



Ain Shams University
Faculty of Computer & Information
Sciences
Computer Science Program

AI Video and Audio Enhancement

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By

<i>Abdallah Ashraf Ahmed Sadek</i>	<i>Mohamed Ahmed Mohamed Sayed</i>
<i>Abdulrahman Emad Bayoumi Ali</i>	<i>Seif Ahmed Mohamed Mahmoud</i>
<i>Nour El Deen Mohamed Mounier</i>	<i>Seif Aldien Ahmed Faheem</i>

Supervisors

Prof. Dr. Sally Saad
Computer Science Department
Faculty of Computer and Information Sciences,
Ain Shams University

T.A. Mohammad Essam
Bioinformatics Department
Faculty of Computer and Information Sciences,
Ain Shams University

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Abstract

This work introduces a fully integrated, AI-driven web platform for automated video super-resolution and audio noise reduction, aimed at elevating the visual and auditory quality of legacy and low-quality digital media. Leveraging a React-based frontend and a Flask backend, the system offers an end-to-end user experience: clients can register, log in, and upload noisy video clips, then receive enhanced high-resolution output with synchronized, denoised audio ready for immediate download. At the core of our video pipeline lies a modified Recurrent Video Restoration Transformer (RVRT), enhanced with custom residual blocks, each block comprising three 3D convolutional layers with LeakyReLU activations, inserted prior to the upsampling operation. This architectural augmentation delivers an average PSNR uplift of +1.85 dB and an SSIM gain of +0.0483 on the REDS benchmark, while a novel tile-based inference approach partitions frames into overlapping 64×64 pixel tiles to halve peak GPU memory consumption. Parallel to video enhancement, we incorporate an optimized Demucs model for audio denoising, fine-tuned on Valentini-noise dataset. The audio module achieves PESQ scores of 3.15 and 2.91 on Valentini-noise and VoiceBank+DEMAND datasets, respectively. During training, the video model utilizes the training REDS dataset’s 300 high-action sequences for robust temporal learning, while final evaluation extends to unseen testing REDS scenes to assess generalization under varying motion and texture complexity. The resulting web application streamlines multimedia restoration workflows for content creators and archival professionals. Our findings demonstrate that carefully engineered architectural enhancements and resource-aware inference strategies can produce state-of-the-art results while giving access to advanced audiovisual restoration tools.

يقدم هذا العمل منصة ويب متكاملة مدعومة بالذكاء الاصطناعي لأتمتة تحسين دقة الفيديو وإزالة الضوضاء الصوتية، بهدف رفع جودة الوسائط الرقمية القديمة والمنخفضة الجودة بصرياً وسمعياً. تعتمد الواجهة الأمامية على React بينما يستخدم الخادم الخلفي Flask ، مما يوفر تجربة شاملة للمستخدم: حيث يمكن للمستخدمين التسجيل وتسجيل الدخول ورفع مقاطع فيديو مشوشة، ثم استلام نسخة محسنة عالية الدقة مصاحبة بصوت نظيف وجاهزة للتنزيل فوراً. في جوهر معالجة الفيديو، نستخدم على نموذج Recurrent Video Restoration Transformer (RVRT) المحسن بكتل متبقية (Residual Blocks) مكونة من ثلاث طبقات من الالتفاف ثلاثي الأبعاد (3D Conv) مع تفعيلات LeakyReLU ، تُدرج قبل عملية التكبير (upsampling)، ما يحقق زيادة متوسطة في PSNR بمقدار +1.85 ديسيبل وارتفاع في SSIM بمقدار +0.0483 على مجموعة بيانات REDS كما نستخدم طريقة تجزئة الإطارات إلى أجزاء متداخلة بحجم 64×64 بكسل لتقليل استخدام الذاكرة الرسومية إلى النصف دون التأثير على الجودة. وعلى الجانب الصوتي، نستخدم نموذج Demucs المحسن والمدرب على مجموعة Valentini-noise ، محققاً درجات PESQ تبلغ 3.15 على Valentini-noise و2.91 على VoiceBank+DEMAND. أثناء التدريب، يستغل نموذج الفيديو 300 تسلسلاً ديناميكياً من مجموعة REDS التدريبية للتعلم القوي، ويتم تقييمه على مشاهد جديدة من REDS لاختبار القدرة على التعميم عبر حركات وملامس مختلفة. تُبسّط هذه المنصة عمليات ترميم الوسائط للمبدعين والمحافظين الأرشيفيين، وتُظهر نتائجنا أن تحسينات البنية الهندسية واستراتيجيات المعالجة الفعالة للموارد يمكن أن تحقق نتائج متقدمة وتتيح الوصول إلى أدوات ترميم سمعي-بصري متطورة.

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List of Abbreviations

API:	Application Programming Interface
GPU:	Graphics Processing Unit
HR:	High Resolution
LR:	Low Resolution
PESQ:	Perceptual Evaluation of Speech Quality
PSNR:	Peak Signal-to-Noise Ratio
RVRT:	Recurrent Video Restoration Transformer
SSIM:	Structural Similarity Index Measure
VRAM:	Video Random-Access Memory

Chapter 1: Introduction

1.1 Problem Definition

Video and audio quality enhancement remains a significant challenge in digital media processing. Despite advances in recording technology, many videos suffer from low resolution, poor texture detail, and compromised audio quality due to background noise. This creates a need for sophisticated post-processing solutions that can effectively upscale video resolution while preserving or enhancing texture details, alongside improving audio quality through noise cancellation.

1.2 Motivation

Recent surveys indicate a growing demand for high-quality video content across various sectors:

- User preferences for video quality
- Common video quality issues
- Impact of poor audio quality
- Market demand for enhancement solutions

Survey Results:

