A Case Study on Autoencoders: Deep Learning Applications in Satellite Image Denoising

Rachel Jasmine Canaman, Genheylou Felisilda, Visaviern Mosqueda, Honey Angel Pabololot, Airyll Sanchez, Joanna Reyda Santos

University of Science and Technology of Southern Philippines – CDO
Lapasan, Cagayan de Oro City, Misamis Oriental, Philippines, 9000
`ustp.edu.ph`

Abstract. Satellite imagery is indispensable for applications such as land-use mapping, disaster monitoring, and environmental assessment. However, these images often suffer from noise due to atmospheric conditions and sensor limitations, compromising their utility [1,2]. This case study explores the application of Denoising Autoencoders (DAEs), particularly Convolutional Denoising Autoencoders (CDAEs), in enhancing satellite images. We demonstrate how CDAEs effectively remove noise while preserving critical features, thereby improving the performance of downstream tasks like land-cover classification [3–6].

Keywords: Autoencoder · Denoising Autoencoder · Convolutional Neural Network · Satellite Image Denoising · Deep Learning

1 Introduction

Satellite images are pivotal for monitoring Earth's surface, supporting urban planning, agriculture, disaster management, and environmental monitoring [1]. However, these images are frequently degraded by Gaussian noise, salt-and-pepper noise, and sensor-induced artifacts [2]. Traditional denoising methods, such as Gaussian or median filters, often fail to preserve fine details and textures [7].

Denoising Autoencoders (DAEs) provide a deep learning solution: they corrupt inputs during training and learn to reconstruct clean images, forcing the network to extract meaningful latent representations [1,3]. This is particularly effective for satellite image restoration, where preserving edges and textures is crucial [4–6].

2 Application of the Chosen Deep Learning Architecture

Autoencoders consist of an encoder that compresses an input image into a latent representation and a decoder that reconstructs the image from this representation. In denoising autoencoders, noisy images serve as inputs, while clean images are used as reconstruction targets [1]. Convolutional layers are commonly adopted to exploit spatial features in images [2].

2.1 Architecture Overview

Autoencoders consist of an encoder, compressing the input image into a latent representation, and a decoder, reconstructing the image from this representation [1]. In denoising autoencoders, noisy images serve as inputs, while clean images are used as reconstruction targets. Convolutional layers exploit spatial features to improve denoising performance [2,4,8].

Loss Functions. To train denoising autoencoders, the reconstruction quality is measured using the following key metrics:

Mean Squared Error (MSE). The MSE measures the average squared difference between predicted and ground-truth pixels:

$$LMSE = \frac{1}{N}\sum_{i=1}^{N} \left\| x^{(i)} - \hat{x}^{(i)} \right\|^2$$

where N is the number of training samples, $x^{(i)}$ is the clean ground-truth image, and $\hat{x}^{(i)}$ is the reconstructed image.

Structural Similarity Index (SSIM). To capture perceptual similarity, the SSIM compares structural information between the reconstructed and reference images:

$$SSIM(x, \hat{x}) = \frac{(2\mu_x\mu_{\hat{x}}+C_1)(2\sigma_{x\hat{x}}+C_2)}{(\mu_x^2+\mu_{\hat{x}}^2+C_1)(\sigma_x^2+\sigma_{\hat{x}}^2+C_2)}$$

where μ and σ represent mean and variance, and C_1 and C_2 are constants for stabilization.

Peak Signal-to-Noise Ratio (PSNR). PSNR expresses the denoised image quality in decibels:

$$PSNR\ (x, \hat{x}) = 10 \cdot log_{10}(\frac{MAX_I^2}{MSE})$$

where MAX_I is the maximum possible pixel value (e.g., 255 for 8-bit images).

Combined Loss Function. To balance pixel-wise accuracy and structural similarity, a weighted combination is often used:

$$L = \alpha \cdot LMSE + \beta \cdot (1 - SSIM(x, \hat{x}))$$

where α and β balance pixel accuracy and structural similarity.

