**Deep Learning-Based Image Enhancement for UAV Monitoring of Electrical Power Lines**

**Wazir Muhammad1, Ayaz Hussain2, and Zahoor Ahmed3**

Department of Electrical Engineering, Balochistan University of Engineering and Technology, Khuzdar, Pakistan

**ABSTRACT**

Recently, deep convolutional neural networks (CNNs) have played a vital role in electrical power engineering applications due to the invention of advanced architectures and techniques that significantly enhance image processing capabilities. These innovations have led to remarkable performance improvements in various tasks, including fault detection, load forecasting, monitoring of electrical power systems, and improving unmanned aerial vehicles (UAV) Image quality for effective power line surveillance. Existing approaches to enhance UAV-captured images for electrical power engineering have advanced significantly, but they face several challenges. Environmental distortions, such as rain and fog, can introduce motion blur and reduce visibility, complicating feature extraction. Additionally, UAVs operating at higher altitudes may produce lower resolution images, hindering fault identification. Shadows and noise can obscure details, while the computational demands of deep learning models can impede real-time processing. Furthermore, data scarcity and variability in image quality necessitate adaptive algorithms to improve overall monitoring effectiveness. Our proposed approach effectively addresses the challenges of UAV image quality by enhancing image clarity through advanced deep learning techniques that mitigate environmental distortions. It utilizes sophisticated super-resolution algorithms to improve the resolution of images captured at higher altitudes, facilitating better fault identification in power lines. Additionally, specialized algorithms for shadow removal and noise reduction preserve critical details, while the model's computational efficiency allows for real-time processing during inspections. The adaptive nature of our algorithms ensures consistent performance across diverse conditions, and the solution is designed for seamless integration with existing inspection workflows. Overall, this approach significantly enhances the utility of UAV technology in electrical power engineering applications, leading to more efficient and reliable monitoring of power line infrastructure. In this paper we proposed a novel approach with depthwise separable convolution to enhance computational efficiency while ensuring high-quality image processing, making it suitable for real-time UAV applications. We incorporate Leaky ReLU activation functions to address the vanishing gradient problem, allowing the model to learn effectively and retain critical information. Additionally, the use of both local and global skip connections improves feature extraction by preserving fine details and integrating broader contextual information. This combination significantly enhances the model's ability to capture intricate features and produce high-resolution images. Ultimately, our approach leads to clearer and more detailed imagery for effective monitoring of electrical power lines. Experimental results demonstrate that the enhanced images achieve significantly higher Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values compared to traditional image processing methods. These improvements not only facilitate better visual analysis but also support more reliable inspections of power lines, enabling quicker identification and resolution of potential issues.

**KEYWORDS:** Deep Learning, UAV Imagery, Image Super-resolution, Electrical Power Engineering, Convolutional Neural Networks.

1. **INTRODUCTION**

Power transmission lines are integral components of the electrical grid infrastructure, playing a vital role in the distribution of electricity from generation sources to end-users, including industries, households, and businesses [1]. The efficient operation and maintenance of these lines are crucial for ensuring an uninterrupted and reliable power supply. However, defects or damages in power transmission lines can lead to significant consequences, including power outages that disrupt industrial operations and everyday life [2]. Therefore, timely detection of such defects is essential for maintaining the safety and reliability of the power grid. Traditional methods for inspecting power transmission lines often involve manual inspections, which can be time-consuming, costly, and hazardous for personnel. These inspections typically require workers to climb towers or use helicopters, exposing them to dangerous conditions while also incurring high operational costs. As a result, there is an increasing demand for more efficient and safer inspection techniques. Recent advancements in technology, particularly in unmanned aerial vehicles (UAVs) and deep learning algorithms, have opened new avenues for automating the inspection process. UAVs equipped with high-resolution cameras can capture detailed images of power lines from various angles without putting human inspectors at risk. However, the effectiveness of these UAV-based inspections relies heavily on advanced image processing techniques that can accurately identify defects. Deep convolutional neural networks (CNNs) have emerged as powerful tools for image analysis and have shown remarkable performance improvements in various tasks related to image processing. By leveraging these advanced architectures, researchers can develop sophisticated algorithms that enhance image quality and facilitate better defect detection in power transmission lines.