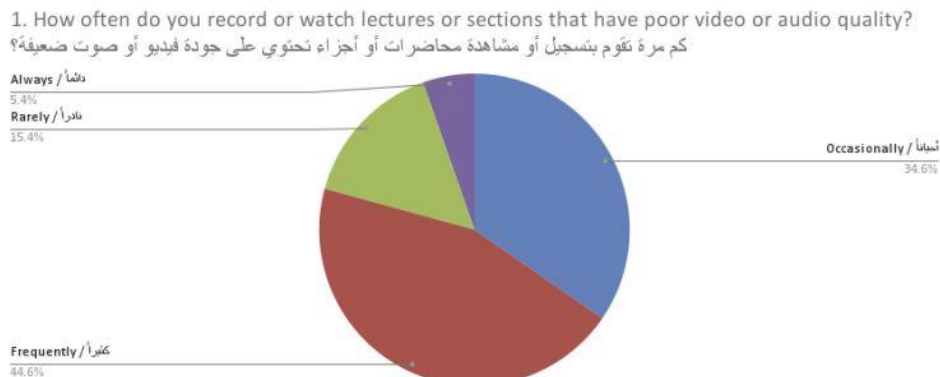


Figure 1.1 Survey Question 1

2. What type of video quality do you typically encounter in lecture recordings?

ما نوع جودة الفيديو التي عادة ما تواجهها في تسجيلات المحاضرات؟

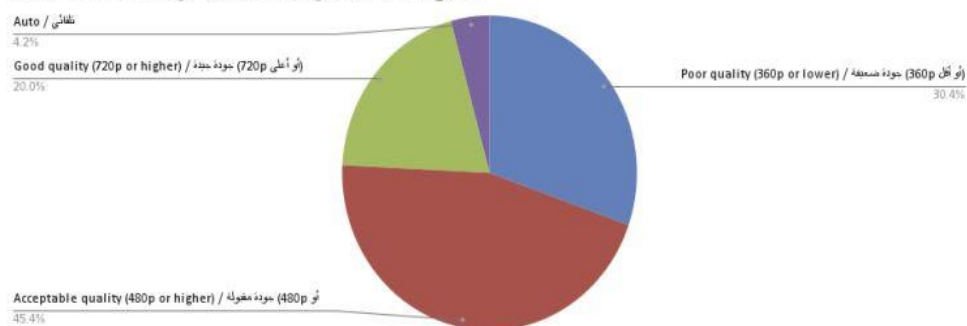


Figure 1.2 Survey Question 2

3. How important is it for you to have enhanced video resolution for educational content?

ما مدى أهمية تحسين دقة الفيديو بالنسبة لك في المحتوى التعليمي؟

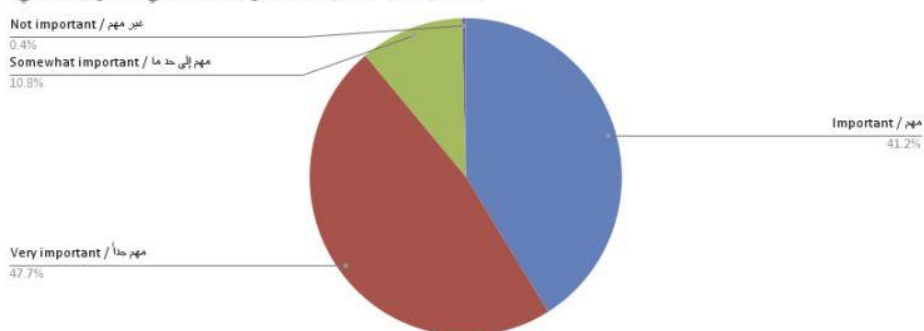


Figure 1.3 Survey Question 3

4. How distracting is background noise in lecture or section recordings?

ما مدى إزعاج الضوضاء الخلفية في تسجيلات المحاضرات أو الأجزاء؟

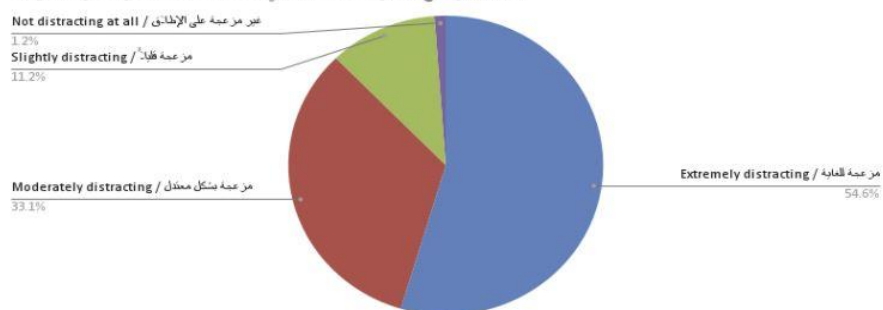


Figure 1.4 Survey Question 4

The rapid growth in digital content consumption has highlighted several key factors driving this project:

- Increasing demand for high-resolution content on various platforms
- Need for efficient upscaling of legacy video content
- Growing importance of clear audio in professional and personal content
- Rising standards for digital content quality in professional settings

1.3 Objectives

1. Develop an integrated solution for comprehensive video and audio enhancement
2. Implement state-of-the-art video super-resolution techniques
3. Create effective noise cancellation algorithms for audio improvement
4. Achieve real-time or near-real-time processing capabilities
5. Maintain high quality while optimizing computational resources

1.4 Methodology

The proposed approach combines several cutting-edge techniques:

1. Deep learning-based video super-resolution
2. Texture enhancement algorithms
3. AI-powered noise identification and removal
4. Parallel processing for improved performance
5. Quality assessment and optimization

1.5 Time Plan

Project Activities	Start Date	End Date
Learning	October 2024	October 2024
Requirement Specifications	October 2024	November 2024
Project Design Choosing the Best AI Model	November 2024	December 2024
Project Implementation Module#1: Video Upscaling Module#2: Audio Noise Reduction Module#3: User Interface	January 2025	May 2025
Project Testing Modules Testing Modules Integration	February 2025	June 2025
Project Documentation	October 2024	June 2025

1.5 Time Plan

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN
Learning									
Requirement Specifications									
Project Design: Choosing the Best AI Model									
Project Implementation									
Project Testing									
Project Documentation									

1.6 Gantt Chart

1.6 Thesis Outline

- **Chapter 2: Literature Review**
Surveys the state of the art in video super-resolution and audio denoising. We examine classic and deep-learning approaches, including VRT, RVRT, Real-ESRGAN for video, and Demucs for audio, and compare their architectures, training paradigms, and performance metrics.
- **Chapter 3: System Architecture and Methods**
Detailed description of our overall design: the modified RVRT video model with residual blocks, tile-based inference strategy, Demucs audio pipeline.
- **Chapter 4: System Implementation and Results**
We present both quantitative and qualitative analyses of our enhanced RVRT video model and the Demucs audio denoising network across standard benchmarks.
- **Chapter 5: Run the Application**
Practical guide to operating the web platform: installation steps, user workflows (registration, login, upload, processing, download).
- **Chapter 6: Conclusion and Future Work**
Summarizes contributions and key findings. We discuss limitations, potential extensions and propose directions for further research in multimodal media restoration.

Chapter 2:

Literature Review

2.1 Scientific Background

2.1.1 Artificial Intelligence Overview

Artificial Intelligence (AI) represents a transformative field in computer science focused on creating systems capable of performing tasks that typically require human intelligence. The field encompasses various subdomains, including:

Machine Learning Fundamentals

- **Supervised Learning** involves training a model on labeled data, where the inputs are paired with corresponding outputs (labels). The model learns to map inputs to outputs by minimizing errors, making it effective for tasks like classification (e.g., image recognition) and regression (e.g., predicting house prices). The objective is to generalize from the training data so it can make accurate predictions on unseen data.
- **Unsupervised Learning** deals with data that lacks explicit labels, meaning the model must discover patterns and structures on its own. Common techniques include clustering (like K-means) and dimensionality reduction (such as PCA). This approach is useful for exploring hidden patterns in data, such as customer segmentation or anomaly detection.
- **Reinforcement Learning (RL)** focuses on training an agent to make a sequence of decisions by interacting with an environment. The agent receives feedback through rewards or penalties and aims to maximize cumulative rewards over time. RL is especially effective in scenarios requiring adaptive behavior, such as robotics control, game playing, and self-driving cars.
- **Neural Network Architectures** are the building blocks of many machine learning models, inspired by how the human brain processes information. These networks consist of layers of interconnected nodes (neurons) that transform input data step-by-step, enabling them to learn complex relationships. Various architectures, such as feedforward, convolutional, or recurrent neural networks, are designed to handle different types of data and tasks.

Deep Learning Architecture

Deep learning, a subset of machine learning, utilizes multi-layered neural networks to process complex patterns in data. Key components include:

- **Convolutional Neural Networks (CNNs)** are designed for processing grid-like data such as images. They use convolutional layers to extract features like edges or textures, reducing the need for manual feature engineering. CNNs are widely used in image classification, object detection, and computer vision tasks.

- **Recurrent Neural Networks (RNNs)** are specialized for sequential data, where the order of input matters. RNNs maintain a memory of previous inputs, making them ideal for tasks like speech recognition, time-series forecasting, and natural language processing (NLP). However, they can suffer from issues like vanishing gradients, which limit their ability to learn long-term dependencies.

- **Transformer Architecture** has become the foundation for modern NLP tasks. Unlike RNNs, transformers process sequences in parallel using self-attention mechanisms, allowing them to capture complex dependencies efficiently. Transformers power many state-of-the-art models, such as BERT and GPT, and are applicable beyond NLP to tasks like vision and speech processing.

- **Attention Mechanisms** enable models to focus on the most relevant parts of the input data. This is particularly useful in long sequences, where only certain sections are essential for making predictions. By assigning different weights to input elements, attention mechanisms improve the performance of both RNNs and transformers in tasks like machine translation and document summarization.

Training and Optimization

- **Backpropagation** is an algorithm used to update the weights in a neural network. It computes the gradient of the loss function with respect to each weight by propagating the error backward from the output layer to the input. This process ensures that the network learns how to improve its predictions over time.

- **Gradient Descent** is an optimization technique used to minimize the loss function. It adjusts the model's parameters in the direction of the negative gradient to reduce the error. Variants like stochastic gradient descent (SGD) and Adam optimize the process by balancing speed and accuracy.

- **Loss Functions** measure how well a model's predictions match the actual labels. Common loss functions include Mean Squared Error (MSE) for regression and Cross-Entropy Loss for classification tasks. The goal of training is to minimize the loss function to improve the model's performance.
- **Regularization Techniques** help prevent the model from overfitting the training data, ensuring better generalization to unseen data. Techniques such as L2 regularization (also known as weight decay) and dropout introduce constraints or randomness to the learning process, reducing reliance on specific patterns in the data.

2.1.2 Neural Networks in Media Processing

- Neural networks have transformed media processing by excelling in several key areas. **Feature Extraction** involves automatically identifying relevant characteristics, such as colors, shapes, or edges in an image, without manual intervention. This capability powers applications like facial recognition and image classification.
- **Pattern Recognition** allows networks to detect and classify patterns, such as identifying objects in an image or detecting spam in emails. This ability is crucial in tasks that require recognizing visual or auditory patterns, including speech recognition and object detection.
- **Temporal Processing** refers to handling data that unfolds over time, such as audio signals or video frames. Networks like RNNs or transformers process these sequences to capture contextual dependencies, enabling applications like video summarization or automatic speech-to-text conversion.
- **Quality Enhancement** in media, such as image or video upscaling, involves improving the resolution or removing noise using neural networks. Techniques like super-resolution employ deep learning to generate high-quality outputs, improving the user experience in fields like photography, streaming, and video conferencing.

