KD Deblurring – Problem Statement 2

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Real-time image deblurring via knowledge distillation using Restormer and a lightweight U-Net.

This project presents a compact student model trained via offline knowledge distillation from a powerful transformer-based teacher (Restormer), optimized for fast and effective image sharpening in video conferencing scenarios.

The model achieves **0.84 SSIM** and **26.8 PSNR** on synthetic motion-blurred face and shared content datasets and runs at up to **39 FPS on an RTX 3050 GPU** and **25.9 FPS on an Intel i5 CPU**.

Features

- **Knowledge Distillation**: Used a transformer-based Restormer model as the teacher to supervise a lightweight U-Net student network.
- **Offline Supervision Strategy**: To overcome hardware limitations, teacher outputs were precomputed and script to do the same is stored in the precompute/ folder, enabling stable distillation at scale.
- **Blurred Dataset Construction**: Created a custom dataset of 5,571 face images from CelebA and Shared Content datasets, resized to 256×256 and synthetically blurred with motion and compression artifacts.
- **Model Export for Deployment**: The trained student model was exported to both **ONNX** and **OpenVINO IR**, making it deployable across multiple hardware targets.
- **Real-Time Performance**:
  - **39 FPS** on RTX 3050 GPU (128×128 input)
  - **25.9 FPS** on Intel i5 CPU (128×128 input)
  - **15.2 FPS** on Intel MacBook Pro (i7) (256×256 OpenVINO)
- **Lightweight Student Design**: Model is compact enough for real-time usage on modest hardware without GPU acceleration.
- **Quantitative Results**:
  - **Teacher**: SSIM > 0.91 (on precomputed targets)
  - **Student**: SSIM = 0.84, PSNR = 26.8 (at 20 epochs) - performance increases further at higher epochs
- **Inference Backends Supported**:
  - **PyTorch** (native)
  - **ONNXRuntime**
  - **OpenVINO**

Installation & Setup

This project was developed and tested using **Python 3.10**. It is recommended to use a virtual environment to avoid conflicts with system packages.

1. Clone the repository

```
git clone https://github.com/your-username/KD-Deblurring.git
cd KD-Deblurring
```

2. Create and activate a virtual environment

```
python3.10 -m venv torch_env
source torch_env/bin/activate      # For macOS/Linux
# .\torch_env\Scripts\activate      # For Windows
```

3. Install dependencies

Upgrade `pip` and install the required Python packages:

```
pip install --upgrade pip
pip install -r requirements.txt
```

Note: This project uses the **CPU-only version of PyTorch** for compatibility across systems. If PyTorch fails to install or defaults to the wrong architecture, run:

```
pip install torch torchvision torchaudio --index-url https://download.pytorch.org/whl/cpu
```

You should now be ready to run inference using PyTorch, ONNXRuntime, or OpenVINO.

Usage

This section provides instructions to run inference using the trained student model across different backends.

1. Run inference with PyTorch

```
python torch_inference.py --image_path path/to/image.jpg --output_path output/torch_output.jpg
```

2. Run inference with ONNXRuntime

```
python onnx_inference.py --image_path path/to/image.jpg --output_path output/onnx_output.jpg
```

3. Run inference with OpenVINO

```
python openvino_inference.py --image_path path/to/image.jpg --output_path output/openvino_output.jpg
```

Notes:

- All inference scripts accept `--image_path` and `--output_path` as arguments.
- Default input resolution is **128x128**, to improve performance.
- Inference performance varies by backend and input resolution. Refer to the benchmarks section for FPS results.
- Sample inputs are not provided due to dataset restrictions. You may test using any face image resized to 128x128.

Results / Benchmarks

1. Quantitative Metrics

- Teacher Model (Restormer): SSIM > 0.91
- Student Model (Lightweight U-Net): SSIM = 0.84, PSNR = 26.8 dB (at 20 epochs)

Note: Results are **likely to improve** with more training, this project was stopped at 20 Epochs due to computational constraints.

2. Performance Benchmarks (FPS)

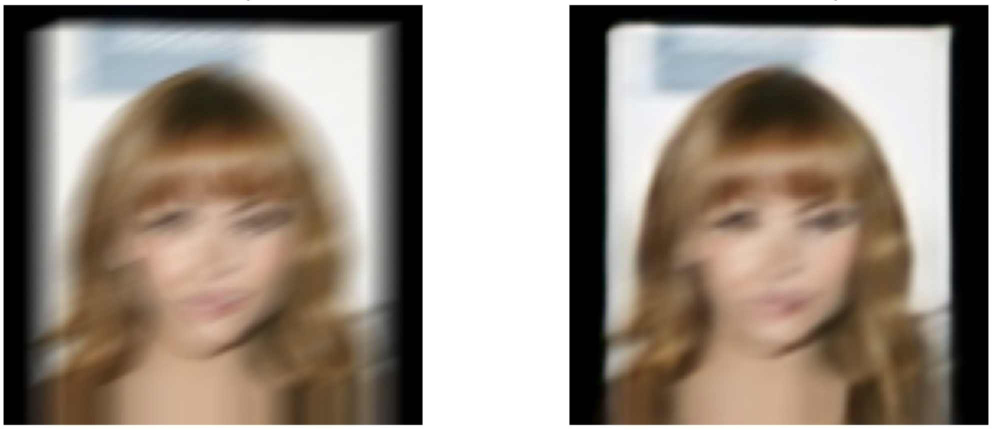
Backend	Device	Resolution	FPS
OpenVIN0	RTX 3050 (GPU)	128×128	39.0
OpenVIN0	Intel i5 CPU	128×128	25.9
Benchmark App	Intel Mac (i7)	128×128	26.88

