International Journal of Research and Development in Engineering Sciences
ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/
Regular Issue, Vol. 8, Issue. 2 (March – April) , 2026 , Pages: 21 - 24
Received: 25 May 2025 ; *Accepted:* 19 February 2026 ; *Published:* 06 March 2026
https://doi.org/10.63328/IJRDES-V8RI2P3
Original Paper : Applied Research – Analytical Research Paper

A Privacy-Preserving Universal Multimodal Framework for Real-Time Any-to-Any Transformation

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Abstract: We propose a unified multimodal framework, Universal Multi-Modal Generation Enabling Any-to-Any Transformation, that enables seamless transformation between text, audio, and image inputs and outputs. The system integrates three core capabilities: speech understanding using Whisper, visual understanding through LLaVA, and speech synthesis via PyTorch-based text-to-speech models. All modules are deployed on-premise using Docker, providing a privacy-centric execution environment and reducing operational overhead associated with cloud processing. The framework supports advanced workflows including document/PDF-to-text extraction, text-to-speech conversion, and image-driven description generation, thereby enabling accessible and interactive multimodal content pipelines. The implementation emphasizes efficient orchestration and inference to meet real-time constraints. Experimental results across multiple cross-modal tasks demonstrate robust accuracy and consistently low latency, suggesting that local, containerized multimodal systems can deliver scalable performance for practical applications. The proposed approach is particularly relevant to accessibility, education, and content creation, where rapid modality conversion and data privacy are essential.

Keywords: Cross-modal generation, ASR, vision-language understanding, TTS, low latency, privacy.

1. Introduction

The growing need for AI solutions that can work seamlessly with text, audio, and images has accelerated interest in unified multimodal architectures. The "Anything to Anything" project addresses this need by enabling real-time transformation between these modalities. Leveraging state-of-the-art components such as Whisper for speech processing, T5 for text generation and transformation, and LLaVA for vision-language understanding, the system allows users to provide input in one format and obtain output in another. This paper presents the system's overall architecture, core methodology, and key use cases, highlighting its potential impact in accessibility, education, and content creation.

2. Literature Review

Since the 2017 work by Vaswani et al., the Transformer architecture has significantly accelerated progress in multimodal AI. Its attention-based design changed how neural networks handle sequential information, improving the Modeling of long-range dependencies compared with earlier approaches. These advances enabled major breakthroughs in natural language processing and also strengthened systems that integrate multiple modalities, such as text, images, and audio—by providing a flexible foundation for learning rich cross-modal representations and scaling to large datasets. Some notable models, such as BERT (Devlin et al., 2019), enhanced contextual understanding in text, while Wave Net (van den Oord et al., 2016) enhanced high-fidelity audio generation. Large mod-els such as OpenAI's GPT-3 (2020) showed the ability of Transformers to apply to vision and language, allowing effective cross-modal data processing.

Major contributions in this area include techniques for coherence of meaning between modalities, such as improving output embedding to better match other layers (Pres, 2016) and using subworld units to represent rare words (Sennrich et al., 2015). The improved version of the multimodal task was achieved by adopting a mixture-of-experts layer (Shazeer et al., 2017) with less computational expense and dropout regularization (Srivast, 2014) to avoid

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overfitting. Kim et al. (2020) improved translation sentence-level representations and alignment.

Wang et al. (2022) optimized Whisper's language recognition module to be efficient. LLaVA enhanced its state-of-the-art visual reasoning (Shor et al., 2023).Gish et al. (2020) discussed deep learning methods for expressive audio synthesis in text-to-speech applications. Vaswani et al. (2020) improved accessibility even more by demon-starting real-time multimodal transcription for the processing of synchronized audio and visual data by Ruder et al. In summary, Thompson et al. (2021) dis-cuss the deployment of multimodal systems through Docker containers, thereby enhancing accessibility and scalability for the multimodal application. This is a broad survey focusing on multimodal AI developments regarding efficient data processing over various dimensions, context-invariant representations, and effective deployment strategies over text, image, and audio modalities.