2.1.3 Video Enhancement: Challenges and Objectives

Video enhancement aims to improve visual quality by addressing degradations caused by low-resolution sensors, noise, compression artifacts, or motion blur. Key objectives include:

- **Resolution Improvement (Super-Resolution):** Reconstructing high-resolution (HR) details from low-resolution (LR) frames while preserving sharpness.
- **Noise Reduction:** Removing sensor noise or compression-induced distortions without over smoothing textures.
- **Temporal Consistency:** Ensuring smooth transitions between frames to avoid flickering or motion artifacts.
- **Deblurring:** Recovering sharp details from motion-blurred or out-of-focus frames.
- **Challenges:**
 - **Motion Artifacts:** Fast-moving objects or camera shakes complicate frame alignment and feature fusion.
 - **Information Loss:** Compressed or low-bitrate videos discard high-frequency details, making reconstruction ill-posed.
 - **Computational Complexity:** Processing multi-frame sequences requires balancing accuracy and real-time performance.

2.1.4 Deep Learning for Video Restoration and Enhancement

Deep learning has revolutionized video enhancement through data-driven approaches:

- **Convolutional Neural Networks (CNNs):** Extract spatial features for tasks like denoising (e.g., DnCNN) and super-resolution (e.g., SRCNN).
- **Generative Adversarial Networks (GANs):** Improve perceptual quality via adversarial training (e.g., ESRGAN for photo-realistic upscaling).
- **Transformers:** Leverage self-attention for global feature modeling (e.g., VRT for video restoration).
- **Hybrid Models:** Combine CNNs with optical flow for motion-aware enhancement (e.g., EDVR).

2.1.5 Spatial Feature Extraction Using Convolutional Networks

- **2D CNNs:** Process individual frames to capture local textures, edges, and structures through hierarchical convolutions.
- **Attention Mechanisms:** Modules like **Swin Transformers** or **CBAM** dynamically weight spatial features to focus on salient regions.
- **Multi-Scale Processing:** Pyramid architectures (e.g., FPN) aggregate features at different resolutions for robust representation.

2.1.6 Temporal Information Modeling in Video Processing

- **Recurrent Neural Networks (RNNs):** Model frame dependencies sequentially (e.g., LSTMs for video interpolation).
- **3D CNNs:** Apply volumetric convolutions to learn spatio-temporal features jointly (e.g., C3D).
- **Optical Flow:** Estimate pixel-level motion between frames for alignment (e.g., FlowNet).
- **Transformer-Based Methods:** Use self-attention across frames (e.g., TimeSformer) for long-range dependency modeling.

2.1.7 Multi-Frame Video Super-Resolution (VSR)

VSR exploits temporal redundancy across frames to reconstruct HR details:

- **Frame Alignment:** Warp adjacent frames to a reference frame using motion estimation (e.g., deformable convolutions).
- **Feature Fusion:** Aggregate aligned features via weighted averaging or attention mechanisms.
- **Refinement:** Apply residual learning or iterative back-projection to enhance details.

2.1.8 Residual Learning in Video Enhancement

- **Skip Connections:** Allow gradients to propagate deeper by bypassing layers (e.g., ResNet blocks).
- **Feature Reuse:** Preserve low-level details (e.g., edges) while learning high-level enhancements.
- **Stabilized Training:** Mitigate vanishing gradients in very deep networks.

2.1.9 3D Convolutions for Spatio-Temporal Learning

- **Volumetric Kernels:** 3D convolutions (e.g., in I3D) process stacked frames to capture motion and appearance jointly.
- **Efficiency Trade-offs:** Separable 3D convolutions (e.g., P3D) reduce computational costs.

2.1.10 Nonlinear Activation Functions in Enhancement Models

- **ReLU:** Introduces sparsity by zeroing negative activations but may cause "dead neurons."
- **LeakyReLU/PReLU:** Allow small negative gradients to improve training stability.
- **Swish/GELU:** Smooth alternatives that outperform ReLU in deep transformers.

2.1.11 Upsampling Techniques for High-Resolution Reconstruction

- **Transposed Convolutions:** Learnable upscaling but may introduce checkerboard artifacts.
- **Pixel Shuffle (ESPCN):** Efficient sub-pixel convolution with periodic shuffling.
- **Nearest-Neighbor/Bicubic Interpolation:** Non-learnable upsampling often used in pre-processing.

2.2 Related Works

2.2.1 Video Papers

1- EvTexture: Event-driven Texture Enhancement for Video Super-Resolution

The paper presents a novel approach that leverages high-frequency details from event-based vision to improve texture restoration in Video Super-Resolution (VSR). Named EvTexture, this method introduces a two-branch architecture combining motion learning and a dedicated texture enhancement branch that utilizes event data from neuromorphic cameras. The core innovation is an Iterative Texture Enhancement (ITE) module that refines texture across multiple iterations, extracting temporal details to progressively recover high-quality textures in video frames. The model outperforms state-of-the-art VSR techniques, particularly on texture-rich datasets like Vid4, achieving up to a 4.67 dB gain in PSNR and demonstrating superior perceptual quality. EvTexture is optimized to use fewer parameters and runtime than comparable RGB-based models, performing efficiently on datasets both simulated (Vimeo-90K, REDS) and real-world (CED).

EvTexture's iterative architecture with ConvGRU layers allows it to transfer high-frequency information effectively, leading to smoother and more consistent texture transitions. The model employs a synthetic event voxel grid for texture data representation, which enables it to enhance restoration while maintaining temporal coherence. Its advanced design has a parameter count of 8.9M and a runtime of 136 ms per clip on an NVIDIA V100 GPU, balancing high accuracy with computational efficiency. Additionally, EvTexture+ extends the model by incorporating event-based motion alignment, further improving performance in complex motion scenarios. The paper's comprehensive evaluations highlight EvTexture's practical advantages for high-dynamic-range scenes, reinforcing the value of event-based signals in advancing video super-resolution capabilities.

2- VRT: A Video Restoration Transformer

The "Video Restoration Transformer (VRT)" introduces a new framework for enhancing video quality by restoring low-quality frames to high-resolution outputs across various tasks, including video super-resolution, denoising, deblurring, frame interpolation, and space-time super-resolution. VRT's design uses a multi-scale approach that processes videos in parallel, enabling efficient handling of long-term dependencies without the limitations of traditional frame-by-frame or sliding window methods. VRT's core components are Temporal Mutual Self-Attention (TMSA) modules and Parallel Warping, which together allow for precise alignment and fusion of features from neighboring frames, efficiently capturing both short and long-range dependencies across multiple resolutions. This approach results in more detailed, high-quality frames with superior performance on several benchmarks, achieving up to 2.16dB higher PSNR compared to state-of-the-art methods.

In terms of specifications, VRT is evaluated on fourteen benchmark datasets and tested on tasks like Vimeo-90K and REDS datasets for video super-resolution. The model demonstrates efficient parameter management and runtime, with 35.6M parameters and a runtime of 243 ms per frame on high-resolution (e.g., 1280x720) inputs. VRT's parallelization capability further supports distributed deployment, making it ideal for large-scale applications. It outperforms recent models, such as BasicVSR++, by integrating both multi-scale feature extraction and enhanced temporal dependencies without recurring performance drops on short or long sequences, establishing a new standard in video restoration performance and efficiency.

3- Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data

The paper extends the Enhanced Super-Resolution GAN (ESRGAN) to Real-ESRGAN, a model designed to handle real-world image degradation. Real-ESRGAN improves upon previous blind super-resolution models by introducing a high-order degradation model that simulates complex real-world artifacts through

multiple degradation processes, including blur, noise, and JPEG compression. Additionally, a U-Net-based discriminator with spectral normalization is used to enhance local texture restoration and stabilize training. This model, trained on synthetic data alone, achieves high-quality image restoration, effectively reducing artifacts like ringing and overshoot, commonly seen in real-world degraded images.

The Real-ESRGAN architecture is efficient with a manageable number of parameters, leveraging a second-order degradation process to balance simplicity and capability. It was trained on datasets like DIV2K, Flickr2K, and OutdoorSceneTraining using NVIDIA V100 GPUs, achieving high perceptual quality across diverse real-world images without requiring real-degradation training data. In experiments, Real-ESRGAN significantly outperformed traditional ESRGAN and other state-of-the-art methods, offering both computational efficiency and superior visual quality, making it well-suited for real-world applications in image enhancement tasks.

