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A GAN-Powered Web Framework for Multi-Domain Artistic Style Transfer

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Abstract: *This project aims to develop a comprehensive Art Style Transfer System utilizing Generative Adversarial Networks(GANs)to enhance artistic expression across multiple media, including static images, videos, and live camera feeds. By merging the content of one image with the stylistic elements of another, this system seeks to generate visually compelling outputs that maintain the integrity of the original content while embodying the characteristics of selected artworks. The proposed solution employs a multi-faceted approach: using CycleGANs for image style transfer, Temporal Coherence (Teco)GANs for video style transfer, and Fast Style Transfer techniques for real-time applications with live camera action. The generator in each model synthesizes stylized outputs, while the discriminator assesses the authenticity of these outputs, ensuring high fidelity in the final results. Training the models on a diverse dataset of artworks paired with corresponding content images allows for the refinement of the style transfer process across different media types. To facilitate user interaction, the project features a web-based application developed using Flask, enabling users to upload source images and videos while selecting desired artwork styles. For live camera integration, the application leverages efficient algorithms to deliver immediate stylistic transformations in real time. The backend, built with TensorFlow and Keras, manages the training and inference processes of the various models. This project demonstrates the versatility and effectiveness of GANs and associated techniques in achieving high-quality art style transfer across multiple platforms, providing a novel tool for artists, designers, and enthusiasts to explore their creativity while showcasing the intersection of technology and art..*

Keywords: Art Style Transfer, GANs, CycleGAN, Temporal CoherenceGAN, Fast Style Transfer, Real-Time Video, Live Camera Feed, TensorFlow, Keras, Flask, Neural Style Transfer, Artistic Expression, Deep Learning

I. INTRODUCTION

Art has always been a reflection of human creativity, emotion, and culture. As technology continues to evolve, the boundaries of artistic expression are being pushed further, enabling new forms of digital creativity. One such advancement is artistic style transfer, a process that uses deep learning to reimagine ordinary contentsuch as photos or videosin the visual style of famous artworks or artistic genres. With just a single algorithm, a photograph can be transformed to resemble different famous painting styles, creating a unique fusion of content and style.

In this project, we explore and implement a multi-domain artistic style transfer system that leverages three powerful GAN-based models, each tailored for a specific media type:CycleGAN is used for image style transfer, allowing transformations between two image domains without requiring paired data. This makes it ideal for scenarios where direct content-style matches are not available.

TecoGAN is employed for video style transfer, ensuring that stylistic changes remain consistent across frames and avoiding the flickering effects common in frame-by-frame approaches.

Fast Neural StyleTransfer is integrated for real-time stylization of live camera feeds, making it suitable for interactive and latency-sensitive applications such as virtual art installations or creative video conferencing.

To make this technology accessible beyond academic research and into the hands of everyday users, we have developed a web-based application that brings together all three of these models into a single user-friendly platform. Users can upload an image, choose a style, and download the transformed resultor apply the same to videos or even stream their camera feed in real time, experiencing live stylization in action.

This research project aims to bridge the gap between state-of-the-art AI models and real-world usability. By providing an intuitive interface, efficient backend processing, and support for multiple media types, our system caters to a wide audience, from artists, designers, and educators to hobbyists and general users with no technical background.

Moreover, the growing demand for creative AI tools in the entertainment, marketing, and education sectors highlights the relevance of such applications. Our work not only contributes technically by integrating and optimizing multiple GAN-based models, but also addresses user accessibility, deployment challenges, and real-time responsiveness.

II. LITERATURE SUREY

Neural style transfer has become a prominent technique in the field of computer vision, enabling the transformation of content images by imitating the artistic style of another image. This section categorizes existing work based on the methods used, ranging from classical CNN-based approaches to recent advancements in GAN-based real-time and AR applications.

Gatys, Ecker, and Bethge (2016) introduced a pioneering approach using convolutional neural networks (CNNs) to separate and recombine content and style features from images. Their method leverages the deep representations in pre-trained CNNs to preserve the content of a source image while transferring the style of another. This work laid the groundwork for numerous follow-up studies and has had a significant impact on digital art and computer vision research [1].To enable style transfer without requiring paired datasets, Huang and Belongie (2017) proposed CycleGAN, which uses cycle-consistency loss to achieve unpaired image translation. This innovation has greatly expanded the applicability of style transfer in domains where collecting paired training data is difficult [2].Zhu et al. (2017) extended this approach by introducing improved adversarial training techniques, allowing for more stable and high-fidelity transformations across multiple domains [3].Choi and Kim (2021) integrated attention mechanisms into GAN-based models to improve the quality of stylization by focusing on key features of the content and style images. This allows better preservation of intricate details, making the approach suitable for high-fidelity design tasks [4].In related work, Park et al. (2021) introduced Style-AttnGAN, which dynamically assigns attention weights to stylistic components, enhancing multi-domain adaptability and generating visually coherent results [5].Video style transfer poses additional challenges due to the need for temporal coherence between frames. Zhang and Xie (2022) proposed a GAN-based method that maintains consistent style application across video sequences, making it applicable to animation and film production [6].Ruder et al. (2018) addressed this by using optical flow constraints in conjunction with CNN-based stylization to preserve motion consistency, avoiding flickering and abrupt transitions [7].Wu, Chen, and Wang (2023) introduced a lightweight model optimized for real-time style transfer in live video. Their approach achieves a balance between speed and stylization quality, targeting use cases like interactive installations and mobile experiences [8].Johnson et al. (2016) also proposed a fast feed-forward style transfer model using perceptual loss, which can generate high-quality stylized images in real time, making it suitable for deployment on low-latency systems [9].Kim and Lee (2023) developed a multi-style transfer framework utilizing ensemble learning, allowing the simultaneous blending of multiple artistic styles in a single output. This supports user creativity by enabling dynamic and diverse results [10].Li et al. (2023) proposed Interactive StyleGAN, which allows users to control stylization parameters in real time. This empowers users with fine-grained control over the final artistic output, enhancing creative workflows [11].Zhao, Zhang, and He (2024) explored the integration of style transfer into augmented reality (AR) systems. Their work focuses on applying artistic styles to real-world environments via mobile AR devices, enabling immersive and interactive experiences in environments like museums and galleries [12].

