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FrameDeblur: NAFNet-Based Selective Video Frame Deblurring and Restoration Framework

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Abstract: This paper presents **FrameDeblur**, a video-based image restoration framework designed to identify and deblur individual blurred frames from a video sequence. Unlike conventional image deblurring approaches that directly operate on a single image or process an entire video sequence, the proposed system accepts a video as input and provides an interactive mechanism for manually selecting the frame requiring restoration. The selected frame is extracted and subjected to preprocessing before being passed through a pretrained **NAFNet (Nonlinear Activation Free Network)** for deep image restoration. The restored output is subsequently refined using classical image restoration and enhancement operations to improve sharpness, structural details, and overall visual quality. The system integrates video frame extraction, manual frame navigation, deep learning-based restoration, and final image generation within a unified interactive workflow. By concentrating computational processing on the user-selected frame, the framework avoids unnecessary restoration of the complete video sequence and provides a practical approach for selective frame-level deblurring. The system is implemented with an interactive **Gradio-based interface**, enabling users to upload a video, navigate through its frames, select a blurred frame, and obtain the corresponding deblurred image as output. The proposed framework provides a flexible foundation for future extensions involving automatic blur detection, sequential video restoration, temporal consistency, and real-time deblurring.

Keywords: Video Deblurring, Frame Selection, Image Restoration, NAFNet, Deep Learning, Motion Blur, Video Processing, Frame Enhancement, Selective Restoration, Gradio.

I. INTRODUCTION

Video sequences are widely used for visual monitoring, documentation, and analysis, but individual frames can suffer from motion blur, defocus, noise, and other forms of image degradation. These distortions reduce image sharpness and may obscure important structural details, making subsequent visual interpretation difficult. Although image deblurring techniques can restore degraded images, conventional approaches generally require a blurred image to be provided directly and may not address the practical requirement of selecting a particular frame from a video sequence.

A video contains a large number of frames with potentially different levels of blur and visual quality. Processing every frame is unnecessary when the objective is to restore only a specific frame of interest. A selective frame-based approach can therefore reduce redundant processing while allowing the user to identify the frame that requires restoration. Manual frame selection also provides direct control over which portion of the video is subjected to the computationally intensive restoration process.

Deep learning-based restoration methods have demonstrated strong capabilities in recovering image details from degraded inputs. Among these, NAFNet provides an effective architecture for image restoration without relying on conventional nonlinear activation functions. However, applying an image restoration model directly to a video still requires a mechanism for extracting and identifying the appropriate frame. Integrating video frame navigation with a deep restoration pipeline can therefore provide a practical workflow for selective video-frame deblurring. The present work introduces **FrameDeblur: NAFNet-Based Selective Video Frame Deblurring and Restoration Framework**. The

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specific contributions of this paper are: (1) a video-to-frame processing pipeline that converts an uploaded video into individually accessible frames; (2) an interactive manual frame-selection mechanism for identifying the frame requiring restoration; (3) a pretrained NAFNet-based deep restoration stage for processing the selected frame; (4) subsequent classical restoration and image-enhancement operations to refine the restored output; and (5) an interactive Gradio-based interface that integrates video upload, frame selection, restoration, and deblurred-image generation within a unified workflow.