2.2 Convolutional Autoencoders (CAEs)

Convolutional Denoising Autoencoders (CDAEs) extend classical autoencoders with convolutional and transposed-convolutional layers, preserving edges and textures more effectively than fully connected layers. Their operation can be summarized as:

$$h = f_{\theta}(\tilde{x}), \;\; \hat{x} = g_{\varphi}(h)$$

where $\tilde{x}$ is the noisy input, h is the latent representation, $\hat{x}$ is the reconstruction, and *(fθ, gφ)* are encoder and decoder functions [3–6].

CDAEs learn hierarchical spatial features and are particularly effective for satellite image denoising, radar image enhancement, and remote sensing classification.

The following schematic highlights the key components of a Denoising Autoencoder, showing how the encoder compresses the input into a latent representation and how the decoder reconstructs the clean output.

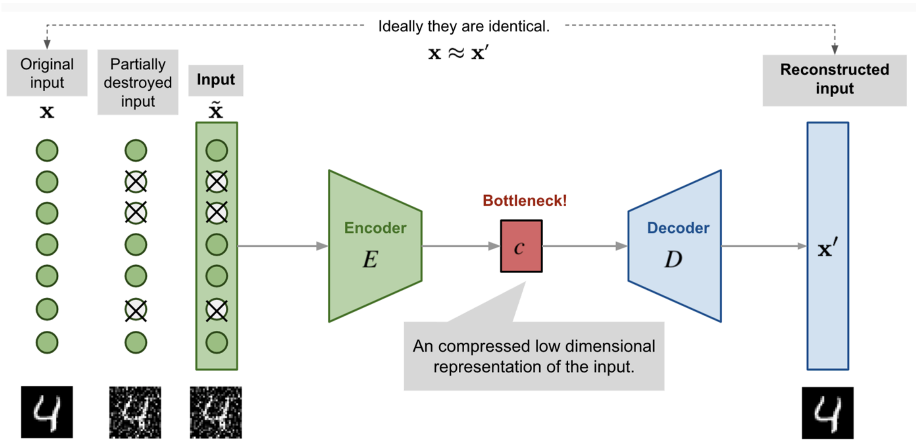

Fig. 1. Visual Representation of Denoising Autoencoder Architecture

The next illustration compares noisy and reconstructed outputs to demonstrate the typical improvement in visual clarity achieved after the CDAE has been trained.

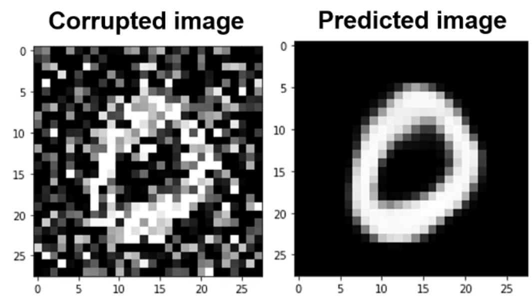

Fig. 2. Denoising results

2.3 Real-World Application: Satellite Image Denoising

A satellite image of an urban-agricultural region may contain haze and sensor noise. Using a CDAE:

Problem. Noisy images obscures land boundaries.

Solution. CDAE learns spatial noise-removal patterns.

Outcome. Denoised image reveals clearer boundaries, improving automated land-cover classification [3,6,8].

An example from remote sensing shows the effect of CDAE processing on real satellite imagery, where atmospheric noise is removed and land boundaries become more distinct.

