Report: Image Denoising and Classification

1. Denoising Method

We used a U-Net autoencoder for image denoising. Its encoder–decoder structure with skip connections preserved local detail while reducing noise.

- **Architecture: encoder + decoder with skip connections.**
- **Loss Function:**
  - **MSE Loss (pixel-wise fidelity).**
  - **SSIM Loss (structural preservation).**
  - **Weighted hybrid: Loss = 0.8 * MSE + 0.2 * (1 – SSIM).**
- **Evaluation Metrics:**
  - **PSNR (Peak Signal-to-Noise Ratio)**
  - **SSIM (Structural Similarity Index)**

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2. Classification Approach

After denoising, flower classification was performed using a custom CNN (StrongCNN) across 5 categories (daisy, dandelion, rose, sunflower, tulip).

- **Architecture:**
  - **5 convolutional blocks with GroupNorm + ReLU + MaxPooling.**
  - **Global average pooling.**
  - **Fully connected classifier with dropout.**
- **Training:**
  - **Loss: CrossEntropyLoss**
  - **Optimizer: AdamW with LR scheduling (ReduceLROnPlateau)**
  - **Trained for 200 epochs.**

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3. Key Design Decisions

- **Using a U-net autoencoder with an up sample, down sample and bottleneck class.**

- **Group Normalization chosen over Batch Norm for small batch stability.**
- **Transforms were reduced (removed rotations/jitter) to ensure denoised, clean, and noisy images aligned correctly during visualization.**

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4. Observations from Evaluation

Baseline (noisy vs clean):

- **PSNR: ≈13.5dB**
- **SSIM: ≈0.19**

Final Denoiser Performance:

- **Training: PSNR ≈ 24.5 dB, SSIM ≈ 0.75**
- **Validation: PSNR ≈ 24.5 dB, SSIM ≈ 0.74**

For classification:

- **Classifier achieved steadily improving accuracy with validation stabilizing after around a 100 epochs.**
- **Training accuracy: 90%**
- **Validation accuracy: 71%**

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5. Challenges and Solutions

- **Flipped/rotated images in visualization → Removed heavy augmentations (flip, rotation). After a lot of trial n error involving changing denoisers, models, adding transformations, I discovered the model performed best when the noisy, denoised and clean image all had the same transformations.**
- **Choosing Resnet v/s U-net for denoising. In an earlier to denoise some images and extract text, I'd used a Resnet + CRNN model but in this case the output images were very distorted and the metrics showed similar results. After further research, I discovered ResNet solves the problem of training *very deep networks* by learning residual mappings (good for classification) whereas U-Net Autoencoder solves the problem of *reconstructing dense, spatially detailed outputs* by using encoder-decoder skips (good for segmentation/denoising).**

- **Overfitting risk → Used dropout, LR scheduling, and validation monitoring.**

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6. Conclusion

By combining U-Net denoising with a robust CNN classifier, we improved classification accuracy on noisy flower images. The denoiser improved PSNR and SSIM by ~11 dB and 0.6, respectively, providing cleaner inputs and boosting classifier performance.