

Abstract

In the modern digital era, image clarity is essential for both human perception and downstream AI tasks. This project demonstrates the design and simulation of a robust Convolutional Autoencoder (CAE) developed to denoise images affected by synthetic Gaussian and impulse noise. Using the CIFAR-10 dataset, the model implements a collapsed core architecture, an Encoder-Decoder CNN to learn compressed representations and reconstruct clean versions of corrupted images. The project explores key concepts such as MSE vs. Perceptual Loss, bottleneck design, and generalization to unseen noise levels.

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Chapter 1

Introduction

Digital images are frequently corrupted by noise during acquisition or transmission, often appearing as unwanted graininess or artifacts that obscure critical details. Traditional linear filters, such as the Gaussian or mean filter, attempt to smooth out this noise but often fail to distinguish between random interference and structural information. Consequently, these methods tend to blur sharp edges and fine textures, resulting in a loss of visual clarity and vital diagnostic data in fields like medical imaging. This limitation necessitates a more intelligent solution, such as non local means or edge-preserving anisotropic diffusion, which can selectively smooth uniform regions while keeping boundaries intact. By leveraging the geometric features of an image, these advanced algorithms ensure that noise is suppressed without sacrificing the underlying structural integrity.

1.1 Problem Statement

The challenge lies in digital images being degraded by unknown noise, which compromises data reliability and causes traditional filters to blur essential structural details. There is a critical need for an automated, deep learning-based blind denoising framework that can adaptively suppress noise while preserving sharp edges and fine textures.

1.2 Objectives

- Design and train an Encoder-Decoder CNN for denoising.
- Implement synthetic Gaussian and Impulse noise on the CIFAR-10 dataset.
- Evaluate performance using PSNR metrics and visual quality.

1.3 Project Scope

This project builds a custom "DenoisingNet" from scratch to clean up noisy images using the CIFAR-10 dataset. Instead of using ready-made tools or pre-trained models, it focuses on teaching a unique neural network how to remove noise while keeping the original image details sharp.

Chapter 2

Proposed System

The project proposes a DenoisingNet architecture built from scratch without pre-trained denoisers.

2.1 System Architecture

The model consists of three main components:

- **The Encoder:** Three convolutional layers (32, 64, 128 filters) using 3×3 kernels and BatchNorm, with max-pooling for dimensionality reduction.
- **The Bottleneck:** A dense 256-filter layer that captures the "essence" of image data while discarding noise.
- **The Decoder:** Mirroring the encoder, it uses Nearest Neighbor interpolation (upsampling) and convolutional layers to restore spatial resolution to 32×32 .

Chapter 3

Methodology and Implementation

3.1 Tools and Technologies

- Hardware: Google Colab T4 GPU.
- Language: Python 3.
- Framework: PyTorch.
- Dataset: CIFAR-10 (60,000 32×32 color images).

3.2 Noise Synthesis

A custom `NoisyCIFAR10` class was implemented to synthesize two types of noise:

1. **Gaussian Noise:** Additive white noise with varying standard deviations.
2. **Impulse Noise:** Salt-and-Pepper noise replacing pixels with extreme values.

Chapter 4

Experiments and Results

4.1 Training Progress

Training was conducted over 50 epochs. The loss metrics showed steady convergence, with MSE loss dropping from an initial 0.0153 to a final 0.0041.

4.2 Results

Performance was measured using Peak Signal-to-Noise Ratio (PSNR):

```
... Gaussian DataLoader for std=0.05 created with 10000 samples.  
Gaussian DataLoader for std=0.1 created with 10000 samples.  
Gaussian DataLoader for std=0.15 created with 10000 samples.  
Gaussian DataLoader for std=0.2 created with 10000 samples.  
Gaussian DataLoader for std=0.25 created with 10000 samples.  
Impulse DataLoader for ratio=0.05 created with 10000 samples.  
Impulse DataLoader for ratio=0.1 created with 10000 samples.  
Impulse DataLoader for ratio=0.15 created with 10000 samples.  
Impulse DataLoader for ratio=0.2 created with 10000 samples.  
Impulse DataLoader for ratio=0.25 created with 10000 samples.  
Test DataLoaders for Gaussian and Impulse noise created for various intensity levels.
```

Figure 4.1: Denoising Performance and noise Categories

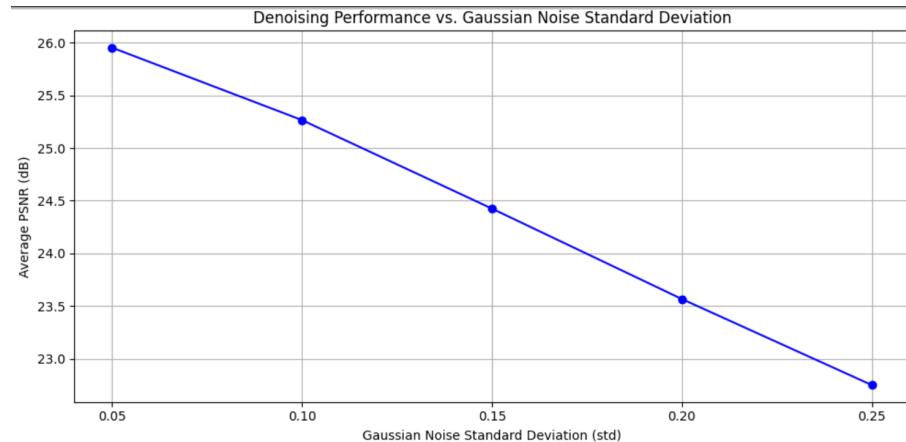


Figure 4.2: Gaussian Noise Standard deviation Graph

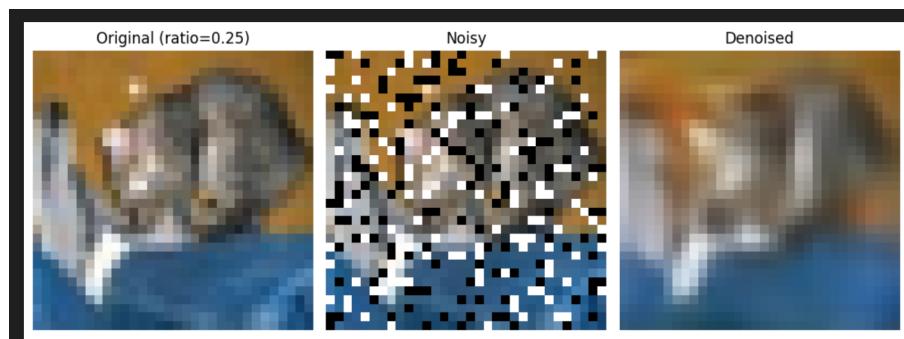


Figure 4.3: Results

Chapter 5

Conclusion

The project successfully implemented a custom Encoder-Decoder CNN that provides robust image restoration against Gaussian and Impulse noise. Unlike traditional filters that blur details, this deep learning approach effectively suppresses noise while preserving sharp object boundaries and structural integrity. The results confirm that a data-driven framework can recover fine textures that are typically lost in conventional workflows. Future efforts will focus on enhancing computational efficiency to support higher-resolution images and improving generalizability across diverse real-world conditions.