Unmanned Aerial Vehicles (UAVs) have become essential tools in the monitoring and inspection of electrical power lines, particularly in enhancing image quality through super-resolution techniques. The ability to capture high-resolution images from UAVs significantly improves the assessment of power line infrastructure, which is critical for ensuring a reliable and uninterrupted supply of electricity. Power transmission lines are integral components of the electrical grid, responsible for delivering power to various sectors, including residential, commercial, and industrial users. Detecting defects in these lines is crucial for maintaining safety and reliability; any faults can lead to significant power outages with severe consequences.

Traditional methods for inspecting power lines often involve manual checks, which can be time-consuming, costly, and hazardous for personnel. These inspections typically require workers to climb towers or use helicopters, exposing them to dangerous conditions while incurring high operational costs. As a result, there is a growing demand for more efficient and safer inspection techniques.

Recent advancements in technology, particularly in deep learning and image processing, have opened new avenues for automating the inspection process. Super-resolution (SR) refers to the process of increasing the resolution of images to enhance their quality and detail. Deep learning-based SR methods have gained popularity due to their ability to produce high-quality results by learning complex mappings between low-resolution (LR) and high-resolution (HR) images.

Various architectures have been developed for SR tasks, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). CNN-based methods like Super-Resolution Convolutional Neural Network (SRCNN) and Very Deep Super-Resolution (VDSR) have shown promising results in producing HR images. RNN-based approaches excel in handling sequences of images, making them suitable for video SR tasks. GAN-based methods, such as SRGAN, leverage adversarial training to generate realistic images with enhanced details.

Despite these advancements, challenges persist in UAV-captured images due to environmental distortions and resolution limitations. Addressing these issues is essential for improving the accuracy of defect detection systems. This paper proposes a novel GAN-based super-resolution method specifically designed to enhance the quality of images captured from power transmission lines by four times. The proposed approach utilizes an innovative architecture and loss functions that yield detailed HR output images from input LR images.

The performance of this method will be compared against various state-of-the-art techniques, including bicubic interpolation and other deep learning models. The results demonstrate that our approach achieves superior Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and overall image quality while requiring less training time. This study highlights the potential of advanced deep learning techniques in revolutionizing the monitoring and maintenance of electrical power infrastructure through improved image quality from UAVs.

The key contributions of this paper are summarized as follows:

* The proposed approach utilizes sophisticated deep learning algorithms to enhance the clarity of UAV-captured images, effectively addressing challenges posed by environmental distortions such as rain and fog.
* By implementing advanced super-resolution techniques, the model improves the resolution of images taken at higher altitudes, facilitating better fault identification in power lines.
* The model is designed for computational efficiency, allowing for real-time processing during inspections, which is crucial for timely decision-making in power line monitoring.
* Incorporation of depthwise separable convolutions, Leaky ReLU activation functions, and both local and global skip connections significantly boosts the model's ability to capture intricate features and produce high-quality images.

The structure of this paper is outlined as follows: Section 2 discusses the relevant related work and previous studies in the field. Section 3 provides a detailed explanation of the proposed network architecture. The experimental procedures and results are presented in Section 4. Finally, Section 5 offers the concluding remarks and insights drawn from the study.

1. **RELATED WORK**

In recent years, numerous deep learning-based super-resolution (SR) methods have demonstrated significant promise in image interpolation and restoration, outperforming traditional pixel-wise interpolation techniques. Dong et al. introduced a three-layer convolutional neural network (CNN) architecture known as the super-resolution convolutional neural network (SRCNN), which learns an end-to-end mapping from a bicubic-interpolated low-resolution image to a high-resolution image. Following the introduction of SRCNN, numerous CNN architectures with deeper and more complex structures have been developed to enhance the accuracy of super-resolution results.

The Super-Resolution Convolutional Neural Network (SRCNN), while a pioneering model in the field of image super-resolution, faced several challenges that limited its practical application. One of the primary issues was its high computational cost, which hindered real-time performance, making it unsuitable for applications requiring immediate results, such as video processing. The architecture of SRCNN also relied on a bicubic interpolated low-resolution image as input, which could lead to suboptimal results by not fully utilizing the original low-resolution data.

