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A Novel Approach for Identifying and Eliminating the Degradations in Real Time Images

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ABSTRACT Satellite imagery plays a crucial role in various applications, but the quality of the images can be degraded by noise. Accurate noise detection is essential for effective image enhancement and analysis. This project proposes a hybrid approach for noise detection and enhancement in satellite images by integrating deep learning and conventional techniques. We use a convolutional neural network (CNN) model along with Daubechies wavelet coefficient and statistically extracted coefficient paired with feature components extracted after applying median and high-pass filter for noise detection, to classify the type of noise in satellite images. The CNN model is trained on a dataset of images with various noises, learning to discriminate between different noise patterns. After classifying the type of noise, we apply a enhancement approach utilizes deep learning techniques by leveraging U-Net based CNN model to reduce noise levels in an image.

INDEX TERMS CNN, Median Filter, High-Pass Filter, Image Enhancement, Wavelet Transform, Fast Fourier Transform U-Net.

I. INTRODUCTION

A. BACKGROUND

In recent years, real-time image processing has become a fundamental component for a range of various applications, including autonomous driving, medical imaging, surveillance systems, and satellite monitoring. The ability to accurately identify, classify, and enhance images in real-time holds significant importance in terms of safety, decision-making, and automation. Although real-time image acquisition often faces various forms of degradation and noise. The presence of image noise can make it difficult to accurately detect and analyze image features, such as edges or textures, and can also introduce errors in image classification and recognition tasks [1]. Noise in images caused by environmental conditions, sensor limitations, transmission errors, and other factors may reduce the quality of the captured data, complicating further analysis. Therefore, it is of great significance and practical value to study image enhancement algorithms to improve the performance of imaging devices [5].

There are many forms of noise, including but not limited to Gaussian noise, impulse noise, Rayleigh noise, lognormal noise, and Poisson noise. Gaussian noise often emerges during image acquisition due to sensor thermal fluctuations, which appear as random variations in pixel intensity. Impulse noise, also known as salt-and-pepper noise, is distinguished by sudden spikes in pixel intensity and usually is a result of transmission errors. These noise types may mask important features in images and can also result in improper classification or identification from image analysis algorithms. To resolve these issues, we require an accurate and computationally efficient method for detection and differentiation among noise types in real images, along with appropriate enhancement techniques for restoring image quality.

In general, the basic principle of image enhancement is to improve the quality and visual comprehensibility of an image so that it is more suitable for the specific applications and the observers [5]. Convolutional neural network (CNN) is a strong tool in deep learning that can be used for both noise detection and picture enhancement. CNN, or ConvNet, is an artificial neural network used to analyze visual images [1]. Convolutional neural networks exhibit impressive capabilities in identifying patterns within data, rendering them highly effective for applications such as noise classification. Each CNN consists of an input, hidden, and output layer, and the input layer includes the input matrix [1]. Traditional methods like wavelet transforms and histogram-based techniques are widely used for image denoising and enhancement. Wavelet approaches are practical tools for good data representations and feature extractions compatible with the most available classification algorithms [1]. Recent approaches overcame high computational costs by combining the strengths of deep learning with conventional techniques, resulting in hybrid models that offer both accuracy and efficiency in real-time images. In conjunction with a deep neural network, the wavelet transform permits the generation of dependable features that are locally stable to tiny deformations [1].

B. LITERATURE SURVEY

In paper [1], a hybrid approach is used for noise detection and identification by integrating deep wavelet transforms along with machine learning techniques. They combine deep wavelet decomposition with a support vector machine (SVM) classifier. The wavelet transform extracts necessary frequency features from the images, followed by the SVM for noise classification.The study in [2] presents a modified histogram equalization method for enhancing the performance of the CNN in medical segmentation. They unified the adaptive histogram with CNN-based segmentation to improve contrast and feature extraction.

The research [4] discusses addressing noise removal in images by altering the receptive field of the CNN through dilated kernels. This allows networks to obtain more contextual information without increasing computational complexity. The authors also designed and compared three CNN architectures and came to the conclusion that an optimized receptive field generated the best results in terms of noise reduction. In this paper [8], CNN-based architectures for both noise classification and denoising are applied. The first step in noise classification is transfer learning. After that, these noisy images are denoised using the blind denoising algorithm and CNN-based image denoising algorithm to obtain denoised images. The paper [9] uses a convolutional neural network (CNN) for noise classification and a UNET model for the denoising process. The study focuses on automating the task of detecting noise types in images, which is crucial for improving processing efficiency.

In [7], investigates the performance of various machine learning approaches for classifying complex noise patterns in Quick Response (QR) code images. The study compares multiple models, including Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN), to determine the most effective method for noise classification. In [5], advancements in image enhancement techniques are discussed, highlighting both traditional and deep-learning-based approaches. Limitations of conventional techniques like histogram equalization and wavelet transforms are analyzed in real-time applications. It also emphasizes remarkably improved performance around emerging trends in deep learning.

Plateau Limit-based Tri-Histogram Equalization (PLTHE) is proposed in [3] to enhance the visual quality of the im- age. This method splits the image histogram into three sub-histograms depending on a plateau limit. It helps prevent over-enhancement and excessive contrast stretching, which is usually observed in traditional histogram equalization techniques. This approach [6] focuses on eliminating various types of noise, including impulse noise and Gaussian noise, by using a pixel density-based filtering technique. The PDTMF method improves the median filter by trimming outlier pixels based on pixel density, allowing for better preservation of image details while removing noise.

The research paper by J. Fischer et al[13] focuses on evaluating machine learning techniques, particularly the random forest classifier and neural networks for identifying fractions of refuse-derived fuel (RDF) using image analysis. Two methods are being tested in the paper, the random forest classifier which utilizes feature extraction (color histograms and Haralick-textures) and Xception neural network with transfer learning.

This paper [14] discusses about a CNN model for image denoising which focuses on enhancing image quality while preserving fine details like edge and textures. This model uses a loss function that balances noise reduction and image fidelity. This study compares CNN's performance against traditional methods such as median filters and wavelet-based techniques. Experimental results show that the proposed CNN model can effectively remove Gaussian noise and improve the performance of traditional image filtering methods significantly [14]. This paper by Saifullah et al [15] proposes a CNN-based medical image segmentation approach enhanced by histogram equalization. Histogram equalization is used as a preprocessing step to improve visibility of image details. Results indicate that combining histogram equalization with CNN improves accuracy in detecting edges and boundaries.