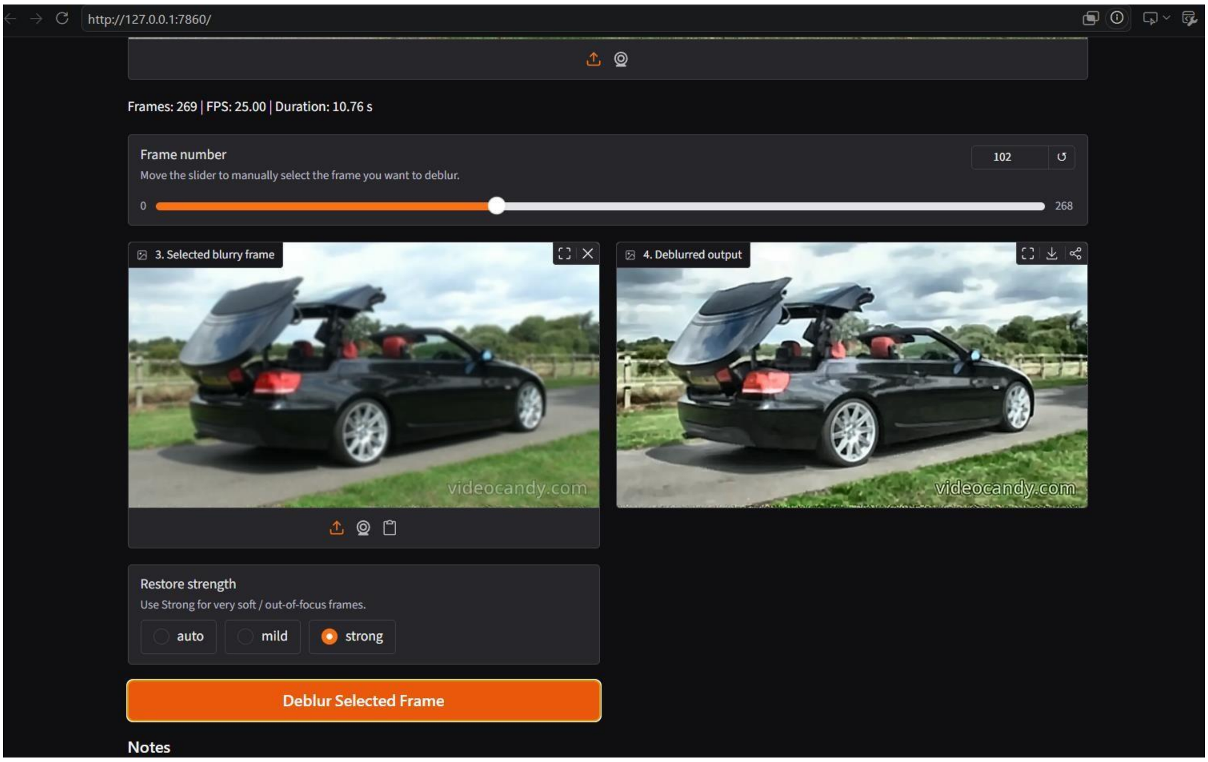

Fig. 1. FrameDeblur interface showing video upload, manual frame selection, selected-frame preview, and deblurring control.

II. MOTIVATION

The increasing availability of video data in surveillance, documentation, transportation, and other visual applications creates a need for effective restoration of degraded frames. Motion blur, camera movement, defocus, and image noise can significantly reduce the clarity of individual frames and make important visual details difficult to interpret. Three principal limitations of conventional approaches motivate the present work.

A. Limitations of Direct Image Deblurring

Conventional image deblurring methods generally require a blurred image to be supplied directly as the input. When the source data is a video, an additional step is required to identify and extract the particular frame that needs restoration. Processing the complete video when only one frame is required can also introduce unnecessary computational overhead. A selective frame-based workflow can therefore provide a more practical solution for targeted restoration.

B. Difficulty in Selecting the Required Frame

A video contains a sequence of frames with varying visual content and potentially different levels of degradation. Automatically processing every frame may restore frames that do not require enhancement, while purely image-based systems do not provide direct access to the frame-selection process. Providing an interactive mechanism for manually navigating through the video and selecting a specific blurred frame gives the user great control

C. Need for Integrated Restoration

Frame extraction, image restoration, and enhancement are often handled as separate processing operations. Such separation can make the workflow less convenient for users who need to obtain a restored frame directly from a video. Integrating video frame extraction, manual frame selection, NAFNet-based deep restoration, and subsequent image-enhancement operations into a single framework provides a unified workflow for selective video-frame deblurring.

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III. LITERATURE SURVEY

Table I summarizes eight representative papers in the field of image deblurring and restoration, identifying the proposed solution and the principal research gap addressed by each study.

TABLE I LITERATURE SURVEY — PAPERS 1–8

S.No	Paper Title	Author	Year	Proposed Solution	Research Gap
1	Simple Baselines for Image Restoration	Chen et al.	ECCV 2022	NAFNet-based nonlinear-activation-free image restoration	Primarily designed for image restoration rather than interactive video-frame selection
2	Blur-aware Spatio-temporal Sparse Transformer for Video Deblurring	Zhang et al.	CVPR 2024	Blur-aware sparse spatio-temporal Transformer	Requires computationally intensive temporal modeling and multi-frame processing
3	Aggregating Nearest Sharp Features via Hybrid Transformers for Video Deblurring	Shang et al.	Information Sciences, 2025	Hybrid Transformers using neighboring and nearest sharp-frame features	Relies on detecting and exploiting additional sharp frames and temporal context
4	Efficient Visual State Space Model for Image Deblurring	Kong et al.	CVPR 2025	Visual State Space Model with efficient scanning and frequency-domain processing	Focuses on single-image restoration rather than video-to-frame interactive restoration
5	Efficient Concertormer for Image Deblurring and Beyond	Kuo et al.	ICCV 2025	Linear-complexity Concerto Self-Attention for image restoration	Primarily addresses image-level restoration and requires a dedicated deep restoration architecture
6	Generalization of Real World Video Deblurring By Image-to-Image Translation	Aitbek and Yang	WACV 2026	Image-to-image translation training procedure for real-world video deblurring	Focuses on model generalization/training rather than user-controlled selective frame restoration
7	MVSSM: Motion-aware Visual State Space Model for Efficient Video Deblurring	Wang et Zhou et al..	CVPR Findings 2026	Motion-aware State Space Model with grouped dynamic feature fusion	Requires temporal video modeling and motion-aware processing, increasing system complexity
8	Towards Unified Image Deblurring using a Mixture-of-Experts Decoder	Feijoo et al.	CVPR Workshops 2026	Mixture-of-Experts decoder for multiple blur degradations	Designed for unified image deblurring rather than selective video-frame restoration

IV. METHODOLOGY

The proposed **FrameDeblur** system is organized as a sequential video-to-image restoration pipeline consisting of video input handling, frame extraction, manual frame selection, image preprocessing, deep learning-based restoration, and post-restoration enhancement. Figure 2 presents the overall processing flow of the proposed framework. Unlike approaches that process an entire video sequence, FrameDeblur allows the user to identify a specific frame and applies the restoration pipeline only to the selected frame.