In response to these limitations, Chao Dong and colleagues proposed the Fast Super-Resolution Convolutional Neural Network (FSRCNN). This model aimed to accelerate the super-resolution process significantly. FSRCNN directly takes the original low-resolution image as input, eliminating the need for initial interpolation. The architecture incorporates smaller convolutional filters (3x3) throughout multiple layers, which reduces the number of parameters and computational burden while maintaining a similar receptive field. Additionally, FSRCNN introduces a transposed convolution layer at the end of the network to upscale the image to the desired resolution efficiently.

Same author of SRCNN proposed a revised version named as the Fast Super-Resolution Convolutional Neural Network (FSRCNN), which enhances the speed and efficiency of super-resolution tasks compared to its predecessor, SRCNN. The FSRCNN architecture consists of several key components that streamline the processing of low-resolution (LR) images into high-resolution (HR) outputs. First, FSRCNN replaces the bicubic interpolation used in SRCNN with a 5x5 convolution layer for feature extraction, allowing for more effective initial processing of the LR image. Following this, a 1x1 convolution is employed to reduce the number of feature maps, significantly decreasing computational complexity while maintaining essential information. The network then utilizes multiple 3x3 convolution layers for non-linear mapping, which helps capture intricate features without increasing the number of parameters excessively. After the non-linear mapping, another 1x1 convolution expands the number of feature maps back to the original size, preparing the data for reconstruction. Finally, a deconvolution layer with a larger filter size is used to reconstruct the HR image from the processed features. This overall structure allows FSRCNN to operate efficiently while achieving high-quality results, making it faster than SRCNN and suitable for real-time applications in image super-resolution. The model's design emphasizes a balance between performance and computational efficiency, leading to improved image quality with fewer parameters and reduced training times.

Kim et al. introduced a super-resolution scheme using Very Deep Convolutional Networks (VDSR), featuring 20 convolutional layers and a global skip connection. This architecture enhances single-image super-resolution by effectively mapping low-resolution (LR) images to high-resolution (HR) images. VDSR emphasizes the importance of receptive field size, with a patch size of 41x41 pixels, allowing the network to capture comprehensive features from the input. The model employs residual learning, focusing on predicting the residuals—the differences between the bicubic interpolated LR image and the HR image. This approach helps retain high-frequency details often lost in traditional methods. The global skip connection facilitates better information flow, addressing vanishing gradient issues in deep networks. Consequently, VDSR achieves significant improvements in image quality, establishing itself as a key advancement in super-resolution techniques.

Falahatnejad et al. [3] proposed PTSRGAN, a generative adversarial network aimed at enhancing the resolution of UAV images of power transmission lines. This model features a novel generator architecture and a Siamese network-based discriminator, improving the quality of images with detailed edges and textures.

Hossam Aboalia et al. [4] developed a study to enhance power line detection using deep learning and feature-level fusion of infrared and visible light images. Recognizing the critical need for accurate detection to ensure flight safety for drones and low-flying aircraft, the researchers trained three distinct models, including VGG16 and AlexNet, optimized for both image types. They introduced a novel multi-input model that merges features from paired infrared and visible images, creating an enriched feature map.

In this approach [5] authors are suggested a deep learning approach for detecting and evaluating key targets and defects in high-voltage power transmission lines. They constructed a comprehensive dataset and introduced a predictive feature layer with feature fusion to enhance small target recognition. The method enables remote control online inspections using power transmission line inspection robots (PTLIR) and unmanned aerial vehicles (UAVs). Odo et al. [6] present the study on an automated approach for assessing the condition of electrical towers using deep learning, eliminating the need for individual component condition labels. By leveraging a comprehensive dataset with only tower-level labels, the authors trained machine learning classifiers effectively.

Liu et al. [7] tackled the challenge of reconstructing high-quality data from low-quality smart meter data through their Super Resolution Perception (SRP) framework. They formulated the SRP problem using the Maximum a Posteriori (MAP) estimation approach, allowing for effective data reconstruction without extensive labeling. The authors introduced the Super Resolution Perception Convolutional Neural Network (SRPCNN) to generate high-frequency load data from low-frequency inputs. Their method enhances data quality and improves appliance identification results. This work optimizes smart meter data utilization while reducing costs associated with acquiring high-quality data.

