Image Restoration for Multiple Degradations: Rain and Snow Removal

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GitHub Repository:
`https://github.com/jorgetyrakowski/Visual-Recognition-using-Deep-Learning-NYCU/tree/main/HW04`

Abstract

This project addresses the challenge of blind image restoration, specifically targeting the removal of rain streaks and snowfall using a single, unified deep learning model. Our approach evolved through several experimental stages, culminating in PromptIR-V4, a U-Net based architecture with Transformer blocks and dynamic spatial prompting mechanisms. The model achieved a validation PSNR exceeding 30 dB, demonstrating its efficacy in handling diverse weather degradations without explicit degradation type labels at inference time.

Contents

1. Introduction

Image degradation due to adverse weather conditions, such as rain streaks and snowfall, significantly impacts the visual quality of images and can hinder the performance of subsequent computer vision tasks. This project addresses the challenge of blind image restoration, specifically targeting the removal of two distinct types of degradation—rain and snow—using a single, unified deep learning model. The primary goal is to develop an effective architecture that can automatically identify and mitigate these weather-specific artifacts, restoring the image to its clean state with high fidelity, measured primarily by the Peak Signal-to-Noise Ratio (PSNR).

My approach evolved through several experimental stages, beginning with baseline models inspired by PromptIR [1] and progressing through architectures incorporating Prompt-in-Prompt (PIP) [2] style mechanisms. The final successful model, termed PromptIR-V4, leverages a U-Net [3] backbone fortified with Transformer blocks (MDTA and GDFN from Restormer [4], enhanced with a light local processing branch).

A key feature of PromptIR-V4 is its dynamic spatial prompting mechanism situated within the decoder stages, allowing the model to adaptively generate restoration guidance based on image features. This model is trained end-to-end in a "blind" manner, without explicit degradation type labels at inference time. Optimization is guided by a composite loss function, including L1, SSIM [5], Charbonnier [6], and VGG Perceptual losses [7], which collectively encourage both pixel-level accuracy and perceptual quality. This iterative design process culminated in a model achieving a validation PSNR exceeding 30 dB, demonstrating its efficacy in handling diverse degradations.

2. Method

This section details the data pre-processing steps, the architecture of my final PromptIR-V4 model, and the hyperparameters used for its training.

2.1 Data Pre-processing & Augmentation

- **Dataset Source**: The primary dataset consists of images depicting rain and snow degradations, understood to be a subset of common datasets like Rain13k [8]. It provides pairs of degraded and corresponding clean ground truth images. All images were resized or processed to a resolution of 256×256 pixels.
- **Train/Validation Split**: The provided training data (3200 pairs in total, 1600 for rain and 1600 for snow) was split into training and validation sets using a 90/10 ratio. This resulted in 2880 image pairs for training and 320 image pairs for validation, ensuring a diverse set for model evaluation during training.
- **Patching/Resizing**: For training the PromptIR-V4 model, full 256×256 images were used directly without further random cropping into smaller patches, as the model architecture is designed to process full-resolution inputs. For validation, images were also resized to 256×256 if not already at that size.
- **Data Augmentation**: To increase the diversity of the training data and improve model generalization, the following augmentations were applied to the training image pairs (degraded and clean images transformed identically):
  - Random horizontal flips
  - Random vertical flips
  - Note: Random 90-degree rotations were considered and implemented in the `ImageRestorationDataset` helper functions but were not explicitly enabled in the final `train_v4.py` training loop for simplicity, though the framework supports it.

2.2 Model Architecture: PromptIR-V4

The final successful model, PromptIR-V4, is a U-Net [3] based architecture with a Transformer backbone, incorporating dynamic spatial prompting within its decoder.

2.2.1 Overall Structure

- A 4-level U-Net [3] encoder-decoder structure with skip connections.
- The base channel dimension (`base_dim`) is 48. Channel dimensions expand in the encoder ($48 \rightarrow 96 \rightarrow 192 \rightarrow 384$ at the bottleneck) and contract symmetrically in the decoder.