This paper [16] uses an adaptive trimmed median filter (ATMF) for efficient detection of impulse noise from mammogram images. This study proposes ATMF which adaptively adjusts filtering window based on noise level detected. Noisy pixels are identified by comparing them with a dynamic threshold. In [20] , a modified trimmed median filter (MTMF) technique is utilized, where a portion of outlier pixels is trimmed before applying median operation. Experimental results demonstrates that MTMF outperforms standard median filter by achieving PSNR up to 36.8 dB.

The paper [18] proposes a artificial neural network (ANN) integrated with wavelet transform to enhance image. Wavelet transform is applied to separate high-frequency details from low-frequency details. Then ANN is trained to enhance high-frequency components and suppress noise in low-frequency bands. This paper [19] presents a novel approach for image denoising with a CNN, a deep learning framework with layers designed for denoising is used and optimized using mean squared error(MSE) as a loss function. This approach outperforms traditional filtering methods by reaching PSNR values as high as 32.1 dB. In [17], Gaussian noise is detected and estimated using a deep convolutional neural network. This network is trained on synthetic images with different levels of gaussian noise, which allows it to generalize well across various noise levels. Experiments indicate that this model accurately detects the presence and intensity of noise.

In [21], a paired medical image enhancement approach is proposed to improve the diagnosis of intracranial hemorrhage. The study utilizes advanced image enhancement techniques to refine medical images, improving contrast and feature visibility, which aids in more accurate diagnosis. The method enhances paired images, ensuring consistency between different imaging modalities and reducing noise artifacts.

The study in [22] introduces RDC-UNet++, an end-to- end deep learning model for enhancing multispectral satellite images. The proposed architecture integrates residual dense connections into the UNet++ framework to improve color and texture detail preservation. Experimental results on large multispectral datasets show that RDC-UNet++ outperforms existing satellite image enhancement models in terms of structural similarity and peak signal-to-noise ratio (PSNR), making it a promising solution for real-time remote sensing applications.

The research in [23] presents UNetFormer++, an enhanced deep learning model for aerial image segmentation in land cover detection. This model integrates nested skip connections into the UNetFormer framework, leveraging both convolutional neural networks (CNNs) and Transformers for improved segmentation accuracy. The study demonstrates that UNetFormer++ achieves higher Dice and Intersection over Union (IoU) scores compared to traditional CNN-based segmentation models, making it an effective tool for automated land cover classification.

C. DATASET ACQUISITION

The dataset used in this research consists of 2,000 satellite images, each with five different types of noise, resulting in a total of 10,000 noisy images. The original images are colour images resized to a resolution of 256x256 pixels to maintain a manageable input size suitable for deep learning models. To enhance the dataset's variability and improve the model's generalization, data augmentation techniques such as random rotations and horizontal and vertical flips are applied. These augmentations help mitigate redundancy and prevent overfitting by exposing the model to a broader range of image variations. This augmented dataset provides a diverse and extensive set of noisy images, enabling the model to learn effectively across different noise conditions, which is essential for building a robust noise detection and image enhancement framework. This well-prepared dataset thus serves as a strong foundation for training the U-Net model, allowing it to handle real-world noise variations in satellite images effectively.

A data set [10] containing 14000 images, with one of the nine possible noise distributions present in each of the images [8]. Out of total images, 7600 images are related to noises we are working on in this paper. The dataset used for training of classification model consists of 6600 noisy images of five noise classes. This dataset is based on the Berkeley segmentation dataset BSDS300 (321 × 481). We use python script to map the images to their labelled noise class and extract required features. Fig. 1 displays a snippet from our dataset.

II. PROPOSED METHODOLOGY

This research proposes a unique method to detect and minimize image degradation in satellite images in order to improve image quality. In the identification process, we utilize a dual-channel CNN that takes in image pixel values post-resizing and normalization along with statistical features derived from the image. To isolate noise-specific elements in the image, the image undergoes high-pass and median filters and by calculating Daubechie's wavelet transform coefficients.These three components are then utilized to estimate the noise component in the image. This noise component extracted represents the deterioration in the image instead of emphasizing image details. Next, the noise component is used to calculate statistical features such as skewness and kurtosis of local variances, skewness and kurtosis of the image, power spectrum mean and standard deviation through fast Fourier transform, and gradient coherence. These values are inputted into the CNN to identify the type of degradation present in the image. In the next stage, we employ a specialized U-Net model trained on noisy and clean image pairs for the enhancement process. The proposed model architecture is displayed in Fig. 2.

A. NOISE IDENTIFICATION

The proposed noise identification model presents an innovative approach to noise classification in satellite imagery by integrating multiple sophisticated techniques including filtering methods, wavelet transformation, comprehensive feature extraction, and deep learning classification. This model addresses the complex challenge of identifying various noise types such as Gaussian, Poisson, Salt & Pepper, Rayleigh, and Lognormal noise, which commonly affect satellite images during acquisition and transmission. The model's architecture is structured into four main stages: Preprocessing by using filters, wavelet decomposition, feature extraction, and

FIGURE 1. Sample dataset

deep learning classification, each playing a crucial role in accurate noise identification.

The pre-processing stage employs two sequential filters that work in tandem to prepare the image for analysis. The first component is the Median Filter, a non-linear digital filtering technique that excels at removing impulse noise while preserving edges - a critical feature for satellite image analysis. Unlike mean filters that can blur edges, the median filter examines each pixel and replaces it with the median value of neighboring pixels, effectively eliminating extreme values caused by noise while maintaining important structural information. The filter's kernel size is adaptively chosen (typically 3x3 or 5x5) based on the estimated noise density, with larger kernels used for images with higher noise concentrations. Following the median filter, a High-Pass Filter is applied to enhance edge details and fine textures. This filter works by attenuating low-frequency components (gradual intensity variations) while amplifying high-frequency components (sudden intensity changes), effectively sharpening edges and fine details that might have been slightly softened by the median filter. The combination of these filters creates a robust pre-processing pipeline that both reduces noise and enhances important image features necessary for accurate noise classification.

The second stage utilizes the Daubechies Wavelet Transform, a sophisticated mathematical tool for image analysis. This transform decomposes the image into multiple frequency bands, providing a comprehensive multi-resolution analysis of the image content. The Daubechies wavelet was specifically chosen for its properties of compact support and smoothness, which make it particularly effective for image analysis. At each decomposition level, the trans- form produces approximation coefficients (representing low-frequency components) and detail coefficients (representing high-frequency components) in horizontal, vertical, and diagonal directions. This multi-level decomposition is crucial because different types of noise manifest differently across these frequency bands. For instance, Gaussian noise tends to affect all frequency bands uniformly, while impulse noise like Salt & Pepper is more prominent in high-frequency bands. The wavelet decomposition effectively separates the noise components from the underlying image structure, facilitating more accurate noise characterization in subsequent stages.