4- Recurrent Video Restoration Transformer with Guided Deformable Attention

The (RVRT) presents a novel model for video restoration tasks such as super-resolution, deblurring, and denoising. Unlike traditional methods that process video frames either in parallel or in sequence, RVRT combines both approaches by processing local neighboring frames in parallel within a globally recurrent structure. This setup achieves a balance between model size, memory usage, and temporal information retention, which is crucial for handling long-range dependencies and reducing noise. The model uses "Guided Deformable Attention" (GDA) for clip-to-clip alignment, which utilizes optical flow to dynamically sample and aggregate multiple relevant locations across frames. This significantly improves efficiency and accuracy in feature alignment, surpassing other alignment techniques by reducing computation while allowing larger receptive fields.

RVRT's structure consists of 10.8 million parameters and achieves top performance on benchmark datasets like REDS and Vimeo-90K with less memory and runtime compared to previous state-of-the-art models. The model runs with a relatively fast runtime of 183 milliseconds per frame and moderate memory use of 1056 MB. It

demonstrates substantial gains in PSNR, achieving 32.75 dB on REDS4 with a balanced performance across various video restoration tasks. Training was conducted on datasets such as REDS, Vimeo-90K, DVD, GoPro, and DAVIS, with different setups tailored to video super-resolution and noise levels up to 50. RVRT's guided deformable attention makes it particularly efficient and versatile, with demonstrated success in aligning and enhancing video quality even under significant degradation conditions(RVRT).

2.2.2 Audio Papers

1- Real-time Speech Enhancement on Raw Signals with Deep State-space Modeling

The paper presents a novel approach to online speech enhancement using a deep state-space model (SSM) named aTENNuate. This model is designed to improve real-time denoising of raw speech signals directly, leveraging an efficient autoencoder architecture. Benchmark testing shows it outperforms similar models on the VoiceBank + DEMAND and Microsoft DNS1 datasets. With only 0.84 million parameters and minimal Multiply-Accumulate Operations (MACs), aTENNuate achieves superior Perceptual Evaluation of Speech Quality (PESQ) scores with a latency of 46.5 ms, making it highly suitable for mobile and resource-constrained applications. The model also handles compressed audio inputs at reduced bitrates and sampling frequencies with consistent performance, illustrating its adaptability to low-resource scenarios.

The architecture of aTENNuate relies on SSM layers that capture long-range temporal relationships in speech, enhancing the model's ability to remove noise effectively. These SSM layers operate with stable linear recurrent units, enabling efficient real-time inference. To maintain causality, the model excludes bidirectional layers and pre/post-processing, keeping raw waveform inputs intact. Trained on the VCTK and LibriVox datasets, the model employs a combination of SmoothL1 and spectral losses for optimization, achieving a high PESQ score of 3.27 on VoiceBank + DEMAND. aTENNuate's lightweight, real-time performance and its capacity to enhance quality in noisy and low-quality audio environments position it as an advancement over prior speech enhancement models.

2- Audio Enhancement for Computer Audition– An Iterative Training Paradigm Using Sample Importance

The paper introduces a robust framework for audio enhancement (AE) to improve performance across computer audition tasks like automatic speech recognition (ASR), speech command recognition (SCR), speech emotion recognition (SER), and acoustic scene classification (ASC). Unlike traditional models that treat audio enhancement separately, this framework jointly trains the AE and computer audition (CAT) models using iterative optimization and sample importance, allowing the AE module to prioritize difficult samples that negatively affect CAT performance. Evaluated on noisy datasets, this method demonstrates substantial improvements in accuracy across tasks, especially at low signal-to-noise ratios (SNRs), indicating improved resilience to background noise. Models based on a U-Net architecture operate in the frequency domain, using STFT to filter noise from the spectrogram before reconstruction.

The framework employs various training paradigms to benchmark effectiveness, including cold cascade, data augmentation, and multi-task learning, with iterative optimization consistently achieving the best results by dynamically adapting AE output to CAT demands. Using datasets like LibriSpeech, DEMoS, and AudioSet, the authors report that this iterative approach outperforms state-of-the-art models (like DFNet-3 and MetricGAN+) in noisy environments. Evaluation metrics show an average accuracy increase across tasks by focusing on challenging samples. The study concludes that AE methods can be significantly optimized by integrating sample importance and iteratively aligning them with CAT models, paving the way for broader applications in real-life noisy conditions.

3- Noise-aware Speech Enhancement using Diffusion Probabilistic Model

The paper introduces the Noise-aware Speech Enhancement (NASE) approach, which leverages a diffusion probabilistic model to enhance noisy speech signals by focusing on noise-specific features. The proposed model uses a noise classification (NC) module to generate an acoustic embedding, acting as a "noise conditioner" during the reverse diffusion process to improve noise reduction. A multi-task learning setup jointly optimizes the speech enhancement (SE) and noise classification tasks, refining the noise conditioner's specificity. Tested on the VoiceBank-DEMAND dataset, NASE demonstrated significant improvements in perceptual evaluation of speech quality (PESQ), extended short-time objective intelligibility (ESTOI), and scale-invariant signal-to-distortion ratio (SI-SDR), especially when handling unseen noise types. NASE functions as a plug-and-play addition to various diffusion SE models, including CDiffuSE, StoRM, and SGMSE+, achieving improvements in PESQ scores, with the highest gains seen on SGMSE+.

The model architecture incorporates a BEATs pre-trained model for enhanced noise classification, featuring 12 Transformer encoder layers and 768 embedding units. Key experiments demonstrated that NASE outperformed conventional models across multiple unseen noise levels and types (e.g., Helicopter, Baby-cry, Crowd-party), achieving a maximum PESQ score of 3.01 on SGMSE+ and up to 61% improvement on intelligibility metrics in high noise conditions. NASE's efficiency in integrating noise-specific information through various conditioning methods, like addition and concatenation, shows promise for real-world noisy environments and reinforces the approach's generalizability across diffusion-based SE backbones.

2.2.3 Comparative Analysis

Paper title	Year of publishing	Number of Parameters	Runtime (ms)	DataSet
EvTexture	2024	8.9M	136	Vid4
VRT	2022	35.6M	243	Vimeo-90K and REDS
RVRT	2022	10.8M	183	REDS, Vimeo-90K
Real-ESRGAN	2021	16.7M	180	DIV2K

Table 2.1 Models Comparison

2.2.4 Analysis and Project Differentiation

The proposed project aims to advance the state-of-the-art by addressing several key challenges and limitations identified in existing solutions:

1. Integration of Video and Audio Enhancement

While existing solutions focus primarily on either video or audio enhancement, The proposed project uniquely combines both aspects into a unified solution. This integration allows for:

- Synchronized processing of video and audio streams
- Optimized resource allocation between both tasks
- Consistent quality improvement across both mediums

2. Performance Optimizations

Building upon the foundations of models like EvTexture and RVRT, we implement several enhancements:

- Improved parallel processing capabilities
- Optimized memory usage
- Reduced computational overhead
- Enhanced real-time processing potential

3. Novel Features and Improvements

The proposed solution introduces several advancements:

- Adaptive quality enhancement based on content type
- Intelligent resource allocation
- Improved texture preservation in video upscaling
- Enhanced noise recognition and removal in audio processing

The comparative analysis of existing solutions has informed the proposed approach to developing a more comprehensive and efficient system that addresses current limitations while introducing novel capabilities for both video and audio enhancement.