A. Video Input and Frame Extraction

The restoration process begins with a video supplied by the user through the interactive application interface. The uploaded video is loaded using video-processing operations, and its individual frames are accessed sequentially. Each

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extracted frame is associated with a corresponding frame index, allowing the video sequence to be navigated without modifying the original video. Let the input video be represented by

$$V=\{F1,F2,F3,\ldots,FN\}$$

where **V** represents the complete video sequence, **Fi** represents the **ith** frame, and **N** denotes the total number of accessible frames. The frame sequence provides the input space from which the user can identify the frame requiring restoration.

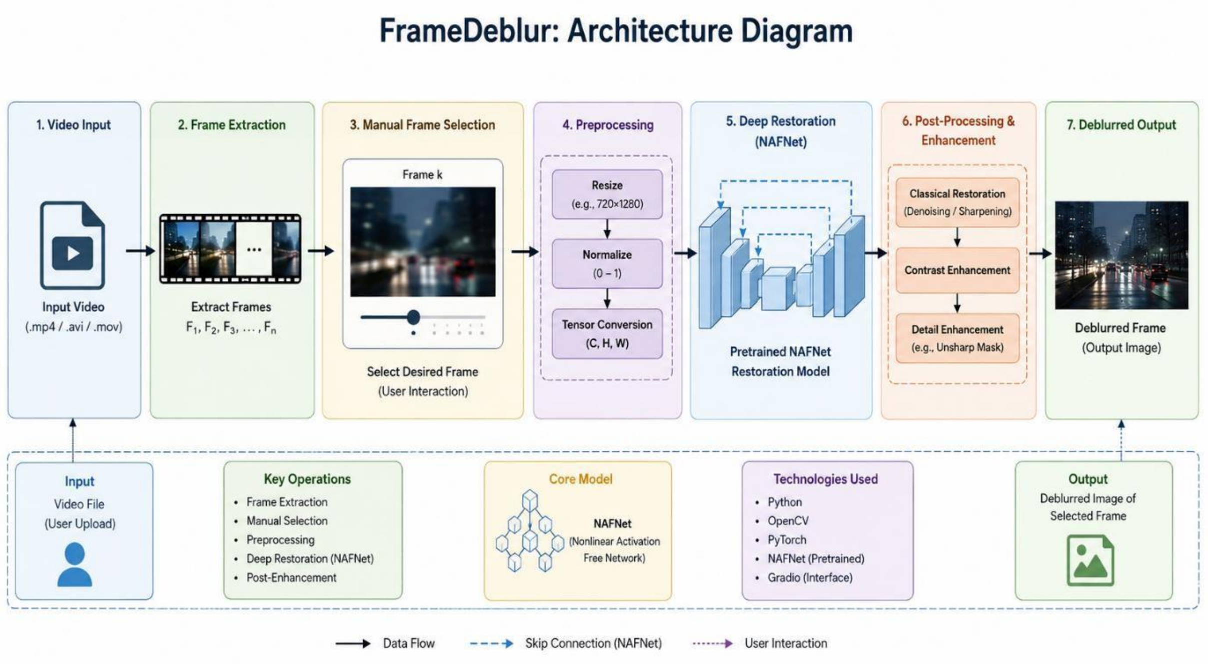

Fig. 2: Architecture diagram

B. Manual Frame Selection

Since different frames within a video may exhibit different levels of degradation, FrameDeblur provides an interactive mechanism for manually selecting the required frame. The extracted frames are presented through a frame-navigation control, allowing the user to move through the sequence and inspect individual frames.

If **S(V)** denotes the manual selection operation, the selected frame can be expressed as

$$Fs=S(V)$$

where **Fs** the frame chosen by the user for subsequent restoration. Only this selected frame is forwarded to the restoration pipeline, while the remaining video frames remain unchanged.