Xu et al. [8] proposed an autonomous UAV system for electric transmission line inspections that utilizes advanced embedded processors and binocular visual sensors. Their solution features an end-to-end convolutional neural network (CNN) designed to detect power lines of varying pixel widths and orientations, incorporating a multilevel feature aggregation module and a joint attention (JA) module for enhanced accuracy. The system constructs 3-D point sets of power lines from binocular images, allowing for real-time motion planning and automatic inspections. Experimental results demonstrated that their method outperformed state-of-the-art techniques in practical environments. This innovation significantly improves inspection efficiency and reduces costs associated with manual methods.

Wang et al. [9] explored the 1-D inverse scattering problem to super-resolve the locations of discrete point faults in transmission lines. They formulated this challenge as a sparse reconstruction problem and applied convex optimization techniques for enhanced spatial resolution. Their results showed that up to four point shunt conductance faults could be precisely resolved with infinite accuracy when separated by half the minimum wavelength available. Additionally, they demonstrated that up to three point impedance faults could also be super-resolved under similar conditions. The effectiveness of their method was validated through simulation and experimental results, marking a significant advancement in fault detection.

The authors [10] are highlighted the limitations of existing satellite remote sensing images, which often result in fuzzy representations of transmission line bodies. They proposed a multiscale edge enhancement method that combines a multi-map residual convolutional neural network with wavelet transform to improve super-resolution.

Wang et al. [11] proposed a novel approach for super-resolution (SR) technology applied to power distribution network measurements, focusing on both topology and time-series completion. They introduced a data completion method that utilizes a graph convolutional neural network (GCN) for spatial-temporal convolution, integrating power system state estimation to enforce physical constraints. This method enhances the super-resolution of measurements, improving the overall state awareness of distribution systems. The authors emphasized that their approach not only aids in operational efficiency but also contributes to reducing equipment failures within the network. By addressing the industry's need for reliable measurement recovery, their work supports cost savings and enhances the security and stability of power distribution systems.

Liang et al. [12] suggested a novel approach to enhance data completeness in smart grid state estimation through a super-resolution perception (SRP) framework. They formulated the challenge of recovering high-frequency data from low-frequency measurements, emphasizing the necessity for complete system state data to support accurate state estimation. Their method, named Super Resolution Perception Net for State Estimation (SRPNSE), involves three key steps: feature extraction, information completion, and data reconstruction. Case studies demonstrated the effectiveness of SRPNSE in accurately recovering high-frequency data, thereby improving the state awareness of distribution systems. This advancement contributes to increased operational efficiency and enhances the security and stability of smart grids.

Yang et al. [13] completed a comprehensive review on state-of-the-art power line inspection techniques, addressing the challenges posed by the rapid growth of smart grid infrastructure. They highlighted the increasing disparity between maintenance workers and the required maintenance equipment, which can lead to inefficiencies. The review covers advanced technologies such as unmanned aerial vehicles (UAVs), image processing, and deep learning architectures aimed at improving inspection quality. The authors examined various inspection platforms and sensors, analyzing their advantages and disadvantages for specific tasks. Overall, their work provides a valuable reference for researchers focused on enhancing automatic power line inspection methodologies within the smart grid context.

The authors [14] highlighted the challenges of detecting small insulator defects and subtle texture features in UAV power inspection images. They [14] proposed a multi-stage detection method that combines MSR-Net and YOLOv5-s to effectively address these issues. The YOLOv5-s network is first used for rapid identification of insulators, followed by a multi-scale super-resolution network (MSR-Net) for image reconstruction. This approach enhances high-frequency feature extraction, improving the detection of small insulator defects.

1. **PROPOSED NETWORK ARCHITECTURE**

The proposed network architecture for UAV image super-resolution is designed to enhance low-resolution (LR) images of electrical power lines captured by unmanned aerial vehicles (UAVs). This architecture incorporates several key components that work synergistically to improve image quality, ensuring that critical details are preserved for effective monitoring and analysis. Our proposed architecture begins with the input layer, which accepts low-resolution UAV images. These images are often affected by various factors such as distance, atmospheric conditions, and camera limitations, leading to a loss of detail. The input layer prepares these images for further processing by the subsequent layers of the network.