The feature extraction stage implements a comprehensive set of statistical and spatial analyses to quantify noise characteristics. Using the extracted value from above stages, an estimated noise component is generated, which is used to calculate statistical values like Gradient coherence calculation examines the uniformity and direction of intensity changes across the image, providing insights into edge strength and the presence of structured noise patterns. Local statistical measures include skewness, which quantifies the asymmetry of pixel intensity distributions and can indicate directional noise or lighting inconsistencies, and kurtosis, which measures the "peakedness" of intensity distributions and helps identify the presence of extreme values characteristic of certain noise types. The power spectrum analysis, performed using Fast Fourier Transform (FFT), reveals the energy distribution across different frequencies, which varies significantly between noise types. Fig. 4 shows extracted components from noisy image, which will be used as a input for CNN along with computed statistical features.

The final classification stage employs a deep learning based classification model. The CNN architecture consists of three convolutional 2D layers, each followed by ReLU activation functions that introduce non-linearity and batch normalization to stabilize learning. The convolutional layers are designed to detect increasingly complex patterns in

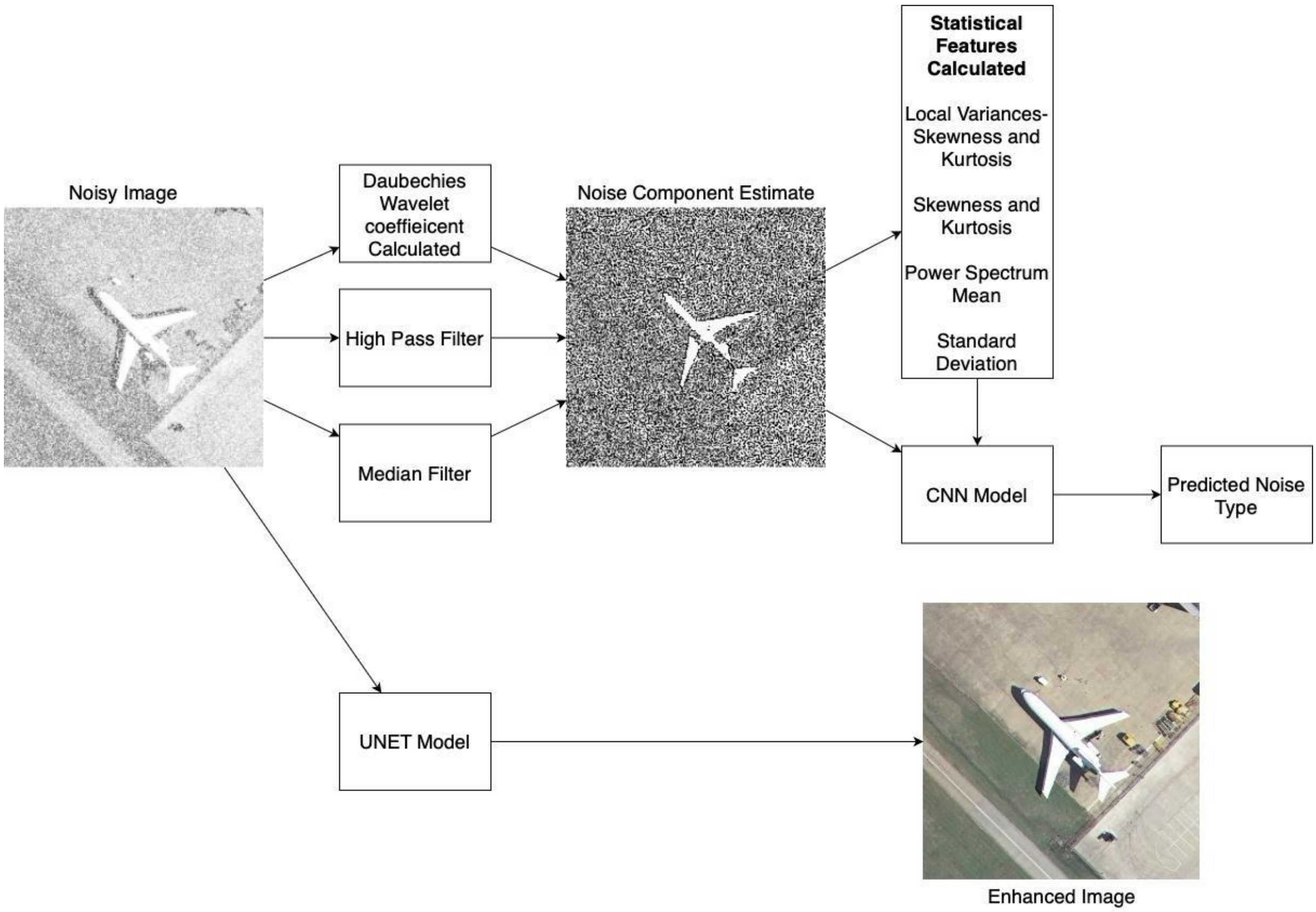

FIGURE 2. Proposed model

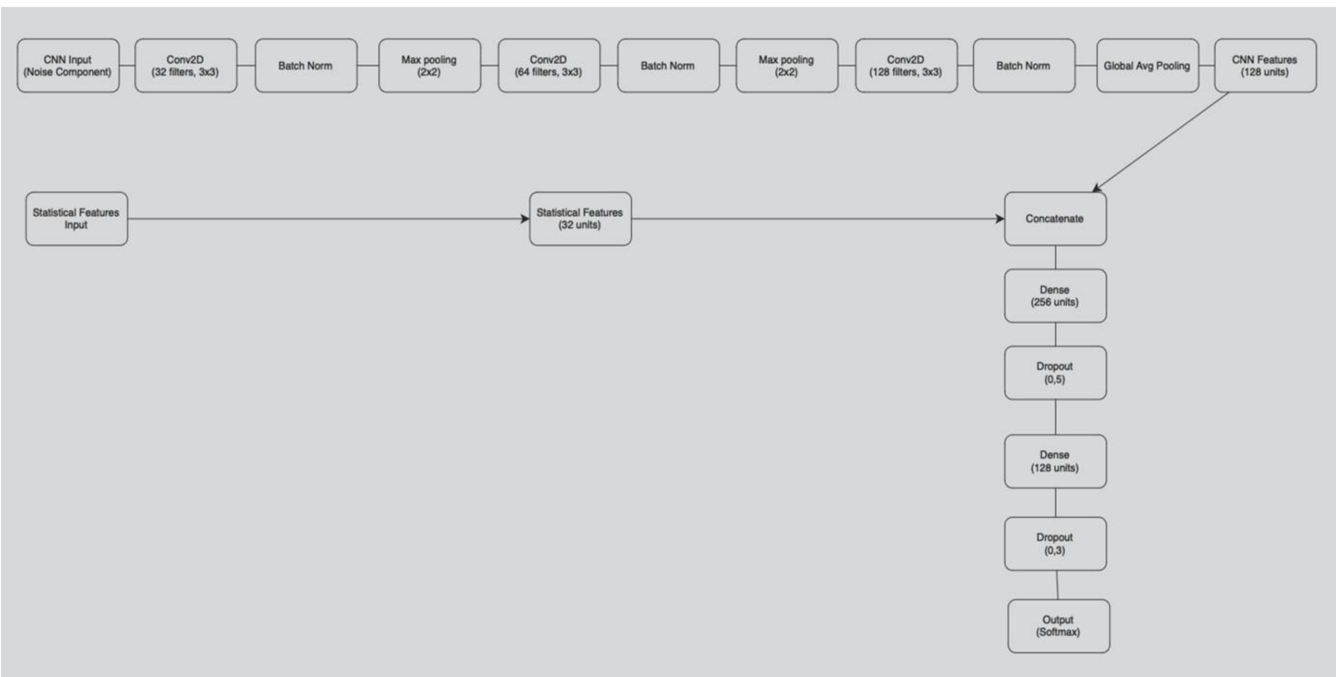

FIGURE 3. CNN Architecture

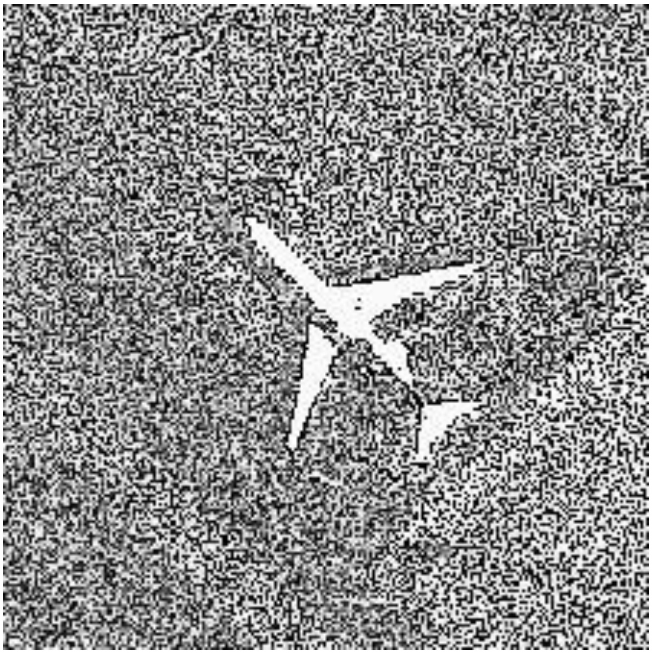

FIGURE 4. Extracted noise components

the noise components, with each layer learning hierarchical representations of noise characteristics. Three maxpooling layers reduce spatial dimensions while retaining important features, followed by a flattening layer that prepares the data for dense processing. The three dense layers progressively refine the feature representations, culminating in a SoftMax activation layer that produces probability distributions across noise classes. The model is trained on an extensive dataset of noise-affected satellite images.

The integration of these multiple techniques—filtering, wavelet analysis, statistical feature extraction, and deep learning classification creates a robust system capable of accurately identifying and classifying different types of noise in satellite images. This information can then be used to apply appropriate denoising techniques and improve image quality for subsequent analysis tasks. Each layer used in the CNN model is displayed with workflow in Fig. 3.

B. IMAGE ENHANCEMENT

Our proposed model employs a redesigned U-Net-based Convolutional Neural Network (CNN) architecture to address image degradation removal in real time, while preserving high-quality restoration. Originally developed for segmentation and reconstruction tasks, the U-Net architecture has been adapted in this work to efficiently eliminate noise and reconstruct images with spatial and contextual fidelity. Fig. 6 displays proposed noise enhancement model, where a noisy image is used as input for U-Net model, which provides an enhanced image for output.

