Effect of Noise Level and Brightness/Contrast on Image Denoising Performance: Classical vs. Neural Network Denoisers

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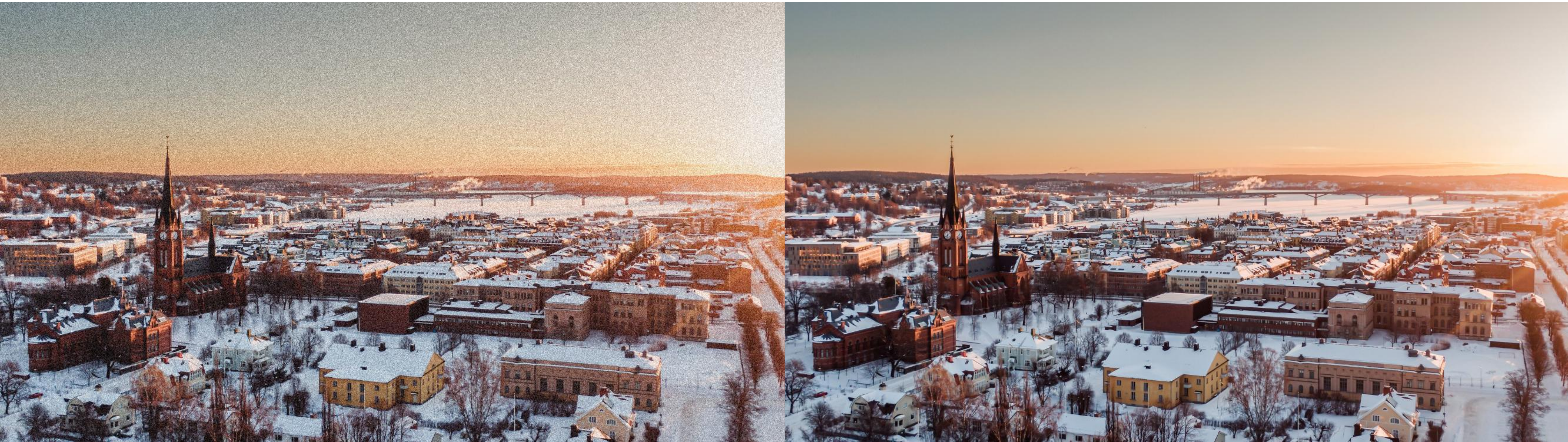


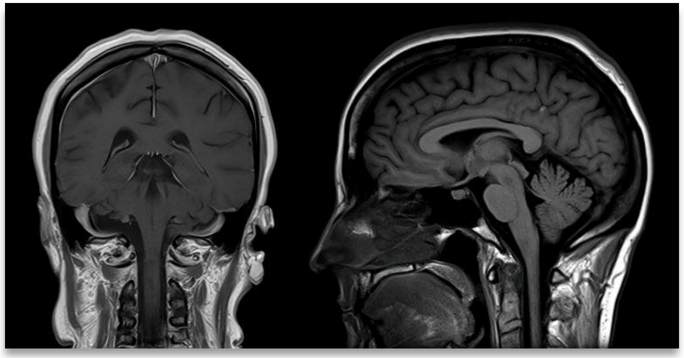
Introduction & Motivation

Background:

- Imaging devices are now everywhere: **phones, surveillance, medical imaging**
- Image quality is **critical** for accurate analysis and decision-making

Problem:

- Low-cost sensors provide **high noise** and low-quality images
- Real world scenarios present **illumination changes** and **contrast variations**



Research questions

How do noise level, brightness, and contrast affect the performance of classical and neural network–based image denoisers?

1. Are **neural network** denoisers more robust than **classical** ones under higher **noise levels**?

2. Do **brightness/contrast** changes significantly improve or degrade image denoising performance?

3. Do **brightness/contrast** changes interact with **noise type** and **level** to influence denoiser performance?

Expected results

1. Are **neural network** denoisers more robust than **classical** ones under higher **noise levels**?
   - Classical methods: performance degrades at higher noise; visible artifacts.
   - Neural networks: expected to maintain stronger performance.

