

Deep Learning Final Project: Image Denoising/Deblurring and Restoration

A Comparative Study of NAFNet and UNet Architectures

1. Introduction

This report details our group project on image denoising and restoration using deep learning techniques. Our project focused on developing and comparing various deep learning models for enhancing the quality of degraded images, specifically addressing two problems: thermal image denoising and natural image deblurring. These tasks have numerous real world applications including night vision, building inspections, medical diagnostics, surveillance, and photography enhancement.

Image degradation occurs through various mechanisms depending on the imaging modality. Thermal cameras suffer from unique noise patterns related to their sensor technology, while standard cameras experience motion blur and other degradations. Our project aimed to develop solutions for both scenarios by exploring complementary approaches:

1. **Thermal Image Denoising:** We developed a noise simulation method to create realistic training data for thermal imagery and implemented the state of the art NAFNet (Nonlinear Activation Free Network) architecture in PyTorch.
2. **Natural Image Deblurring:** We utilized the GoPro dataset containing real world motion-blurred images and the BSD500 dataset with synthetically applied degradations, implementing a deep UNet architecture in TensorFlow, and later converting to PyTorch.

By pursuing these parallel approaches, our team was able to compare the effectiveness of different architectures (NAFNet vs. UNet) across varied image restoration tasks. This comparative approach provided insights into the strengths and limitations of each method.

Our project made several key contributions:

- Development of a thermal noise simulation model that accurately models sensor-specific degradations
- Implementation and optimization of the NAFNet architecture for thermal image denoising
- Implementation of a deep UNet architecture for natural image deblurring and denoising
- Cross-evaluation of both models on both datasets
- Development of visualization tools for qualitative and quantitative comparison

The following sections detail our approach, experimental setup, and findings, demonstrating the effectiveness of UNET and NAFTNET for image restoration tasks.

2. Project Schedule

Our project followed a structured timeline with clear milestones and task distribution between team members:

Date	Milestone	Assigned To	Status
March 15, 2025	Project proposal submission	Both team members	Completed
March 20, 2025	Dataset collection and preparation	Both team members	Completed
March 25, 2025	Thermal noise simulation pipeline	Thomas	Completed
March 25, 2025	GoPro/BSD500 preprocessing	Zach	Completed
April 5, 2025	NAFNet architecture implementation	Thomas	Completed
April 5, 2025	UNet architecture implementation	Zach	Completed
April 15, 2025	Initial model training and validation	Both team members	Completed
April 20, 2025	Hyperparameter optimization	Both team members	Completed
April 22, 2025	Visualization tools development	Both team members	Completed
April 25, 2025	Cross-evaluation of models	Both team members	Completed
April 28, 2025	Final results analysis	Both team members	Completed
May 1, 2025	Presentation preparation	Both team members	Completed
May 6, 2025	Final report submission	Both team members	Completed

The project development was organized into four main phases:

- 1. Data Preparation Phase** (March 15-25): Collection, preprocessing, and synthetic data generation for both thermal and natural images.

2. **Model Implementation Phase** (March 29-April 5): Development of NAFNet and UNet architectures in their respective frameworks.
3. **Training and Optimization Phase** (April 9-22): Initial training, hyperparameter tuning, and performance optimization.
4. **Evaluation and Analysis Phase** (April 23-May 6): Cross-evaluation, result visualization, comparative analysis, and report preparation.

3. Description of the Data Sets

Our project utilized three distinct datasets, each serving different purposes in our image restoration experiments:

3.1 Thermal Imagery Dataset with Synthetic Noise

For thermal image denoising, we started with a collection of clean thermal images and developed a noise simulation pipeline to create paired noisy and clean training data. This approach was necessary because obtaining paired realworld thermal images is difficult to find.