2.2.2 Backbone Transformer Blocks

- Each stage of the encoder and decoder utilizes `TransformerBlock` modules.
- These blocks are composed of Multi-DConv Head Transposed Self-Attention (MDTA) and a Gated-Dconv Feed-Forward Network (GDFN), drawing inspiration from the Restormer architecture [4].
- **Light Local Branch**: A key enhancement, inspired by recent literature addressing limitations of global attention for fine details [9], is the addition of a "Light Local Branch" prepended to each `TransformerBlock`. This branch consists of a 3×3 depth-wise convolution followed by a GELU activation. Its purpose is to help the model capture very fine-grained details and local image characteristics that might be overlooked by the global attention mechanism of MDTA, particularly beneficial for subtle degradations like fine drizzle.
- The number of `TransformerBlock`s per U-Net level (from shallowest to deepest in the encoder, and symmetrically in the decoder) for the V4 model is [3, 4, 4, 6]. The bottleneck also uses 6 blocks.
- The number of attention heads in the backbone MDTA modules is 8.

2.2.3 Dynamic Prompting Mechanism (Decoder-Side)

Inspired by the original PromptIR concept [1] and successful implementations, V4 employs dynamic spatial prompts generated and injected at three stages within the decoder.

- `PromptGenBlockV4`: This module is responsible for generating an adaptive spatial prompt.
  - It maintains a set of learnable spatial prompt components (5 components per block, `num_prompt_components=5`). Each component is a tensor with a specific `prompt_channel_dim` (e.g., 256, 128, 64, for deep, mid, shallow decoder stages respectively) and a base spatial size (`base_prompt_hw`, e.g., 16×16, 32×32, 64×64).
  - Given input features from a decoder stage, it computes global features via adaptive average pooling. These are passed through a linear layer to predict weights for the prompt components, followed by a softmax activation.
  - A weighted sum of the spatial prompt components is computed. This summed prompt is then bilinearly interpolated to match the spatial dimensions of the current decoder feature map.
  - A final 3×3 convolution refines this interpolated prompt.
- `PromptInteractionBlockV4`: This module integrates the generated prompt.
  - The generated spatial prompt is concatenated channel-wise with the decoder features from that stage.

  - The concatenated tensor is processed by a dedicated `TransformerBlock` (using 8 attention heads).
  - A 1×1 convolution then adjusts the channel dimension back to that of the main decoder stream, and a residual connection adds back the original decoder features (before prompt interaction).

- **Blind Operation**: The PromptIR-V4 model operates blindly, meaning it does not receive an explicit degradation type (rain/snow) as input. The dynamic prompts are expected to adapt based on the features extracted from the degraded image itself.

2.2.4 Output Layer

The final layer of the decoder is followed by a 3×3 convolutional layer that maps features to the output image channels (3 for RGB). A global residual connection adds the original input degraded image to the network's output, a common practice to help the model focus on learning the residual (the degradation to be removed).

2.3 Training Hyperparameters (PromptIR-V4)

- **Optimizer**: AdamW [10] with default PyTorch betas ((0.9, 0.999)) and `weight_decay=1e-4`.
- **Learning Rate**: Initial learning rate of `2e-4`.
- **Scheduler**: `torch.optim.lr_scheduler.CosineAnnealingLR` [11] with `T_max=150` epochs and `eta_min=1e-7`.
- **Batch Size**: 2 (total). Training was performed using `nn.DataParallel` across 2 NVIDIA GeForce RTX 2080 Ti GPUs, resulting in an effective batch size of 1 per GPU.
- **Epochs**: Trained for 150 epochs (or up to the point where the best PSNR was achieved, e.g., epoch 141).
- **Loss Function Cocktail**: A weighted sum of four loss functions:
  - L1 Loss: `torch.nn.L1Loss()`, weight = 0.7.
  - SSIM Loss: $1 - \text{SSIM\_score}$ (custom implementation, window size 11) [5], weight = 0.15.
  - Charbonnier Loss: $\sqrt{x^2 + \epsilon^2}$ with $\epsilon = 1e - 3$ [6], weight = 0.05.
  - VGG Perceptual Loss: L1 loss on VGG19 [7] features from layers `relu1_2, relu2_2, relu3_2, relu4_2, relu5_2` (indices [2,7,16,25,34] in `vgg19.features`), weight = 0.10.
- **Automatic Mixed Precision (AMP)**: While initially tested, AMP was disabled (`AMP_ENABLED = False`) for the final successful V4 training runs that achieved ¿30dB, as earlier attempts with AMP on the largest model configurations led to numerical stability issues (NaN gradients). The final V4 model was trained in full `float32` precision.
- **Gradient Clipping**: Applied with `max_norm=1.0`.