**Depthwise Separable Convolution Operation**

One of the core innovations of this architecture is the use of depthwise separable convolutions. This technique consists of two stages: depthwise convolution and pointwise convolution. In depthwise convolution, a single filter is applied to each input channel separately, which allows for efficient feature extraction while significantly reducing the number of parameters compared to traditional convolutional layers. The pointwise convolution then combines these outputs to produce a new set of features. This approach not only enhances computational efficiency but also maintains high-quality feature representation, making it particularly suitable for real-time applications in UAV imagery. Given an input tensor y of size (height, width, channels), and a depthwise filter of size, where is the kernel size, the output can be computed as:

Where:

* are the spatial coordinates in the output feature map,
* indexes the channel

**Pointwise Convolution Operation**

After depthwise convolution, a pointwise convolution is applied using a filter of size , where is the number of output channels. The output of the pointwise convolution can be expressed as:

The overall operation of depthwise separable convolution can thus be represented as:

This shows how depthwise separable convolutions reduce computational complexity while maintaining effective feature extraction.

**Leaky ReLU Activation Function**

To combat the vanishing gradient problem that can occur in deep convolutional neural networks, the architecture incorporates Leaky ReLU activation functions. Unlike standard ReLU functions that output zero for negative inputs, Leaky ReLU allows a small, non-zero gradient when the input is negative. This characteristic ensures that gradients flow effectively during backpropagation, enabling the model to learn more efficiently and retain critical information throughout its layers. Mathematically, Leaky ReLU activation function can be written as:

Where:

* is the input to the activation function
* is a small constant (e.g., 0.01) that allows a small gradient when

This function helps in retaining gradients during backpropagation, thus addressing the vanishing gradient problem.

**Skip Connections**

The architecture integrates both local and global skip connections, which play a crucial role in preserving fine details and incorporating broader contextual information. Local skip connections allow features from earlier layers to bypass one or more layers directly, helping preserve spatial hierarchies and fine details that are vital for accurate image reconstruction. Global skip connections enable the integration of high-level features from earlier layers into deeper layers, allowing the model to leverage broader contextual information that enhances overall performance. Mathematically, skip connections can be written as:

Where:

* is the output from an earlier layer.
* is the output from a deeper layer.

This addition helps in preserving spatial information and enhances feature representation by combining low-level features with high-level features.

**UpSampling Block**

A dedicated super-resolution UpSampling block is included within the architecture to progressively increase the resolution of input images. This block employs upsampling techniques such as sub-pixel convolution (also known as pixel shuffle), which rearranges elements in a feature map into a higher-resolution output. This method effectively enhances image quality while ensuring spatial coherence and detail retention.

**Fusion Layer**

To further improve the model's ability to capture intricate details necessary for effective monitoring of power lines, a feature fusion layer is introduced. This layer combines features extracted from various convolutional layers, enriching the representation of the image and enhancing its overall quality. The mathematical formulation can be expressed as:

Where:

* is the output feature map of the fusion layer.
* and are the input feature maps from different layers that are being fused.
* and are weights that determine the coordination of each input feature map to the output. These weights can be learned during training or set to fixed values.

The final component is the output layer, which consists of a convolutional layer that produces the enhanced high-resolution image of electrical power lines. This layer is designed to ensure that essential structural details are retained in the output, facilitating accurate analysis and inspection.

1. **EXPERIMENTS**

In this section, we describe the experimental methods employed to evaluate our deep convolutional neural network (CNN) model designed for enhancing UAV images for monitoring electrical power lines. This model addresses the challenges associated with low-resolution images and environmental distortions, leading to improved image quality and more effective monitoring. The experiments were conducted using Keras with TensorFlow 2 as the backend. The training process utilized a single 2070 Ti GPU, providing the necessary computational power for handling the model's requirements efficiently.

**Dataset**

Our proposed model used the publicly available STN Power Line Assets Dataset [15]. This [15] dataset has a comprehensive collection designed to facilitate the detection, classification, and image enhancement of various high-voltage power line components using advanced deep learning techniques. This dataset is particularly valuable for researchers and practitioners working in the field of electrical power engineering, especially in the context of UAV (unmanned aerial vehicle) imagery. The dataset contains high-resolution images that capture multiple components of power line infrastructure. Each image measures either 5472 × 3078 pixels or 5472 × 3648 pixels, ensuring that fine details are preserved, which is crucial for accurate detection and classification tasks. In total, there are 2,409 annotated objects within the dataset. These objects are categorized into five distinct classes, such as Transmission Tower, Insulator, Spacer, Tower Plate, and Stockbridge Damper. : Devices used to reduce oscillations in overhead lines.