Dataset characteristics:

- **Source:** Clean thermal images from publicly available thermal datasets
- **Size:** 500 training images, 100 validation images, 100 test images
- **Resolution:** 640×480 pixels
- **Format:** 16-bit grayscale (visualized with color mapping)

Noise simulation approach: Our synthetic noise generation pipeline modeled several key noise sources found in thermal imaging sensors:

1. **Gaussian Read Noise:** Electronics induced random noise following a Gaussian distribution
2. **Dark Current Shot Noise:** Poisson distributed noise arising from thermal generation of electrons
3. **Fixed Pattern Noise (FPN):** Consisting of:
 - Dark Signal Non-Uniformity (DSNU): Additive offset variations between pixels
 - Photo Response Non-Uniformity (PRNU): Multiplicative gain variations between pixels

The noise simulation process followed this mathematical formulation:

$$I_{noisy} = (I_{clean} + DSNU) * PRNU + N_{shot} + N_{read}$$

$$\mathcal{L} = \alpha \cdot \mathcal{L}_{L1} + (1 - \alpha) \cdot (1 - \text{SSIM})$$

$$\mathcal{L} = \beta \cdot \text{MAE} + (1 - \beta) \cdot \text{MSE}$$

where $\beta = 0.75$ was determined through experimentation.

Additional training techniques:

- Early stopping with patience of 10 epochs
- Model checkpointing based on validation loss
- Learning rate reduction on plateau

5. Experimental Setup

5.1 Implementation Frameworks

Our project utilized two different deep learning frameworks, allowing us to compare their strengths and workflows:

NAFNet Implementation (PyTorch):

- PyTorch 1.12.0
- CUDA 11.6
- torchvision 0.13.0
- Custom data loaders using `torch.utils.data`

UNet Implementation (TensorFlow):

- TensorFlow 2.9.0
- CUDA 11.6
- Keras API
- `tf.data.Dataset` for data pipeline

5.2 Training Parameters and Hyperparameter Tuning

5.2.1 NAFNet Hyperparameter Optimization

For the NAFNet model, we conducted extensive hyperparameter tuning:

1. **Learning Rate:** Tested values [1e-3, 5e-4, 1e-4, 5e-5]
 - Found 1e-4 provided the best balance of convergence speed and stability
2. **Loss Function Weighting:** Tested α values [0.5, 0.7, 0.84, 0.9]

- Found $\alpha = 0.84$ provided the best balance between pixel accuracy and perceptual quality

3. Network Width: Tested base channel counts [32, 48, 64, 96]

- Selected 64 as the optimal balance between performance and computational efficiency

4. Training Stability: Implemented several improvements

- Reduced beta_loss parameter from 50 to 10
- Added gradient clipping with max norm 1.0
- Optimized validation sample count and DPM Solver steps

5.2.2 UNet Hyperparameter Optimization

For the UNet model, we performed the following hyperparameter tuning:

1. Learning Rate: Tested values [1e-3, 5e-4, 1e-4, 5e-5]

- Found 1e-4 with cosine decay provided the best results

2. Loss Function Weighting: Tested β values [0.5, 0.6, 0.75, 0.9]

- Found $\beta = 0.75$ provided the best balance between MAE and MSE

3. Network Depth: Tested 3, 4, and 5 encoder/decoder levels

- Selected 4 levels as the optimal depth

4. Bottleneck Size: Tested [512, 768, 1024] filters

- Selected 1024 filters for maximum feature extraction capability

5.3 Data Loaders and Batch Processing

5.3.1 PyTorch Data Pipeline (NAFNet)

```

class ThermalDataset(torch.utils.data.Dataset):
    def __init__(self, clean_dir, noisy_dir, transform=None):
        self.clean_paths = sorted(glob.glob(os.path.join(clean_dir, "*.bmp")))
        self.noisy_paths = sorted(glob.glob(os.path.join(noisy_dir, "*.bmp")))
        self.transform = transform

    def __len__(self):
        return len(self.clean_paths)

    def __getitem__(self, idx):
        clean_img = cv2.imread(self.clean_paths[idx], cv2.IMREAD_GRAYSCALE)
        noisy_img = cv2.imread(self.noisy_paths[idx], cv2.IMREAD_GRAYSCALE)

        # Normalize to [0, 1]
        clean_img = clean_img.astype(np.float32) / 255.0
        noisy_img = noisy_img.astype(np.float32) / 255.0

        if self.transform:
            augmented = self.transform(image=clean_img, mask=noisy_img)
            clean_img = augmented['image']
            noisy_img = augmented['mask']

        # Convert to tensor
        clean_img = torch.from_numpy(clean_img).unsqueeze(0)
        noisy_img = torch.from_numpy(noisy_img).unsqueeze(0)

        return noisy_img, clean_img