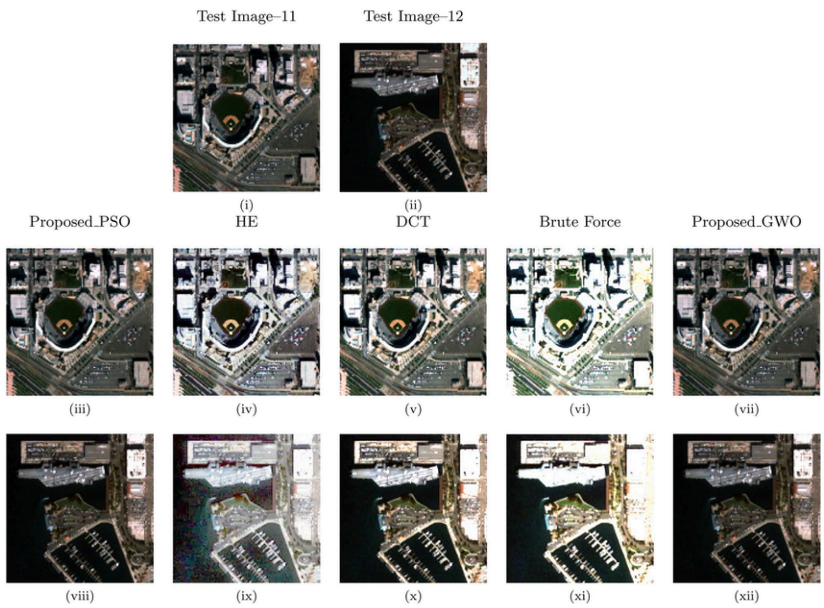

Fig. 3. Original and denoised satellite images using CDAE for remote sensing.

Recent enhancement studies provide further evidence of the model's ability to sharpen structural details, particularly for building and road detection in complex landscapes.

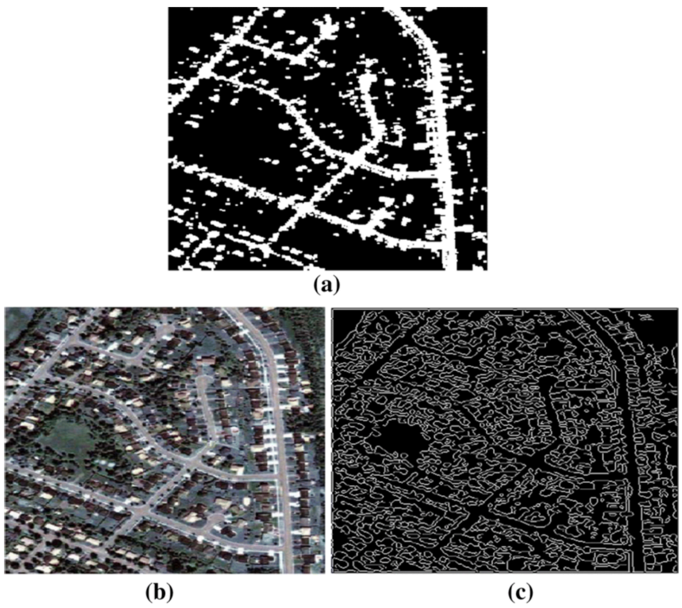

Fig. 4. Enhanced building and road detection after CDAE denoising [9,10].

Practical implementations also demonstrate how radar satellite images can be denoised directly in Python, reinforcing the adaptability of CDAE methods across sensor types.

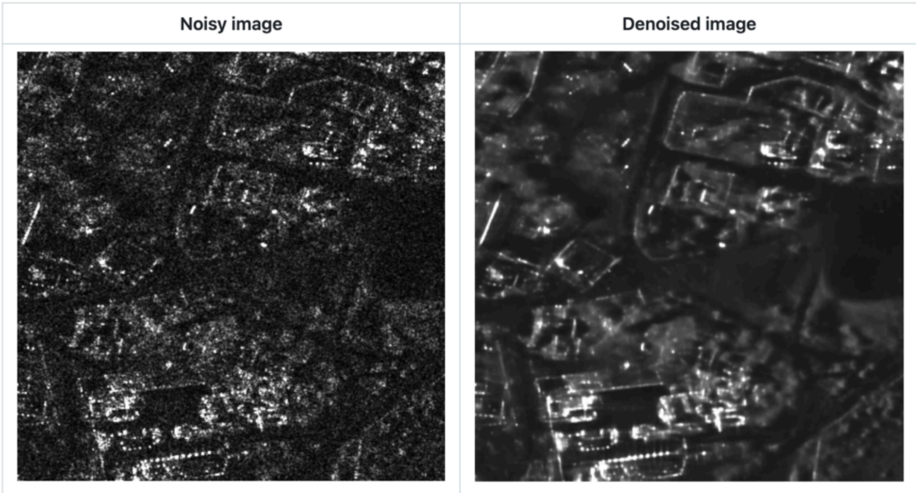

Fig. 5. Online example of radar satellite image denoising using Python [11].