III. SYSTEM ARCHITECTURE

The proposed system is designed as a modular, web-based platform capable of performing artistic style transfer on three types of media: static images, pre-recorded videos, and live camera feeds. The architecture is composed of four primary

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layers: the Client Layer, the Application Layer, the Processing Layer, and the Data Layer. Each layer performs a dedicated set of tasks that contribute to the overall workflow of the system, from user interaction to neural processing and data management.

A. Client Layer

The Client Layer serves as the point of interaction between the user and the system. It consists of a web-based application accessible through any modern browser. Users can upload content (images or videos), select a preferred artistic style from available options, and view or download the stylized results. Additionally, users can activate their device's webcam for real-time style transfer using the live camera mode. The goal of this layer is to offer an intuitive and responsive user experience.

B. Application Layer

This layer acts as the communication bridge between the user interface and the underlying machine learning models. It contains two main components:

- **Frontend:** Developed using HTML, CSS, and JavaScript, the frontend presents the user interface elementssuch as file upload buttons, style selection menus, and result display areas. It ensures that users can easily interact with the application regardless of the device or screen size.
- **Backend:** Built with Flask (or Django), the backend manages the core application logic. It receives input from the frontend, validates the media, and sends it to the appropriate style transfer model. It also handles routing of different tasks (image, video, or live stream processing) and returns the results to the frontend.

C. Processing Layer

The Processing Layer is the heart of the system, where all style transformation tasks are performed. This layer uses three different deep learning models, each tailored for a specific type of input:

- **CycleGANfor Image StyleTransfer:**When a user uploads a static image, the system routes it to a CycleGAN model. CycleGAN is well-suited for image-to-image translation tasks without requiring paired training data. It learns how to map content images to stylized outputs by training on two separate image domains. This allows it to produce high-quality artistic transformations.
- **TecoGAN for Video Style Transfer:**For video inputs, the system uses TecoGAN, a model designed to handle temporal consistency across frames. One of the common issues in video stylization is flickering due to frame-by-frame variation. TecoGAN addresses this by using optical flow and temporal losses to ensure that consecutive frames are styled consistently, resulting in smooth and coherent video outputs.
- **Fast Neural Network for Live Camera Feed:**When the live camera mode is activated, a lightweight, fast style transfer network is used. This model is optimized for real-time performance and low latency. It allows users to see the stylized transformation of their camera feed instantly, making it ideal for demonstrations or interactive art applications.

D. Data Layer

The Data Layer handles the storage and management of user content and system outputs. It consists of:

- **File Storage:** Uploaded images, videos, and stylized results are temporarily saved to local or cloud storage to enable quick access and retrieval.
- **Database:** A structured database stores user profiles and metadata related to the uploaded and generated content. This includes information such as upload timestamps, selected styles, and file references. The database also supports future features like user history, favourites, and content management.

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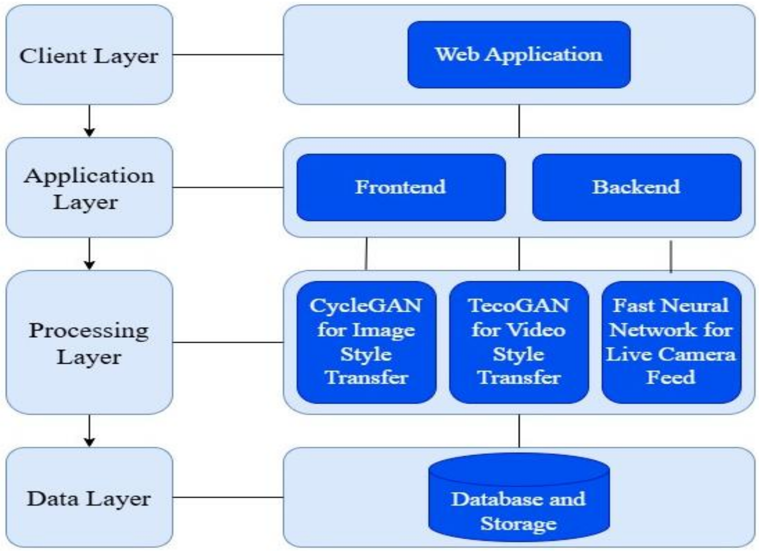

Fig.1 General architecture of the system with different layers

This layered architecture enables the system to support multiple input types, maintain high performance, and provide a smooth user experience across devices. It also ensures that new models or features can be integrated with minimal changes to the existing setup.

IV. SYSTEM WORKFLOW

This flowchart illustrates the complete workflow of the proposed style transfer system. It begins with user input selection and guides the data through appropriate model pipelines (CycleGAN, TecoGAN, or Fast Neural Network), performing necessary preprocessing, style application, and output generation.