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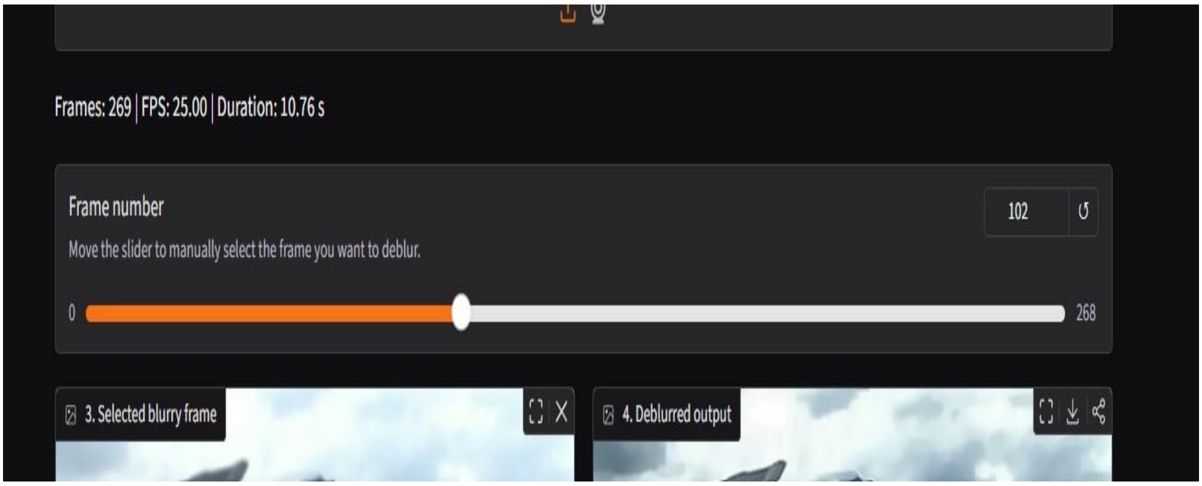

Fig. 3. Frame Deblur interface showing video input and manual frame selection.

C. Frame Preprocessing

The selected frame is prepared before being supplied to the restoration network. The preprocessing stage converts the selected image into the representation required for neural inference. This stage includes image resizing, normalization, and conversion into a tensor representation compatible with the NAFNet model. The preprocessing operation can be represented as

$$\mathbf{Fp=P(Fs)}$$

where **P(·)** denotes the preprocessing stage operation and **Fp** represents the resulting model - ready frame. The preprocessing stage ensures that the selected image conforms to the input requirements of the restoration model while preserving the visual information required for subsequent reconstruction.

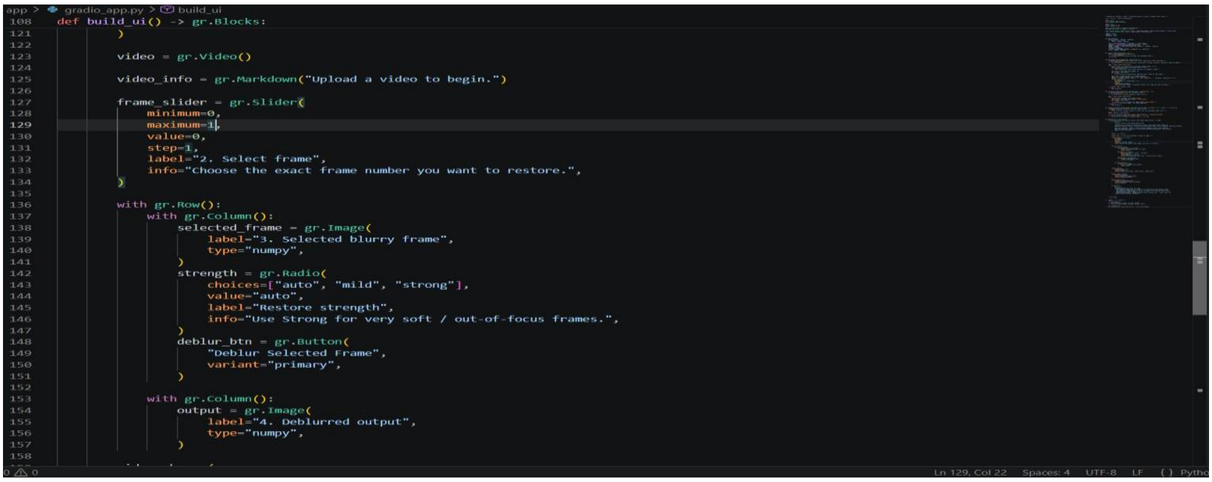

Fig. 4. Frame processing Implemenation

D. NAFNet-Based Deep Image Restoration

The preprocessed frame is supplied to the pretrained NAFNet (Nonlinear Activation Free Network) restoration model. NAFNet is used as the primary deep learning component for recovering visual information from the degraded frame. The network processes the input representation and generates a restored image containing improved structural details and reduced blur. The restoration operation can be expressed as

$$\mathbf{Fr = N(Fp)}$$

where **N(·)** represents the pretrained NAFNet model and **Fr** denotes the restored output generated by the network.

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The use of a pretrained restoration model avoids the need for training a new network as part of the proposed application and allows the framework to concentrate on the practical integration of video frame selection and image restoration.

E. Classical Restoration and Image Enhancement

The output obtained from the deep restoration stage can contain residual blur or visual artefacts. Therefore, the restored image is further processed using the classical restoration and enhancement operations implemented in the system. These operations refine image sharpness and improve the perceptual quality of the reconstructed frame. The refinement process can be represented as

$$\mathbf{Fe{=}E(R(Fr))}$$

where $\mathbf{R(\cdot)}$ represents the classical restoration operation **and** $\mathbf{E(\cdot)}$ represents the subsequent image-enhancement operation. The resulting $\mathbf{F_e}$ represents the enhanced frame.