2. Do **brightness/contrast** changes significantly improve or degrade image denoising performance?
   - Extreme brightness/contrast → likely to reduce quality.

3. Do **brightness/contrast** changes interact with **noise type** and **level** to influence denoiser performance?
   - Combined effects of factors (noise × brightness × contrast) still largely unexplored.

Research method

Phase 1 → Phase 2 → Phase 3

Research method

Phase 1: Denoisers implementation → **Phase 2** → **Phase 3**

Phase 1: Denoisers Implementation

Development environment:

- **Jupyter Notebook** for modular, reproducible experimentation
- Language: **Python**

Classical denoiser: BM3D – Block Matching and 3D Filtering

- **bm3d** official python library [1]

Neural Network denoiser: DRUNet

- **DRUNet** implementation from original authors [2]

Validation and consistency check:

- Test both implemented denoisers on the original papers' **datasets** (BSD68, Set12).

[1] https://pypi.org/project/bm3d/
[2] https://github.com/cszn/DPIR

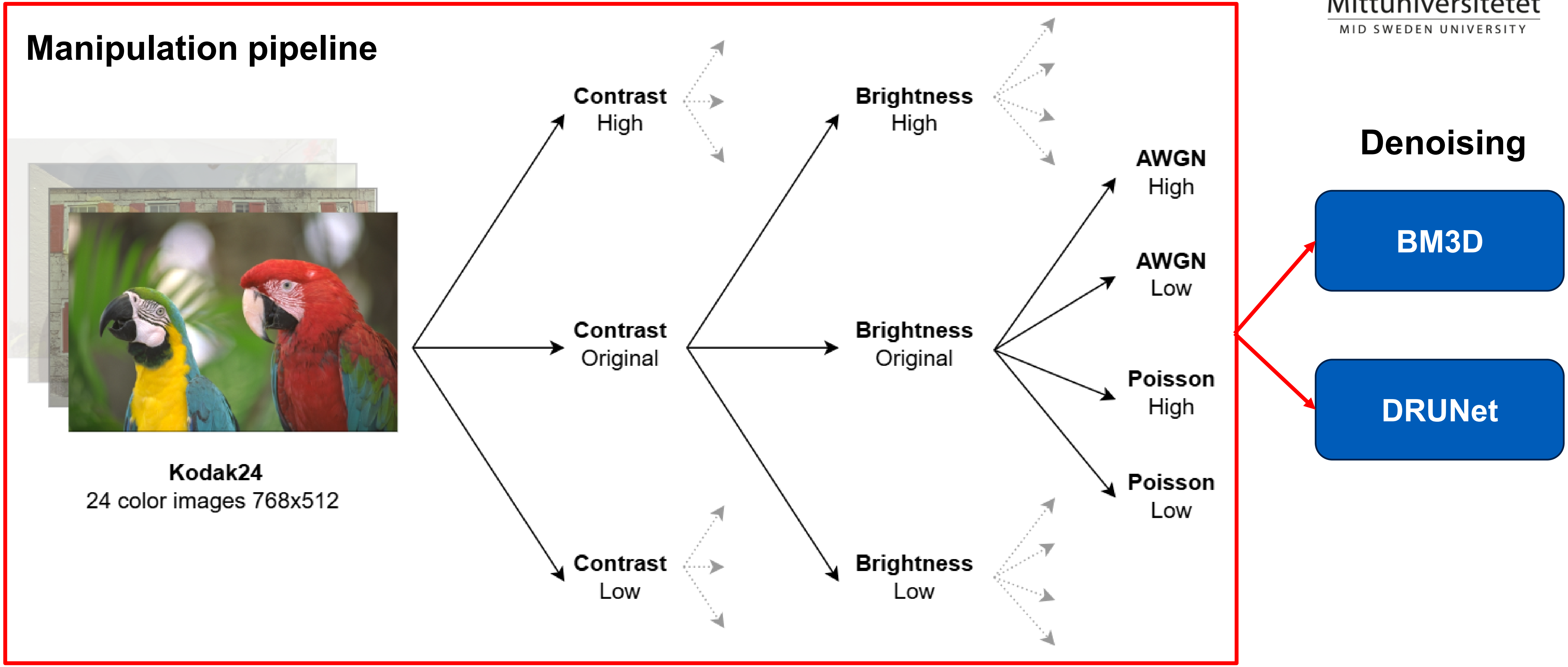
Research method

Phase 1:
Denoisers implementation

Phase 2:
Image manipulation and denoising

Phase 3

Phase 2: Image manipulation and denoising



Total images: 24 x 3 x 3 x 4 = 864 x 2 = 1728

Phase 2: Image manipulation and denoising – cont.