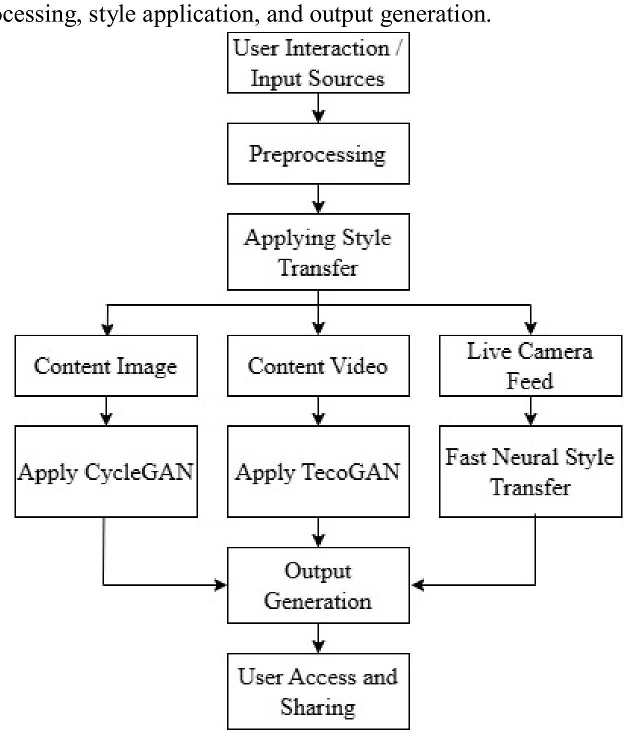

Fig. 2Work Flow of the System

Figure 2 presents the workflow diagram of the proposed artistic style transfer system, capturing the entire end-to-end process from user input to output generation.

The system begins with the user selecting the type of input—image, video, or live camera feed. Based on this choice, the input is either uploaded or captured in real time. The user then selects the desired artistic style, which serves as a condition or reference for the model.

The system uses an internal routing mechanism to forward the input to the appropriate deep learning model:

CycleGAN is used for image input, focusing on unpaired image-to-image translation.

TecoGAN is employed for video input, ensuring smooth temporal transitions across frames.

Fast Neural Style Transfer is used for live input, optimized for speed and real-time processing.

Before inference, the input undergoes a preprocessing step, such as resizing, normalization, or frame extraction, to ensure compatibility with the model's input requirements. The selected model then performs inference, applying the chosen style to the content.

After inference, the result passes through a postprocessing stage, where outputs are formatted correctly for display or download. For video inputs, frames are recombined into a single video. For live feeds, the output is displayed in real time.

Finally, the stylized result is presented to the user through the web interface, and the session ends or restarts based on the user's interaction.

V. METHODOLOGY

This section details the design, model selection, training, and implementation steps taken to develop an artistic style transfer system using deep learning. The methodology highlights the use of Generative Adversarial Networks (GANs) and their key components—Generator and Discriminator—to create high-quality, stylized outputs from images, videos, and live camera feeds.

A. Overview of GAN Framework

At the core of this system are Generative Adversarial Networks (GANs), a class of machine learning frameworks where two neural networks, a Generator (G) and a Discriminator (D), compete against each other.

- **Generator (G):** Takes input data (such as a content image) and attempts to create an output (stylized image) that is indistinguishable from real, styled artwork.
- **Discriminator (D):** Evaluates both real style images and those generated by the Generator, and learns to distinguish between authentic and generated outputs.

During training, the Generator learns to “fool” the Discriminator by generating more realistic stylized content, while the Discriminator improves at detecting fakes. This adversarial process results in high-quality, visually realistic outputs.

B. Input Handling and Style Selection

Users interact with the system through a web interface where they can choose the type of input—image, video, or live feed—and select from a list of predefined artistic styles. These styles are trained on well-known artworks and can range from classic painters like Van Gogh to sketch and cartoon-like styles. Once a style and input are selected, the data is passed to the backend for processing. The backend identifies the input type and routes it to the corresponding GAN model. Images are resized and normalized; videos are broken down into frames at a consistent frame rate (typically 24 FPS); and for live feeds, frames are continuously captured from the webcam using OpenCV and sent to the model in real time.

C. Model Architecture and GAN Components

All three style transfer models used in this system follow the GAN architecture, though they are tailored for different types of data. Each model is built around a Generator that produces the stylized output, and a Discriminator that evaluates the realism of the output during training.

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In the CycleGAN model for image stylization, there are two Generators and two Discriminators. One Generator converts content images into a styled version (X → Y), while the second performs the reverse (Y → X). Corresponding Discriminators evaluate whether an image is a real style sample or a generated one. The model is trained using both adversarial loss to ensure realism, and cycle-consistency loss to preserve content structure. The Generator uses residual blocks and transposed convolutions to reconstruct high-quality stylized images.

In the TecoGAN model for video stylization, the architecture is extended to handle sequences of frames. The Generator not only stylizes individual frames but also uses motion information from previous frames, captured using optical flow, to maintain temporal consistency. TecoGAN incorporates a temporal Discriminator that evaluates the smoothness between frame transitions. A special Ping-Pong loss is used to enforce coherence by training the Generator on forward and backward frame sequences. This helps reduce flickering and ensures that moving objects remain visually consistent throughout the video.

For real-time applications, the system uses a Fast Neural Style Transfer Network, which is a lightweight CNN trained using adversarial learning principles. During training, a Discriminator guides the Generator to produce stylized outputs that look like real art. The model is optimized using a combination of perceptual loss (to preserve semantic content), style loss (to match the visual texture of the target style), and adversarial loss (to encourage realistic outputs). Once training is complete, the Discriminator is discarded, and the Generator alone is used during inference, enabling fast performance suitable for live camera feed processing.

D. Model Deployment and Integration

All models are implemented using PyTorch and integrated into a modular backend built with Flask. The backend exposes API endpoints that accept user inputs and return stylized outputs.

The frontend is developed using HTML, CSS, and JavaScript, and allows users to upload files, select styles, and view the results. For video and camera inputs, OpenCV is used to manage frame capture and conversion.