Our proposed model employs a redesigned U-Net-based Convolutional Neural Network (CNN) architecture to address image degradation removal in real time, while preserving high-quality restoration. Originally developed for segmentation and reconstruction tasks, the U-Net architecture has been adapted in this work to efficiently eliminate noise and reconstruct images with spatial and contextual fidelity. As illustrated in Fig. 5, the architecture follows a classic encoder-decoder structure with skip connections, enabling precise recovery of image details that might otherwise be lost during down-sampling.

The encoder is designed to progressively reduce the spatial dimensions of the input image while increasing the depth of its feature maps. This hierarchical transformation captures multi-scale spatial and contextual features crucial for noise removal. Each level of the encoder employs a DoubleConv block, consisting of two 3x3 convolutional layers with batch normalization and ReLU activation functions. This configuration enables the model to extract complex spatial patterns while maintaining training stability. Following each DoubleConv block, a 2x2 max-pooling layer reduces the spatial resolution by half, ensuring the capture of dominant features while preserving computational efficiency. At every stage, the high-resolution outputs of the encoder are stored in skip connections, which later provide the decoder with detailed spatial information essential for accurate reconstruction.

At the heart of the architecture lies the bottleneck, which serves as the interface between the encoder and decoder. This layer operates at the lowest spatial resolution and captures the most abstract and condensed representation of the input image. Constructed using a DoubleConv block with an increased number of filters, the bottleneck extracts high-level semantic features while discarding redundant information. This ensures that the decoder begins with a rich and informative feature map for reconstruction.

The decoder progressively restores the spatial resolution of the image by reversing the down-sampling process. Each stage of the decoder begins with a 2x2 transpose convolution layer that doubles the spatial dimensions of the feature maps, effectively up-sampling them. The up-sampled feature maps are then concatenated with the corresponding high-resolution outputs from the encoder via skip connections. These skip connections integrate fine-grained spatial details from the encoder with the high-level contextual features generated by the bottleneck, significantly improving the reconstruction accuracy. After concatenation, the feature maps undergo further refinement through a DoubleConv block, ensuring the output is well-detailed and accurate.