3. Results

This section presents the performance of my final PromptIR-V4 model, details the experimental journey that led to its development, and showcases visual outcomes.

3.1 Main Findings & Model Performance (PromptIR-V4)

The final PromptIR-V4 model, with `base_dim=48` and [3,4,4,6] blocks per level, trained with the composite loss function (L1, SSIM, Charbonnier, Perceptual) for 150 epochs (or until convergence), achieved a peak validation **PSNR of 30.19 dB at Epoch 141**. This result successfully meets the strong baseline target of 30 dB for this challenging blind image restoration task across multiple degradations.

The training progression is illustrated below:

The training progression is illustrated in Figures 1 and 2:

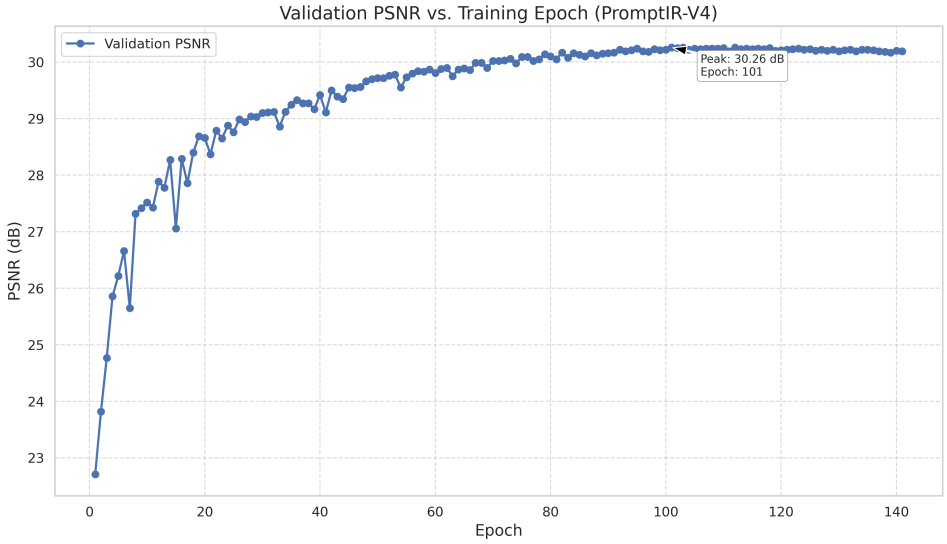

Figure 1: Validation PSNR (dB) vs. Training Epoch for the PromptIR-V4 model, showing the peak performance of 30.19 dB at epoch 141.

