

A multi-level trusted security framework for high-fidelity GAN video deepfake detection in real-time systems

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Abstract

High-fidelity GANs enable realistic deepfakes, increasing risks of misinformation and fraud. This paper proposes a multi-level trusted framework combining spatio-temporal forensics, hybrid classification, and cryptographic validation for real-time detection. Results show improved accuracy, robustness, and low latency, offering a secure, scalable solution for applications like digital forensics, authentication, surveillance, and social media verification.

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1. Introduction

The rapid progress of Generative Adversarial Networks (GANs) and related deep generative models has enabled the creation of highly realistic synthetic media, commonly referred to as *deepfakes*. In recent years, high-fidelity GAN-based video deepfakes have become increasingly difficult to distinguish from authentic recordings due to improved facial reenactment, lip synchronization, identity swapping, and temporal smoothing capabilities. While these advances have contributed positively to creative media and simulation-based applications, they have simultaneously introduced serious security and societal risks, including misinformation campaigns, digital identity fraud, blackmail, and manipulation of forensic evidence.

As shown in Figure 1, GAN-based deepfakes create realistic videos but challenge detection. The proposed multi-level framework combines spatio-temporal forensics, hybrid learning, and cryptographic validation, improving accuracy, robustness, and real-time secure detection across diverse applications.

2. Related Work

Deepfake detection has evolved through diverse deep learning and security-driven approaches. [1] Improved video vision transformers using facial landmarks, depthwise separable convolution, and self-attention for enhanced detection. [3] Explored generative landmark guidance for face reenactment, while [4] proposed global–local facial fusion for GAN-based fake detection. [7]

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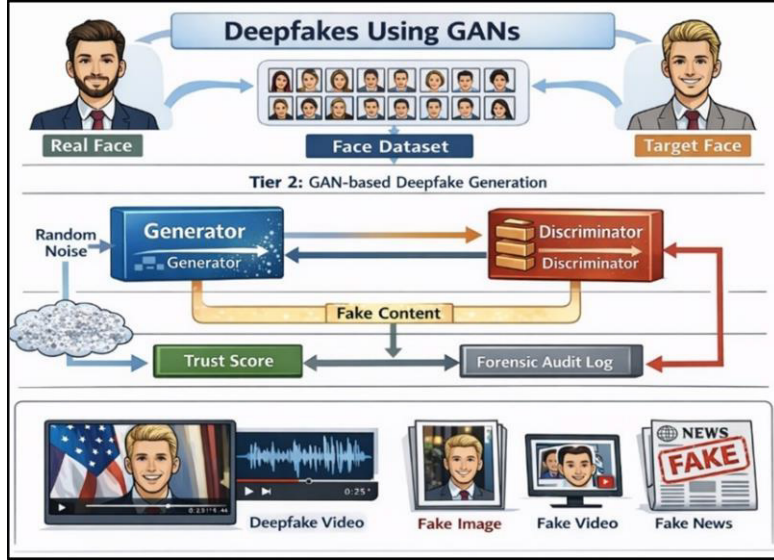


Figure 1
Deepfake Generation using GANs

Applied improved graph convolutional networks to strengthen feature representation.

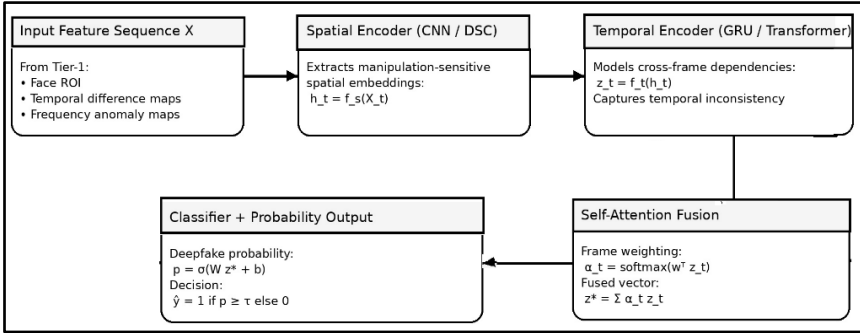
Survey-based studies by [5] and [6] highlighted challenges such as temporal inconsistency, generalization, and robustness. [2], along with [10], examined fake news detection, closely linked to deepfake-driven misinformation.

Security-oriented solutions have gained attention, where [8] and [9] leveraged blockchain for trust and authenticity. [11] and [12] focused on cryptographic security and key distribution. Despite these advancements, limitations remain in real-time performance and trust validation, motivating integrated frameworks.