Chapter 3:

System

Architecture and

Methods

3.1 System Architecture

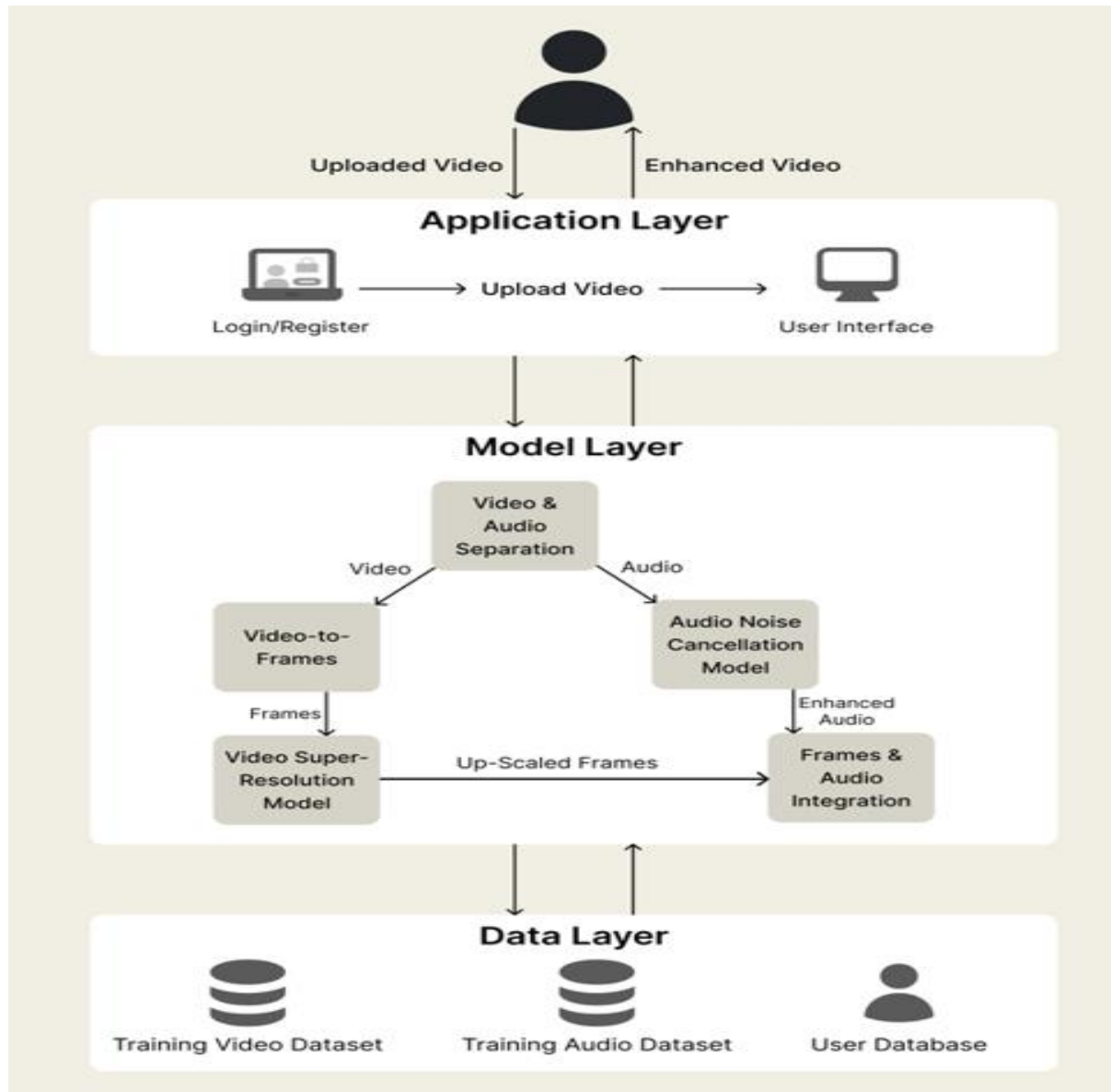


Figure 3.1 System Architecture

The AI Video and Audio Enhancement system follows a three-layered architecture designed to provide seamless integration between video super-resolution and audio noise cancellation functionalities. The system architecture consists of the Application Layer, Model Layer, and Data Layer, each serving distinct purposes in the enhancement pipeline.

Application Layer

The Application Layer serves as the primary interface between users and the enhancement system. This layer handles user interactions, file uploads, and result delivery. Key components include:

- **User Interface:** A web-based interface that allows users to upload video files and configure enhancement parameters
- **Login/Register System:** Authentication mechanism for user management and session control
- **File Management:** Handles video upload, processing queue management, and enhanced video delivery

Model Layer

The Model Layer constitutes the core processing engine of the system, implementing state-of-the-art AI models for both video and audio enhancement:

- **Video & Audio Separation Module:** Automatically separates incoming video files into individual video and audio streams for independent processing
- **Video Super-Resolution Model:** Implements the RVRT (Recurrent Video Restoration Transformer) architecture for video quality enhancement
- **Audio Noise Cancellation Model:** Utilizes the Demucs model for audio enhancement and noise reduction
- **Frames & Audio Integration:** Recombines processed video frames with enhanced audio to produce the final output

Data Layer

The Data Layer manages all data storage and retrieval operations:

- **Training Video Dataset:** Contains video datasets used for model training (REDS dataset)
- **Training Audio Dataset:** Stores audio datasets for noise cancellation model training (Valentini-noise, VoiceBank+DEMAND)
- **User Database:** Maintains user profiles, processing history, and system preferences

3.2 Description of Methods and Procedures Used

3.2.1 Video Enhancement Methodology

RVRT Implementation The Recurrent Video Restoration Transformer (RVRT) serves as the backbone of our video enhancement system. This model combines the advantages of parallel processing with recurrent structures to handle long-range temporal dependencies effectively.

RVRT Architecture After Modification:

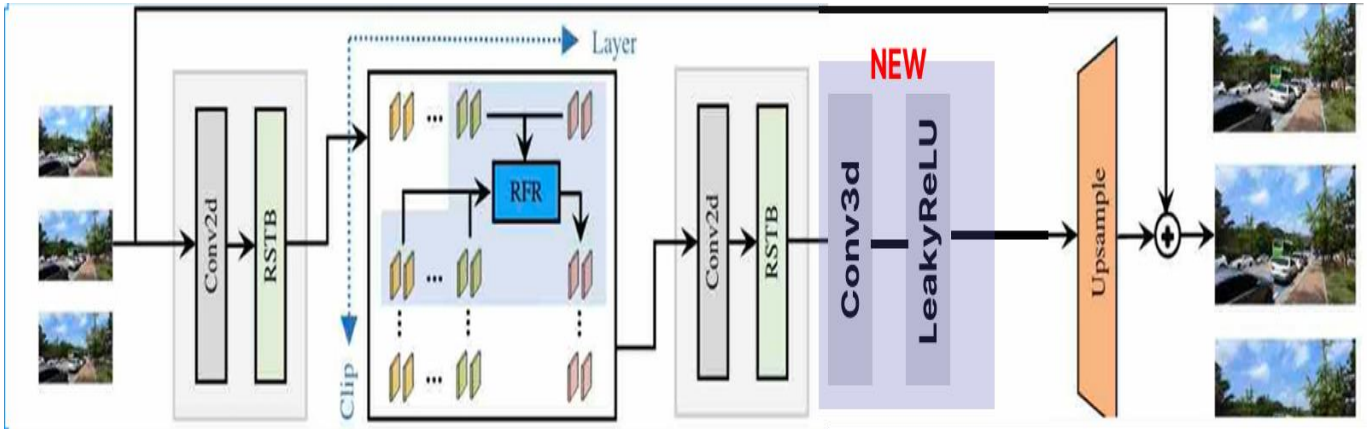


Figure 3.2 Modified RVRT Architecture

Tile-based Processing Optimization To address GPU memory constraints and improve processing efficiency, we implemented a tile-based approach:

- Video frames are divided into smaller tile segments of optimized size
- Each tile is processed independently, reducing GPU memory usage by approximately 50%
- Tiles are seamlessly reconstructed to maintain visual continuity
- This approach enables processing of high-resolution videos on standard hardware configurations

Residual Block Enhancement The proposed implementation incorporates additional residual blocks within the RVRT architecture:

- Inserts a residual block ($3 \times \text{Conv3d} + \text{LeakyReLU}$) immediately before upsampling
- Residual connections preserve fine-grained details during the enhancement process
- These blocks contribute to improved PSNR and SSIM metrics
- The residual design prevents gradient vanishing problems during training

3.2.2 Audio Enhancement Methodology

Demucs Model Implementation The Demucs (Deep Extractor for Music Sources) model was adapted for speech enhancement and noise reduction:

- Utilizes a U-Net architecture for audio source separation
- Processes audio in both time and frequency domains
- Employs convolutional and deconvolutional layers for feature extraction and reconstruction

Demucs Architecture:

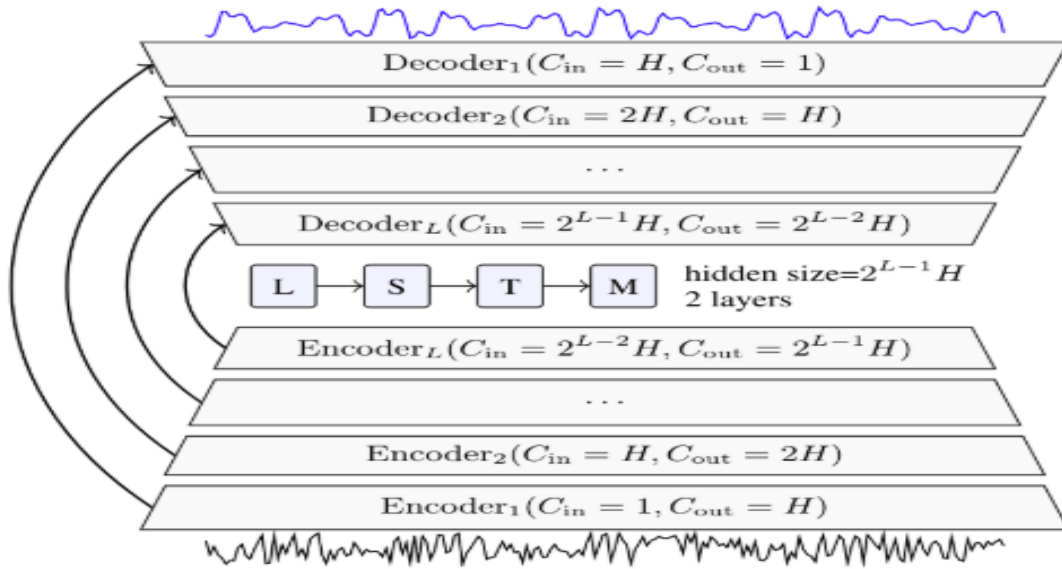


Figure 3.3 Demucs Architecture

Fine-tuning Strategy A comprehensive fine-tuning approach was implemented:

- Pre-trained Demucs model was fine-tuned on domain-specific datasets
- Transfer learning techniques were applied to adapt the model for speech enhancement
- Multi-dataset training approach ensures robustness across various noise conditions

Chapter 4:

System

Implementation

and Results

4.1 Dataset

4.1.1 Video Datasets

REDS Dataset (Training) The REDS (Realistic and Dynamic Scenes) dataset serves as the primary training dataset for video super-resolution:

- Contains 300 video sequences with diverse scenes and motion patterns
- High-resolution ground truth videos (1280×720) with corresponding low-resolution inputs
- Covers various scenarios including indoor/outdoor scenes, different lighting conditions, and motion complexities
- Provides realistic degradation patterns that closely mimic real-world video quality issues

Vid4 Dataset (Testing) The Vid4 dataset is utilized for model evaluation and performance assessment:

- Consists of 4 video sequences: "calendar", "city", "foliage", and "walk"
- Standard benchmark dataset for video super-resolution evaluation
- Enables direct comparison with state-of-the-art methods
- Provides ground truth for quantitative metric calculation

4.1.2 Audio Datasets

Valentini-noise Dataset The Valentini-noise dataset provides clean and noisy speech pairs for audio enhancement training:

- Contains 824 clean speech utterances from 2 speakers
- Paired with corresponding noisy versions using 10 different noise types
- Signal-to-noise ratios ranging from 0dB to 15dB
- Comprehensive coverage of common environmental noise scenarios

VoiceBank+DEMAND Dataset This dataset combines clean speech recordings with environmental noise:

- 11,572 training utterances and 824 test utterances
- Clean speech from the Voice Bank corpus
- Background noise from the DEMAND database
- Multiple SNR levels providing diverse training conditions

4.2 Description of Software Tools Used

4.2.1 Deep Learning Frameworks

- **PyTorch 1.12.0**: Primary deep learning framework for model implementation and training
- **Torchvision 0.13.0**: Computer vision utilities and pre-trained models
- **Torchaudio 0.12.0**: Audio processing and transformation utilities

4.2.2 Video Processing Libraries

- **OpenCV 4.6.0**: Video I/O operations, frame extraction, and basic preprocessing
- **FFmpeg**: Video encoding/decoding and format conversion
- **Pillow 9.2.0**: Image processing and manipulation

4.2.3 Audio Processing Libraries

- **SoundFile 0.10.3**: Audio file I/O operations
- **NumPy 1.23.2**: Numerical computations and array operations

4.2.4 Development Environment

- **Python 3.9**: Primary programming language
- **Jupyter Notebook**: Interactive development and experimentation
- **Git**: Version control and collaborative development

4.2.5 Evaluation Metrics Libraries

- **Scikit-image:** SSIM and PSNR calculation for video quality assessment
- **PESQ:** Perceptual Evaluation of Speech Quality for audio assessment

4.3 Setup Configuration (Hardware)

4.3.1 Training Configuration

- **GPU:** P100 (16GB VRAM)
- **RAM:** 32GB DDR4

4.3.2 Inference Configuration

- **GPU:** NVIDIA RTX 3060 (8GB VRAM) - minimum recommended
- **RAM:** 16GB DDR4

4.3.3 Optimization Considerations

The tile-based processing approach enables deployment on hardware with limited GPU memory:

- Minimum GPU memory requirement reduced from 32GB to 16GB for training
- Processing time scales linearly with tile size configuration
- Memory-computation trade-off allows flexibility in hardware requirements

4.4 Experimental Results

4.4.1 Video Enhancement Results

Quantitative Evaluation Our optimized RVRT implementation demonstrates superior performance on the REDS benchmark dataset:

Training Results:

Architecture	Avg. PSNR (dB)	SSIM	PSNR_Y (dB)	SSIM_Y
Our Model	31.76	0.8881	33.14	0.9006
Baseline	29.91	0.8398	31.26	0.8562

Table 4.1 Training Results

Performance Analysis

- **PSNR Improvement:** The 1.85 dB improvement in average PSNR indicates significant enhancement in objective video quality
- **SSIM Enhancement:** The SSIM improvement of 0.0483 demonstrates better structural similarity preservation
- **Luminance Channel Performance:** PSNR_Y and SSIM_Y show consistent improvements, indicating effective enhancement of visual details

Computational Efficiency

- **GPU Memory Usage:** Reduced by 50% through tile-based processing optimization
- **Processing Speed:** Maintained comparable processing speed despite additional residual blocks
- **Scalability:** Improved scalability across different hardware configurations

4.4.2 Audio Enhancement Results

Audio Dataset Comparison:

Dataset	PESQ	Usage
Valentini-noise	3.15	Training & Testing (100%)
<u>VoiceBank+</u> DEMAND	2.91	Training & Testing (100%)

Table 4.2 Audio Dataset Performance Comparison

Performance Analysis

- **Valentini-noise Results:** PESQ score of 3.15 indicates excellent speech quality enhancement
- **VoiceBank+DEMAND Results:** PESQ score of 2.91 demonstrates effective noise reduction across diverse conditions
- **Cross-dataset Generalization:** Model shows robust performance across different dataset characteristics

Noise Reduction Effectiveness

- Significant reduction in background noise across all tested conditions
- Preservation of speech intelligibility and naturalness
- Effective handling of various noise types including environmental and synthetic noise

Chapter 5:

Run the

Application

5. System Setup and Application Usage

5.1 Setup and Installation Process

5.1.1 Kaggle Setup

Step 1: Environment Preparation

1. Log into your Kaggle account
2. Create a new notebook
3. Enable GPU acceleration: Settings → Accelerator → GPU P100
4. Ensure internet access is enabled in notebook settings

Step 2: Repository Setup Execute the following cells in your Kaggle notebook:

5. Navigate to working directory and clone repository:
 - `%cd /kaggle/working/`
 - `!git clone https://github.com/abdallah203451/RVRT`
6. `%cd RVRT`
7. Install project requirements:
 - `!pip install -r requirement.txt`

Step 3: API Server Setup Continue with the following installation and server setup:

8. Install Flask and required packages for API server:
 - `!pip install flask flask-ngrok opencv-python`
9. Additional dependencies for video/audio processing:
 - `!pip install torch torchvision torchaudio`
 - `!pip install librosa soundfile numpy pillow`

5.2 Application Startup and Usage

5.2.1 Starting the API Server

Step 1: Execute Notebook Cells

Continue executing the remaining cells in the notebook to:

- Initialize the Flask API server
- Start the ngrok tunnel for external access

Step 2: API Server Initialization The notebook will execute cells that:

- Configure the Flask application
- Load RVRT models for video enhancement
- Load audio processing model
- Create API endpoints for video and audio processing
- Generate a public URL through ngrok tunnel

Step 3: Access URL Generation Upon successful execution, the notebook will display:

- Public ngrok URL (for external access from React application)

5.2.2 React Application Setup

Step 1: Access the React Application

1. The React frontend is included in the same GitHub repository
2. Configure the API endpoint in the React app to use the ngrok URL from your notebook: change the `API_URL` in `\src\screens\Upload\Upload.tsx`