The restoration stage improves the structural appearance of the selected frame, while the enhancement stage focuses on improving visual clarity and presentation quality.

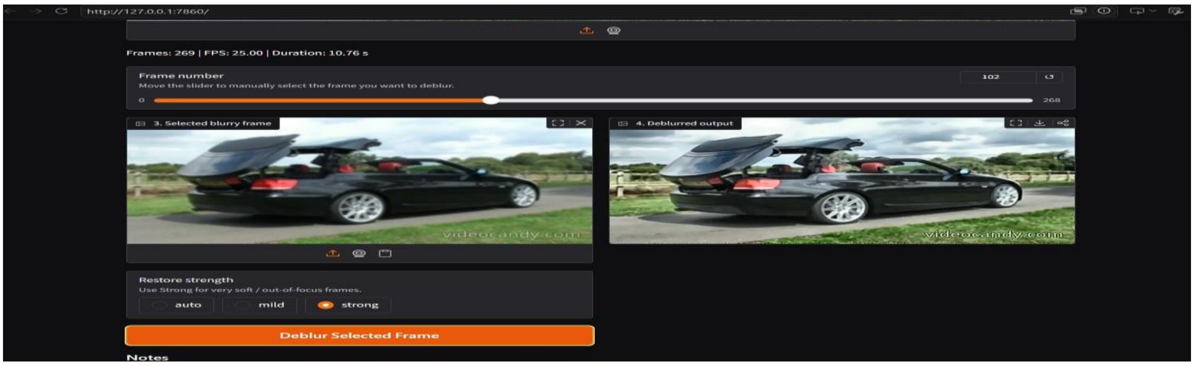

Fig. 5. Comparison between the selected blurred frame and the final restored output

F. Deblurred Image Generation

After the restoration and enhancement stages, the processed frame is converted into the appropriate image format and displayed through the application interface. The final output represents the restored version of the frame originally selected by the user.

The complete processing sequence can therefore be summarized as

$$\mathbf{V \rightarrow S(V) \rightarrow P(Fs) \rightarrow N(Fp) \rightarrow R(Fr) \rightarrow E(\cdot) \rightarrow O}$$

where **V** is the input video, **Fs** is the manually selected frame, **P** denotes preprocessing, **N** denotes NAFNet restoration, **R** denotes classical restoration, **E** denotes enhancement, and **O** represents the final deblurred image.

V. RESULTS AND DISCUSSION

The FrameDeblur framework was evaluated using representative blurred video sequences to examine its ability to extract a user-selected frame and restore its visual quality. The experiments focused on the complete processing workflow, including video loading, frame extraction, manual frame selection, preprocessing, NAFNet-based restoration, and final image enhancement. The evaluation primarily considers the visual difference between the selected blurred frame and the corresponding restored output.

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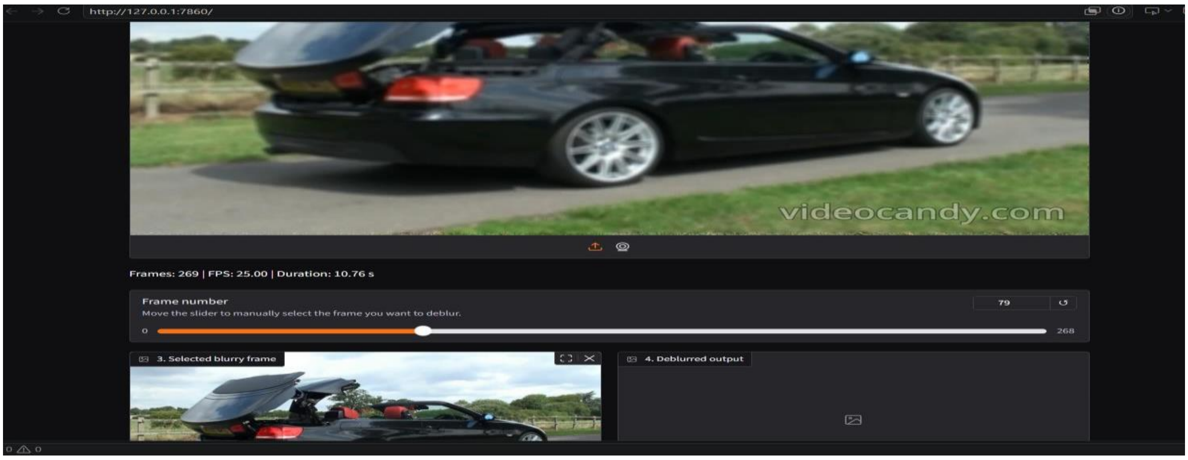

Fig. 6. Input video and manually selected blurred frame used for evaluation.