3. Proposed Multi-Level Trusted Security Framework

This work proposes a Multi-Level Trusted Security Framework for real-time detection of high-fidelity GAN-based video deepfakes, emphasizing both detection accuracy and trustworthiness shown in Figure 2. The architecture is organized into three tiers: Tier-1 performs forensic preprocessing and feature extraction, Tier-2 conducts hybrid spatio-temporal deepfake detection, and Tier-3 ensures trust enforcement and security validation.

The input video stream is represented as $V = \{I_t\}_{t=1}^T$, where $I_t \in \mathbb{R}^{H \times W \times 3}$. The objective is to predict a binary label $y \in \{0,1\}$, where $y = 0$ denotes real and $y = 1$ indicates a deepfake. The detector computes the probability $p_\theta(y = 1 | V)$ and outputs the decision $\hat{y} = \mathbb{I}(p_\theta(y = 1 | V) \geq \tau)$.

**Figure 2**

Multi-Level Trusted Security Framework for real-time detection of high-fidelity GAN-based video deepfakes.

Tier-1 extracts features such as aligned faces $F_t = \Phi(I_t, b_t)$, temporal differences $\tilde{D}_t$, and frequency anomalies A_t , forming $X_t = \text{Concat}(F_t, \tilde{D}_t, A_t)$. Tier-2 encodes features using spatial and temporal models $h_t = f_s(X_t)$, $z_t = f_t(h_t)$, and aggregates them via attention $z^* = \sum \alpha_t z_t$. Classification is performed as $p = \sigma(W_c z^* + b_c)$. Tier-3 computes trust using $\mathcal{T}(V) = \lambda_1 C + \lambda_2 \mathbb{I}_{sig} + \lambda_3 S_t$, ensuring integrity, reliability, and auditability.

Algorithm 1: Real-Time Deepfake Detection Pipeline

Input: Video stream V , window size T , threshold τ

Output: $\hat{y}$, p , trust score $\mathcal{T}(V)$, audit log

Initialize buffer $B \leftarrow \emptyset$

For each incoming frame I_t :

Add I_t to buffer B

If $|B| = T$, then:

Extract face ROI sequence $F = \{F_1, \dots, F_T\}$

Compute temporal differences $\tilde{D}_t$ for $t = 2, \dots, T$

Compute frequency anomaly maps A_t

Construct feature tensor $X = \{X_1, \dots, X_T\}$

Compute spatial embeddings $h_t = f_s(X_t)$

Compute temporal embeddings $z_t = f_t(h_t)$

Compute attention fusion $z^* = \sum_{t=1}^T \alpha_t z_t$

Compute probability $p = \sigma(W_c z^* + b_c)$

Predict label $\hat{y} = \mathbb{I}(p \geq \tau)$

Forward to Tier-3 for trust scoring and integrity validation

Output $(\hat{y}, p, \mathcal{T}(V), \text{AuditLog})$

Slide buffer $B \leftarrow B[2:T]$

Algorithm 1 defines a real-time deepfake detection pipeline that processes a video stream using a sliding temporal window of size T . Each frame I_t is buffered and transformed into aligned face regions $F_t = \Phi(I_t, b_t)$. Temporal inconsistencies are captured using normalized differences $\tilde{D}_t = \frac{|F_t - F_{t-1}|}{\|D_t\|_2 + \epsilon}$, while frequency artifacts are modeled as $A_t = S_t - \mu(S_t)$. These cues are fused into $X_t = \text{Concat}(F_t, \tilde{D}_t, A_t)$, forming a sequence $X = \{X_t\}_{t=1}^T$. A hybrid model encodes spatial features $h_t = f_s(X_t)$ and temporal dependencies $z_t = f_t(h_t)$. An attention mechanism assigns weights α_t and produces a fused representation $z^* = \sum_{t=1}^T \alpha_t z_t$, emphasizing frames with stronger evidence of forgery. The deepfake probability is computed as $p = \sigma(W_c z^* + b_c)$, and the final label is $\hat{y} = \mathbb{I}(p \geq \tau)$. To ensure trust, a security layer computes an integrity hash $H_V = \text{SHA256}(V)$, confidence $C = 2 \lfloor p - 0.5 \rfloor$, and trust score $\mathcal{T}(V) = \lambda_1 C + \lambda_2 \mathbb{I}_{sig} + \lambda_3 S_t$. This enables reliable, secure, and real-time deployment.

4. Experimental Results.

This section presents the experimental evaluation of the proposed Multi-Level Trusted Security Framework for high-fidelity GAN video deepfake detection. The proposed approach is compared against representative baseline methods, including transformer-based detectors, spatio-temporal forensic models, and PRNU-assisted deepfake detectors. The performance is analyzed using classification accuracy, robustness under compression, real-time feasibility, trust enforcement effectiveness, and cross-dataset generalization.