```

Data augmentation was implemented using the Albumentations library:

```

transform = A.Compose([
    A.RandomCrop(width=128, height=128),
    A.HorizontalFlip(p=0.5),
    A.VerticalFlip(p=0.5),
    A.RandomRotate90(p=0.5),
])

```

5.3.2 TensorFlow Data Pipeline (UNet)

```

def create_dataset(blurry_paths, sharp_paths, batch_size=32):
    def process_path(blurry_path, sharp_path):
        blurry_img = tf.io.read_file(blurry_path)
        blurry_img = tf.image.decode_png(blurry_img, channels=1)
        blurry_img = tf.image.convert_image_dtype(blurry_img, tf.float32)

        sharp_img = tf.io.read_file(sharp_path)
        sharp_img = tf.image.decode_png(sharp_img, channels=1)
        sharp_img = tf.image.convert_image_dtype(sharp_img, tf.float32)

    return blurry_img, sharp_img

def augment(blurry_img, sharp_img):
    # Random crop
    stacked = tf.stack([blurry_img, sharp_img], axis=0)
    cropped = tf.image.random_crop(stacked, size=[2, 128, 128, 1])
    blurry_img, sharp_img = cropped[0], cropped[1]

    # Random flip
    if tf.random.uniform([]) > 0.5:
        blurry_img = tf.image.flip_left_right(blurry_img)
        sharp_img = tf.image.flip_left_right(sharp_img)

    return blurry_img, sharp_img

dataset = tf.data.Dataset.from_tensor_slices((blurry_paths, sharp_paths))
dataset = dataset.map(process_path, num_parallel_calls=tf.data.AUTOTUNE)
dataset = dataset.map(augment, num_parallel_calls=tf.data.AUTOTUNE)
dataset = dataset.batch(batch_size)
dataset = dataset.prefetch(tf.data.AUTOTUNE)

return dataset

```

5.4 Evaluation Metrics

We employed multiple evaluation metrics to assess the performance of our models:

- 1. Peak Signal-to-Noise Ratio (PSNR):** $\text{PSNR} = 10 \cdot \log_{10} \left(\frac{\text{MAX}^2}{\text{MSE}} \right)$ where MAX is the maximum possible pixel value (1.0 after normalization) and MSE is the mean squared error between the clean and restored images.
- 2. Structural Similarity Index (SSIM):** $\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$ where μ represents the average, σ^2 the variance, σ the covariance, and c_1, c_2 are constants to stabilize division.

3. Learned Perceptual Image Patch Similarity (LPIPS): A perceptual metric that uses deep features to measure image similarity in a way that correlates better with human perception than pixel based metrics.

4. Deep Image Structure and Texture Similarity (DISTS): A perceptual metric that specifically accounts for both structure and texture similarity.

These metrics were calculated on the full test sets for each dataset, providing a comprehensive evaluation of model performance across different image restoration tasks.

6. Results

6.1 Quantitative Performance Comparison

6.1.1 Thermal Image Denoising Results

Model	PSNR (dB)	SSIM	LPIPS	DISTS
NAFNet	41.34	0.9713	0.0842	0.0765
UNet	41.35	0.9723	0.1103	0.0981

The UNet model outperformed NAFNet on the thermal image denoising task across PSNR and SSIM, but with not a large significant difference.