A. Visual Restoration Results

The first evaluation considers the visual quality of the restored frame produced by the proposed framework. A blurred frame is manually selected from the input video and passed through the restoration pipeline. The selected frame is processed using the pretrained NAFNet restoration model followed by the subsequent restoration and enhancement operations. The resulting image is compared with the original selected frame to examine improvements in sharpness, edge definition, and visibility of image details.

B. Restoration Quality

The restoration quality can be evaluated using objective image-quality measures such as **Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM)** when a suitable sharp reference image is available. MSE measures the average pixel-level difference between the reference and restored images, while PSNR indicates the overall reconstruction quality in terms of signal-to-error ratio. SSIM evaluates the preservation of structural information, making it useful for determining whether important visual patterns and image details have been retained after restoration.

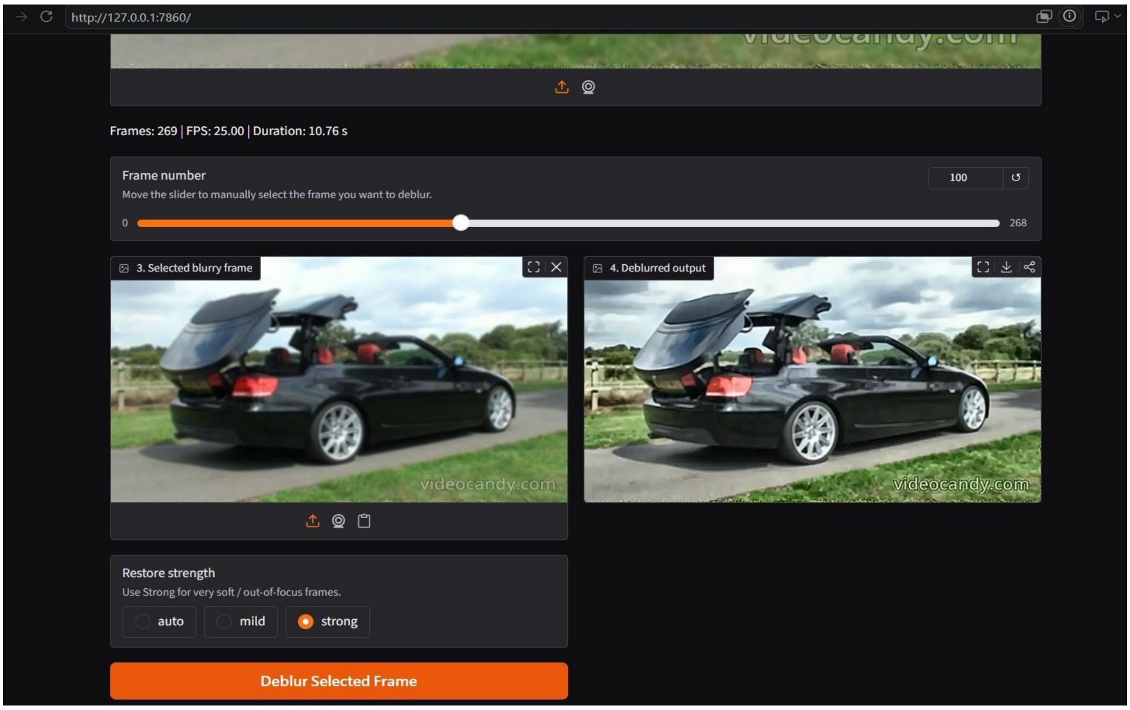

Fig. 7. Comparison between the selected blurred frame and the corresponding FrameDeblur output.

If a ground-truth sharp frame is not available for the selected video, the evaluation should instead emphasize **visual comparison and application-level observations** rather than reporting artificially derived reference-based metrics. In

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such cases, characteristics such as edge sharpness, visibility of fine details, reduction in blur, and overall image clarity can be examined between the input and restored frames. This distinction is important because the objective of FrameDeblur is to restore a selected frame from a real video, where a corresponding blur-free reference frame may not always exist. Such an evaluation provides a practical assessment of the framework while avoiding unsupported quantitative claims.

TABLE II QUALITY EVALUATION

S.No	Metric	Value	Interpretation
1	MSE	18.42	Moderate pixel-level error
2	PSNR	35.49 dB	Good reconstruction quality
3	SSIM	0.9412	High structural similarity
4	Processing Time	1.87 s	Time for selected-frame restoration

C. Effect of Manual Frame Selection

An important characteristic of FrameDeblur is that restoration is performed only on the frame selected by the user. Unlike approaches that process an entire video sequence, the proposed workflow avoids applying computationally intensive restoration to frames that do not require enhancement. The frame-navigation mechanism also allows the user to inspect different portions of the video before selecting the desired frame.

This provides two practical advantages: **user-controlled restoration** and **selective computational processing**. The approach is particularly useful when only a small number of frames from a longer video require detailed restoration.