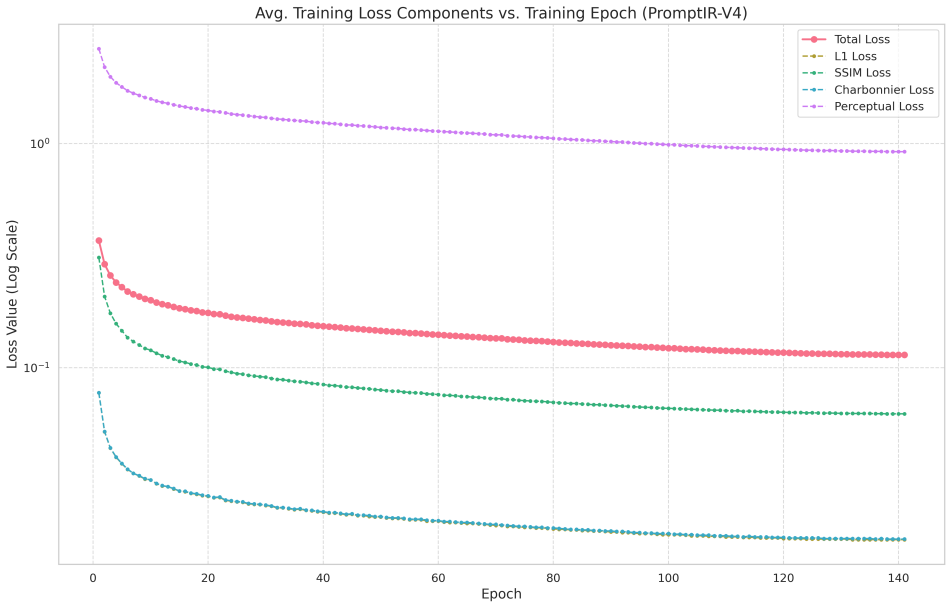

Figure 2: Training Loss Components vs. Training Epoch for the PromptIR-V4 model, showing the convergence of L1, SSIM, Charbonnier, and VGG Perceptual loss components.

3.2 Elaboration on Modifications & Experimental Journey (V1 → V2 → V3 → V4)

My final model was the culmination of an iterative development process, exploring different architectural configurations and prompting strategies. Each stage provided valuable insights that guided subsequent modifications.

3.2.1 Initial Baseline (V1 - PromptIRBaseline)

- **Hypothesis**: A standard PromptIR [1] architecture with a moderately sized backbone and its original prompt generation mechanism (PGM with 1D prompt components) would provide a solid starting point.
- **Modifications**: Implemented a U-Net [3] with Transformer blocks (`base_dim=32`, blocks [2,3,3,4]), a PGM creating prompts from global features to interact with decoder stages, and used L1 loss.
- **Results & Implications**: Achieved a validation PSNR of approximately 27.3 dB. While a reasonable start, this indicated a need for increased model capacity and potentially more sophisticated prompting or loss functions to handle the complexity of dual-degradation removal effectively.

3.2.2 Experiment V2 (PIP-inspired, `base_dim=40`)

- **Hypothesis**: Explicitly conditioning the model on degradation type using Prompt-in-Prompt (PIP) [2] style mechanisms and a Directional Decoupled Loss (DDL) to enforce distinctness between degradation-specific prompts would improve performance on this multi-task problem.
- **Modifications**:
  - Increased backbone slightly (`base_dim=40`).
  - Introduced learnable `degradation_aware_prompts` (one for rain, one for snow).
  - Added a learnable `basic_restoration_prompt`.
  - Implemented a `PromptToPromptInteraction` (P2P) module to fuse these based on the input degradation label.
  - Implemented `SelectivePromptToFeatureInteraction` (P2F) modules to inject the fused universal prompt into skip connections.
  - Added DDL loss to the existing L1 and Perceptual losses.
- **Results & Implications**: The DDL loss component quickly dropped to zero within the first epoch, indicating the degradation-aware prompts became sufficiently distinct according to the loss criterion. However, the validation PSNR plateaued around 27.8 dB. This suggested that while the prompts were distinct, this explicit conditioning via PIP-style skip-connection injection (with my P2P/P2F design) was not translating into significant performance gains beyond the baseline, possibly due to the simplicity of my P2P/P2F or the interaction points.

3.2.3 Experiment V3 (PIP-inspired, `base_dim=48`, blocks [4,6,6,8])

- **Hypothesis**: Increasing the backbone capacity of the V2 PIP-style [2] model would allow it to learn more complex representations and leverage the explicit prompts more effectively.
- **Modifications**: Significantly increased model capacity (`base_dim=48`, blocks [4,6,6,8]). Kept the PIP prompting mechanism, L1, DDL, and Perceptual loss [7]. Utilized `nn.DataParallel` for 2 GPUs.