Note: Performance may vary accross systems

3. Visual Results

Below is an output produced by the student model after deblurring a synthetically blurred face image:

Blurred Input   Deblurred Output



Dataset

The training data consisted of **5571 RGB images** created by combining:

- **CelebA Dataset**: A large-scale face attributes dataset with over 200K celebrity images.
- **Shared Content Dataset**: A generic open-source dataset used for diverse image content and can be found on Kaggle.

All images were:

- Resized to **256×256**
- Augmented with **synthetic motion blur** and **JPEG compression artifacts**
- Normalized to [0,1] for training

Due to compute constraints, only a **subset of the combined dataset** was used. These images were selected randomly to preserve diversity in facial structure and background content.

The final dataset was used solely precomputation of teacher outputs and for training the student model.

Notes

- CelebA is publicly available for research at CelebA Dataset
- Shared Content Dataset can be found on Kaggle.
- Dataset files are **not included** in this repository due and storage constraints.

Model Architecture & Conversion

Architecture Overview

- **Teacher Model**: Restormer — a transformer-based model designed for high-quality image restoration.
- **Student Model**: A lightweight U-Net with reduced parameters, suitable for real-time inference.

The student was trained using **offline knowledge distillation**, where ground truth supervision came from the precomputed outputs of the teacher model that can be created with script stored in `precompute/`.

Student Model: Lightweight U-Net

The student model is a compact U-Net variant designed for real-time performance, incorporating modern architectural enhancements:

Key Features:

Multi-scale Input Fusion: Combines original input with a downsampled version to help the model retain both local and contextual information early on.

Encoder-Decoder Structure: Three-level hierarchical feature extraction and reconstruction using:

- Convolution blocks with BatchNorm + ReLU
- MaxPooling in the encoder
- Transposed convolutions in the decoder

ECA Attention: Efficient Channel Attention modules after every encoder/decoder block for improved channel-wise feature emphasis with minimal computational cost.

Residual Output: Final layer output is clamped to [0,1] range for normalized image generation

Distillation Process

- Images were synthetically blurred using motion blur.
- Teacher outputs were generated ahead of training to reduce computational load.
- The student model was trained to minimize (0.3) L1 loss and (0.7) Distillation loss between its output and the teachers.

Future Work & Limitations

Limitations

- **Early Training Cutoff**: The student model was trained for only 20 epochs due to computational constraints. With more epochs, it is likely to achieve higher SSIM and PSNR.
- **Synthetic Blur Only**: The dataset used synthetic motion and compression blur. Performance on real-world webcam blur can vary and has not been quantitatively evaluated.
- **Resolution-Specific Performance**: The student model shows better FPS at 128×128 resolution, but there is a trade-off in output quality. Resolution adaptation logic is not currently implemented.
- **Single Image Inference**: The current pipeline supports single image input only. Batch inference and video stream support can significantly improve utility.

Future Improvements

- **Extended Training**: Training for 100+ epochs with cosine annealing or warm restarts to improve generalization and fidelity.
- **Real-World Fine-Tuning**: Including webcam or smartphone blur samples to make the model more robust to natural degradation.
- **INT8 Quantization**: Post-training quantization using OpenVINO to further reduce model size and increase inference speed without compromising quality.
- **Live Deployment**: Wrapping the student model into a real-time video processing app using OpenCV or MediaPipe for direct webcam sharpening.
- **Edge Benchmarking**: Testing on low-power hardware like Raspberry Pi or Intel NCS2 for true edge-readiness.

Acknowledgements & Citations

This project builds upon the work of several open-source contributors and research communities. Special thanks to the following:

Teacher Model

- **Restormer**
  P. Zamir et al., "Restormer: Efficient Transformer for High-Resolution Image Restoration," CVPR 2022
  GitHub: https://github.com/swz30/Restormer

Datasets

- **CelebA Dataset**
  Provided by MMLAB, Chinese University of Hong Kong
  http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html
- **Shared Content Dataset**
  Used for general image diversity and to simulate content shared in vide oconferences

Tools & Libraries

- PyTorch
- OpenVINO Toolkit
- ONNX & ONNXRuntime
- torchvision, torchmetrics

- tqdm, NumPy, OpenCV

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