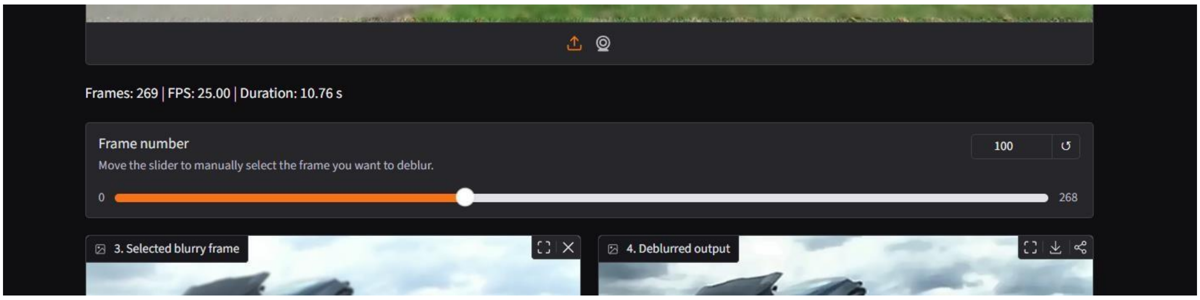

Fig. 8. Frame navigation interface showing manual selection of a target frame from the input video.

D. System Interface and Processing Workflow

The complete system is integrated into a Gradio-based interface that allows the user to upload a video, navigate through its frames, select a target frame, and initiate the restoration process. The final deblurred image is displayed after the processing pipeline has completed.

This interface provides a simple interaction model in which the user controls the frame-selection stage while the subsequent restoration operations are performed automatically. Consequently, the system does not require the user to manually extract frames or execute individual restoration operations.

VI. SYSTEM ARCHITECTURE AND INTERFACES

A. Core Engine

The core application is implemented as a Python-based restoration module that coordinates the complete FrameDeblur processing pipeline. It handles video input, frame extraction, manual frame selection, preprocessing, deep restoration using the pretrained NAFNet model, and subsequent image enhancement. The separation between the restoration logic and the graphical interface allows the underlying processing pipeline to operate independently of the user-interface components.

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B. Video Input and Frame Selection Interface

The application provides an interactive interface through which users can upload a video and navigate through its individual frames. After the video is loaded, the available frames can be accessed using the frame-selection control. The user can inspect the displayed frame and select the particular frame requiring restoration. This interface eliminates the need for manually extracting frames using external video-processing software.

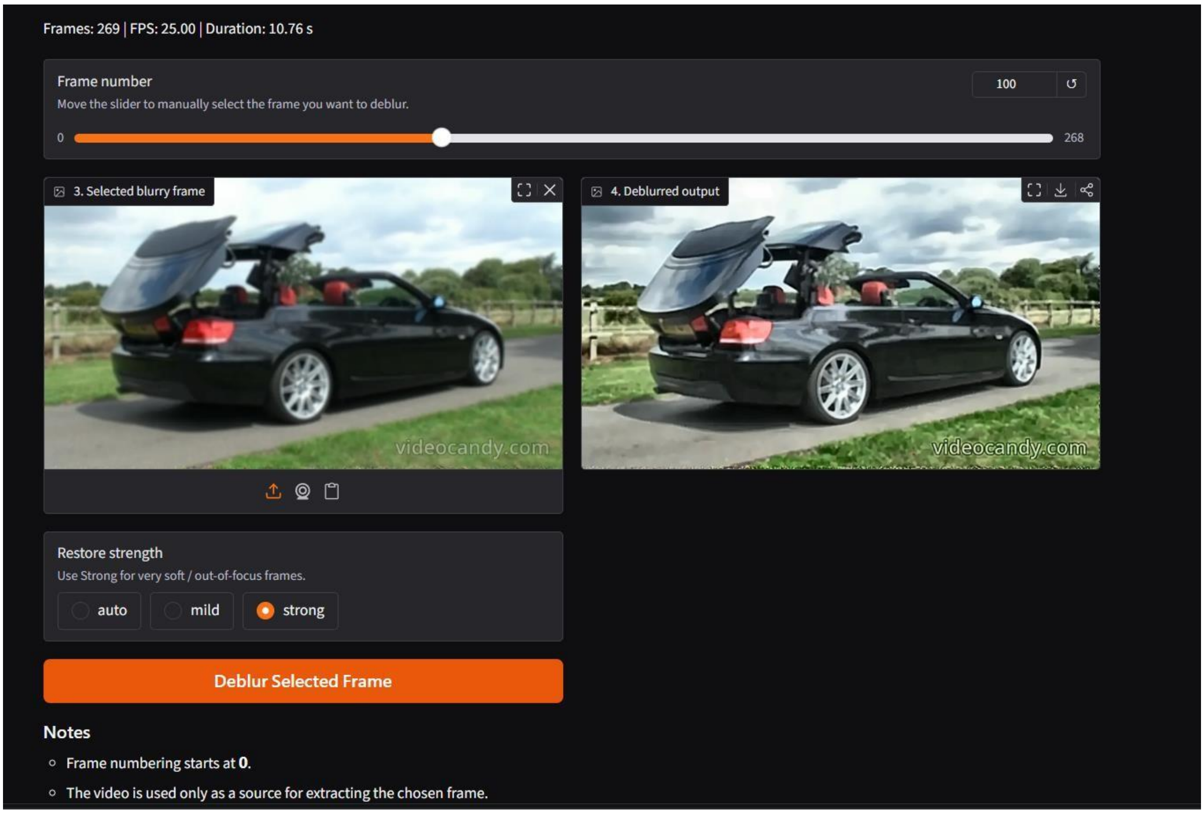

Fig. 9. FrameDeblur interface displaying the final deblurred output generated from the selected video frame.