To illustrate related techniques, the following workflow outlines the process of remote sensing image classification using a Stacked Denoising Autoencoder (SDAE).

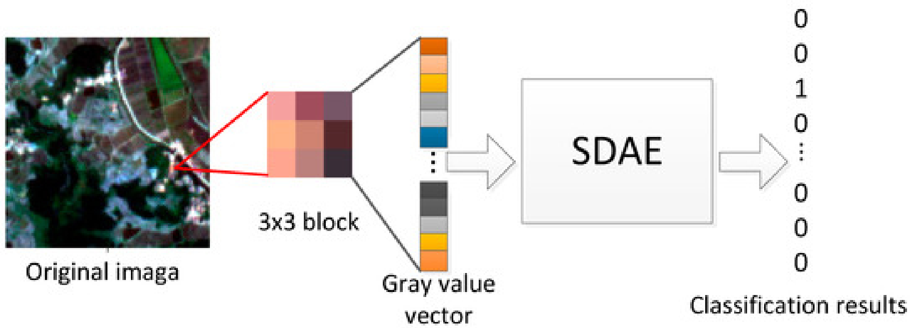

Fig. 6. The process of remote sensing image classification method based on SDAE [3].

3 Impact and Benefits

Improved Image Quality. Convolutional Denoising Autoencoders (CDAEs) excel at removing a wide range of noise—such as Gaussian, speckle, and sensor-induced artifacts—while preserving critical details of satellite imagery [4-8].

Unlike classical filtering techniques, which often blur edges and diminish fine textures, CDAEs learn data-driven noise-removal patterns that maintain sharp boundaries and subtle spatial variations.

This capability produces clearer and more visually accurate satellite images, providing a reliable foundation for downstream analysis and interpretation.

Enhanced Analysis Accuracy. The clarity achieved by CDAE-processed images directly improves the performance of automated tasks such as land-cover classification, change detection, and disaster impact assessment [3,6].

With reduced noise and preserved structural details, classifiers can better distinguish between similar land features—such as agricultural fields and urban surfaces—leading to higher accuracy in predictive models and better evidence-based decision making [3,6,7,8].

Studies have shown that integrating CDAE-based preprocessing can raise classification accuracy significantly, which is critical for timely and evidence-based decision-making in environmental monitoring.

Adaptability. CDAEs are highly flexible and can be trained on diverse datasets from various satellite platforms, including Sentinel-2 and Landsat-8 [4,6].

Their convolutional architecture captures spatial patterns that generalize well to differing sensor resolutions and atmospheric conditions, reducing the need for manual tuning.

This adaptability ensures that CDAE-based denoising techniques can be seamlessly incorporated into multiple remote-sensing workflows [4,6,11], supporting applications from urban planning to large-scale ecological surveys.

4 Conclusion

Denoising Autoencoders—particularly their convolutional variants (CDAEs)—have proven highly effective in enhancing satellite imagery. By reconstructing high-quality images from noisy inputs, CDAEs preserve critical spatial features such as edges, textures, and fine structures, which are essential for accurate land-cover classification, urban planning, and environmental monitoring. Their ability to learn hierarchical representations enables robust performance even when the data are affected by haze, sensor noise, or varying illumination. Integrating CDAEs into operational remote-sensing pipelines significantly improves both the visual interpretability of satellite products and the reliability of downstream analytics, leading to better-informed decision-making in disaster response, agriculture, and climate studies.

Future work may focus on hybrid architectures that combine CDAEs with attention mechanisms or transformer-based modules to further improve denoising in very high-resolution imagery [5,6]. Incorporating physics-informed priors and multi-sensor data fusion (e.g., combining optical and radar data) could also enhance generalization across diverse environmental conditions. In addition, leveraging self-supervised learning strategies and cloud-native processing platforms would enable scalable, real-time satellite image denoising, supporting next-generation Earth observation missions and time-critical applications [7–11].

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