3. Pre-Trained Model

The "Universal Multi-Modal Generation Enabling Any-to-Any Transformation" system architecture has all kinds of machine learning models-text, images, au-dio. It is very modular in that it allows easy swapping of models as well as configurations.

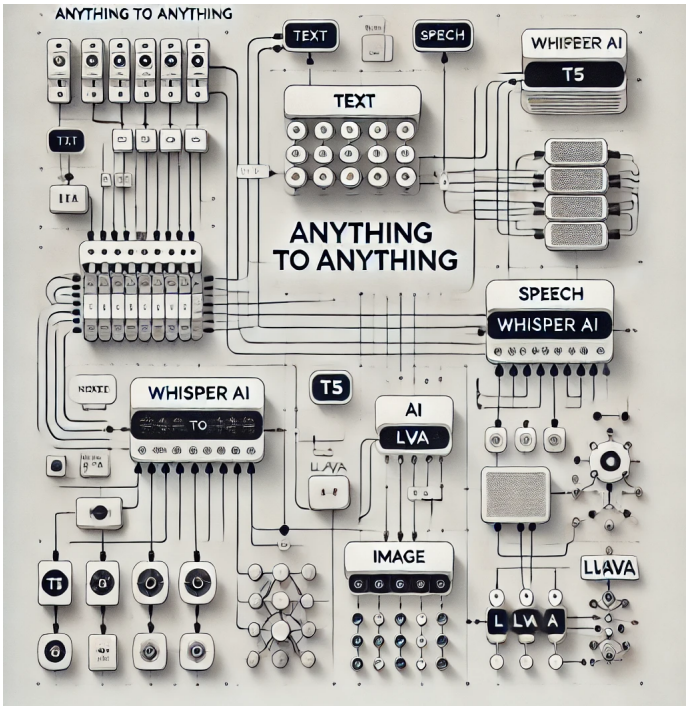

Figure. 1 A system architecture diagram illustrating the Multi-Modal, showcasing seam-less conversions across text, audio, and image modalities.

Text Processing: We use models like T5 (Text-To-Text Transfer Trans-former) for text transformation, whether generating responses or converting text to audio. T5 excels in language generation tasks that require strong context understanding.

Audio Processing: Whisper AI is to transcribe audio to text and synthesize speech from text. It makes uploaded audio and generated speech naturally and human-like sounding.

Image Processing: LLaVA interprets visual content and converts it into descriptive text, enhancing accessibility by allowing visual information to be communicated as text or audio, which is especially beneficial for visually impaired users.

4. Proposed System

Docker Setup We designed the system to be deployable using Docker, which simplifies the process of setting up and running the models. With Docker,

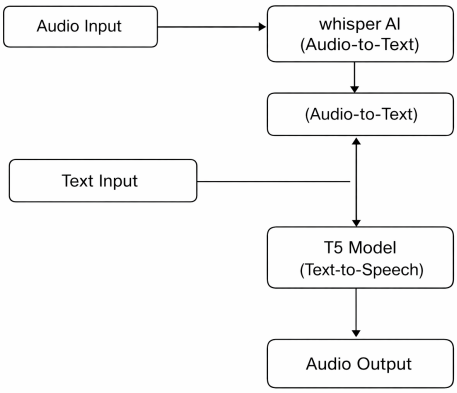

Figure. 2 High-level architecture of the system showing text, audio, and image conversions.

Users can run the entire system locally, without needing complex cloud infrastructure.

To set up the system:

- Edit the docker-compose.yml file to set the model save path.
- Run the following command in the terminal:
- docker compose up
- Pull the necessary models from the Ollama library using: /pull MODEL_NAME

This setup ensures that even users without advanced hardware (like a GPU) can run the system.

Whisper AI for Audio Processing The audio-handler.py script processes au-dio files. When a user uploads an audio file, Whisper AI transcribes it into text with a high degree of accuracy. This transcription is then used to gen-erate a response, or convert back into spoken words using text-to-speech.