Finally, the decoder outputs the restored image through a 1x1 convolution layer, which reduces the depth of the feature map to match the desired output channels. For input images with three channels (e.g., RGB images), the output also contains three channels, maintaining the original depth and ensuring compatibility for downstream tasks. By preserving the spatial dimensions of the input, the model produces enhanced images that are visually coherent and free from degradation. The proposed U-Net architecture thus effectively combines hierarchical feature extraction with precise reconstruction, making it highly suitable for real-time image enhancement.

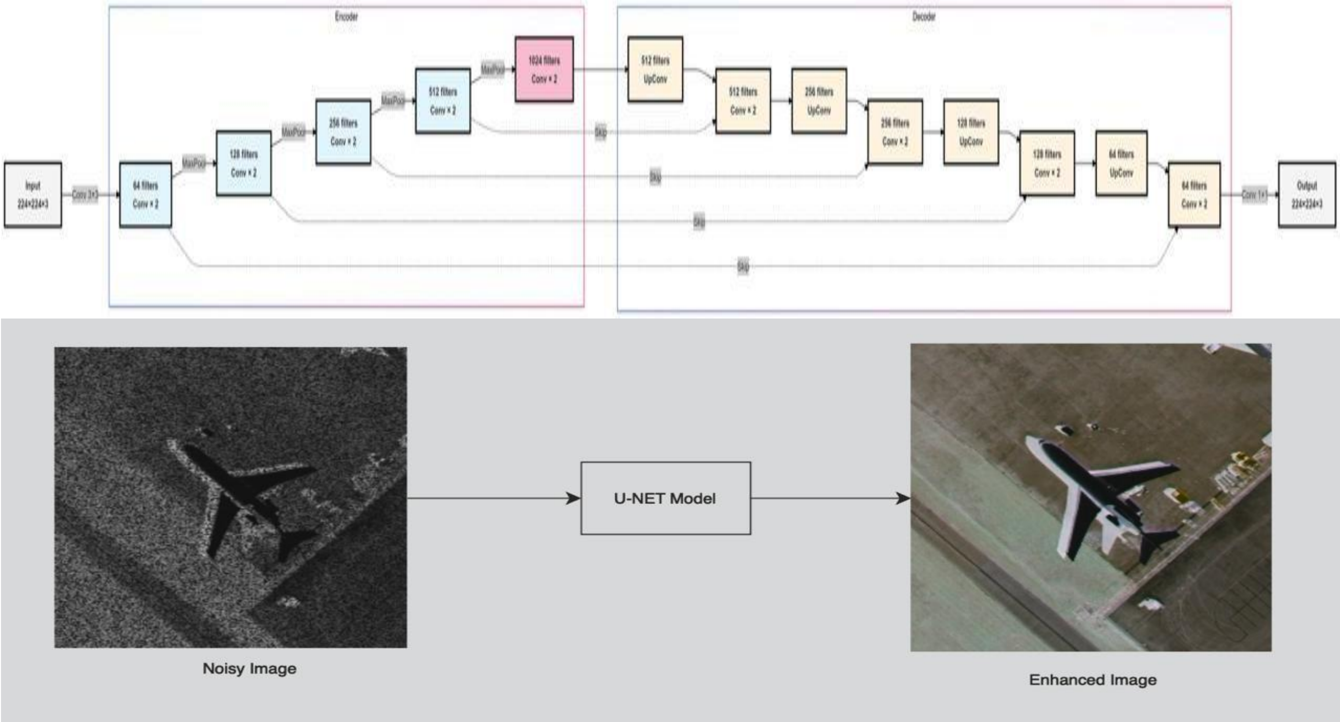

FIGURE 6. Proposed noise elimination model

III. RESULTS AND DISCUSSION

For noise detection and classification, the CNN model achieved a high training accuracy of 94.08%, with a corresponding loss value of 0.146, demonstrating strong capability in learning the noise characteristics within the training set. Validation results indicate a validation accuracy of 91.29% with a loss value of 0.185, showing that the model generalizes well to unseen data, although a slight drop in accuracy suggests some degree of overfitting. On the test dataset, the model achieved an accuracy of 89%, reflecting its effectiveness in accurately classifying noise types even outside the training data. The confusion matrix of the results on testing dataset is shown in Fig. 7, where true values are mapped against predicted values by proposed model.

The proposed U-Net architecture demonstrated its effectiveness in real-time image degradation removal by leveraging its encoder-decoder structure with skip connections. The model efficiently extracted multi-scale spatial and contextual features through the encoder while preserving fine-grained details using skip connections. The bottleneck layer captured high-level semantic features, providing the decoder with rich representations for reconstruction. The decoder progressively restored spatial resolution and integrated detailed spatial

information with contextual features to achieve precise image enhancement. This architecture ensured the production of visually coherent, high-quality restored images, validating its suitability for real-time image enhancement tasks. In Fig. 8, a satellite image of an airplane affected by gaussian noise is displayed. The same image was also used as input for identification model and it accurately classified it for gaussian

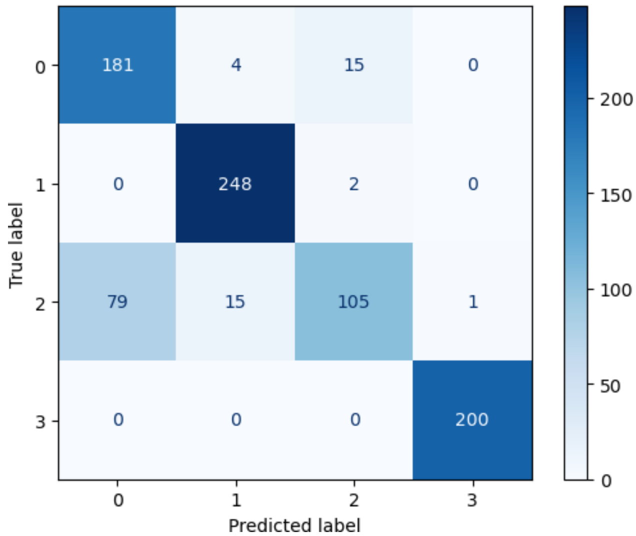

FIGURE 7. Confusion matrix

noise. Fig. 9 shows output of the enhancement model after removing noise degradations from Fig. 8.

The figures above displays the output for all the five types of noise namely Possion (Fig. 10), Rayleigh (Fig. 11), Salt and Pepper (Fig. 12), Lognormal (Fig. 13), Gaussian (Fig. 14).

The output consists of the original noisy image input, extracted noise image, image histogram, noise histogram and the enhanced image given by the model.