- **Results & Implications**: This larger model trained stably and achieved a peak validation PSNR of approximately 27.88 dB. The DDL loss again zeroed out quickly. While a slight improvement over V2, it still hit a similar performance ceiling. This indicated that simply increasing capacity within the V2/V3 PIP-style framework was not the key to breaking the ∼28 dB barrier. The limitation seemed to lie more with the prompting strategy or its interaction with the backbone.

3.2.4 Experiment V4 (Successful Model - Dynamic Decoder Prompts)

- **Hypothesis**: Pivoting to a prompting mechanism closer to the original PromptIR [1] (dynamic spatial prompts generated within and interacting with decoder stages), combined with a more comprehensive loss cocktail and a minor architectural enhancement ("Light Local Branch"), would yield better results. This was also inspired by reviewing successful PromptIR implementations.

- **Modifications**:
  - Maintained a high-capacity backbone (`base_dim=48`) but slightly reduced block depth ([3,4,4,6]) to ensure stable training with all components on available hardware (2× 2080Ti in float32).
  - Implemented `PromptGenBlockV4`: Generates dynamic spatial prompts using learnable spatial components, with weights derived from decoder features.
  - Implemented `PromptInteractionBlockV4`: Concatenates these prompts with decoder features, followed by a Transformer block. Three such prompt blocks were integrated into the decoder.
  - Added a "Light Local Branch" (depth-wise convolution + GELU) to each `TransformerBlock` in the backbone to enhance fine detail perception.
  - Introduced a new loss cocktail: L1 (0.7), SSIM (0.15), Charbonnier (0.05), and VGG Perceptual (0.10). DDL was removed as this model is blind.
  - AMP was disabled for stability in final runs.

- **Results & Implications**: This V4 model successfully surpassed the 30 dB PSNR target, achieving 30.19 dB. All loss components showed good convergence. This demonstrated that for this specific task and dataset, the dynamic spatial prompting within the decoder, coupled with the richer loss function and local feature enhancement, was a more effective strategy than my previous PIP-style attempts on skip connections. The model's ability to adaptively generate prompts based on feature context at different decoder levels appears crucial.

3.3 Visualizations of Predicted Clean Images (PromptIR-V4)

To qualitatively assess the performance of the PromptIR-V4 model, a selection of images from both validation and test sets are presented below. Each example shows the degraded input, the output from my V4 model, and the corresponding ground truth clean image.