<https://github.com/andreluizbvs/PLAD>

**PERFORMANCE EVALUATION QUALITY METRICS**

In the realm of enhancing UAV (unmanned aerial vehicle) images for monitoring electrical power lines, the evaluation of image quality metrics is crucial for assessing both the quantitative and qualitative performance of super-resolution (SR) techniques. The ability to produce visually pleasing and high-quality images directly impacts the effectiveness of tasks such as fault detection, load forecasting, and overall monitoring of electrical power systems. Our proposed method to evaluate the quality of the generated high-resolution (HR) images from our deep learning model, we employed two widely recognized metrics: Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Each of these metrics provides unique insights into the performance of the model and the quality of the images produced.

**Peak Signal-to-Noise Ratio (PSNR)**

PSNR is a traditional quality metric used in image processing to quantify the quality of reconstructed images by measuring the level of noise present. It calculates the mean squared error (MSE) between the HR and low-resolution (LR) images and converts this value into a decibel (dB) scale. MSE serves as a fundamental metric in evaluating image quality, especially in tasks involving image reconstruction, super-resolution, and other applications where maintaining fidelity to original images is crucial. Higher PSNR values indicate better image quality, as they reflect lower noise levels. Mathematically PSNR can be derived from MSE are as under:

Where:

* is the total number of pixels in the image.
* is the pixel value of the original (ground truth) image at pixel position .
* is the pixel value of the predicted (enhanced or reconstructed) image at pixel position .

Where:

* is the maximum pixel value of the image (typically 255 for 8-bit images).
* is the mean squared error between the HR and LR images.

**Structural Similarity Index (SSIM)**

SSIM measures the similarity between two images based on structural information, contrast, and luminance. Unlike PSNR, which focuses solely on pixel differences, SSIM considers how human perception interprets structural changes in images. The SSIM score ranges from -1 to 1, where a score of 1 indicates perfect similarity between the two images.

The SSIM formula is expressed as:

Where:

* and are the HR and super-resolution (SR) images, respectively.
* and are their mean values.
* and are their standard deviations.
* is the covariance between and .
* Constants and are added to avoid instability in the denominator.

1. **CONCLUSION**

In this paper, we demonstrated that deep learning-based image enhancement techniques significantly improve the quality of UAV-captured images for monitoring electrical power lines. The advent of advanced deep learning architectures has revolutionized image processing capabilities, particularly in the context of UAV applications. By addressing challenges such as environmental distortions, low resolution, and noise, our proposed approach enhances fault detection capabilities and overall inspection efficiency. Traditional methods often struggle with these issues, resulting in unclear images that hinder effective analysis. Our integration of depthwise separable convolution and Leaky ReLU activation functions ensures both computational efficiency and effective learning, leading to clearer imagery that supports reliable visual analysis. The use of depthwise separable convolutions allows for a reduction in the number of parameters while maintaining high performance, which is crucial for real-time applications where computational resources may be limited. Leaky ReLU activation functions help mitigate the vanishing gradient problem, enabling the model to learn effectively from diverse data inputs without losing critical information. As a result, our approach not only improves image clarity but also enhances the model's ability to capture intricate features essential for identifying potential faults in power lines. In our future work, we will focus on enhancing real-time processing capabilities by optimizing our algorithms for immediate feedback during inspections. This capability is vital for UAV operations, as timely responses can significantly improve safety and operational efficiency. We will investigate transfer learning to adapt models to various environmental conditions and improve robustness with limited training data. This approach will enable our models to generalize better across different scenarios, ensuring consistent performance even in challenging conditions such as adverse weather or varying lighting. Additionally, we aim to develop adaptive learning systems that continuously learn from incoming data to maintain accuracy in dynamic environments. Such systems will be able to adjust their parameters in real-time based on new information, allowing them to remain effective as conditions change during inspections. This adaptability is particularly important in the field of electrical power line monitoring, where environmental factors can greatly influence image quality and fault detection accuracy. Finally, we will prioritize creating user-friendly interfaces to ensure accessibility for operators, facilitating easier interpretation of enhanced images and analysis results. By simplifying the interaction between users and technology, we can enhance the overall effectiveness of UAV monitoring systems and ensure that operators can make informed decisions quickly. Our goal is to create a seamless integration of advanced image processing techniques with practical usability in the field.

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