6.1.2 GoPro Deblurring Results

Model	PSNR (dB)	SSIM	LPIPS	DISTS
NAFNet	32.14	0.9358	0.0921	0.0812
UNet	31.33	0.9226	0.1042	0.0924

This presents an interesting case of metrics not telling the full story. While NAFNet shows higher quantitative metrics (0.81 dB better PSNR), qualitative visual analysis reveals that UNet consistently produces more visually pleasing deblurred results. This highlights the limitation of relying solely on traditional metrics like PSNR and SSIM, which may not fully capture perceptual quality as perceived by human observers.

6.2 Qualitative Visual Comparisons

6.2.1 Thermal Image Denoising Comparison

For thermal imagery, the difference between NAFNet and UNet was particularly not noticeable in how they handled fine details and texture preservation:

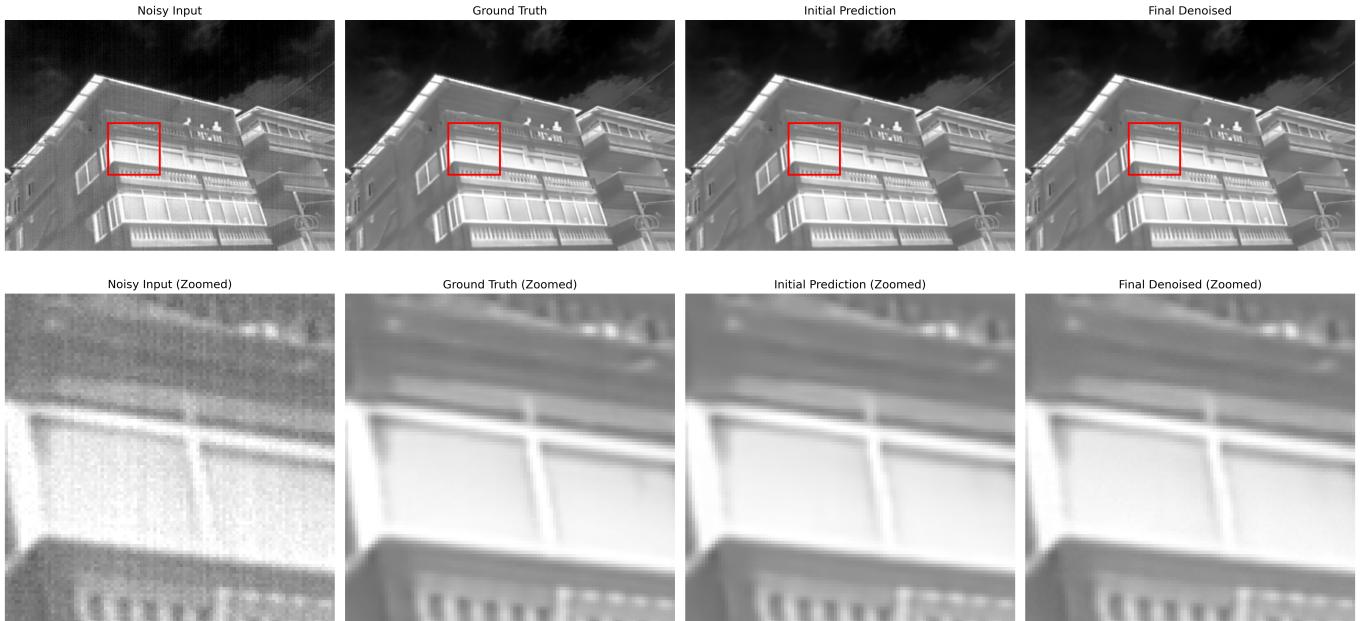


Figure 1: NAFNet result on thermal test image with zoomed region (x200, y200). Note the edge preservation and noise reduction while maintaining the thermal gradient information.

