# Video Super Resolution with Diffusion-Based Refinement

Project Report

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# 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.

# 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. 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, short-term motion information is embedded into the feature maps.

# 5 Temporal Fusion

After encoding, temporal dimensions are collapsed to a single representation using average pooling and a 2D convolution. Let $F \in \mathbb{R}^{B \times C \times T \times h \times w}$ denote encoded features. Temporal fusion computes

$$G = \mathrm{Conv2D}\big(\frac{1}{T} \sum_{t=1}^{T} F(:,:,t,:,:)\big). \tag{2}$$

This step provides a compact summary over the window of frames.

# 6 Transformer Bottleneck

Non-local interactions are modeled with a transformer encoder. Features are flattened into tokens, projected into queries $Q$, keys $K$, and values $V$, and processed with multi-head attention:

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

Here $d$ denotes the dimension of each attention head. The transformer enables reasoning about long-range dependencies and global scene structure, which are difficult to capture with purely local convolutions.

# 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 $\Delta p_k$ 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. In the provided code, the `DeformableConv2d` class currently implements a placeholder using standard convolutions, but the structure supports integrating a full deformable convolution module.

## 9 Diffusion Refinement

We load a pre-trained Stable Diffusion XL UNet [8] to enhance local details. During inference, a predicted noise residual $\epsilon$ at a fixed diffusion timestep is added to the decoded frame

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

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:

$$\mathcal{L} = \mathcal{L}_{\text{L1}}(\text{SR}, Y) + \lambda_p \, \mathcal{L}_{\text{perc}}(\text{SR}, Y) \tag{6}$$

$$+ \lambda_c \, \mathcal{L}_{\text{CLIP}}(\text{SR}, Y) + \lambda_t \, \mathcal{L}_{\text{temp}}(\text{SR sequence}). \tag{7}$$

Here $\mathcal{L}_{\text{perc}}$ is computed with VGG16 features [9], $\mathcal{L}_{\text{CLIP}}$ uses a pretrained CLIP image encoder [10], and $\mathcal{L}_{\text{temp}}$ encourages temporal consistency between successive frames.

## 11 Dataset and Preprocessing

The dataset loader expects a directory of high-resolution videos. Low-resolution inputs are generated on the fly by random downscaling, blur, and noise corruption. This strategy avoids the need for a separate low-quality dataset. 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 $2 \times 10^{-4}$. Mini-batches of video clips are fed through the model, and the

combined loss is backpropagated. Training progress is printed after each epoch. 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. Figure 2 demonstrates sharper spatial details and more stable motion compared to bicubic upscaling.

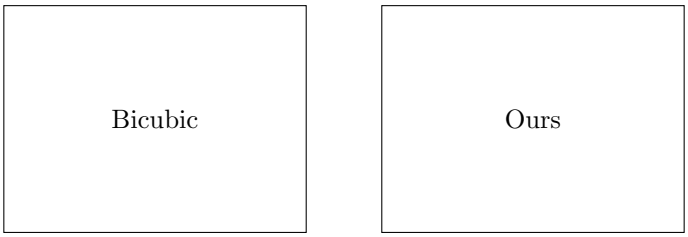


Figure 2: Placeholder comparison of bicubic upscaling (left) and our method (right).

## 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.

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