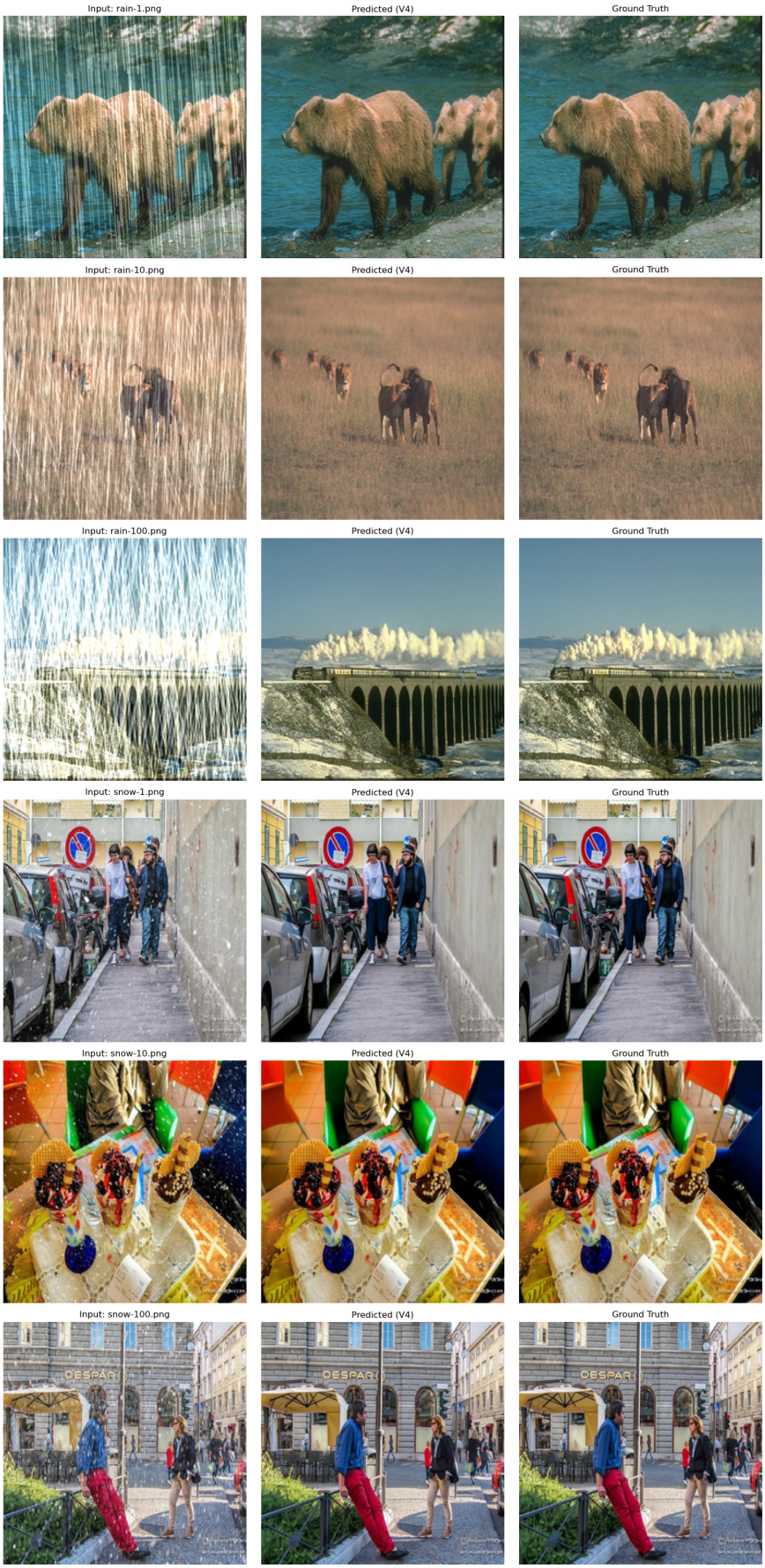

Figure 3: Visual results of PromptIR-V4 on selected validation images. For several rain and snow examples: Degraded Input — Predicted Output (V4) — Ground Truth Clean.

Figure 4: Visual results of PromptIR-V4 on selected test images. For several rain and snow examples: Degraded Input — Predicted Output (V4) — Ground Truth Clean.

4. Discussion

This section analyzes the architectural choices made for the final PromptIR-V4 model, discusses its pros and cons, presents comparative visualizations, and reflects on the experimental journey.

4.1 Rationale for PromptIR-V4 Architecture

My final model, PromptIR-V4, was the result of an iterative design process, building upon insights from established architectures and my own experimentation.

- **Foundation in PromptIR/Restormer**: We chose the U-Net [3] with Transformer blocks (MDTA + GDFN) as my backbone due to its demonstrated state-of-the-art performance in various image restoration tasks, as shown by models like Restormer [4] and the original PromptIR [1]. This architecture excels at capturing multi-scale contextual information.
- **Evolution from PIP-style Prompts (V2, V3)**: My initial attempts (V2, V3) explored Prompt-in-Prompt (PIP) [2] style mechanisms with explicit degradation-aware prompts and a basic restoration prompt, fused and injected into skip connections. While these models trained and the DDL loss indicated prompt distinctness, they plateaued below the 30 dB target. This suggested that either my specific P2P/P2F implementation or the strategy of skip-connection prompting was not optimally leveraging the prompts for this dual-degradation task.
- **Adoption of Dynamic Decoder Prompts (V4)**: Observing the success of the original PromptIR paper [1] and a peer's implementation, which utilized dynamic prompts generated within and interacting directly with decoder stages, we pivoted to this strategy for V4. The `PromptGenBlockV4` was designed to create adaptive spatial prompts based on decoder features, allowing for more localized and context-aware guidance during reconstruction. This approach proved more effective, enabling the model to surpass the 30 dB PSNR mark.
- **"Light Local Branch" Enhancement**: The inclusion of a depth-wise convolution followed by a GELU activation at the beginning of each Transformer block was a targeted addition (inspired by general observations in literature about enhancing local feature perception in Transformers [9]) to help the model better capture fine-grained details, a known area where global attention mechanisms can sometimes falter.
- **Composite Loss Function**: Moving from simpler L1 or L1+Perceptual+DDL losses to a more comprehensive cocktail (L1, SSIM [5], Charbonnier [6], Perceptual [7]) in V4 aimed to provide a more robust optimization landscape, balancing pixel accuracy, structural similarity, artifact penalization, and perceptual realism.