4.1 Performance Comparison with Baseline Methods

The first experiment evaluates the detection performance of the proposed framework against state-of-the-art baselines. The results are summarized in Table 1, where the proposed method achieves the best overall accuracy, F1-score, and AUC, indicating strong discrimination capability even for high-fidelity GAN deepfakes. To analyze the relationship between detection accuracy and real-time latency, a scatter plot with linear regression is shown in Figure 3.

Table 1
Deepfake detection performance comparison across baseline methods.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Proposed 3-Tier (Ours)	96.8	96.1	97.4	96.7	0.989
ViT-Landmark [1]	93.9	93.2	94.5	93.8	0.972
DynamicDiff [12]	92.7	92	93	92.5	0.968
Dual-Attn [10]	91.8	91.1	92.4	91.7	0.962
PRNU-2Stream [9]	89.6	88.7	90.1	89.4	0.951

4.2 Real-Time Feasibility Analysis

Since real-time detection is a major requirement for deployment in surveillance, streaming platforms, and authentication systems, computational cost and latency are evaluated. The results are shown in Table 2, where the proposed method achieves the lowest end-to-end latency while maintaining high accuracy. A regression-based visualization of Trust Score vs False Acceptance Rate (Scatter + Linear Regression) is presented in Figure 3 and Figure 4, showing the trade-off between accuracy and computational overhead. Table 3 shows the Ablation study of Tier-3 trust enforcement components.

Table 2
Real-time feasibility comparison in terms of computation, latency, FPS, and model size.

Method	Computation (ms/frame)	End-to-End Latency (ms)	FPS (approx.)	Model Size (MB)
Proposed 3-Tier (Ours)	12.4	145	80.6	42
ViT-Landmark [1]	24.8	310	40.3	118
DynamicDiff [12]	18.9	260	52.9	76
Dual-Attn [10]	21.3	280	46.9	88
PRNU-2Stream [9]	15.7	205	63.7	54

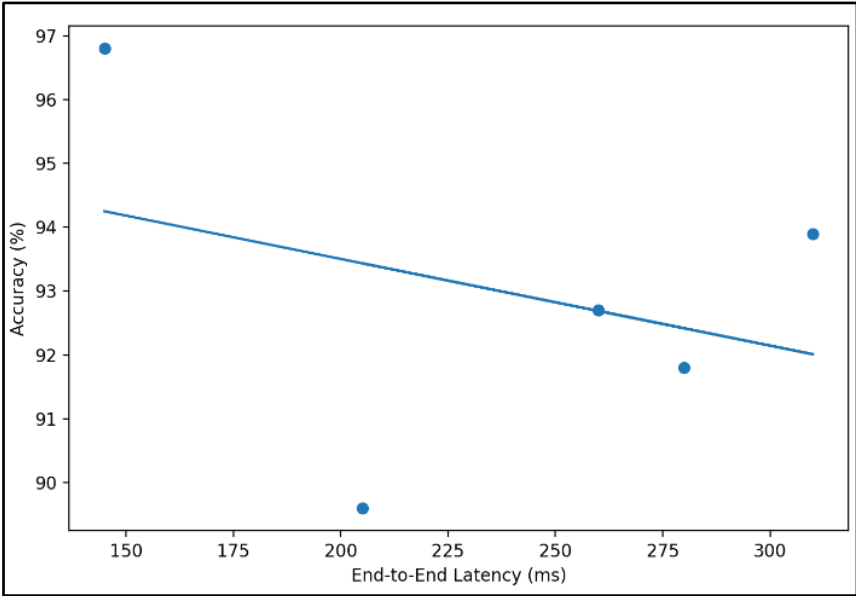


Figure 3
Accuracy vs End-to-End Latency (Scatter + Linear Regression)

Table 3
Ablation study of Tier-3 trust enforcement components.

