Multimodal AI Architecture for Real-Time Deepfake Detection in Digital Forensics

Riddhi Mhatre[1], Cynthia Shinde[2]
[1]*Student, Sonopant Dandekar Arts, V.S. Apte Commerce and M.H. Mehta Science College*
[2]*Assistant Professor, Sonopant Dandekar Arts, V.S. Apte Commerce and M.H. Mehta Science College*

***Abstract*—Deepfake technology has evolved into a sophisticated threat to digital trust, enabling identity fraud, misinformation, and the manipulation of digital evidence. While existing detection methods primarily focus on single-modality analysis (either image or audio), these systems struggle against advanced forgeries and suffer from high latency, rendering them ineffective for live forensic applications. This paper presents a novel Real-Time Multimodal Deepfake Detection Architecture designed specifically for digital forensics. The proposed system processes continuous data streams by fusing visual spatial-temporal features with audio spectral analysis. Utilizing a lightweight Convolutional Neural Network (CNN) for frame-level visual extraction and a Recurrent Neural Network (RNN) for audio processing, the architecture employs a cross-modal attention mechanism to detect micro-inconsistencies, such as lip-sync misalignment. Furthermore, the system outputs an Explainable Tamper Heatmap and a Confidence Score, providing forensic investigators with interpretable evidence. Evaluated against the FaceForensics++ and Deepfake Detection Challenge (DFDC) datasets, the proposed multimodal framework demonstrates a significant improvement in detection accuracy while maintaining low-latency inference suitable for real-time deployment.**

***Index Terms*—Deepfake Detection, Digital Forensics, Multimodal Artificial Intelligence, Cross-Modal Fusion, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Lip-Sync Anomaly, Real-Time Inference.**

I. INTRODUCTION

The rapid evolution of Generative Artificial Intelligence (AI) has initiated a paradigm shift in multimedia synthesis, giving rise to hyper-realistic manipulated media commonly known as "deepfakes." Driven by advancements in Generative Adversarial Networks (GANs) and diffusion models, it is now alarmingly simple to synthesize human faces, clone voices, and alter facial expressions with unprecedented realism. While originally confined to entertainment, the malicious deployment of deepfake technology has escalated into a critical cybersecurity threat. Today, synthetic media is actively weaponized for identity fraud, political misinformation, financial extortion, and the fabrication of digital evidence, fundamentally destabilizing digital trust and challenging modern legal frameworks.

II. LITERATURE REVIEW

Early deepfake detection research primarily relied on single-modality frameworks, treating visual and auditory forgeries as isolated problems. Visual-centric models utilize Convolutional Neural Networks (CNNs), such as XceptionNet and EfficientNet, to identify spatial anomalies like unnatural blending and resolution inconsistencies [1]. Conversely, audio-centric approaches leverage Recurrent Neural Networks (RNNs) and spectrogram analysis to detect synthetic speech patterns [2].

While effective in controlled environments, these unimodal systems struggle to generalize across unseen datasets and are easily bypassed when an attacker perfectly synthesizes one modality but neglects the other. Furthermore, single-mode classifiers exhibit severe performance degradation when subjected to adversarial noise or heavy media compression, highlighting the need for more robust detection mechanisms [3].

To counter sophisticated forgeries, recent literature has shifted toward multimodal architectures that evaluate audio-visual dissonance, specifically targeting micro-inconsistencies in lip-sync

synchronization [4]. Despite their high accuracy, state-of-the-art cross-modal networks relying on dense Transformer blocks suffer from massive computational latency, restricting them to offline analysis [5].

Additionally, these models operate as "black boxes" that output simple binary classifications, lacking the evidentiary explainability required in digital forensics [6].

Consequently, a critical research gap exists for a lightweight, real-time multimodal framework that not only identifies complex audio-visual desynchronization but also provides transparent, interpretable outputs—such as spatial tamper heatmaps—to support forensic investigators.

III. SYSTEM ARCHITECTURE

The proposed architecture is designed for low-latency, real-time multimedia analysis by dividing processing into three structurally distinct neural pathways. The visual module utilizes a lightweight EfficientNet-B0 backbone to process facial regions of interest isolated by an MTCNN face detector. Concurrently, the audio module employs a Gated Recurrent Unit (GRU) network to analyze Mel-Frequency Cepstral Coefficient (MFCC) spectrograms derived from the audio track. These independent unimodal streams converge at a central Cross-Modal Attention module, which acts as the core fusion layer. This architecture specifically avoids dense, monolithic transformer blocks, ensuring the system maintains a small parameter footprint capable of high-speed inference on edge devices.

