].

4.8. Ablation analysis

The contribution of the major framework components is evident from the observed performance trends. EDSR reconstruction produced the largest gain, increasing classification accuracy from 58.15% to 74.26%, confirming the importance of restoring lesion texture information. Bayesian optimization further increased accuracy to 75.56% while reducing the standard deviation from 0.74 to 0.30, indicating improved stability. Lesion-aware Color GLCM descriptors additionally provide an interpretable representation of chromatic and spatial disease characteristics. Collectively, these results demonstrate the complementary roles of reconstruction, hyperparameter optimization, and lesion-aware texture analysis.

4.9. Limitations

The PlantVillage dataset was acquired under controlled imaging conditions with relatively uniform backgrounds and illumination. Therefore, the present results should be interpreted as controlled experimental evidence rather than direct validation of field deployment. Future work will evaluate the framework on field-acquired UAV imagery containing natural backgrounds, illumination variation, occlusion, sensor noise, and multiple crop species to assess its generalization under practical agricultural conditions.

4.10. Comparative discussion

As shown in Table 4, RCAN and ESRGAN-DP have demonstrated strong reconstruction performance but require significantly larger computational resources. The present work selected EDSR due to its favorable balance between reconstruction quality and deployment complexity for edge-based agricultural systems. Comparative evaluation with RCAN and transformer-based SR models will be performed in future work.

RCAN and ESRGAN-DP are included only as representative advanced SR architectures discussed in the literature. Direct numerical comparison would not be scientifically appropriate because their reported results were obtained using different datasets, degradation models, training protocols, and evaluation conditions. Therefore, direct implementation of these architectures under the same PlantVillage degradation and classification protocol is reserved for future work.

Table 4. Reported SR performance from literature

Method	Directly evaluated in this study	Optimization	Downstream disease classification
Baseline EDSR	Yes	Default parameters	Yes
Bayesian-optimized EDSR	Yes	Optuna–PSNR	Yes
RCAN	No	—	No
ESRGAN-DP	No	—	No

5. CONCLUSION

This study investigated Bayesian-optimized EDSR for improving lesion-aware crop disease classification under severe LR imaging conditions. A 4× degradation model was applied to PlantVillage images, followed by EDSR, lesion-aware Color GLCM feature extraction, and XGBoost classification. Classification accuracy increased from 58.15% for degraded LR images to 74.26% after baseline SR and 75.56% after Bayesian-optimized SR. The optimized model also improved reconstruction quality to 29.00 dB PSNR and 0.87 SSIM and reduced the cross-validation standard deviation from 0.74 to 0.30, indicating more consistent classification performance. Bayesian optimization was performed using PSNR as the objective rather than classification accuracy; therefore, the contribution lies in evaluating whether reconstruction-oriented optimization translates into measurable downstream classification benefits. The results demonstrate improved lesion-texture discriminability, classification accuracy, and stability following optimized SR. Although the evaluation was limited to the controlled PlantVillage dataset, the framework provides a computationally efficient preprocessing approach for LR agricultural image analysis. Future work will evaluate the method on field-acquired UAV imagery, alternative advanced SR architectures, and edge-enabled smart agriculture platforms.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

This study utilized publicly available PlantVillage image datasets and did not involve human participants, animals, or identifiable personal data.

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