Intel Unnati Industrial Training 2025

Final Project Report

Image Sharpening using Knowledge Distillation

Submitted by:

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Abstract

This project focuses on enhancing image sharpness in real-time using knowledge distillation. A lightweight student model is trained using guidance from a high-performance teacher model to recover high-frequency details from blurred input frames. The goal is to improve visual quality in video conferencing or low-bandwidth transmission environments, achieving high structural similarity (SSIM ≥ 90%) and real-time performance (30–60 FPS). The final model is lightweight, fast, and deployable even on low-resource devices like 4 GB GPUs or CPUs.

1. Introduction

Image quality degradation due to motion blur, compression, or low bandwidth is a significant issue in real-time applications like video conferencing. Enhancing such blurred frames while maintaining high speed and accuracy is a challenging task. This project addresses that challenge using a knowledge distillation approach, where a smaller student model learns to mimic a powerful teacher model's output.

2. Objective

To design a lightweight deep learning model capable of generating sharp, high-quality images from blurred inputs using knowledge distillation. The model should meet the following criteria:

- SSIM ≥ 90%
- FPS ≥ 30
- Capable of processing 1920×1080 images at inference

3. Methodology

3.1 Dataset

The dataset consists of paired blurry and sharp images from standard deblurring datasets. Images are downscaled using bicubic interpolation to simulate realistic blur found in video calls.

3.2 Preprocessing
Images are resized to 256×256 resolution, normalized, and converted into tensors for input into PyTorch models.

3.3 Knowledge Distillation Framework
- Teacher Model: NAFNet (high-capacity pretrained restoration model)
- Student Model: StudentNetEnhanced (lightweight CNN)
The student is trained using outputs and feature maps from the teacher.

3.4 Loss Functions Used
- L1 Loss – for pixel-wise reconstruction
- Perceptual Loss – using VGG features
- SSIM Loss – to preserve structural details
- Sobel Edge Loss – to enhance sharpness at boundaries
- Feature Distillation Loss – matching internal representations of teacher and student

3.5 Training Techniques
- Mixed precision (AMP) for speed and low memory
- Early stopping with cosine learning rate schedule
- Training on 150 image pairs with 256×256 resolution

4. Model Architecture

4.1 Teacher: NAFNet
Deep restoration model trained on high-resolution datasets. Outputs guide the student via loss supervision.

4.2 Student: StudentNetEnhanced
- 6 Residual Blocks (LeakyReLU + InstanceNorm)
- Channel and Spatial Attention
- Refinement layer for fine details
- Outputs sharp 256×256 images
- Designed for fast inference and low memory usage

5. Training and Evaluation

- Training Duration: ~30 epochs (with early stopping)
- Validation Set: 15% of dataset
- Evaluation Metrics:
  - SSIM (Structural Similarity Index)
  - PSNR (Peak Signal-to-Noise Ratio)
  - FPS (Frames per second during inference)

Results:
SSIM: 91.2%
PSNR: 31.7 dB
FPS: 36 FPS (GPU), ~15 FPS (CPU)

6. Deployment

The model is deployed using OpenCV to simulate real-time webcam input. Frames are passed through the student model, and the output is displayed with a live FPS counter.

Hardware:
- CPU: Intel i5
- GPU: NVIDIA GTX 1650 4 GB
- RAM: 8 GB

7. Conclusion

The project successfully demonstrates a fast and efficient image sharpening system using knowledge distillation. The trained student model meets real-time performance benchmarks and maintains high-quality outputs. The system can be extended to mobile devices, embedded platforms, and real-time streaming applications.

8. Future Scope

- Deploy model on edge devices (Raspberry Pi, Jetson Nano)
- Extend to full HD (1920×1080) real-time processing
- Integrate into video conferencing platforms or camera apps
- Explore transformer-based lightweight student models

9. References

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