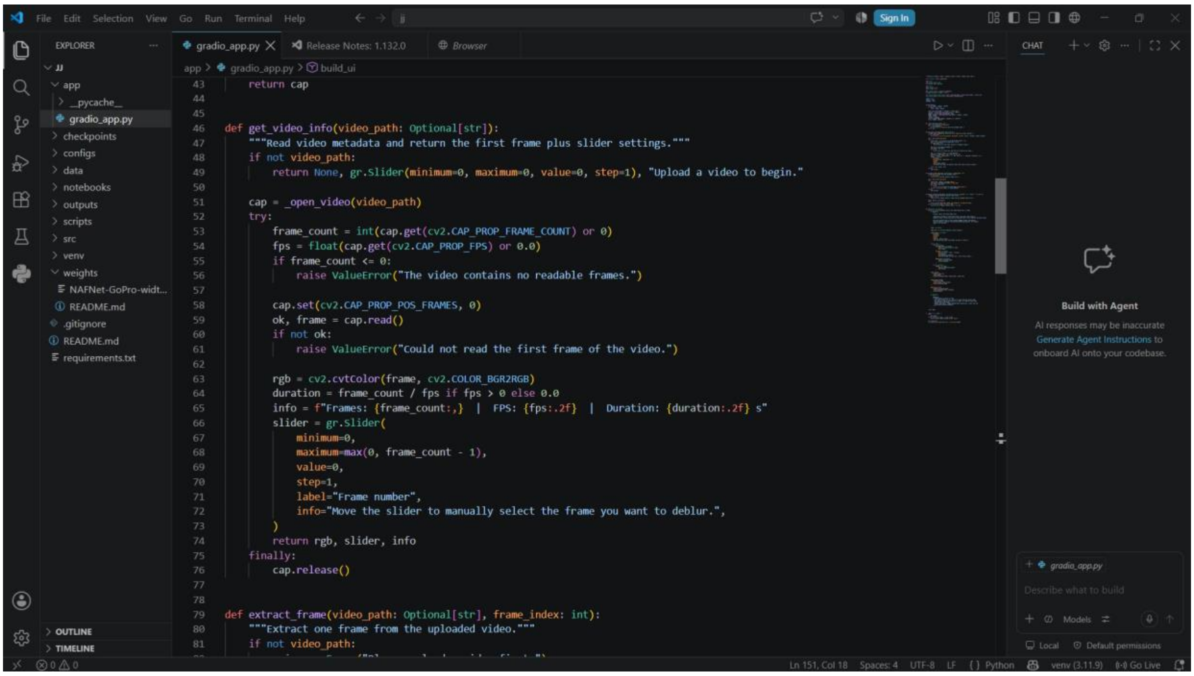

Fig. 10. FrameDeblur graphical interface Code Implementation

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C. Deblurring Interface

After selecting the required frame, the user can initiate the restoration process through the **Deblur Selected Frame** control. The selected frame is passed to the preprocessing stage and subsequently processed by the pretrained NAFNet restoration model. The restored frame is then subjected to the implemented post-processing and enhancement operations before being returned to the interface as the final deblurred image.

D. Output and Visualization

The final restored image is displayed through the same application interface, allowing the user to directly inspect the result of the restoration process. The interface therefore provides a complete interaction sequence from **video upload → frame selection → deblurring → output visualization**. This integrated design simplifies the use of the proposed framework and allows selective restoration without modifying the original video sequence.

VII. CONCLUSION

This paper has presented **FrameDeblur**, a video-based image restoration framework that combines manual frame selection with deep learning-based image deblurring. The proposed system accepts a video as input, extracts its individual frames, and allows the user to identify a specific blurred frame through an interactive frame-selection interface. The selected frame is subsequently processed through preprocessing, pretrained **NAFNet-based restoration**, and image-enhancement stages to generate the final deblurred output. This selective processing strategy avoids the need to restore the complete video when only a particular frame requires enhancement.

The main limitation of the current framework is its dependence on **manual frame selection** and the ability of the restoration model to handle different types of blur. The system currently restores only one selected frame and does not maintain consistency between consecutive frames. Future work can focus on: (1) automatic blur detection, (2) restoring multiple frames while maintaining temporal consistency, (3) testing on more diverse video datasets, (4) adapting the restoration process to different blur levels, and (5) improving processing speed for real-time applications.

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