The backend is responsible for input validation, preprocessing, routing to the appropriate model, and sending back the stylized result to the frontend for display or download.

E. System Requirements and Tools Used

Hardware Requirements

- Processor: Intel i5 or higher (i7 recommended for better performance)
- RAM: Minimum 8GB (16GB preferred for smooth processing)
- GPU: NVIDIA GTX 1060 or higher, with 4GB VRAM and CUDA support
- Storage: At least 50GB free space (SSD recommended)
- Camera: 720p or 1080p webcam for live input

Software Requirements

- Operating System: Windows 10/11, Ubuntu 18.04+, or macOS
- Programming Language: Python 3.8+
- Deep Learning Frameworks: PyTorch or TensorFlow 2.0+ (for GANs)
- Backend Framework: Flask or Django (for web application backend)

Libraries:

- OpenCV – for video and image processing
- NumPy – for numerical computations
- Pillow – for image handling
- FFmpeg – for video encoding/decoding
- GPU Acceleration**:** CUDA 11.0+ with cuDNN support

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VI. RESULTS AND DISCUSSIONS

A. Results

This section presents the outcomes of the proposed artistic style transfer system across three domains: static images, videos, and live camera feeds. To effectively illustrate the outcomes of our style transfer models, we present a selection of stylized images within the Results section. These visuals include side-by-side comparisons of the original content, the reference style, and the final stylized output.Each image is accompanied by a descriptive caption to clarify the transformation and highlight the effectiveness of the applied model.

Style Image **Content Image** **Stylized Output**

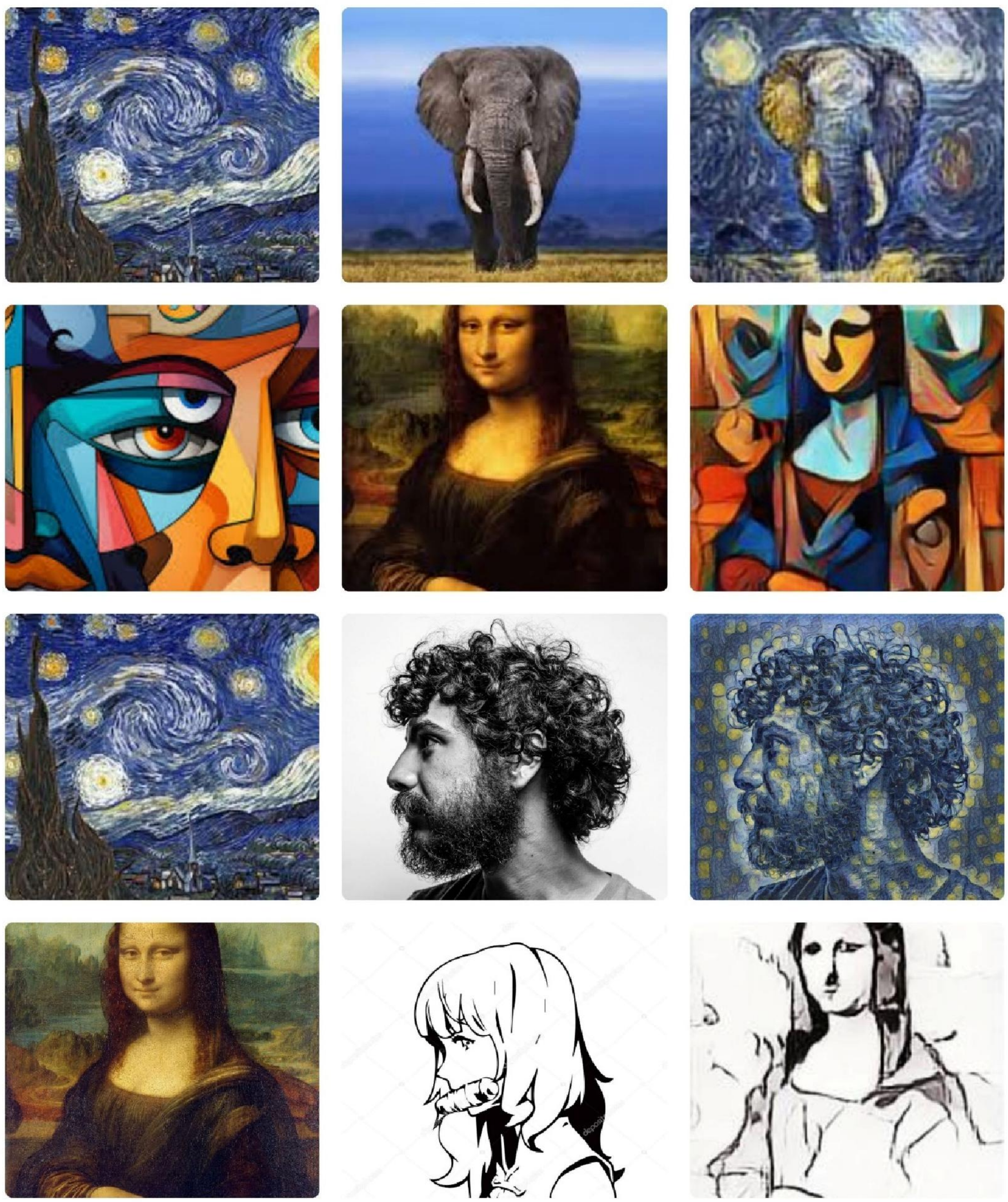

Fig. 3 Image Style Transfer

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Image Style Transfer:
In the case of image-based style transfer using CycleGAN, the output is shown in the figure. 3 clearly demonstrates a strong preservation of the original image's structure while successfully adopting the artistic elements of the style image. Important content features such as shapes and outlines are retained, but the overall colour scheme, brushstroke patterns, and textural effects from the style image are clearly imposed. The model proves effective for static artistic transformations and produces outputs that are visually comparable to manually painted artworks.