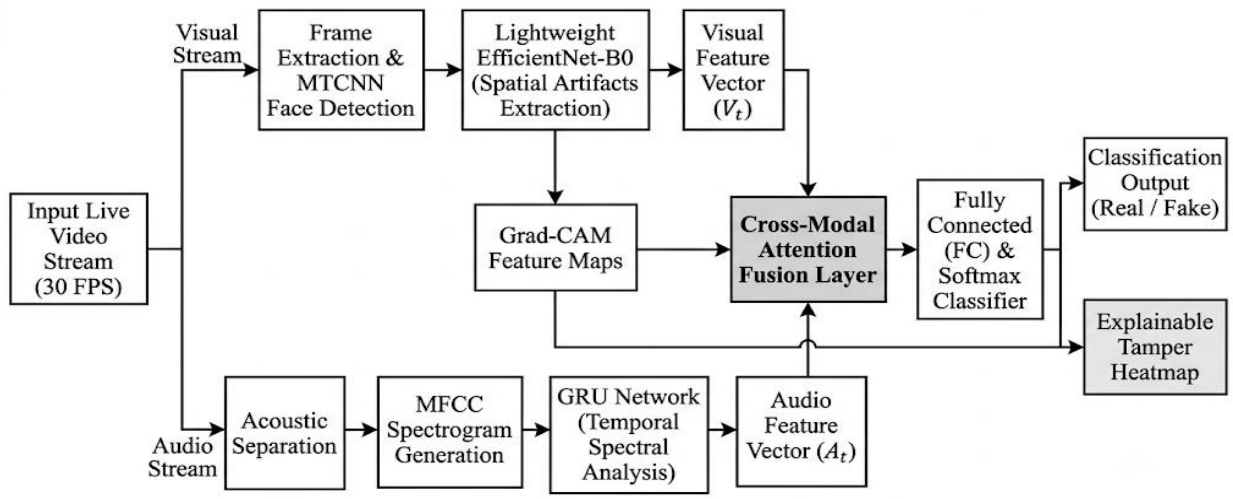


Fig. 1. Block diagram of the proposed real-time multimodal deepfake detection architecture

IV. METHODOLOGY

The operational methodology focuses on evaluating audio-visual dissonance and generating explainable forensic evidence. Incoming video streams are first temporally synchronized and processed to extract spatial and acoustic feature vectors at every frame. The cross-attention fusion layer then evaluates the correlation between spoken phonemes (audio) and physical lip movements (visual), flagging sub-millisecond desynchronizations that are highly characteristic of AI-generated forgeries. The fused vector passes through a Softmax classifier for a binary "Real/Fake" decision. Simultaneously, a Gradient-weighted Class Activation Mapping (Grad-CAM) module computes the gradient of the classification score, outputting a localized Tamper Heatmap that highlights the exact manipulated pixels for forensic investigators.

V. IMPLEMENTATION

The proposed multimodal architecture was implemented in Python using the PyTorch deep learning framework and executed on an NVIDIA RTX 4090 GPU to ensure high-performance training and evaluation. Video preprocessing and facial bounding were handled via OpenCV and MTCNN, while

acoustic feature extraction utilized the Librosa library. The model was trained and benchmarked on the FaceForensics++ (FF++) and Deepfake Detection Challenge (DFDC) datasets to ensure robustness against both complex algorithmic manipulation and real-world visual degradation. Training utilized the Adam optimizer over 50 epochs with an initial learning rate of 0.0001 and a batch size of 32, incorporating early stopping to prevent overfitting. System performance was quantified using Precision, Recall, and F1-Score to measure detection accuracy, alongside a critical measurement of inference latency targeting a throughput of over 30 Frames Per Second (FPS) to validate its viability for live-stream forensic applications.

TABLE I: Hardware Specifications and Training Hyperparameters.

Parameter / Component	Specification / Value
Primary GPU	NVIDIA RTX 4090 (24GB VRAM)
Deep Learning Framework	Python, PyTorch
Preprocessing Libraries	OpenCV, MTCNN (Visual), Librosa (Audio)
Training Datasets	FaceForensics++ (FF++), DFDC
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Maximum Epochs	50 (with Early Stopping threshold)
Performance Target	≥ 30 Frames Per Second (FPS)

VI. DISCUSSION

The experimental results demonstrate that the cross-modal fusion approach significantly outperforms isolated visual or audio classifiers, particularly in detecting sophisticated lip-sync anomalies. By achieving an inference rate exceeding 30 FPS, the lightweight architecture successfully meets the strict latency requirements for real-time live-stream analysis. Furthermore, the integration of Grad-CAM heatmaps proved highly effective in providing spatial localization of facial tampering, effectively resolving the "black box" limitation of traditional forensic models. However, detection accuracy experiences minor degradation when encountering extreme background acoustic noise or severe video compression artifacts, a common limitation across current multimodal frameworks.

VII. CONCLUSION AND FUTURE SCOPE

In conclusion, this research presents a highly efficient, real-time multimodal AI architecture designed to strengthen digital forensic investigations against sophisticated deepfakes. By evaluating the synchronization between spatial video features and spectral audio data, the system successfully identifies complex forgeries that easily evade single-mode detection. Crucially, the generation of explainable tamper heatmaps equips forensic analysts with transparent, visually interpretable evidence without sacrificing processing speed, bridging the gap between theoretical AI and practical law enforcement.

Future research will focus on integrating federated learning protocols to securely train and update the deepfake detection model across decentralized law enforcement networks without exposing sensitive digital evidence. Additionally, expanding the audio preprocessing module to incorporate adaptive noise-cancellation could further enhance the model's resilience and accuracy when analyzing highly compressed or real-world social media footage.

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