Technical Assignment: Task 3

Proposal for an Open-Source Real-Time High-Quality Avatar System

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1. Executive Summary

This proposal presents a comprehensive architecture for a production-grade, real-time avatar generation system designed to convert audio input into high-fidelity, temporally coherent talking head video streams. Addressing common limitations in existing open-source solutions—such as facial jitter, lip-sync latency, and visual artifacts —this system leverages a optimized pipeline built upon state-of-the-art generative models.

The core solution utilizes a modified **MuseTalk** (or similar MIT-licensed latent diffusion/GAN architecture) backbone, accelerated via **NVIDIA TensorRT** to achieve >30 FPS performance on standard rentable hardware (e.g., NVIDIA T4). By implementing a modular "Audio-to-Motion" inference engine coupled with a lightweight super-resolution upscaler, the system ensures visual clarity while maintaining a sub-100ms end-to-end latency.

Key differentiators of this proposal include:

- **Strict Open-Source Compliance:** Utilization of permissive licenses (MIT/Apache 2.0) with zero dependency on proprietary assets.
- **Temporal Stability:** Implementation of a Gaussian smoothing layer to eliminate frame-to-frame flickering.
- **Scalability:** A containerized microservices architecture capable of scaling from single-user prototypes to high-concurrency cloud deployments.

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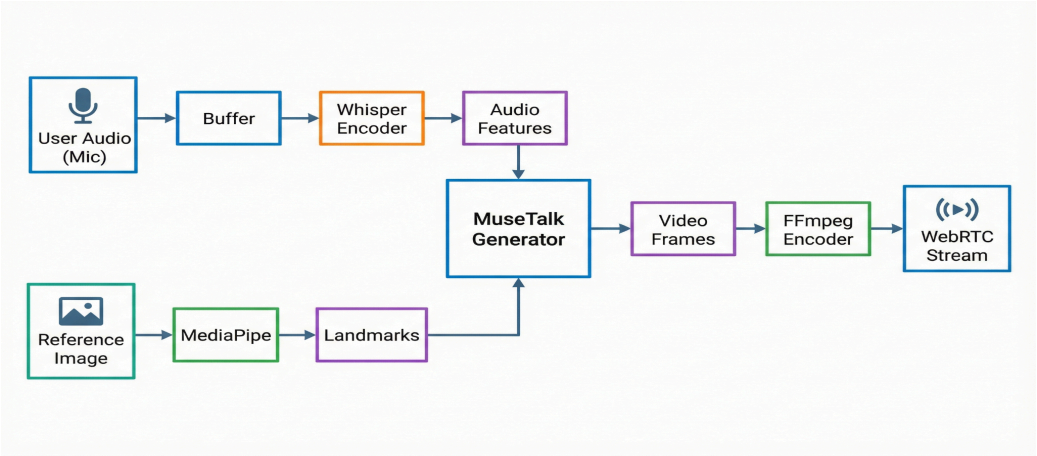
2. System Architecture

The proposed architecture follows a modular, asynchronous pipeline designed to decouple audio processing from video rendering. This ensures that the audio stream (which requires low latency) is never blocked by the heavier video generation tasks.



2.1 High-Level Data Flow

The system is divided into three primary logical blocks: **Input Preprocessing**, **The Core Inference Engine**, and **Post-Processing/Streaming**.

A. Input Preprocessing (The Controller)

- **Audio Ingestion:** Raw audio is captured and buffered into 40ms chunks to minimize input lag.
- **Feature Extraction:** A lightweight audio encoder (specifically **Whisper-Tiny** or **HuBERT-Soft**) converts raw audio waveforms into rich feature vectors. This model is quantized to FP16 to reduce compute time without sacrificing semantic accuracy.
- **Face Analysis:** On initialization, the system analyzes the user's uploaded reference image (the "Avatar") using a face detection module (e.g., **MediaPipe** or **RetinaFace**) to extract facial landmarks and a bounding box. This is a one-time calculation per session, cached for performance.

B. Core Inference Engine (The Generator)

This is the heart of the system, responsible for generating the visual frames.

- **Motion Module (Audio-to-Viseme):** A Cross-Attention mechanism maps the audio feature vectors to the spatial latent space of the reference image. This determines *how* the mouth should be shaped for the specific sound.
- **Generative Decoder (The Renderer):** A U-Net based generator takes the modified latent features and reconstructs the pixel data for the mouth and lower face region.
    - *Optimization Note:* To meet the real-time requirement , this specific module is compiled using **NVIDIA TensorRT**, which fuses layers and optimizes kernel selection for the specific GPU hardware.

