# Assignment 1 Report

Course: Dependable and Secure AI-ML (AI60006)  
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## 1. Introduction

This report presents the implementation and analysis of various image processing techniques and Convolutional Neural Network (CNN) visualizations. The key objectives include:  
- Implementing pixel expansion techniques.  
- Introducing different types of noise into images.  
- Evaluating image quality metrics before and after applying noise.  
- Implementing denoising techniques and analyzing their effectiveness.  
- Investigating CNN feature maps and the impact of noise on CNN activations.

## 2. Methodology

The assignment was divided into two main sections:  
  
1. **Image Processing:**  
 - **Pixel Expansion:** Different expansion strategies such as Constant, Gradient, and Random expansion.  
 - **Noise Addition**: Gaussian, Salt & Pepper, and Poisson noise were applied.  
 - **Image Quality Analysis**: The effect of noise was measured using MSE, PSNR, and SSIM.  
 - **Denoising**: Various filters were applied to remove noise and recover the original image.  
  
2. **CNN Feature Extraction**:  
 - **Visualizing filters from convolutional layers** to understand edge and texture detection.  
 - **Passing images through CNN** and extracting feature maps at different depths.  
 - **Analyzing the robustness of CNN to noisy images** by observing classification confidence.

## 3. Implementation

The following steps were implemented for each task:  
- **Pixel Expansion**: Enlarging each pixel using different interpolation strategies.  
- **Noise Addition**: Applying controlled noise levels to observe their effects.  
- **Image Quality Metrics**: Measuring the level of distortion using standard metrics.  
- **Denoising Techniques**: Implementing filters to restore the degraded image.  
- **CNN Feature Extraction**: Passing noisy images through VGG16 and comparing feature maps.  
- **Classification Confidence Analysis**: Measuring how noise affects CNN classification results.

## 4. Results and Observations

### 4.1 Image Quality Analysis

The effect of different types of noise was measured using three key metrics:  
- **Mean Squared Error (MSE)**: Measures pixel-wise differences between the original and noisy image.  
- **Peak Signal-to-Noise Ratio (PSNR)**: Measures the quality degradation in decibels.  
- **Structural Similarity Index (SSIM)**: Measures the perceptual similarity between images.

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| --- | --- | --- | --- |
| Noise Type | MSE | PSNR (dB) | SSIM |
| Gaussian | 9670.99 | 8.28 | 0.070 |
| Salt & Pepper | 732.89 | 19.48 | 0.392 |
| Poisson | 135.73 | 26.80 | 0.582 |

**Observations:**  
- Gaussian noise causes the highest MSE and lowest SSIM, indicating significant distortion.  
- Salt & Pepper noise results in sharp intensity variations, leading to noticeable artifacts.  
- Poisson noise has a relatively lower impact compared to the other types of noise.

### 4.2 Denoising Results

Three denoising techniques were applied to the noisy images:  
- **Median Filter**: Good for removing Salt & Pepper noise but less effective against Gaussian noise.  
- **Bilateral Filter**: Retains edges while reducing noise, effective against Gaussian noise.  
- **Non-Local Means**: Works well for texture preservation but is computationally expensive.

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| Denoising Method | MSE | PSNR (dB) | SSIM |
| Median Filter | 9639.30 | 8.29 | 0.087 |
| Bilateral Filter | 7946.11 | 9.12 | 0.197 |
| Non-Local Means | 9683.79 | 8.27 | 0.090 |

**Observations**:  
- Bilateral filtering provided the best noise reduction while preserving textures.  
- Median filtering was effective against Salt & Pepper noise but reduced fine details.  
- Non-Local Means filtering performed well but had a higher computational cost.

### 4.3 CNN Feature Extraction

Feature maps extracted from different convolutional layers revealed the following:  
- **Early layers detect simple patterns like edges and gradients.**- **Mid layers extract more complex textures and shapes.**- **Deep layers focus on high-level object representations.**Noise significantly alters these feature maps, particularly in deeper layers, affecting classification accuracy.

### 4.4 Classification Confidence Drop Due to Noise

The CNN's classification confidence was evaluated for the original and noisy images. The results are summarized in the table below:

|  |  |  |
| --- | --- | --- |
| Image Type | Predicted Class | Confidence |
| Original | Class 2 | 0.98 |
| Gaussian | Class 5 | 0.73 |
| Salt & Pepper | Class 8 | 0.46 |
| Poisson | Class 2 | 0.91 |

**Observations**:  
- Classification confidence dropped significantly for images with Salt & Pepper noise.  
- Gaussian noise caused moderate confidence reduction but retained some classification accuracy.  
- Poisson noise had the least impact, indicating the CNN is relatively robust to this type of noise.

## 5. Conclusion

The study highlights the impact of different noise types on image quality and CNN feature extraction. Denoising techniques help mitigate noise effects, but certain types of noise (e.g., Salt & Pepper) still lead to significant classification confidence drops. The CNN feature maps revealed how noise affects different layers, ultimately influencing model performance. Further exploration of advanced denoising techniques could improve robustness against noise-induced distortions.