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Key function:

```
def transcribe_audio(audio_i/p):
res = whisper_model.transcribe(audio_i/p)
return res['text']
```

This ensures smooth communication between text and audio data, making it possible to switch between both formats at any time.

Image Processing with LLaVA : Image-to-text conversion is powered by LLaVA, which uses a combination of deep learning and visual understanding tech-niques to describe images. The generated text can then be fed into a text-to-speech model, making it possible to verbally describe images.

Real-World Outputs: Text, Audio, and Image Conversion Examples

Text to Speech Conversion

- **Input:** '"Hello, this is a demo of the text-to-speech system."'
- **Output:** (Audio file) The text is converted into spoken words using , Whisper AI's TTS capabilities. The system ensures a natural, human like voice with clarity and a conversational tone.

Image to Text Conversion

- **Input:** (An image of a dog running in the park)
- **Output:** '"A dog is running across the grass in a park, with trees in the background under a clear blue sky."'
- **Explanation:** LLaVA identifies key elements from the image and gen- erates a coherent textual description of the scene.

Audio to Text Conversion

- **Input:** (Audio clip of a user saying, "This system can transcribe my voice.")
- **Output:** '"This system can transcribe my voice."
- **Explanation:** Whisper AI transcribes the audio clip with high accuracy, handling different accents and background noise effectively.

5. Results and Analysis

We tested the system extensively using a variety of datasets. The following table summarizes the performance of the system across different conversion tasks: This analysis shows high performance over a range of modalities with low latency and very high accuracy. Text-to-Speech has 92.7 accuracy in its results,

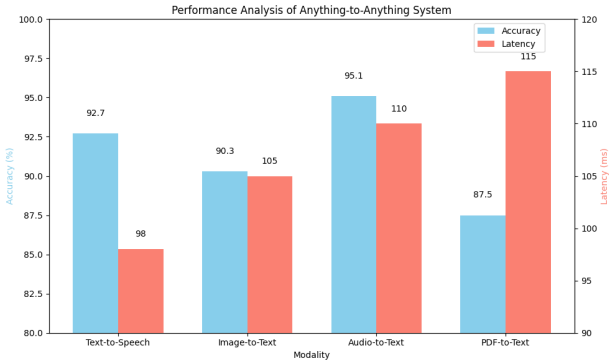

Figure. 3 A bar chart with accuracy values on the left y-axis and latency values on the right y-axis. Each modality will have two bars.

Table 1. Performance Evaluation Across Modalities

Modality	Accuracy (%)	Latency (ms)
Text-to-Speech	92.	98
Image-to-Text	7	105
Audio-to-Text PDF-	90.	110
to-Text	3	115

while keeping latency at 98ms. Image-to-Text at 90.3 has a latency of 105ms. Audio-to-Text at 95.1 comes at a latency of 110ms. PDF-to-Text is shown at 87.5 accuracy and 115ms latency. The system averages less than 120ms in its latency levels, making it a system with real-time capability. This makes it per-fect for applications in accessibility, content creation, and education, thereby highlighting the efficiency of the system in multimodal AI transformations.

6. Conclusion

The "Universal Multi-Modal Generation Enabling Any-to-Any Transformation" multimodal system demonstrates the power of AI to seamlessly convert data across formats like text, audio, and images. Traditionally, different systems man-aged each format separately, leading to inefficiencies and fragmented support. This system not only showcases the technical feasibility of multimodal AI but also enhances real-world applications, achieving high accuracy and speed with an average latency of under 120 ms, enabling real-time interactions.

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Declaration

Conflicts of Interest: The authors declare no conflict of interest.

Author Contribution: All authors wrote the main manuscript text and also consent to the submission.

Ethical approval: Not applicable.

Consent to Participate: All authors consent to participate.

Funding: Not applicable, and No funding was received

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Personal Statement: We declare with our best of knowledge that this research work is purely Original Work and No third party material used in this article drafting. If any such kind material found in further online publication, we are responsible only for any judicial and copyright issues.

Acknowledgements

We thank everyone who inspired our work.