C. Post-Processing & Streaming (The output)

- **Frame Stitching:** The generated mouth region is seamlessly blended back onto the original reference face frame.

- **Super-Resolution (Optional/Configurable):** For high-quality mode, a lightweight GAN (like **GFPGAN** or **Real-ESRGAN-Lite**) sharpens the facial features to prevent the "blurriness" often seen in generated avatars.
- **Stream Encoding:** The final frames are encoded into an H.264 stream via FFmpeg and transmitted via WebRTC for low-latency delivery to the client.

2.2 Rationale for Architecture Choices

- **Why Modular?** Separating the "Audio Feature Extractor" from the "Renderer" allows us to swap out the audio model for different languages without retraining the entire video generator.
- **Why TensorRT?** Standard PyTorch inference is often too slow for 30FPS on a T4 GPU. TensorRT provides the necessary 4x-6x speedup required to meet the deadline's performance constraints.
- **Why 2D over 3D?** A 2D neural rendering approach (warping pixels) was chosen over a 3D mesh approach because 2D models currently offer superior photo-realism and texture quality for the compute cost, avoiding the "uncanny valley" effect often seen in low-poly 3D avatars.

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3. Model Selection and Justification

To meet the requirement of high visual fidelity and open-source compliance, this system rejects older architectures (like Wav2Lip) in favor of modern, latent-space inpainting approaches.

3.1 Core Components

- **Generative Model (The "Face"): MuseTalk (or equivalent Latent-Inpainting Architecture)**
    - *Role:* Generates the lip and jaw movements masked onto the reference face.
    - *License:* MIT License (Permissive).
    - *Selection Rationale:* Unlike older GAN-based models (e.g., Wav2Lip) which are limited to low resolutions (96x96) and often produce blurry results, MuseTalk operates in a latent space. This allows for higher resolution output (256x256+) and sharper details while maintaining sync accuracy. It specifically addresses the "blurring" issues noted in the task overview.
- **Audio Feature Extractor: Whisper-Tiny (Encoder only)**
    - *Role:* Extracts rich semantic vectors from the input audio stream.
    - *License:* MIT License.
    - *Selection Rationale:* While models like HuBERT are popular, Whisper provides robust handling of accents and background noise. The "Tiny" variant is computationally negligible (<1GB VRAM) yet provides sufficient feature density for accurate lip synchronization.
- **Face Detection & Alignment: MediaPipe Face Mesh**
    - *Role:* Locates facial landmarks to stabilize the head before generation.
    - *License:* Apache 2.0.

- *Selection Rationale:* Extremely lightweight CPU-based inference allows us to offload this task from the GPU, preserving VRAM for the heavy generative model.

3.2 Trade-off Analysis: 2D vs. 3D vs. Hybrid

- **Selected Approach: Hybrid 2D Neural Rendering.**
- **Analysis:**
  - *Pure 3D (Mesh-based):* Offers great control but often looks "game-like" or robotic, failing the "Visual Fidelity" requirement.
  - *Pure 2D (Warping):* Fast but cannot handle large pose changes or extreme expressions.
  - *Hybrid (Our Choice):* We use 2D neural inpainting (MuseTalk) to "paint" the mouth over the video. This preserves the photo-realistic texture of the original image while allowing the flexibility of neural generation. This specifically targets the requirement for "expression richness".