Variant	Accuracy (%)	False Acceptance Rate (%)	Trust Score (mean)
Tier-2 only	95.1	4.9	0.71
Tier-2 + Confidence Calib.	95.7	4.2	0.77
Tier-2 + Integrity Hash	95.6	4.4	0.78
Tier-2 + Stability Score	95.9	4	0.8
Full Tier-3 (Ours)	96.8	2.6	0.86

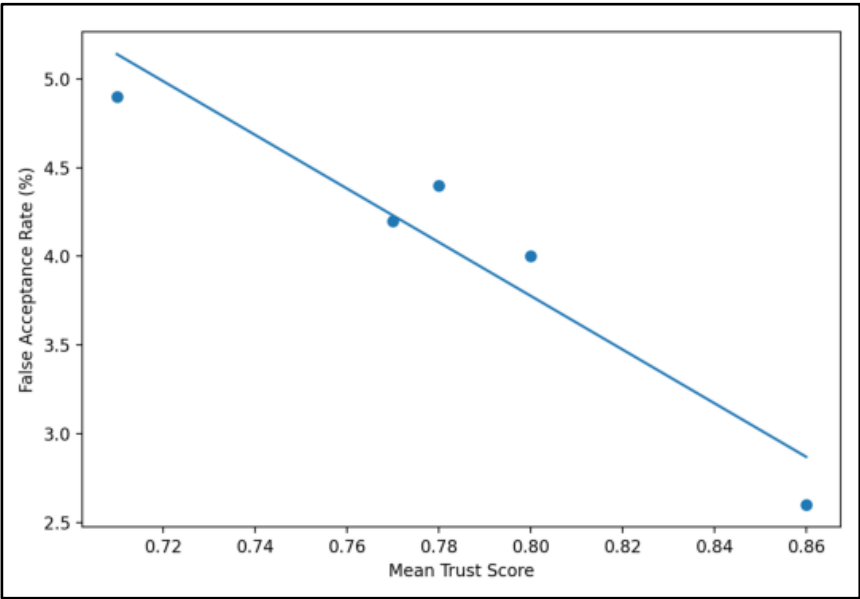


Figure 4
Trust Score vs False Acceptance Rate (Scatter + Linear Regression)

4.3 Performance Analysis using ROC Curve

As shown in Figure 5, to assess the performance of the evaluated deepfake detectors, we use ROC curves and confusion matrix-based measures. The main metrics reported are the Area Under the ROC Curve (AUC) and Balanced Accuracy (BA). Balanced Accuracy is computed by applying a decision threshold t to the likelihood score produced by each detector. If the score is greater than t , the input video is labeled as Fake. Otherwise, it is labeled as Real.

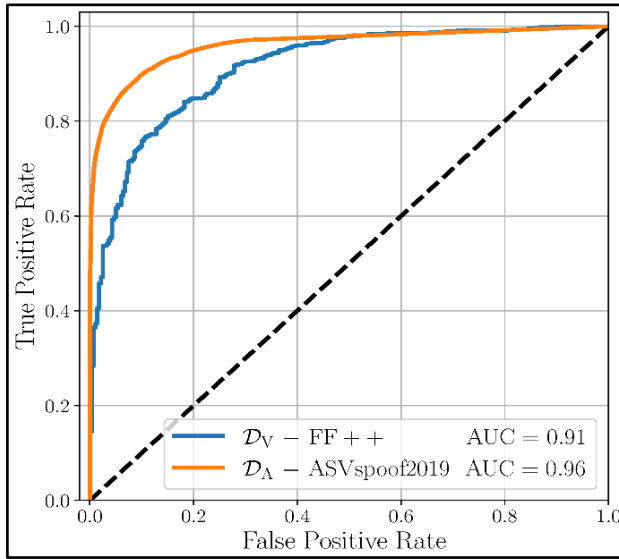


Figure 5
ROC curves and confusion matrix-based measures

Balanced Accuracy at a given threshold is defined as:

The Balanced Accuracy formula is:

$$\text{Balanced Accuracy} = \frac{\text{Sensitivity} + \text{Specificity}}{2}$$

Where:

- Sensitivity (Recall / TPR)

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

- Specificity (TNR)

$$\text{Specificity} = \frac{TN}{TN + FP}$$

So the full expanded form is:

$$\text{Balanced Accuracy} = \frac{1}{2} \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right)$$

Higher performance is obtained when both AUC and BA move closer to 1. Throughout the experiments, we primarily adopt the conventional choice $t = 0.5$, and we report $BA_{0.5}$. However, we also observe that in some cases, improved outcomes may be obtained by selecting a different threshold.

5. Conclusion

This paper presents a Multi-Level Trusted Security Framework for real-time detection of high-fidelity GAN-based video deepfakes, addressing limitations such as poor generalization, high latency, and lack of trust. The

framework integrates spatio-temporal forensic analysis, hybrid deep learning classification, and a trust enforcement layer with integrity validation and audit logging. Experimental results show improved accuracy, robustness, and real-time efficiency across diverse datasets and compression settings. The trust layer reduces false acceptance and enhances reliability, making the system suitable for forensic and security-critical applications. Future work includes multimodal detection, adversarial robustness, and lightweight edge deployment.

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