Image Style Transfer:
For video stylization, which is shown in the figure. 4 TecoGAN was used to ensure not just high-quality frame-wise transformation, but also consistency across consecutive frames. This helped in avoiding temporal artifacts such as flickering, which often occurs in naive video style transfer approaches. The resulting videos maintain the artistic style steadily over time, preserving smooth motion while still applying vibrant artistic textures. However, the processing time was significantly higher, with a short 7–8 second video taking around 15 minutes to process, pointing toward the need for faster computation methods.

Live Camera Feed Style Transfer:
For real-time camera feeds, Fast Neural Style Transfer was applied. Although labeled as "fast," real-world testing revealed some delays due to the heavy computation required for each incoming frame. Still, the live stylized output effectively showcased the selected artistic style in real-time scenes captured by the webcam. Content details remained recognizable, and the style effects were applied smoothly over the live feed.

Web-Based Demonstration of Style Transfer:
The demonstration of the website is included with the results and output of the live camera feed style transfer, which is shown in Figures 5 and 6below.

To better illustrate the effectiveness of the proposed system, sample outputs from the style transfer models are presented. The following figure showcases the original content image, the style reference image, and the resulting stylized output.

Content Video **Stylized Output 1** **Stylized Output 2**

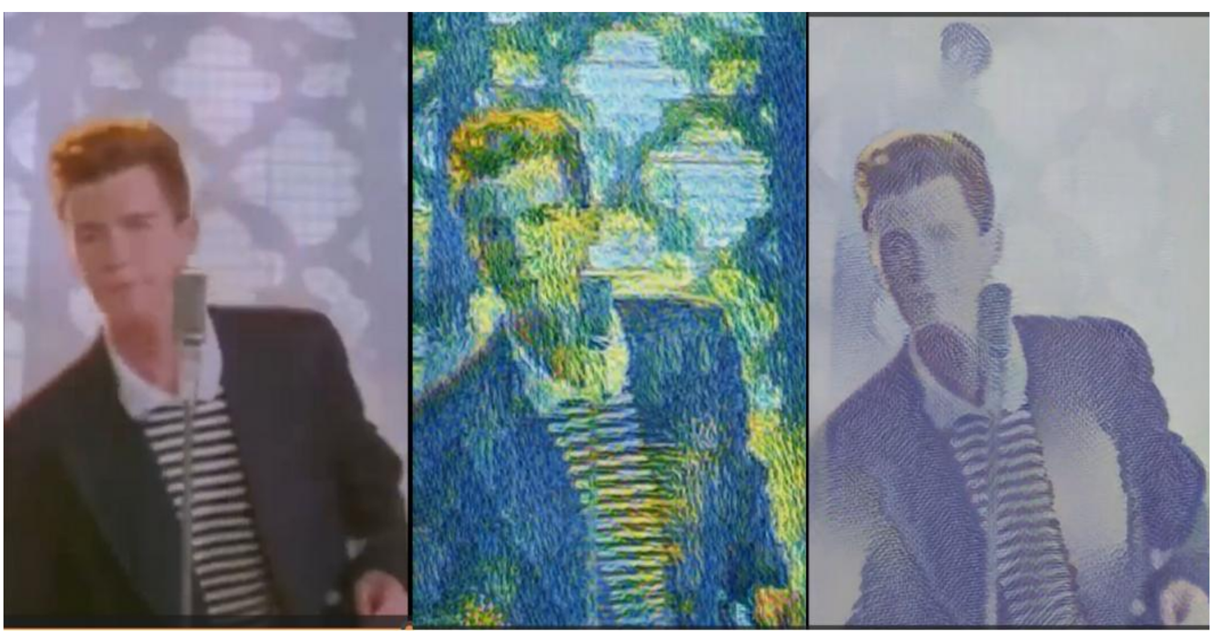

Fig. 4 Video Style Transfer

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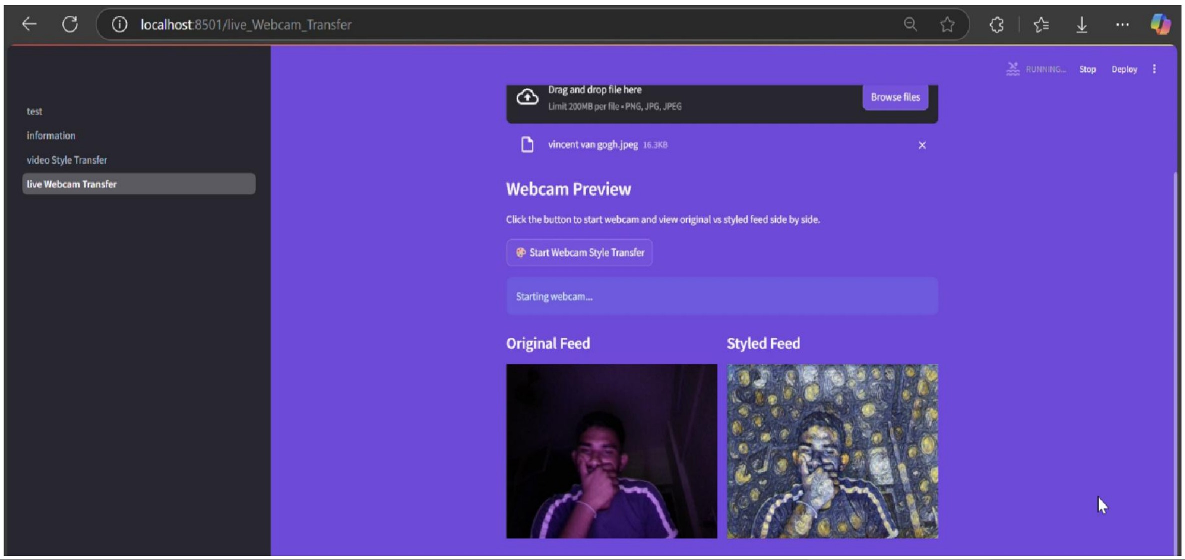
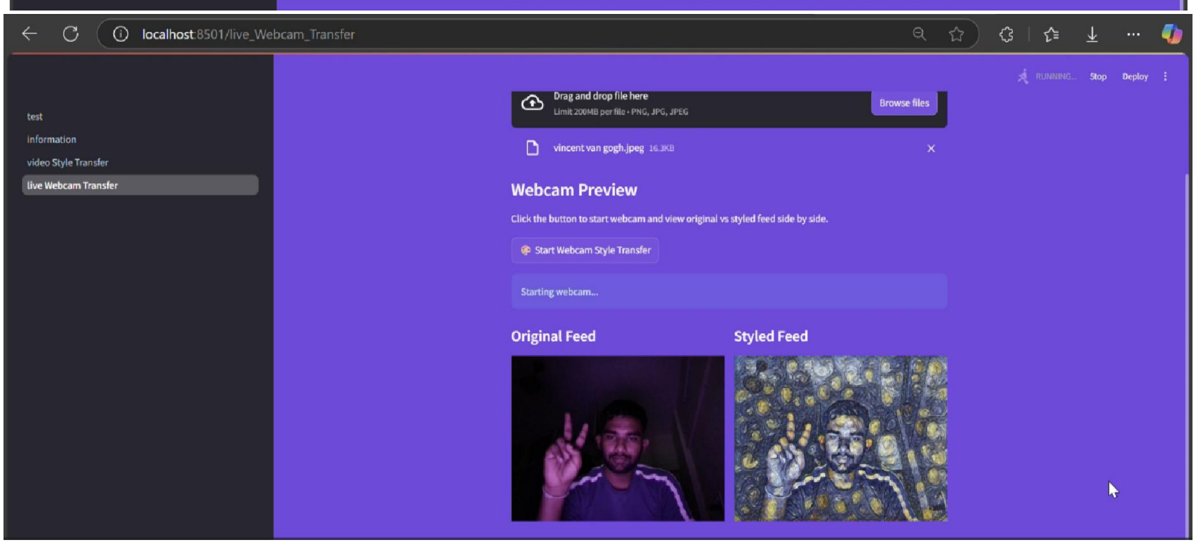
The website captures live input from the user's webcam and applies Fast Neural Style Transfer to generate a stylized video output. The processed output is displayed alongside the original feed within the website, allowing users to easily observe the transformation in real time.Despite the heavy computational requirements, the web application successfully demonstrates the feasibility of integrating live style transfer into a browser-based environment. Minor delays were observed between the captured frame and the stylized output, which is expected due to the frame-by-frame processing approach. Nonetheless, the system provides an interactive and visually engaging experience, enabling users to apply various artistic styles on live video streams without requiring specialized software or installations.This web-based approach also highlights the potential of deploying deep learning models on accessible platforms, opening doors for broader adoption in educational tools, virtual exhibitions, and creative online experiences.