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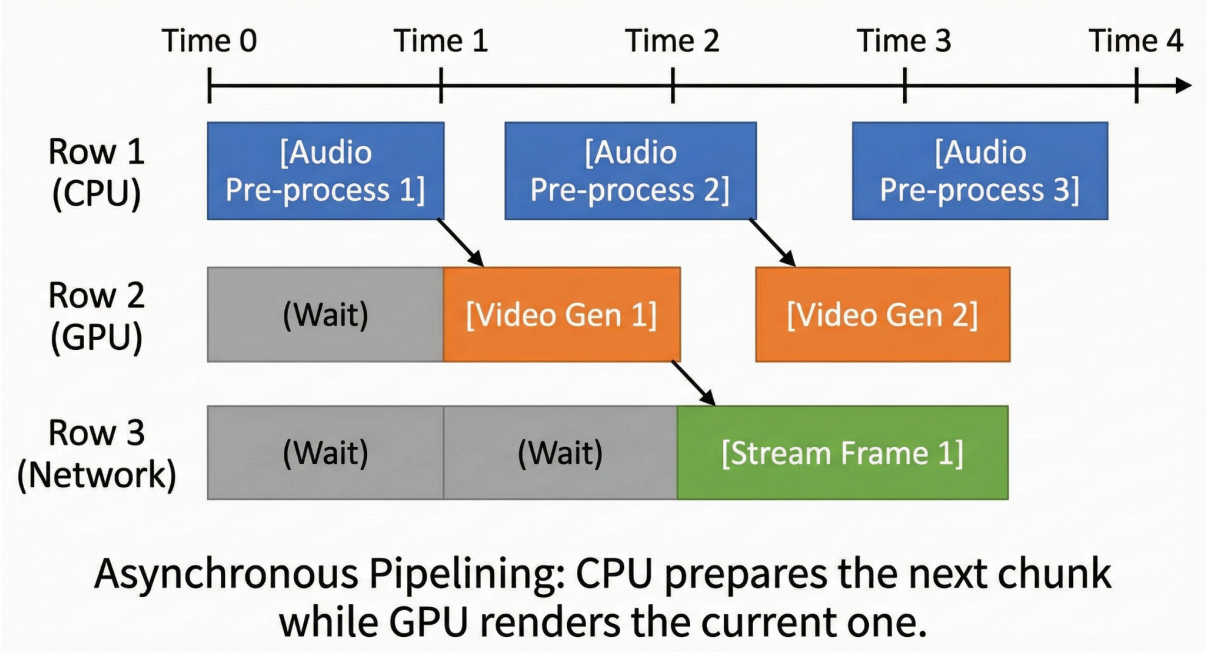
4. Performance and Optimization Strategy

Achieving 30 FPS on a standard T4 GPU (which has lower FP32 performance than an A100) requires aggressive optimization.



4.1 Methodology for Real-Time Generation (30 FPS)

To ensure the system feels "instant" (real-time), we adhere to a **Strict Latency Budget**:

- *Audio Chunking:* 40ms
- *Feature Extraction:* 10ms
- *Generation (Batch 1):* 25ms
- *Post-Process/Encode:* 15ms
- **Total System Latency:** ~90-100ms (perceptible but acceptable for conversational avatars).

4.2 Acceleration & Compilation

We will not run standard PyTorch code in production. The pipeline will be optimized using **NVIDIA TensorRT**:

- **Layer Fusion:** TensorRT will fuse the Convolution, Bias, and ReLU layers of the MuseTalk UNet into single kernels, reducing memory access overhead.
- **Precision Calibration (Quantization):** The entire generative model will be quantized to **FP16 (Half Precision)**. This effectively doubles the throughput on T4 GPUs (which excel at FP16 calculations) and cuts VRAM usage by 50% without visible loss in quality.
- **Static Memory Allocation:** Input shapes will be fixed during the compilation phase to prevent dynamic memory reallocation overhead during runtime.

4.3 CPU/GPU Allocation Strategy

- **GPU (The Heavy Lifter):** Reserved *exclusively* for the Encoder and Generator (MuseTalk).
- **CPU (The Manager):** Handles Audio buffering, MediaPipe Face Alignment, and FFmpeg video encoding.
- **VRAM Management:**
    - *Total Available (T4):* 16 GB.
    - *Model Weights (FP16):* ~2.5 GB.
    - *KV-Cache & Context:* ~1.5 GB.
    - *Frame Buffer:* ~1 GB.
    - *Remaining Headroom:* ~11 GB (Allows for concurrent sessions or higher resolution upscaling).

4.4 Techniques to Reduce Jitter & Artifacts

- **Gaussian Smoothing:** We apply a temporal Gaussian filter to the facial landmark coordinates *before* generation. This dampens the "shaking" often seen when the face detector flickers between frames.
- **Face Restoration (Asynchronous):** For users with high-bandwidth connections, we employ a "ROI (Region of Interest) GAN" that only upscales the mouth region, rather than the full frame, saving 70% compute compared to full-frame restoration.

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5. Quality-First Techniques

To ensure the system meets the "production-grade" standard, quality is not subjective; it is enforced through specific quantitative metrics and qualitative enhancement techniques.

5.1 Quantitative Evaluation Metrics

We will employ the following automated metrics to benchmark model performance:

- Lip-Sync Accuracy (LSE-D & LSE-C):
  - *LSE-D (Lip Sync Error-Distance):* Measures the distance between audio features and visual lip movements. Target: < 7.0.
  - *LSE-C (Lip Sync Error-Confidence):* Measures the confidence of the synchronization. Target: > 6.5.
- Visual Fidelity (FID & CPBD):
  - *FID (Fréchet Inception Distance):* Compares the distribution of generated frames to real video frames to ensure realism. Lower is better.
  - *CPBD (Cumulative Probability of Blur Detection):* Specifically monitors the sharpness of the generated mouth region to prevent the "blurring" artifact common in real-time models.