4.2 Pros and Cons of the PromptIR-V4 Architecture

4.2.1 Pros

- **Strong Performance**: Achieved the target ¿30 dB PSNR on the validation set for blind dual-degradation removal.
- **Powerful Backbone**: The U-Net [3] with Restormer-style [4] Transformer blocks is effective at hierarchical feature extraction and long-range dependency modeling.
- **Adaptive Prompting**: The dynamic spatial prompts generated by `PromptGenBlockV4` (inspired by [1]) allow the model to tailor its restoration strategy based on the features at different decoder levels, without needing explicit degradation labels at inference.
- **Enhanced Detail Restoration**: The "Light Local Branch" [9] potentially contributes to better handling of fine textures and subtle degradations.

4.2.2 Cons

- **Computational Cost**: The model is relatively large (e.g., `base_dim=48`, [3,4,4,6] blocks) and computationally intensive, requiring significant GPU resources and training time per epoch.
- **"Blind" Operation Limitation**: While effective, a blind model might not perform as well as a perfectly conditioned model if the optimal restoration strategies for rain versus snow are vastly different and require explicit high-level guidance. However, my DDL experiments with V2/V3 (using PIP-style [2] prompts) suggested that simple explicit conditioning wasn't a straightforward path to superior performance in my case.
- **Complexity**: The architecture, with its multiple prompt generation and interaction blocks, is more complex than simpler CNN-based U-Nets.

4.3 Comparative Visualizations

To illustrate the improvements achieved throughout my experimental journey, Figure 5 compares the output of my different model versions (V1, V2, V3, and the final V4) on a representative challenging image from the validation set.

