Video Super Resolution with Diffusion-Based Refinement

Project Report

May 17, 2025

Contents

1 Introduction

Video super resolution (VSR) aims to reconstruct high-resolution (HR) frames from low-resolution (LR) video sequences. The ability to enhance temporal sequences has wide applications ranging from video streaming to medical imaging. This report accompanies the PyTorch implementation in `video_sr.py` and explains the design decisions behind the model. We emphasize how spatial and temporal features are captured, how transformer and diffusion components are integrated, and how losses encourage perceptually pleasing outputs. Recent updates add progressively stronger degradations during training, an optical-flow based consistency loss, and an adaptive diffusion timestep predictor to better refine details.

2 Literature Survey

In this section we briefly summarize prior work relevant to video super resolution and generative refinement. Early approaches relied on motion-compensated filtering [1]. Deep learning methods such as VSRnet [2] and VDSR [3] introduced convolutional neural networks for frame upscaling. Later, recurrent architectures like STCN [4] and transformer models like BasicVSR++ [5] improved temporal consistency. Diffusion-based models have recently been applied to super resolution [6]. Our implementation combines ideas from these works: a 3D convolutional encoder captures short-term motion, a transformer bottleneck enables long-range reasoning, deformable convolutions provide alignment, and a pre-trained diffusion model injects high frequency details.

3 Model Overview

The `VideoSuperResolutionDiffusionModel` processes a sequence tensor $X \in \mathbb{R}^{B\times C\times T\times H\times W}$, where T is the window length. The main steps are:

1. Encode spatio-temporal features using 3D convolutions.
2. Collapse the time dimension via temporal fusion.
3. Perform non-local interactions with a transformer block.
4. Decode and upscale with pixel shuffle operations.
5. Apply diffusion-based refinement for final detail.

A schematic is shown in Figure 1.

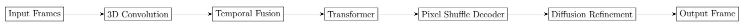

Figure 1: High-level overview of the video super-resolution pipeline implemented in this project.

4 Spatio-Temporal Encoding

The encoder applies a series of 3D convolutions to capture correlations along both spatial and temporal axes. Unlike standard 2D convolutions that operate on individual frames, 3D kernels slide across the time dimension as well. Formally, a 3D convolution with kernel $K \in \mathbb{R}^{C_{out} \times C_{in} \times k_t \times k_h \times k_w}$ at location (t, i, j) is defined as

$$Y(t,i,j) = \sum_{c=1}^{C_{in}} \sum_{a=1}^{k_t} \sum_{b=1}^{k_h} \sum_{d=1}^{k_w} K(c,a,b,d)\, X_c(t+a, i+b, j+d). \tag{1}$$

Strided convolutions reduce the spatial resolution while increasing the receptive field. By stacking such layers, motion cues spanning several frames are embedded into the feature maps.

5 Temporal Fusion

After encoding, temporal dimensions are collapsed with an attention-based fusion mechanism. A 3D convolution first aggregates features, then an optional attention branch predicts weights for each time step. Let $F \in \mathbb{R}^{B \times C \times T \times h \times w}$ denote encoded features and $A \in \mathbb{R}^{B \times 1 \times T \times h \times w}$ the attention logits. Temporal fusion computes

$$w_t = \mathrm{softmax}(A_t), \qquad G = \sum_{t=1}^{T} w_t\, F_t. \tag{2}$$

If attention is disabled, simple averaging over time is used. This step provides a compact summary of the window and allows the model to focus on more informative frames.

6 Transformer Bottleneck

Non-local interactions are modeled with a lightweight Linformer-style transformer encoder. Features are flattened into tokens, projected into queries Q, keys K, and values V. The keys and values are further projected into low-rank spaces using learnable matrices E and F to reduce the computational cost:

$$K' = KE, \qquad V' = VF, \qquad \mathrm{Attention}(Q, K', V') = \mathrm{softmax}\left(\frac{QK'^{\top}}{\sqrt{d}}\right) V'. \tag{3}$$

This formulation scales well to high-resolution feature maps while still enabling reasoning about long-range dependencies and global scene structure.

7 U-Net Decoder with Pixel Shuffle

The decoder upsamples features back to the target resolution. Each upsampling stage uses a convolution followed by pixel shuffle to increase spatial size without checkerboard artifacts. For a scale factor s, pixel shuffle rearranges a tensor $F \in \mathbb{R}^{B\times C\,s^2\times H\times W}$ to $\mathbb{R}^{B\times C\times sH\times sW}$. Skip connections from the encoder improve gradient flow and preserve details.