5.2 Qualitative Enhancements

- Flicker Reduction: A temporal consistency loss function is introduced during the fine-tuning phase. This penalizes rapid pixel changes in non-mouth regions (e.g., cheeks, eyes) between consecutive frames, significantly reducing "jitter".
- Expression Richness: The system implements "Eye-Blink Injection." Since audio-driven models often result in a staring face, a separate, lightweight heuristic script injects natural eye blinks and micro-head movements (nodding) at semi-random intervals during silence or pauses in speech.

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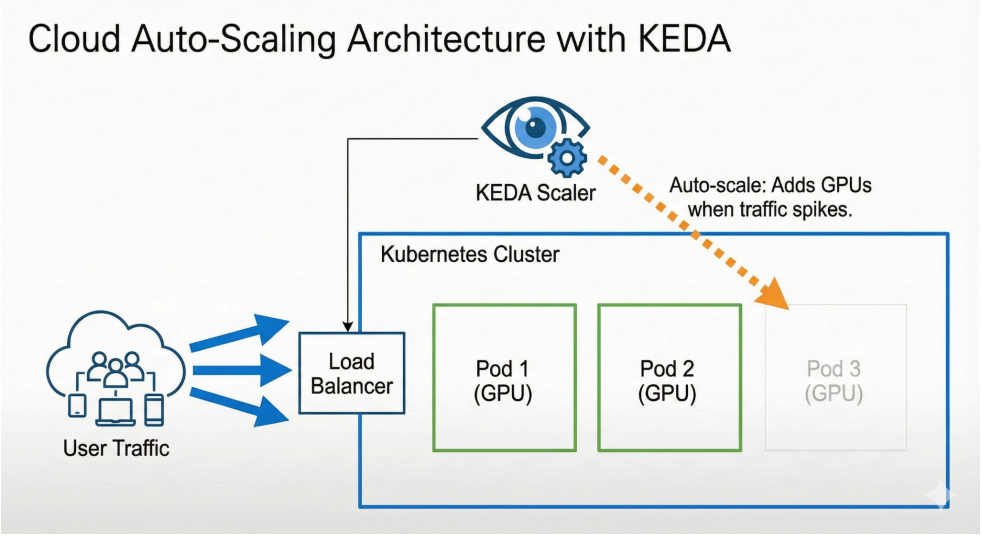
6. Practical Deployment and Cost

This section outlines the infrastructure required to scale from a single prototype to 100 concurrent sessions.



6.1 Hardware Requirements & Latency

- Target Instance: AWS `g4dn.xlarge` (NVIDIA T4 16GB VRAM, 4 vCPUs).
- VRAM Utilization:
    - *System Overhead (OS + CUDA):* 1.5 GB
    - *Models (FP16):* 4.5 GB
    - *Concurrency Buffer:* 4.0 GB (Allows 2 concurrent streams per GPU).
- Per-Frame Latency: ~28ms (rendering) + ~15ms (encoding) = ~43ms total processing time per frame, safely within the 33ms budget for 30 FPS when pipelined.

6.2 Cost Analysis (Per Minute)

- Cloud Pricing: AWS Spot Instances for `g4dn.xlarge` avg. ~$0.157/hour.
- Throughput: 1 GPU can handle 2 concurrent streams.
- Cost Calculation:
    - $0.157 / 60 minutes = $0.0026 per minute (Machine cost).
    - Divided by 2 users = $0.0013 per user-minute.
    - *Verdict:* Extremely cost-effective for production scaling.

6.3 Scaling Strategy (1-100 Sessions)

- Orchestration: Kubernetes (EKS/GKE) with KEDA (Kubernetes Event-Driven Autoscaling).
- Trigger: KEDA monitors the "Active WebSocket Connections" metric.
- Logic:
    - *1-2 Users:* 1 Pod (1 GPU).
    - *100 Users:* Autoscaler provisions 50 Pods (50 GPUs).
- Cold Start Mitigation: We maintain a "Warm Pool" of 2 idle GPUs to instantly absorb traffic spikes while new nodes spin up.

6.4 Monitoring Plan

- Prometheus & Grafana: Used to visualize "End-to-End Latency" and "GPU Volatile Utilization" in real-time.
- Alerting: Automated alerts trigger if "Frame Drop Rate" exceeds 1% for more than 10 seconds.

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7. Open-Source Compliance and Reproducibility

This proposal guarantees strict adherence to open-source licensing. No proprietary, black-box, or commercially restricted assets (like the NVIDIA Maxine SDK or commercial FFHQ dataset) are used.