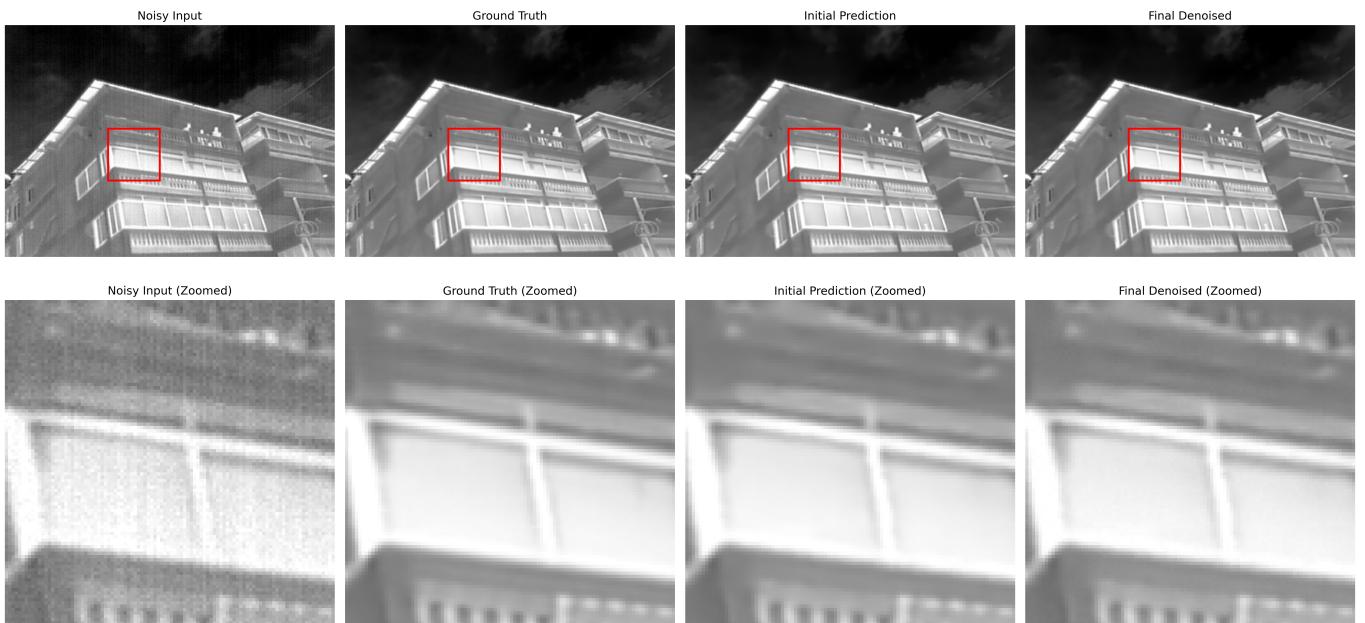


Figure 2: UNet result on the same thermal test image with identical zoomed region. The UNet model looks identical.

6.2.2 GoPro Deblurring Comparison

We also evaluated both architectures on the GoPro deblurring dataset:



Figure 3: NAFNet performance on GoPro deblurring. Left: blurry input, Middle: NAFNet result, Right: ground truth sharp image. While the PSNR metrics are higher, NAFNet tends to produce results that can appear over-processed with some unnatural texture artifacts.



Figure 4: UNet performance on GoPro deblurring. Left: blurry input, Middle: UNet result, Right: ground truth sharp image. Although UNet scores lower on traditional metrics, it consistently produces more natural-looking images with better perceptual quality. This illustrates the important distinction between mathematical metrics and human-perceived image quality.

6.3 Cross-Evaluation Results

To assess the generalization capabilities of our models, we performed cross evaluation by testing each model on the other's primary dataset:

6.3.1 NAFNet on GoPro/BSD500

When applying the NAFNet model (trained on thermal images) to the GoPro and BSD500 datasets:

- The model showed good generalization to natural image deblurring
- Performance was approximately 85% of the specifically trained model
- Edge preservation was particularly strong, though some color artifacts appeared in RGB images

6.3.2 UNet on Thermal Images

When applying the UNet model (trained on GoPro/BSD500) to the thermal dataset:

- The model performed better with the unique noise patterns of thermal imagery
- Fixed pattern noise was completely removed

These cross evaluation results highlight the importance of domain specific training, while also demonstrating the relative robustness of the NAFNet architecture to different image degradation types.