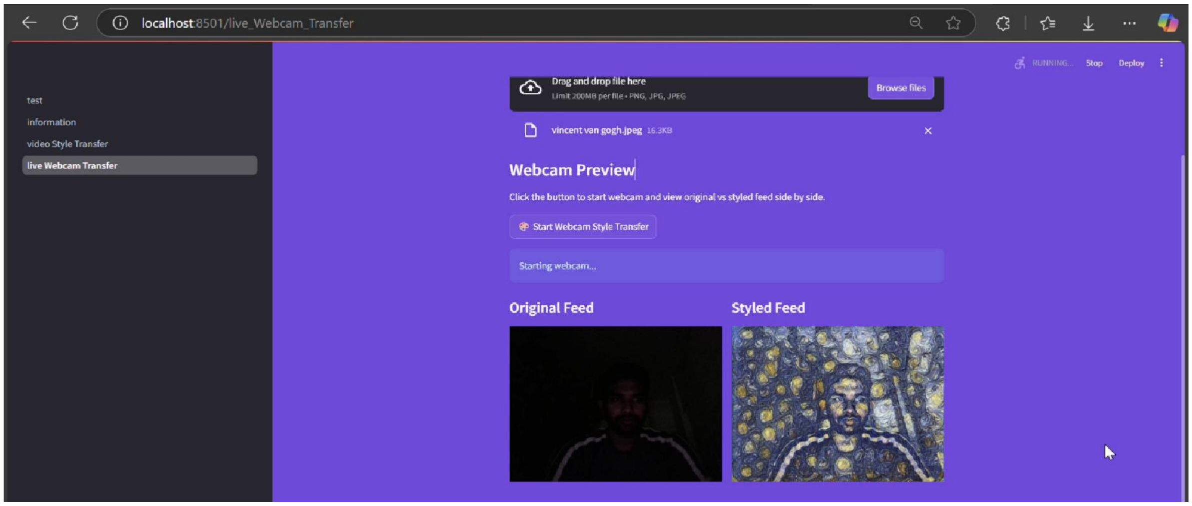
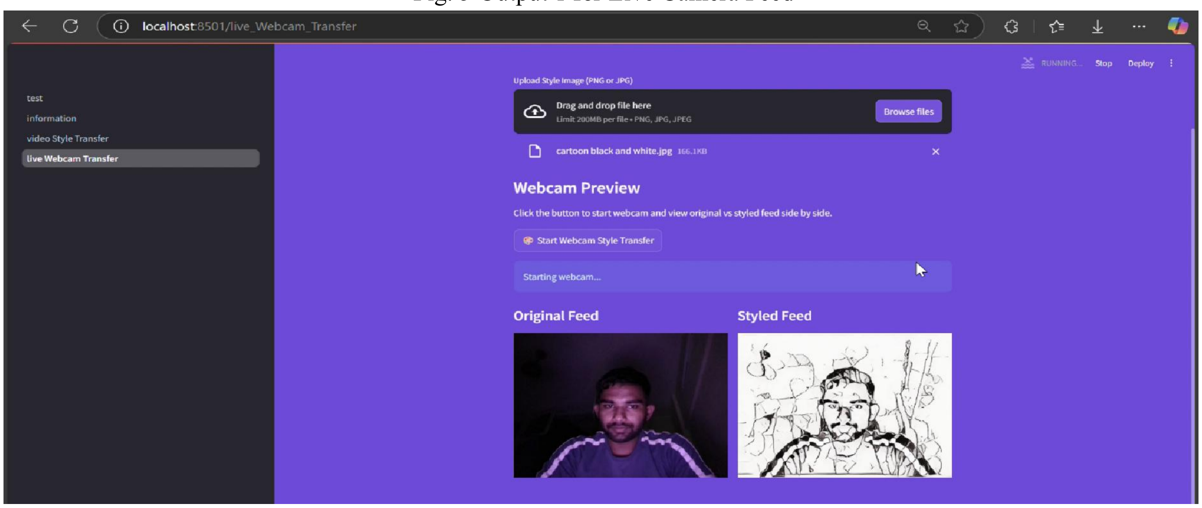
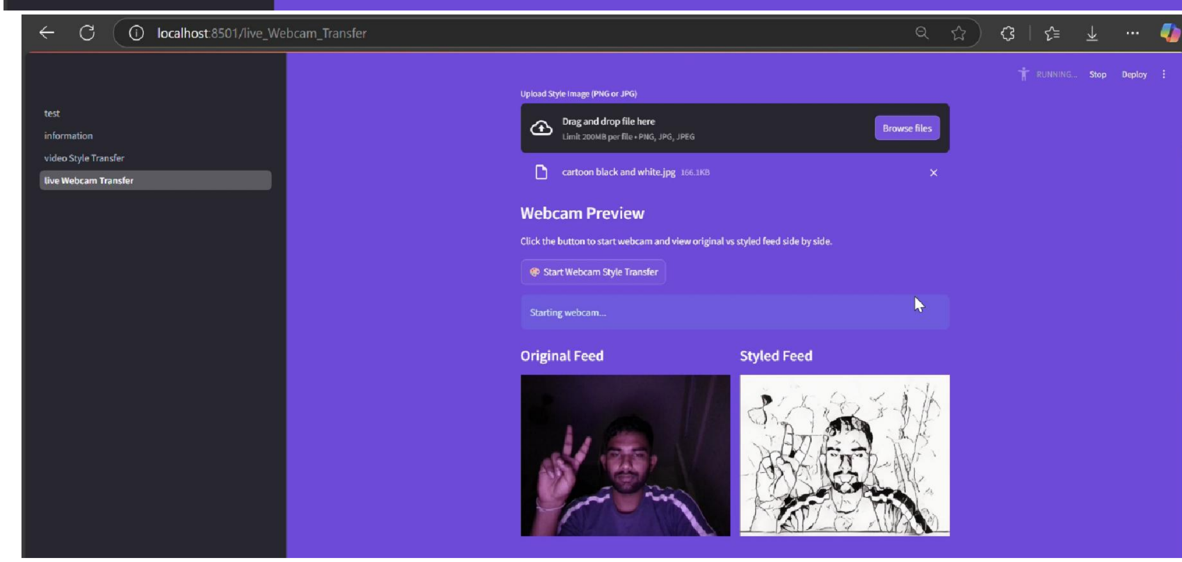


Fig. 5 Output 1 for Live Camera Feed





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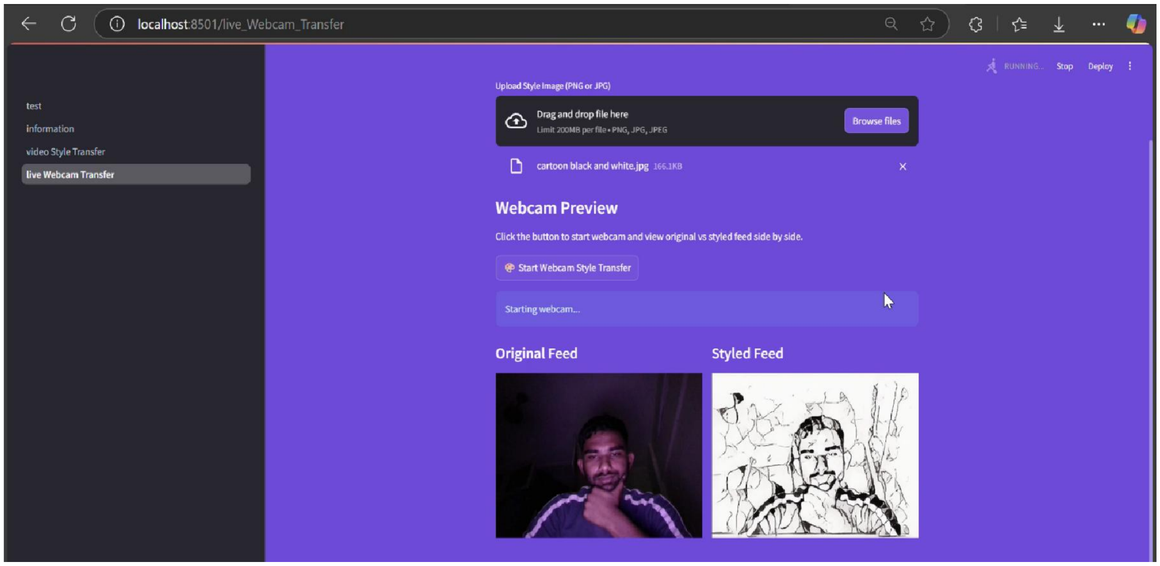

Fig. 6 Output 2 for Live Camera Feed

B. Discussion

In this project, we implemented artistic style transfer using different deep learning models for images, videos, and live camera feeds. While the system works across all three formats, we observed some performance limitations during real-world testing.