FIGURE 8. Noisy image from dataset

FIGURE 9. Enhanced image after using our model.

Table 1 displays a tabular comparison of various CNN models namely DnCNN, FFDNet, RIDNet, DSNet with the proposed U-Net based CNN model on basis of their PSNR values for σ=15.

IV. CONCLUSION

The proposed CNN model demonstrated strong performance in noise classification, achieving a training accuracy of 94.08% with a low loss of 0.146, and a validation accuracy

Metric	DnCNN	FFDNet	RIDNet	DSNet	Pr
PSNR (dB)	33.92	33.97	34.01	33.91	**37.78**
SSIM	0.91	0.92	0.93	0.91	**0.98**
MSE	0.0021	0.0019	0.0018	0.0020	**0.0007**
FSIM	0.94	0.95	0.96	0.94	**0.99**
VIF	0.76	0.78	0.79	0.77	**0.89**

TABLE 1. Comparison of image enhancement models on different metrics.

of 91.29% with a loss of 0.185. While the slight drop in validation accuracy indicates minimal overfitting, the model's ability to generalize is evident. On the test dataset, the model achieved 89% accuracy, highlighting its effectiveness in classifying noise types in unseen data.

For image enhancement, the U-Net model, trained over 100 epochs with the Adam optimizer and MSE loss function, achieved a Peak Signal-to-Noise Ratio (PSNR) of 37.78 dB, significantly improving image clarity by effectively reducing noise while maintaining essential image features. Additionally, the model outperformed existing methods in Structural Similarity Index (SSIM) (0.98), Feature Similarity Index (FSIM) (0.99), and Visual Information Fidelity (VIF) (0.89), demonstrating its ability to preserve perceptual quality and fine details. The model also achieved a Mean Squared Error (MSE) of 0.0007, indicating superior noise reduction with minimal reconstruction loss. The application of early stopping and learning rate reduction ensured efficient training and minimized overfitting.

Overall, the results validate the effectiveness of the CNN-based framework in noise classification and the U-Net model in image enhancement, demonstrating their potential for real-time satellite image analysis, particularly for improving interpretability and quality in satellite imagery.

Future research could focus on improving the CNN architecture for noise identification by incorporating advanced mechanisms such as attention layers or transformer-based architectures. Additionally, real-time applications can benefit from optimizing the framework through model compression, quantization, and lightweight architectures for efficient edge computing. Expanding the system to handle complex noise patterns and developing new metrics to assess restoration quality could further enhance its adaptability. Other potential advancements include adaptive enhancement techniques tailored to noise types, physics-based model integration, and automated hyperparameter optimization (NAS) to streamline model development. These enhancements would significantly improve the framework's applicability and performance across diverse satellite image processing scenarios.