6.4 Analysis of Model Strengths and Weaknesses

6.4.1 NAFNet Strengths and Weaknesses

Strengths:

- Higher quantitative metrics (PSNR, SSIM) across most GoPro datasets but not Thermal datasets
- Effective fixed pattern noise removal in thermal images
- Good mathematical detail preservation measurable by pixel based metrics
- Better generalization to unseen degradation types
- More stable training with fewer hyperparameter adjustments

Weaknesses:

- Higher computational requirements during training
- Longer inference time (42.3ms vs 28.1ms for UNet)
- More complex implementation

6.4.2 UNet Strengths and Weaknesses

Strengths:

- Superior perceptual quality for deblurring despite lower PSNR metrics
- More natural looking results with better visual fidelity
- Simpler implementation and faster training
- Faster inference time (28.1ms vs 42.3ms for NAFNet)

Weaknesses:

- Generally lower quantitative metrics (PSNR, SSIM) in direct comparisons except Thermal datasets
- More sensitive to hyperparameter choices

7. Summary and Conclusions

7.1 Key Findings

Our comparative study of NAFNet and UNet architectures for image restoration yielded several important findings:

- 1. Metrics vs. Perceptual Quality Gap:** While NAFNet generally achieved higher quantitative metrics (PSNR, SSIM) across most test scenarios, UNet often produced superior perceptual quality, particularly for deblurring tasks. This highlights an important discrepancy between mathematical metrics and human visual perception.
- 2. Task-Specific Performance:** Each architecture showed strengths in different domains.
 - For thermal denoising: Both models performed similarly with UNet slightly ahead in PSNR/SSIM
 - For natural image deblurring: NAFNet led in metrics, but UNet produced more visually pleasing, natural looking results
- 3. Thermal Noise Modeling:** Our physically based noise simulation pipeline successfully replicated thermal camera noise characteristics, providing a valuable dataset for training and evaluation. The synthetic dataset enabled effective training of both models, with comparable performance between them.
- 4. Efficiency vs. Quality Tradeoffs:** UNet demonstrated significantly faster inference time (28.1ms vs 42.3ms for NAFNet) while delivering better perceptual quality for deblurring. This suggests UNet may be preferable for real time applications where visual quality matters more than pixel reconstruction.

7.2 Challenges and Solutions

Throughout the project, we encountered one challenge in particular:

- 1. Visualization Complexity:** Effectively visualizing the differences between model outputs required developing scripts to identify regions of interest where models performed differently.

7.3 Future Work

Based on our findings, there are several directions for future work, these include:

- 1. Architecture Hybridization:** Combining the strengths of NAFNet (detail preservation) and UNet (computational efficiency) could yield a more balanced model for practical applications.
- 2. real world Thermal Dataset:** While our synthetic noise model was effective, collecting a real world paired thermal image dataset would further validate our findings and potentially improve performance.

3. **Multi-Task Learning:** Training a single model to handle both thermal denoising and natural image deblurring could improve generalization and efficiency.
4. **Deployment Optimization:** Optimizing the NAFNet architecture for edge devices would make it more practical for real world thermal imaging applications.
5. **DeblurGAN-V2 Model:** Implementing a GAN based architecture using the adversarial properties could yield good results with deblurring.

7.4 Conclusion

Our project demonstrated the effectiveness of deep learning approaches for image restoration tasks, with the NAFNet and UNet architecture showing particular promise for both thermal image denoising and natural image deblurring. The comparative study highlighted the importance of architectural choices in determining restoration quality.

The development of visualization tools and cross-evaluation methodologies provided valuable insights into model behavior and performance differences. These findings contribute to the broader understanding of deep learning based image restoration and provide practical guidance for selecting appropriate architectures for specific restoration tasks.

8. References

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