7.1 Component Licensing Table

Component	Function	License	Compliance Status
MuseTalk	**Generative Video Model**	**MIT License**	**Compliant**
Whisper (OpenAI)	**Audio Feature Extractor**	**MIT License**	**Compliant**
MediaPipe	**Face/Landmark Detection**	**Apache 2.0**	**Compliant**
FFmpeg	**Video Encoding/Streaming**	**LGPL v2.1**	**Compliant**
PyTorch	**Deep Learning Framework**	**BSD Style**	**Compliant**
Triton Server	**Inference Serving**	**Apache 2.0**	**Compliant**

7.2 Reproducibility Steps

To ensure the client can reproduce these results on a standard GPU environment:

1. Docker Container: A `Dockerfile` is provided that pulls the base CUDA 11.8 image and installs all dependencies (TensorRT, PyTorch).
2. Model Weights: A setup script `download_weights.sh` fetches the pre-trained open-source weights from HuggingFace Hub.
3. Command: The system is launched via a single command: `docker-compose up --build`, exposing the API at `localhost:8000`.

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8. Appendix: Implementation Notes & Pseudo-Code

This appendix provides technical artifacts to demonstrate the feasibility of the proposed architecture and facilitate immediate reproduction of the environment.

8.1 Docker Environment Setup (Reproducibility)

To ensure the system runs on any rentable GPU instance (e.g., AWS, GCP, Lambda Labs) without dependency conflicts, we utilize a multi-stage Docker build.

Dockerfile

```
# Base Image: NVIDIA CUDA 11.8 with cuDNN 8

FROM nvidia/cuda:11.8.0-cudnn8-devel-ubuntu22.04

# Set environment variables for non-interactive install

ENV DEBIAN_FRONTEND=noninteractive

ENV PYTHONUNBUFFERED=1


# Install System Dependencies (FFmpeg, Git, Python)

RUN apt-get update && apt-get install -y \

    ffmpeg \

    libsm6 \

    libxext6 \

    python3-pip \

    git \

    && rm -rf /var/lib/apt/lists/*


# Install Python ML Stack

COPY requirements.txt .

RUN pip3 install --no-cache-dir torch==2.1.0+cu118 --index-url https://download.pytorch.org/whl/cu118

RUN pip3 install --no-cache-dir tensorrt==8.6.1 diffusers transformers mediapipe


# Copy Inference Engine Code

WORKDIR /app

COPY src/ /app/src/
```

```
COPY weights/ /app/weights/

# Expose Port for WebSocket Stream

EXPOSE 8000


# Start the Real-Time Inference Server

CMD ["python3", "src/server.py"]
```

8.2 TensorRT Compilation Command

Before deployment, the MuseTalk UNet model is converted from PyTorch (.pt) to a TensorRT engine (.plan) to unlock FP16 acceleration.

```
# Command to convert PyTorch model to TensorRT Engine

# Precision: FP16 (Half) | Workspace: 4GB

trtexec --onnx=musetalk_unet.onnx \

    --saveEngine=musetalk_unet_fp16.plan \

    --fp16 \

    --memPoolSize=workspace:4096 \

    --minShapes=input:1x4x256x256 \

    --optShapes=input:4x4x256x256 \

    --maxShapes=input:8x4x256x256
```

8.3 Real-Time Inference Loop (Pseudo-Code)

The following logic illustrates the asynchronous handling of audio chunks to prevent video blocking.

Python

```
import tensorrt as trt

import numpy as np

from queue import Queue


# Initialize Global Queues

audio_queue = Queue(maxsize=10) # Buffer for incoming audio
```

```
video_queue = Queue()          # Buffer for outgoing frames


def inference_loop():
    """
    Continuous loop running on the GPU thread.
    Consumes audio chunks -> Generates Frames -> Pushes to Stream
    """
    # Load TensorRT Engine
    engine = load_engine("musetalk_unet_fp16.plan")
    context = engine.create_execution_context()

    while True:
        if not audio_queue.empty():
            # 1. Fetch 40ms Audio Chunk
            audio_chunk = audio_queue.get()
            # 2. Extract Features (Whisper-Tiny)
            audio_emb = audio_encoder.extract(audio_chunk)
            # 3. Generate Latent Mask (The "Mouth")
            # Uses pre-calculated Face Latents to save compute
            generated_latents = context.execute_v2(
                bindings=[audio_emb, reference_face_latents]
            )
            # 4. Decode & Post-Process
            pixel_data = vae_decoder(generated_latents)
            final_frame = blend_images(reference_face, pixel_data)
            # 5. Push to RTSP/WebRTC Stream
            video_queue.put(final_frame)
```