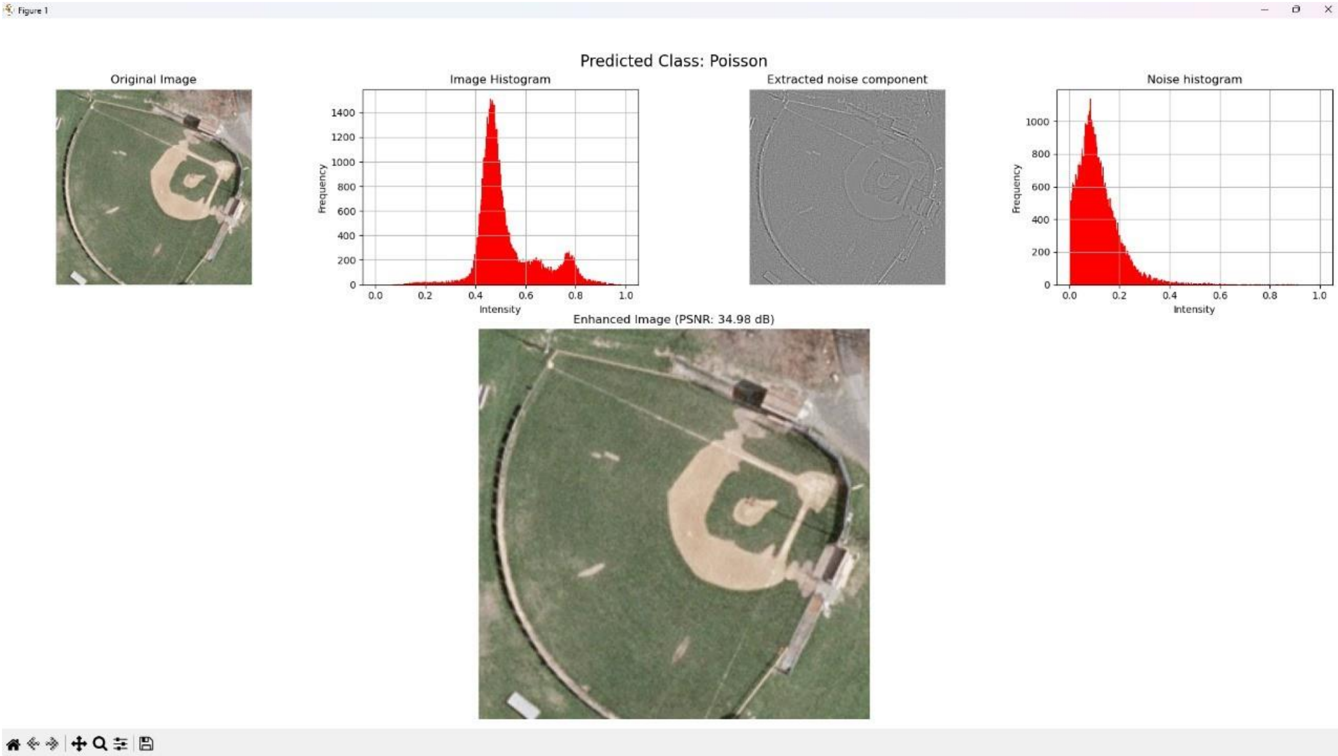

FIGURE 10. Poisson noise extracted component and enhanced image

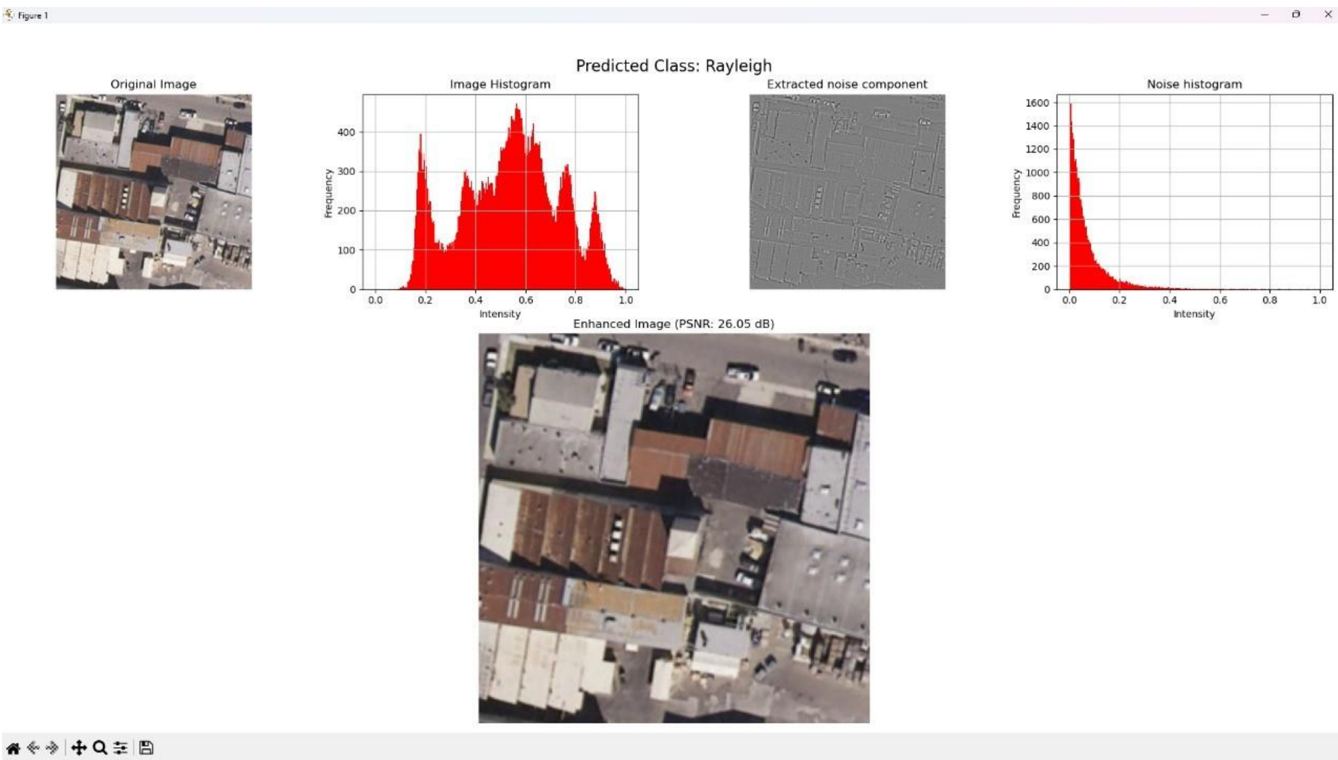

FIGURE 11. Rayleigh noise extracted component and enhanced image

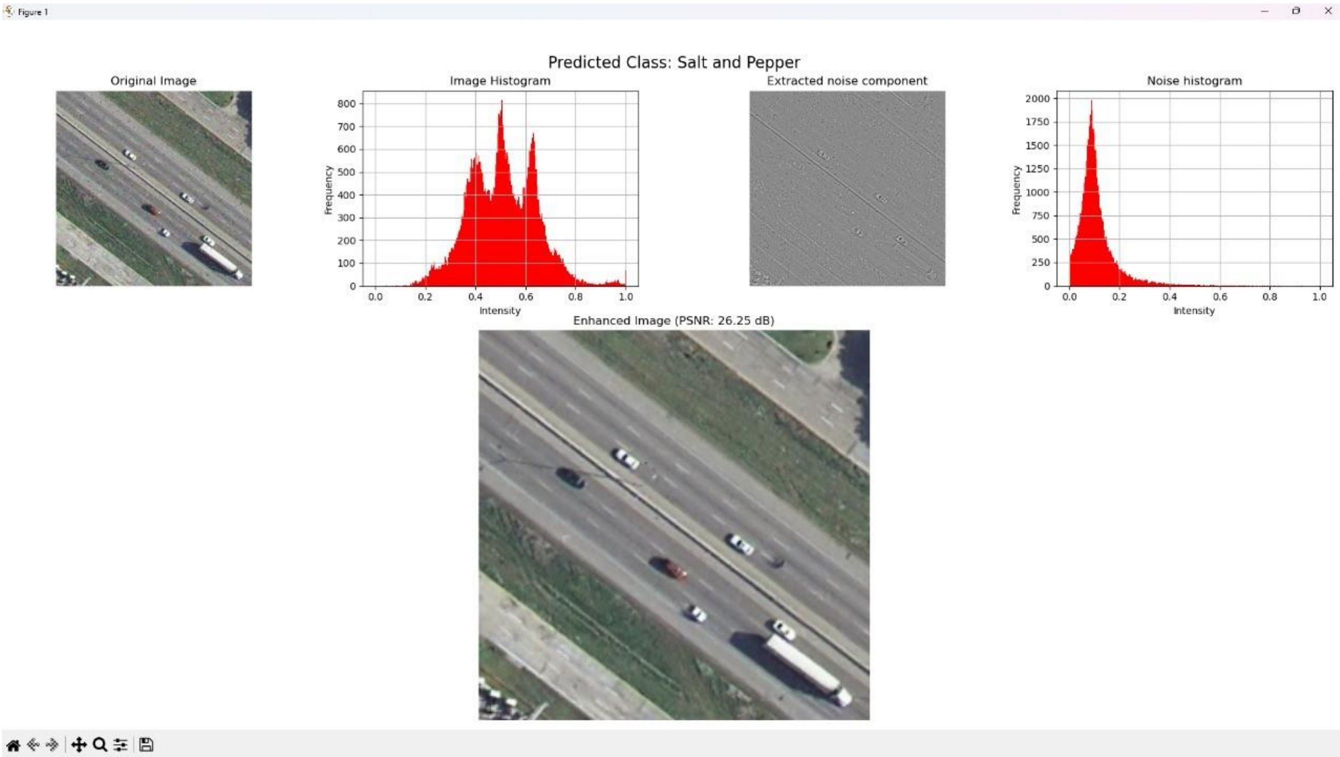

FIGURE 12. Salt and pepper noise extracted component and enhanced image