For image style transfer using CycleGAN, the results were visually impressive, and processing times were reasonable. However, when it came to video and live camera feed stylization, the system faced noticeable delays. A short video of just 7 to 8 seconds took approximately 15 minutes to fully process, making it clear that real-time or near-instant processing is not yet feasible with our current setup.

Similarly, the live camera feed, which was intended to perform style transfer in real-time using Fast Neural Style Transfer, behaved more like a slow video pipeline. There were visible lags, and the frame rate dropped significantly due to the model's computational load. This reduced the interactivity and responsiveness we had aimed for in live scenarios.

These performance issues point to a need for further optimization, such as using faster models, hardware acceleration (like GPU or edge AI), or lighter frameworks designed specifically for real-time applications.

C. Challenges

While the implementation of style transfer across images, videos and live camera feeds was successful, several challenges were encountered during the development and testing :

- **High Processing Time for Videos:** Applying style transfer to short video clips required a significantly long processing time. A 7–8 second video took approximately 15 minutes to stylize, mainly due to the computational complexity of preserving temporal consistency using TecoGAN. This makes the method less practical for longer videos or time-sensitive applications.
- **Real-Time Style Transfer Limitations:** Although Fast Neural Style Transfer was used for the live camera feed to enable real-time processing, the actual performance was much slower than expected. The system processed each frame individually, causing lag and reduced frame rates. As a result, the live feed behaved more like a slow video, undermining the real-time experience.
- **Hardware Constraints:** The processing speed of both video and live feed stylization heavily depended on the available hardware. systems without dedicated GPUs struggled to keep up with the demands of these deep learning models, leading to further delays and inconsistent performance.

- **Memory Usage and Resource Management:** High-resolution images and long-duration videos consumed considerable memory and processing resources. This occasionally led to browser crashes or unresponsive behaviour when running the models through the web interface.
- **Model Complexity and Optimization:** The models used, especially CycleGAN and TecoGAN, are computationally intensive. Without further optimization (e.g., model pruning or quantization), deploying them efficiently in lightweight environments remains a challenge.

VII. FUTURE SCOPE

The field of artistic style transfer continues to evolve rapidly, offering significant opportunities for enhancement and expansion of this project in both technical and user-oriented dimensions. the current system establishes a robust foundation for real-time, multi-domain style transfer using GAN-based models; however, several promising directions remain open for future development:

A. Expansion to 3D and AR/VR Environments

While the current system supports 2D media, future work can focus on extending style transfer to 3D models or augmented/virtual reality (AR/VR). Stylizing 3D scenes or environments in real time would open new possibilities in gaming, virtual exhibitions, and immersive media experiences.

B. Integration with Social Media and Cloud Storage

To enhance accessibility and sharing, the web platform could be integrated with social media platforms, cloud storage (e.g., Google Drive, Dropbox), and collaborative design tools, allowing users to directly stylize and share their content online.

C. Mobile and Cross-Platform Deployment

While the current web application is desktop-focused, optimizing the models for mobile and tablet devices could expand user reach. Techniques like model pruning, quantization, and on-device inference (e.g., using TensorFlow Lite or ONNX) would make the system lightweight and efficient enough for smartphones.

D. Advanced Multi-Style and Dynamic Style Blending

Implementing multi-style fusion capabilities, where users can blend two or more styles interactively, would allow for highly creative and novel results. Techniques such as conditional style transfer or style interpolation could be integrated to support this.

E. Improved Video Frame Consistency and Audio Sync

Although TecoGAN provides good temporal coherence, further enhancement could involve exploring diffusion-based models or transformer-based architectures for even smoother transitions. In addition, future work may include audio-aware video stylization, ensuring that visual changes align rhythmically with sound in multimedia outputs.

F. Dataset Expansion and Style Diversity

Increasing the diversity and quality of both content and style datasets can improve output richness. Incorporating styles from various cultures, modern digital art, or historic movements can promote more inclusive and culturally rich outputs.

G. Educational and Creative Toolkits

Beyond artistic applications, the platform can be extended into educational tools, helping students understand the impact of different art styles, or be integrated into digital storytelling, allowing users to create stylized narratives or comics.

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VIII. CONCLUSION

The proposed art style transfer system, leveraging advanced Generative Adversarial Networks (GANs) such as CycleGAN for images, TecoGAN for videos, and Fast Neural Style Transfer for real-time applications, successfully integrates state-of-the-art models to enable high-quality artistic transformations. The system provides users with an intuitive platform for applying artistic styles to images, videos, and live camera feeds in real-time, emphasizing both functionality and performance. By optimizing GAN-based models for local use, this project addresses challenges related to quality, temporal consistency, and real-time processing without relying on cloud-based solutions. This project serves as a practical and flexible solution for a range of creative applications in the field of art, entertainment, and media. Future extensions can focus on enhancing model efficiency, adding more style customization options, and expanding the system for more diverse artistic use cases, thus pushing the boundaries of how AI can contribute to art and creativity.

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