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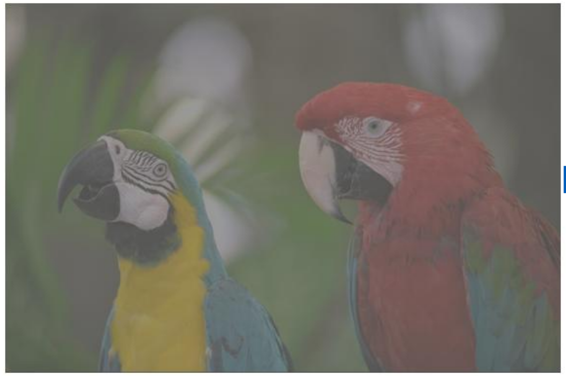
Original image

Contrast: low



Brightness: high

AWGN: low

DENOISING
BM3D/DRUNet

Compare

Save metrics for statistical analysis:
- PSNR
- LPIPS

Phase 2: Image manipulation and denoising – cont.

Collected metrics:

- **PSNR** (Peak signal-to-noise ratio)
    - A **mathematical metric** used to objectively measure the quality of a processed image compared to its original, clean version
    - Higher PSNR = Better reconstruction fidelity (lower error)
- **LPIPS** (Learned Perceptual Image Patch Similarity) [1]
    - A **perceptual metric** that uses a deep neural network to measure the perceived similarity between two images
    - Lower LPIPS = Better perceptual quality (more similar to the original).

[1] Zhang et al. The unreasonable effectiveness of deep features as a perceptual metric. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 586–595, 2018.

Research method

1. **Phase 1:** Denoisers implementation
2. **Phase 2:** Image manipulation and denoising
3. **Phase 3:** Statistical analysis

Phase 3: Statistical analysis

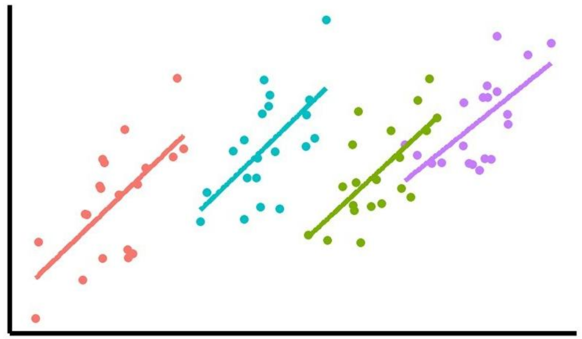
LMM – Linear Mixed-effects Model

- Two separate LMMs will be fitted, one for each performance metric.

PSNR ~ Denoiser_Type ∗ Noise_Type ∗ Noise_Level ∗ Brightness_Level ∗ Contrast_Level + (1 | Image_ID)

Fixed effects:
- Denoiser Type (BM3D vs. DRUNet)
- Noise Type (Gaussian vs. Poisson)
- Noise Level (High vs. Original vs. Low)
- Brightness Level (High vs. Original vs. Low)
- Contrast Level (High vs. Original vs. Low)
- All their interactions -> Research question 3)

Linear Mixed-Effects Models



Random effect:
- Image ID - to account for the inherent **variability between** different base images.

Timeplan

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Table 1: Time plan for the Quantitative Research and Development project

Phase	Start Week	Start Day
Denoisers Implementation	42	13/10/2025
Image Manipulation and Denoising	44	27/10/2025
Statistical Analysis	46	10/11/2025
Writing and Reporting	48	24/11/2025

Thank you!