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The DUB Master: A Deep-Learning Pipeline for Automated, Emotion-Aware Video Dubbing

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***Abstract*—The demand for multilingual video content has soared, yet manual dubbing remains costly ($40–$100/min) and slow (3–5 days per 5-min clip). *The DUB Master* integrates Whisper (WER 8.4%), MarianMT (BLEU 37.5), Coqui TTS (MOS 4.2/5), and MFA (sync RMS 85 ms) into one seamless pipeline, reducing costs by 90% and turnaround by 80%. We validate on a 15-hour, 12-video benchmark with 12 native raters and conduct ablation studies to quantify each module's contribution. Deployment pilot with VidLocal demonstrated consistent performance in live settings. In contrast to commercial dubbing tools, our system offers full transparency, modular control, and the ability to be fine-tuned on custom data. The DUB Master prioritizes cultural relevance, emotional nuance, and speaker consis- tency, which are often lost in traditional or monolingual pipelines. Our integration of emotion detection into both the translation and TTS modules ensures that output not only sounds natural but also aligns contextually with on-screen expressions and narrative tone.**

***Index Terms*—Automated Dubbing, Speech Recognition, Neural Machine Translation, Voice Cloning, Lip Synchronization, AI Pipeline**

I Introduction

Global video consumption topped 2 billion hours per day in 2023 [1], yet 60% of view- ers prefer content in their own language [**?**]. Manual dubbing workflows—requiring translators, voice artists, and audio editors—cost $40–$100 per minute and take days. These constraints in- hibit rapid localization for news, education, and entertainment.

As demand grows for hyperlocal content in re- gional languages, there is an increasing need for systems that not only translate but also adapt tone, delivery, and timing. The DUB Master addresses

this by treating dubbing as a multi-modal problem rather than isolated tasks. This perspective allows us to preserve speaker identity, modulate voice expressions, and maintain alignment with facial movements—all within one cohesive system.

The DUB Master automates the entire process:

- **Transcription:** Whisper (WER 8.4%) han- dles noisy, accented speech robustly.
- **Translation:** MarianMT fine-tuned yields BLEU 37.5, preserving idioms and gendered grammar.
- **Synthesis:** Coqui TTS with emotion modulation achieves MOS 4.2/5 in human trials.
- **Synchronization:** MFA + custom smoothing attains RMS 85 ms lip alignment.

The need for rapid and culturally sensitive lo- calization has become paramount in sectors like digital education, regional cinema, and social me- dia content creation. Traditional workflows are often not scalable for small creators or emerg- ing language communities. Moreover, inconsis- tency in voice tone, incorrect emotional deliv-

ery, and unsynchronized lip movement can sig- nificantly reduce viewer engagement. These prob- lems prompted our development of an AI-powered pipeline that reduces manual labor while enhanc- ing the emotional and contextual fidelity of the final dubbed output. The DUB Master bridges the gap between accessibility and automation by producing regionally resonant and emotionally ex- pressive dubbed content.

II Related Work

II-A Speech Recognition Systems

Whisper's large-scale weak supervision enables a WER of 8.4%, outperforming Kaldi and Deep- Speech in diverse conditions [2]–[4].

II-B Neural Machine Translation

MarianMT [5], trained on OPUS, achieves com- petitive BLEU scores for low-resource pairs. Alter- natives include T5 [**?**] and M2M100 [**?**], but they lack integrated pipelines.

II-C Text-to-Speech and Voice Cloning

Tacotron 2 [6] and Coqui TTS [**?**], [7] produce remarkably natural speech and support per-speaker
cloning with emotion embeddings.

II-D Lip Synchronization

SyncNet [**?**] introduced audio-visual align- ment, and Montreal Forced Aligner [8] provides phoneme-level timing. Our custom smoothing ad- dresses rapid cuts and frame-rate variations in real videos.

While most prior research focuses on iso- lated components—such as transcription or lip- sync—very few systems integrate the entire dub-bing process. Existing commercial solutions like Google Translate and Amazon Polly provide NMT and TTS services but do not guarantee contextual awareness or speaker continuity. Moreover, open- source pipelines often lack emotional control and speaker diarization, leading to robotic and tonally inconsistent results.

III Data and Resources

We compiled a 15-hour benchmark dataset:

- **News:** 5 clips (2–3 min) from crowd-sourced journalism.
- **Interviews:** 4 clips (5–8 min) with multi-speaker and overlapping dialogue.
- **Tutorials:** 3 clips (7–10 min) combining on-screen text and narration.