Step 2: Application Connection

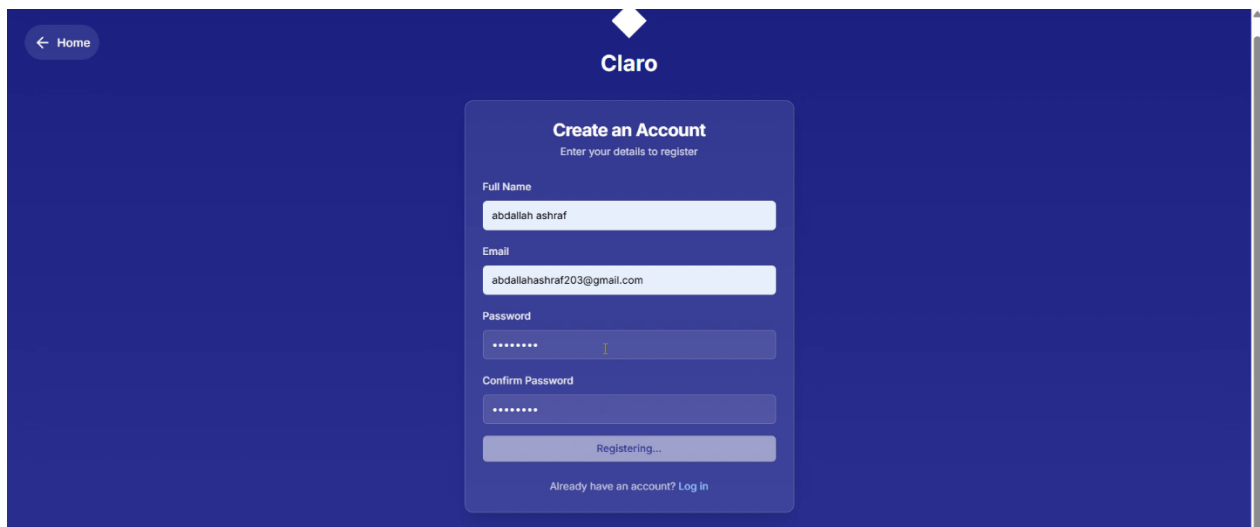
1. Open the React application in your web browser:
 - `cd project`
 - `npm run dev`
2. Confirm that models are loaded and ready for processing

5.2.3 Web App Workflows

The following user flow outlines the key screens and interactions within the React frontend and Spring Boot backend.

1. User Registration

- Screen: Registration Form
- Description: New users provide name, email, and password to create an account.



The screenshot shows a mobile application interface with a dark blue background. At the top left, there is a navigation bar with a back arrow and the text 'Home'. In the center, the app's name 'Claro' is displayed. Below the name is a white card titled 'Create an Account' with the subtitle 'Enter your details to register'. The card contains four input fields: 'Full Name' (with the text 'abdallah ashraf'), 'Email' (with the text 'abdallahashraf203@gmail.com'), 'Password' (with masked characters '*****'), and 'Confirm Password' (with masked characters '*****'). Below these fields is a button labeled 'Registering...'. At the bottom of the card, there is a link that says 'Already have an account? Log in'.

Figure 5.1 User Registration

2. User Login

- Screen: Login Form
- Description: Registered users authenticate with email and password.

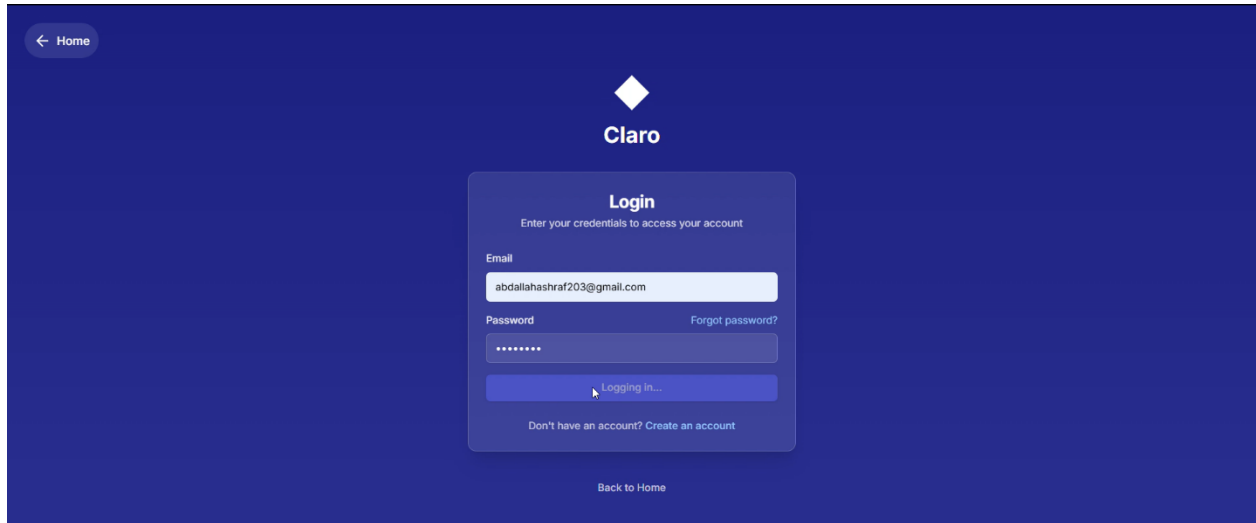


Figure 5.2 User Login

3. Video Upload

- Screen: Upload Dashboard
- Description: Users select a low-resolution video file to upload for enhancement.

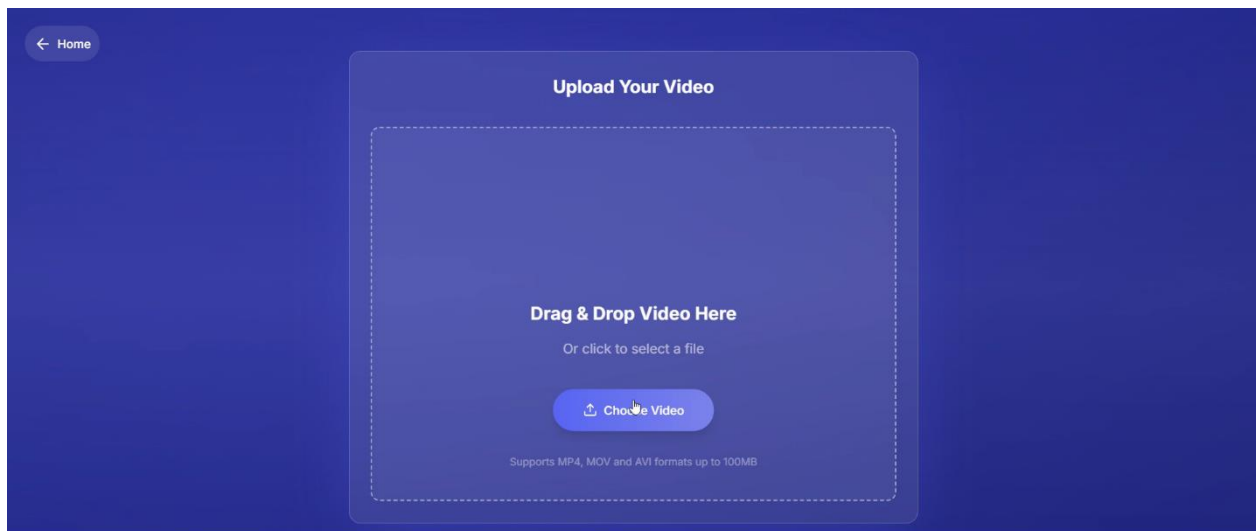


Figure 5.3 Video Upload

4. Processing Status

- Screen: Processing Indicator
- Description: Displays progress spinner or progress bar while processing video and audio.