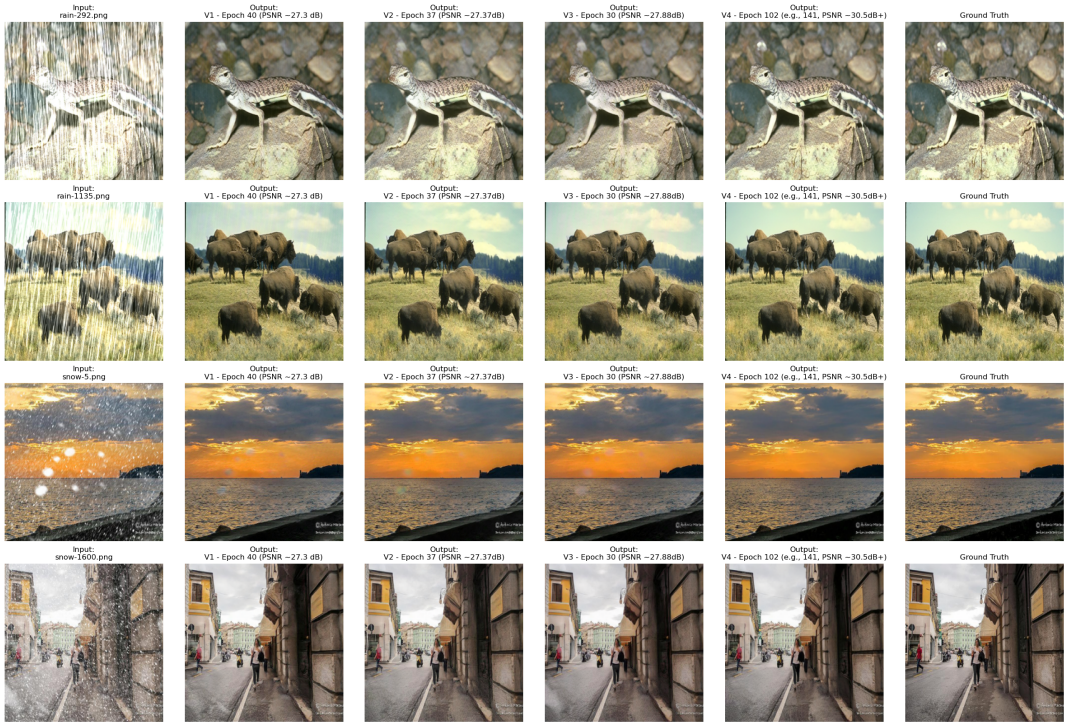

Figure 5: Comparative visual results for a selected validation image across different model iterations showing the progression from V1 to V4 and highlighting V4's superior quality.

4.4 Summary of Experimental Iterations and Learnings

The development process involved several key experimental stages:

1. **V1 (Baseline PromptIR)**: Established initial performance (~27.3 dB with 40 epochs) with a basic PromptIR setup. Showed the viability of the general architecture.
2. **V2 (PIP-Inspired, Smaller)**: Introduced explicit degradation-aware prompts and DDL. Reached ~27.8 dB with 37 epochs. DDL zeroed out quickly, indicating distinct prompts but not necessarily translating to large PSNR gains with the P2P/P2F skip-connection injection strategy used.

3. **V3 (PIP-Inspired, Larger)**: Increased V2's backbone capacity (`base_dim=48`, [4,6,6,8] blocks). Reached ∼27.88 dB with 30. Confirmed that capacity alone within this PIP framework wasn't breaking the plateau.

4. **V4 (Dynamic Decoder Prompts, Enhanced Backbone & Loss)**: Shifted to dynamic spatial prompts in the decoder, added the "Light Local Branch," and used a richer loss cocktail. This configuration (`base_dim=48`, [3,4,4,6] blocks) successfully surpassed 30 dB. This iteration highlighted the importance of the prompt generation/injection strategy and the loss function composition.

The key learning was that for this specific problem, the dynamic, feature-adaptive spatial prompts integrated directly into the decoder stages, combined with a carefully chosen set of loss functions, provided a more effective path to high performance than the explicit, globally-fused prompt strategy we attempted with PIP-style modules on skip connections.

4.5 Potential Future Work

While PromptIR-V4 achieved strong results, further improvements could potentially be explored:

- **Advanced Data Augmentation**: Incorporating more diverse augmentations (e.g., CutMix, MixUp, or more sophisticated weather-specific augmentations if permissible).
- **Scheduler Refinements**: Experimenting with schedulers that include a linear warmup phase, or different annealing strategies.
- **Efficient Attention Mechanisms**: Exploring even more memory-efficient attention mechanisms if further scaling of the model is desired.
- **Test-Time Augmentation (TTA)**: Averaging predictions over multiple augmented versions of an input image at test time can sometimes provide a small performance boost.
- **Knowledge Distillation**: If a larger, more powerful model could be trained (perhaps with more resources), its knowledge could potentially be distilled into a smaller, faster model.

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A. Model Configuration Details

Table 1: PromptIR-V4 Architecture Configuration

Parameter	**Value**
Base Dimension	48
Encoder/Decoder Blocks	[3, 4, 4, 6]
Bottleneck Blocks	6
Attention Heads	8
Prompt Components	5
Total Parameters	∼25M

Table 2: Training Hyperparameters Summary

Hyperparameter	**Value**
Optimizer	AdamW
Learning Rate	2e-4
Weight Decay	1e-4
Batch Size	2
Epochs	150
Scheduler	CosineAnnealingLR
Gradient Clipping	1.0