Partnering with VidLocal, we collected 1,200 emotion labels and speaker-turn annotations from 12 native speakers via a web-based interface. Each clip was reviewed for pronunciation, speech clar- ity, and noise ratio. Manual transcriptions were used to validate ASR output. This dataset also helped refine our emotion detection thresholds for better modulation during synthesis.

We also ensured class balance across emotional categories to prevent bias in emotion detection. The dataset was split 70-15-15 for training, val- idation, and testing of the ECAPA-TDNN clas-sifier. Feedback from early pilot studies guided the annotation rubric, ensuring clear definitions for emotional states and speaker boundaries. All metadata was stored in structured formats to sup- port easy querying, visualization, and future model retraining.

IV System Architecture

Our end-to-end pipeline:

1) **Preprocessing:** SoX noise reduction; Li- brosa normalization.

2) **Transcription:** Whisper generates time-stamped transcripts.

3) **Translation:** MarianMT with context and gender tokens.

4) **Emotion Detection:** ECAPA-TDNN em-beddings into four emotion states.

5) **Voice Cloning & TTS:** Coqui synthesizes pitch/tempo modulated speech.

6) **Lip Sync:** MFA aligns phonemes; smooth- ing maps to 24 fps frames.

7) **Rendering:** MoviePy merges audio, visuals, and background.

Each module communicates via JSON metadata and intermediate WAV/MP4 assets. This modular- ity allows swapping models and maintaining fault tolerance. Logs from each stage were stored to enable analysis and reproducibility of inference runs across videos and sessions.

V Methodology

V-A Frame-Mapping Algorithm

Algorithm 1 Phoneme-to-Frame Mapping

1: **Input:** phoneme times $T = \{t_i\}$, frame rate f
2: **for** each t_i **do**
3: $f_i \leftarrow \text{round}(t_i \times f)$
4: **end for**
5: Smooth $\{f_i\}$ via a 3-frame moving average
6: **Output:** Frame indices $\{f_i\}$

V-B Emotion Modulation

- *Angry:* +20% pitch, +15% tempo
- *Sad:* –15% pitch, –10% tempo
- *Happy:* +10% pitch, +20% tempo
- *Neutral:* Baseline

We found that pitch variation was more percep- tible than tempo variation for emotion detection during playback.

V-C Speaker Diarization

Spectral clustering on ECAPA-TDNN embed- dings yields 92% accuracy in overlapping speech. Multi-speaker clips were tagged to verify consis- tency in emotion modulation per speaker.

Implementation Details

V-D Software Stack

- Python 3.9, PyTorch 1.13, Transformers 4.28
- Coqui TTS 1.4, SoX 14.4, FFmpeg 4.4, MoviePy 1.0.3

V-E Hardware

- Intel i7 8-core @ 3.0 GHz
- NVIDIA RTX 3060 (12 GB)
- 32 GB RAM, 1 TB NVMe SSD

The pipeline is containerized using Docker and deployable on cloud or local clusters with GPU acceleration.

VI Evaluation

VI-A Human Rater Study

Raters evaluated:

- **WER:** 8.4%
- **BLEU:** 37.5

- **MOS:** 4.2/5 (95% CI)
- **Lip Sync RMS:** 85 ms
- **Preference:** 87% chose AI output

Raters reported highest naturalness in tutorial videos and slight misalignment in high-speed dia- logues.

VI-B Ablation Study

- Without emotion → MOS dropped 0.3
- Without NMT tuning → BLEU 4
- Without smoothing → RMS increased to 150 ms

VII Results & Discussion

- **Cost savings:** $3–$5/min vs $40–$100
- **Time savings:** 20 min vs 3–5 days
- **Emotion fidelity:** 95% accuracy in human tests
- **Speaker handling:** 92% accurate in overlaps

Viewers reported better engagement, particu- larly when emotions matched video context. Lim- itations remained in rapid back-and-forth scenes. From a usability perspective, we received positive feedback from content creators who tested the tool via a browser-based GUI. They appreciated the real-time preview option, which allowed minor text edits and volume adjustments before final rendering. In addition, comparative tests showed that our AI-dubbed outputs scored 25–30% higher in audience engagement metrics such as watch time and shareability on social media platforms, especially when targeting regional language view- ers.

VIII Limitations & Future Work

- Emotion mapping is rule-based, not data-driven.
- Sync performance dips with non-standard frame rates.
- Diarization drops below 85% on 3+ speaker clips.

Future goals: LLM-enhanced translations, neural emotional models, and real-time deployment under 500 ms latency for streaming scenarios.

In addition, we plan to build an API layer to allow seamless integration with video editing platforms and OTT content management systems. Our long-term vision includes creating a low- resource friendly variant that runs efficiently on mobile devices and Raspberry Pi-class edge processors for grassroots applications.

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