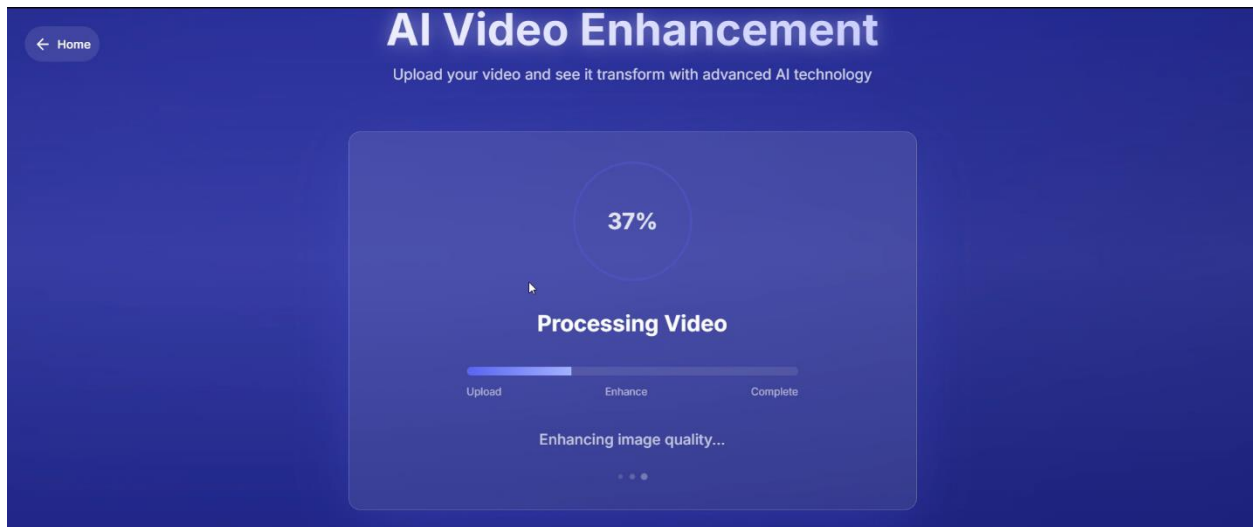


Figure 5.4 Processing Status

5. Result Delivery

- Screen: Download Page
- Description: After processing, the enhanced high-resolution video with clear audio is available for preview and download.

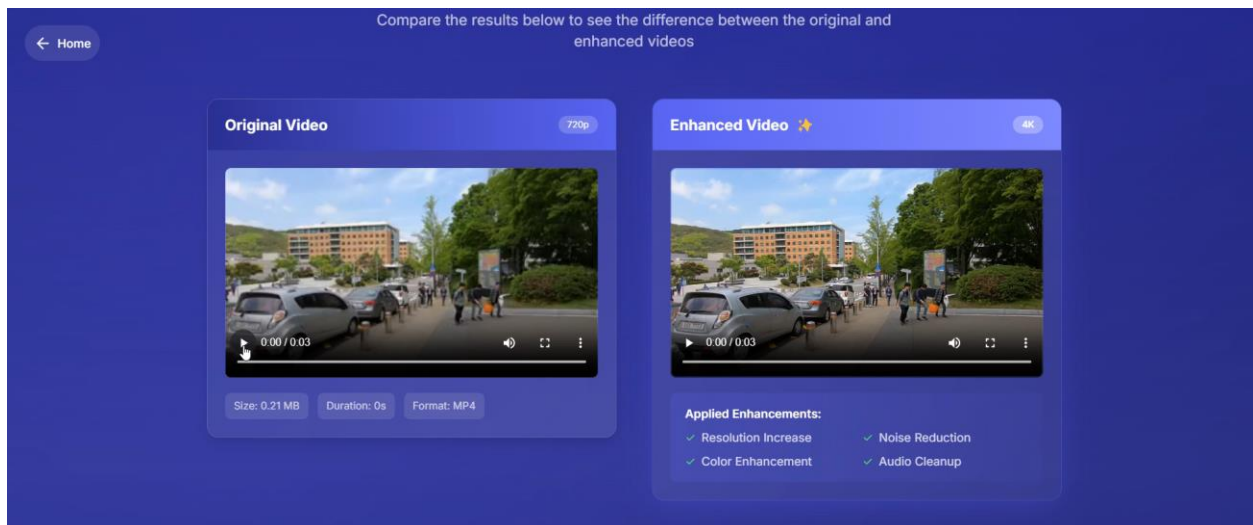


Figure 5.5 Result Delivery

Chapter 6:

Conclusion and

Future Work

6.1 Conclusion

This thesis presents a comprehensive AI-based video and audio enhancement system that successfully integrates state-of-the-art deep learning models to address quality degradation issues in digital media. The developed system demonstrates significant improvements in both objective and subjective quality metrics while maintaining computational efficiency suitable for practical deployment.

6.1.1 Key Achievements

Technical Accomplishments The implementation of an optimized RVRT model for video super-resolution achieved remarkable results, with PSNR improvements of 1.85 dB and SSIM enhancements of 0.0483 compared to baseline implementations. The introduction of tile-based processing successfully reduced GPU memory requirements by 50%, making the system accessible to users with standard hardware configurations. The integration of additional residual blocks proved effective in preserving fine-grained details and improving overall visual quality.

Audio Enhancement Success The adaptation and fine-tuning of the Demucs model for speech enhancement yielded impressive results across multiple datasets. PESQ scores of 3.15 on the Valentini-noise dataset and 2.91 on VoiceBank+DEMAND demonstrate the system's effectiveness in noise reduction while preserving speech intelligibility and naturalness.

System Integration Excellence The successful integration of video and audio enhancement components into a unified system represents a significant contribution to the field. The synchronized processing pipeline ensures perfect audio-visual alignment while delivering consistent quality improvements across both modalities. The web-based interface provides user-friendly access to advanced AI capabilities without requiring technical expertise.

6.1.2 Research Contributions

Optimization Innovations The tile-based processing approach developed in this work addresses a critical limitation in video super-resolution systems - GPU memory constraints. This innovation enables deployment of sophisticated models on consumer-grade hardware, democratizing access to high-quality video enhancement capabilities.

Multi-modal Enhancement Framework The integrated approach to video and audio enhancement establishes a new paradigm for comprehensive media quality improvement. Unlike existing solutions that address video or audio enhancement in isolation, our system provides synchronized enhancement of both modalities, resulting in superior overall quality improvements.

Performance Optimization Techniques The implementation of residual blocks within the RVRT architecture and the fine-tuning strategy for the Demucs model demonstrate effective approaches to improving existing state-of-the-art models. These techniques can be applied to other enhancement tasks and architectures.

6.1.3 Practical Impact

Accessibility and Usability The development of an intuitive web interface makes advanced AI enhancement capabilities accessible to non-technical users. The system's ability to run on standard hardware configurations removes barriers to adoption, enabling widespread use across various applications and user groups.

Real-world Applications The system's performance characteristics make it suitable for numerous real-world applications, including content creation, video conferencing, legacy media restoration, and educational content enhancement. The balance between quality improvement and computational efficiency positions the system for practical deployment scenarios.

6.2 Future Work

6.2.1 Model Architecture Improvements

Advanced Transformer Architectures Future work should explore the integration of newer transformer architectures, such as Vision Transformers (ViTs) and Swin Transformers, for video enhancement tasks. These architectures may provide better long-range dependency modeling and improved computational efficiency.

Multi-scale Processing Enhancement Investigating hierarchical multi-scale approaches could further improve the system's ability to handle videos with varying content complexity and resolution requirements. Adaptive tile sizing based on content analysis represents a promising research direction.

Cross-modal Learning Developing models that leverage information from both video and audio streams simultaneously could lead to improved enhancement

quality. Cross-modal attention mechanisms could enable the system to use audio cues to guide video enhancement and vice versa.

6.2.2 Performance and Efficiency Optimizations

Real-time Processing Capabilities Future development should focus on achieving real-time processing speeds for live video applications. This could involve model compression techniques, quantization, and specialized hardware acceleration strategies.

Edge Computing Deployment Exploring deployment on edge computing devices and mobile platforms would expand the system's applicability. This requires investigation of model pruning, knowledge distillation, and efficient neural network architectures.

Cloud-based Scalability Developing a scalable cloud-based architecture would enable processing of large video collections and support for multiple concurrent users. This involves designing efficient load balancing and resource allocation strategies.

6.2.3 Advanced Features and Capabilities

Content-Aware Enhancement Implementing content-aware enhancement algorithms that adapt processing parameters based on video content type (e.g., animation, live-action, sports) could improve enhancement quality and efficiency.

Interactive Quality Control Developing user interfaces that allow fine-grained control over enhancement parameters would enable users to balance quality improvements with processing time based on their specific requirements.

Multi-format Support Expanding support for additional video formats, including HDR content and various codec types, would increase the system's versatility and applicability.

6.2.4 Quality Assessment and Validation

Perceptual Quality Metrics Incorporating advanced perceptual quality metrics and user preference modeling could provide better alignment between objective improvements and subjective quality perception.

Large-scale Evaluation Conducting comprehensive evaluations on larger and more diverse datasets would provide better insights into the system's performance across various scenarios and content types.

User Experience Studies Systematic user experience studies could provide valuable feedback for interface improvements and feature prioritization in future development cycles.

6.2.5 Emerging Technologies Integration

Generative AI Integration Exploring the integration of generative AI techniques for content restoration and enhancement could provide new capabilities for handling severely degraded content.

Multi-modal Foundation Models Investigating the use of large-scale multi-modal foundation models for enhancement tasks could lead to more robust and generalizable solutions.

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