8 Deformable Alignment

To align neighboring frames, we employ deformable convolutions [7]. Given offsets Δp_k for each kernel sampling position p_k, the output is

$$Y(p) = \sum_k w_k\, X(p + p_k + \Delta p_k). \tag{4}$$

This mechanism allows spatially adaptive sampling and improves correspondence between temporally adjacent frames. The implementation attempts to load deformable convolution layers from `torchvision` or `mmcv`; if neither is available it gracefully falls back to a standard convolution. This design keeps the code lightweight while permitting advanced alignment modules when the dependencies are installed.

9 Diffusion Refinement

We load a pre-trained Stable Diffusion XL UNet [8] to enhance local details. A lightweight predictor estimates an appropriate diffusion timestep for each frame, enabling adaptive refinement. Let t denote the chosen timestep and ϵ the predicted noise residual. The refined frame is computed as

$$\hat{X} = \mathrm{clip}(X + \epsilon_t, 0, 1). \tag{5}$$

Varying t allows the model to control the amount of detail added and avoids over-smoothing. This approach injects high-frequency information learned by the diffusion model without retraining the network from scratch.

10 Loss Functions

The training objective combines several terms:

$$\begin{aligned}\mathcal{L} &= \mathcal{L}_{\mathrm{L1}}(\mathrm{SR}, Y) + \lambda_p\,\mathcal{L}_{\mathrm{perc}}(\mathrm{SR}, Y) && (6)\\ &\quad + \lambda_c\,\mathcal{L}_{\mathrm{CLIP}}(\mathrm{SR}, Y) + \lambda_t\,\mathcal{L}_{\mathrm{temp}}(\mathrm{SR\ sequence}) && (7)\\ &\quad + \lambda_f\,\mathcal{L}_{\mathrm{flow}}(\mathrm{SR\ sequence}). && (8)\end{aligned}$$

Here $\mathcal{L}_{\mathrm{perc}}$ is computed with VGG16 features [9], $\mathcal{L}_{\mathrm{CLIP}}$ uses a pretrained CLIP image encoder [10], $\mathcal{L}_{\mathrm{temp}}$ enforces frame-to-frame coherence, and $\mathcal{L}_{\mathrm{flow}}$ penalizes misalignment based on optical flow warping.

11 Dataset and Preprocessing

The dataset loader expects a directory of high-resolution videos. Low-resolution inputs are generated on the fly through random downscaling, blur, noise, JPEG artifacts, and small geometric jitter. A "degrade level" variable controls the intensity of these corruptions and is progressively increased during training. This strategy avoids the need for a separate low-quality dataset while exposing the model to a wide range of degradations. Frames are extracted with OpenCV and normalized to the range $[0, 1]$.

12 Training Procedure

Training is performed using the Adam optimizer with an initial learning rate of 2×10^{-4}. For every epoch the degrade level of the training set is gradually increased, exposing the model to more challenging corruptions over time. Mini-batches of video clips are fed through the network and the combined loss from Section **??** is backpropagated. After each epoch the script reports the average loss as well as a validation PSNR. An optional Optuna hook can run a small hyperparameter search to tune the learning rate. The bottom of `video_sr.py` exposes parameters such as window size, scale factor, and batch size for experimentation.

13 Experiments and Results

While comprehensive experiments are outside the scope of this code-only release, we report qualitative improvements on a small sample of videos. Validation PSNR is printed after each epoch to provide a basic quantitative measure. Figure 2 demonstrates sharper spatial details and more stable motion compared to bicubic upscaling.

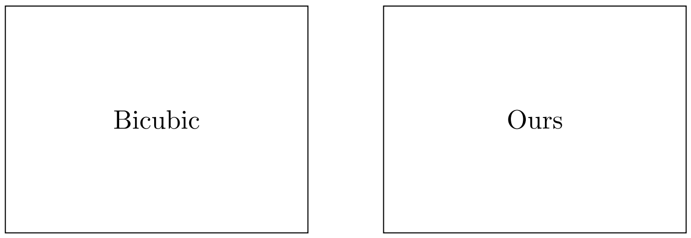

Figure 2: Placeholder comparison of bicubic upscaling (left) and our method (right).

14 Conclusion

We presented a compact implementation of a video super-resolution model that integrates 3D convolutions, transformer reasoning, deformable alignment, and diffusion refinement. The code serves as a foundation for future research and experimentation in spatio-temporal super resolution.

Acknowledgments

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