

# RESEARCH ON TRANSFORMER MODEL AND ATTENTION MECHANISM FOR MONAURAL AUDIO-VISUAL SPEECH SEPARATION

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## What ?

We propose a Transformer-based Audio-Visual Speech Separation framework designed to isolate target speech:

- **Transformer Backbone:** Replaces traditional CNNs to capture global context and long-term audio dependencies.
- **Cross-Modal Attention:** A novel fusion mechanism to dynamically align lip motion and facial attributes with the audio stream.

## Why ?

- **The Challenge:** Audio-only models struggle in noisy, multi-talker environments.
- **The Gap:** Current CNN-based methods struggle with long sequence modeling.
- **The Solution:** Visual cues (faces/lips) provide essential priors to guide separation when audio is corrupted.
- **Applications:** Critical for improving hearing aids and video conferencing quality.

## Overview

Visual Stream Encoder

Audio Stream Encoder

Cross-Modal Attention

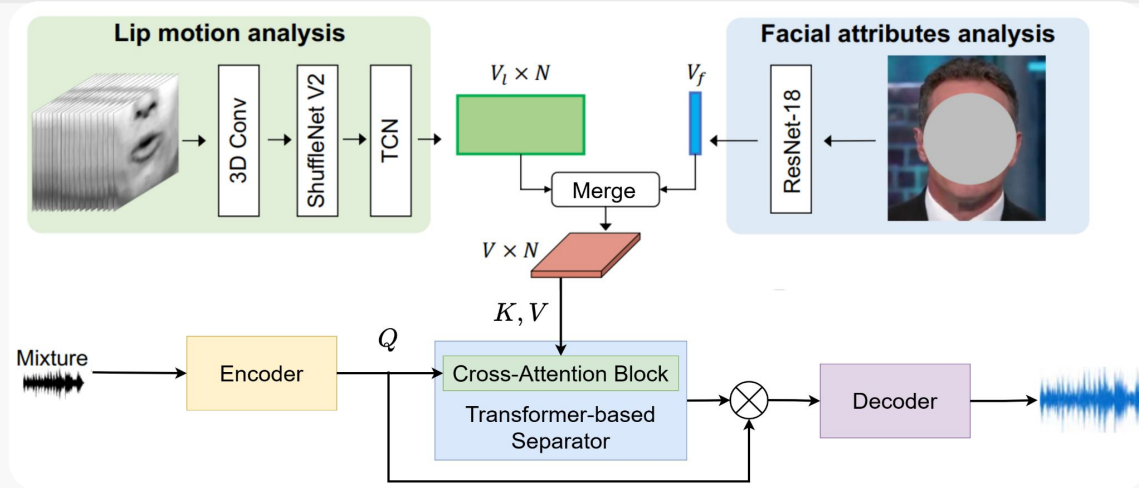


Figure 1. Proposed System Architecture.

## Description

### 1. Visual Stream Encoder

- **Lip Motion Branch:** Extracts temporal features using 3D Conv, ShuffleNet V2, & TCN.
- **Facial Attributes Branch:** Encodes static speaker identity via ResNet-18.
- **Output:** Generates visual embeddings to guide the audio separation.

### 2. Audio Stream Encoder

- **Transformer Backbone:** Captures global context & long-term dependencies, overcoming CNN limits.
- **Semantic Encoding:** Encodes noisy mixture into high-level semantic features.
- **Attention Role:** Generates the Query to retrieve visual cues (Key, Value).

### 3. Cross-Modal Attention

- **Method:** Cross-Attention aligns Audio (Q) with Visual (K, V).
- **Function:** Dynamically filters noise using visual cues.
- **Result:** Robust separation even with occlusions.

## Multi-task learning

- **Joint Learning:** Simultaneously optimizes for Speech Separation and Face-Voice Matching.
- **Embedding Alignment:** Forces separated voice and input face into a shared space to ensure identity consistency
- **Composite Loss:** Minimizes a total loss combining mask prediction and cross-modal constraints.

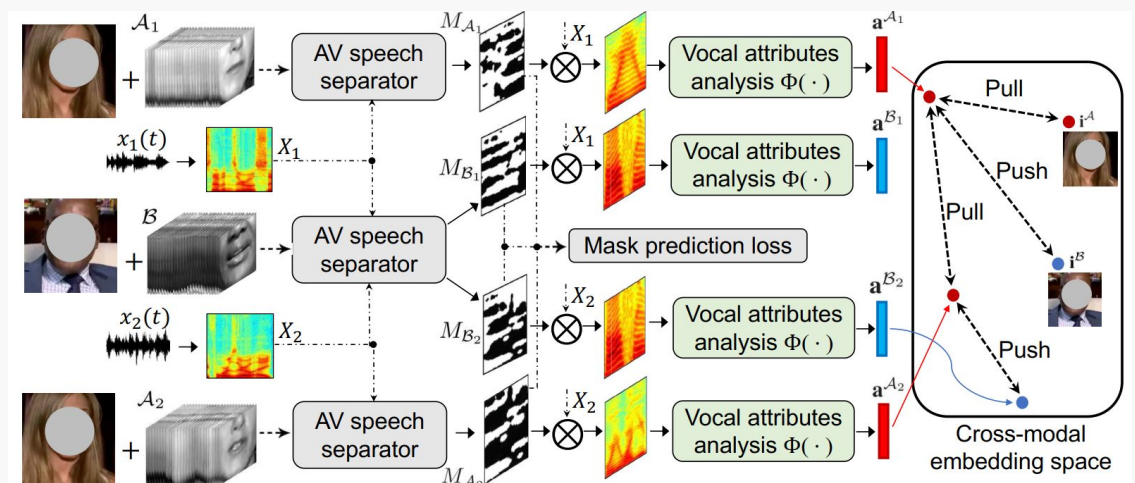


Figure 2. Multi-task learning framework