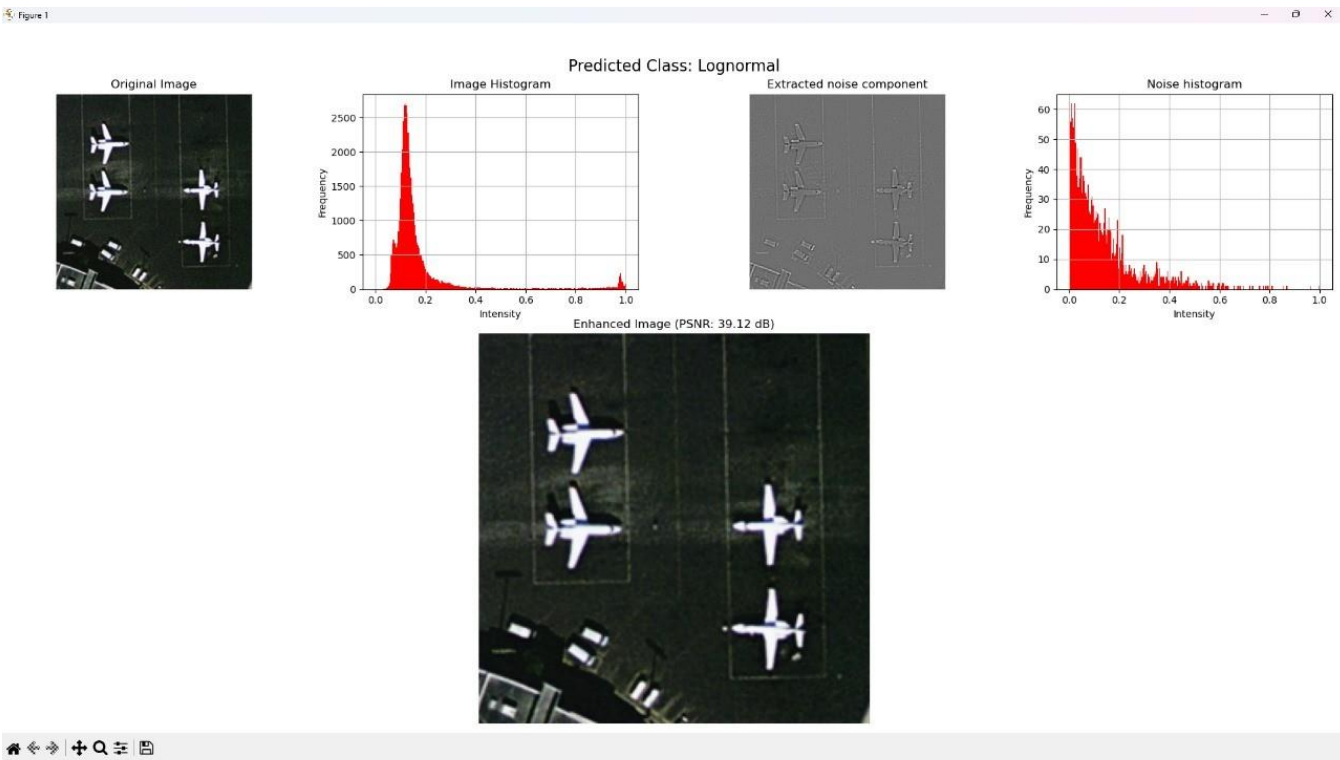

FIGURE 13. Lognormal noise extracted component and enhanced image

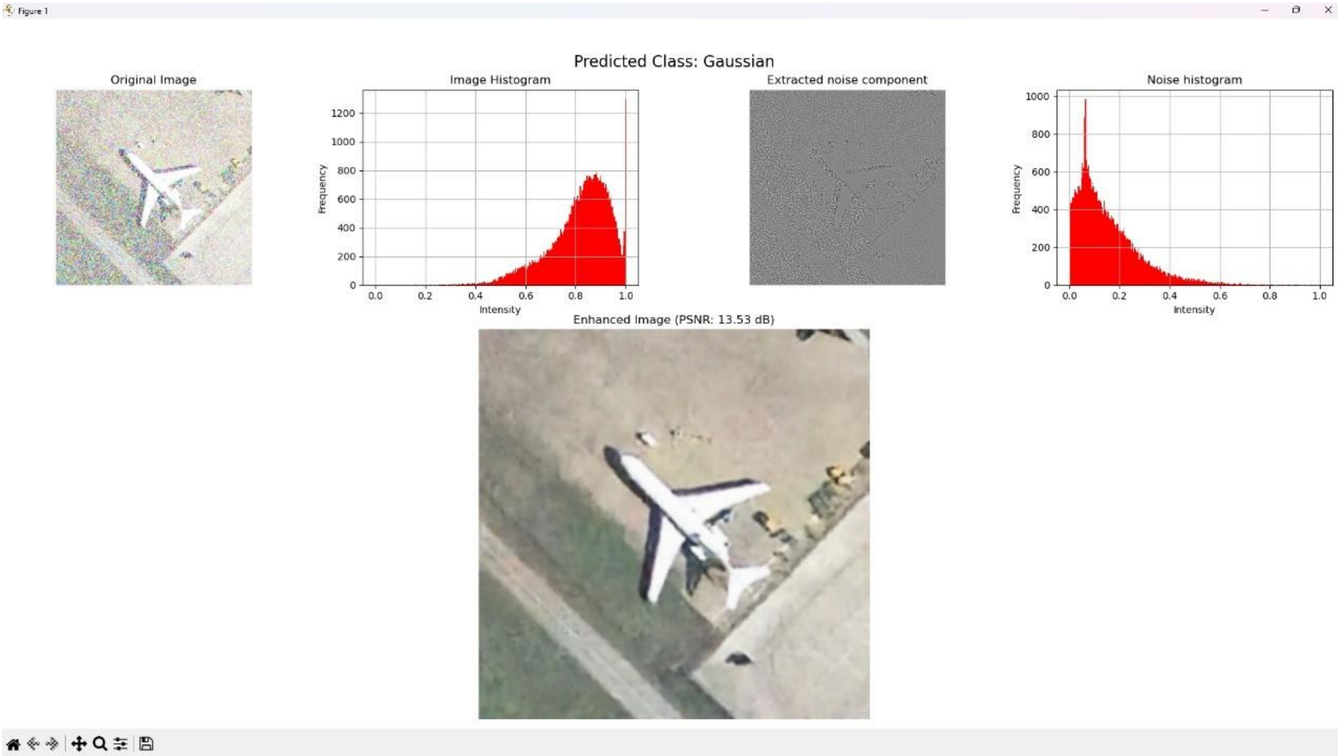

FIGURE 14. Gaussian noise extracted component and enhanced image

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