Denoising Autoencoder for Image Restoration

DLRL Mini Project Report (AY 2025–26)

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1. Title & Student Details

Project Title: Denoising Autoencoder for Image Restoration using Deep Learning
Course: Deep Learning & Reinforcement Learning (DLRL)
Academic Year: 2025–26
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2. Abstract

Image noise significantly degrades visual quality and affects downstream computer vision tasks. This project presents a Deep Learning–based Denoising Autoencoder capable of restoring corrupted grayscale images. A Convolutional Neural Network (CNN)–based autoencoder architecture is trained to reconstruct clean images from noisy inputs. The model is trained on the MNIST dataset with different noise types such as Gaussian, Salt-and-Pepper, and Speckle noise. A user-friendly graphical interface built using Tkinter allows image upload, noise injection, model training, and visualization of denoised outputs. Experimental results demonstrate effective noise removal while preserving important image features, validating the applicability of autoencoders in image restoration tasks.

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3. Problem Statement & Objectives

Problem Statement

Digital images often suffer from noise introduced during acquisition, transmission, or storage. Traditional filtering techniques may remove noise but often blur important details. There is a need for an intelligent system that can automatically learn to remove noise while preserving image structure.

Objectives

- To design and implement a convolutional denoising autoencoder.
- To train the model on noisy and clean image pairs.
- To support multiple noise types for robust learning.
- To visualize training performance and restoration results.
- To develop a GUI-based application for ease of use.

4. Dataset & Preprocessing

The model is trained using a combination of benchmark and real-world image data to improve generalization and robustness.

Datasets Used:

1. **MNIST Dataset:** The MNIST handwritten digit dataset consists of grayscale images of size 28×28 pixels and is used as a standard benchmark for training and evaluation.

2. **Real-World Human Images:** In addition to MNIST, the model is also trained on custom grayscale images of real human subjects. These images simulate practical noise scenarios commonly observed in real-life image acquisition systems, making the model more adaptable beyond synthetic datasets.

Preprocessing Steps:

- Conversion of all images to grayscale format.
- Resizing images to 28×28 pixels for model compatibility.
- Normalization of pixel values to the range [0, 1].
- Reshaping images to include a single channel.
- Artificial noise addition (Gaussian, Salt-and-Pepper, Speckle) to generate corrupted inputs.
- Splitting data into training and validation sets.

A controlled subset of images is used during training to ensure faster convergence while maintaining reconstruction quality.

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5. Methodology / Model Architecture

The system uses a Convolutional Denoising Autoencoder consisting of two main parts:

Encoder

- Convolutional layers with ReLU activation for feature extraction.
- MaxPooling layers for dimensionality reduction.

Decoder

- Convolutional layers for reconstruction.
- UpSampling layers to restore original image size.
- Sigmoid activation in the output layer for normalized pixel output.

Training Details

- Optimizer: Adam
- Loss Function: Binary Cross-Entropy

- Evaluation Metric: Mean Absolute Error (MAE)

The model is trained to minimize reconstruction loss between clean and denoised images.

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6. Results & Performance Analysis

The trained autoencoder successfully removes different types of noise from images.

Observations:

- Gaussian noise is effectively reduced with minimal loss of detail.
- Salt-and-Pepper noise removal improves with increased epochs.
- Validation loss closely follows training loss, indicating minimal overfitting.

Graphical plots of training and validation loss show steady convergence, validating the learning capability of the model.

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7. Application Area & SDG Mapping

Application Areas

- Medical image enhancement
- Satellite and remote sensing image restoration
- Document image cleaning
- Preprocessing for computer vision systems

SDG Mapping

- **SDG 9 – Industry, Innovation and Infrastructure:** Enhances intelligent image processing systems.
- **SDG 4 – Quality Education:** Supports educational tools for learning deep learning concepts.

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8. Conclusion & Future Scope

This project demonstrates the effectiveness of denoising autoencoders for image restoration tasks. The model successfully learns noise patterns and reconstructs clean images. The integration of a GUI makes the system accessible to non-technical users.

Future Enhancements:

- Extension to color images.
- Training on larger and more complex datasets.
- Integration with real-time camera feeds.
- Deployment as a web-based application.

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9. Tools Used & GitHub Link

Tools & Technologies:

- Python
- TensorFlow & Keras
- NumPy
- Tkinter
- Matplotlib
- PIL (Pillow)

GitHub Repository: https://github.com/Tanishbelel/Dlrl-Mpr.git

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10. References

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