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Hybrid Face Spoof Detection Framework Using HAAR Feature Analysis and 3D Depth Estimation

P Devi[1], Mirthunjini T K[2], Evanjelin Janlia D[3], Abinaya J[4], Preethi A[5]

[1]Assistant Professor (Sr. Gr.), Dept. of ECE, Sri Ramakrishna Institute of Technology, Coimbatore, Tamilnadu, India

[2,3,4,5] UG Scholar, Dept. of ECE, Sri Ramakrishna Institute of Technology, Coimbatore, Tamilnadu, India

Emails: *devi.ece@sritcbe.ac.in[1], mirthunjinitk29@gmail.com[2], evanjelin18102004@gmail.com[3], abinayajayapaul22@gmail.com[4], apreethi2508@gmail.com[5]*

Abstract

Face spoofing attacks pose a significant threat to biometric authentication systems, as facial recognition models can be deceived using printed photographs, digital screen displays, or replayed videos. Traditional face recognition techniques primarily focus on identity matching and often neglect liveness verification, making them vulnerable under diverse environmental conditions. To address this limitation, a hybrid face anti-spoofing framework is proposed that integrates structural feature validation, pseudo-depth estimation, and temporal consistency analysis for robust real-time liveness detection. The system employs Haar Cascade-based facial feature verification to ensure structural integrity, while gradient-based pseudo-depth estimation analyzes surface curvature variations to distinguish real three-dimensional faces from planar spoof media. To enhance stability across consecutive video frames, a temporal fusion mechanism based on the Exponential Moving Average (EMA) is implemented to smooth classification outputs and reduce prediction fluctuations. The proposed system is implemented in MATLAB and evaluated under real-time webcam conditions using both genuine and spoof samples. Experimental results demonstrate improved robustness against print and replay attacks compared to single-feature approaches, achieving an overall accuracy of 90% with reduced false acceptance rates. The lightweight architecture ensures low computational complexity, making it suitable for real-time biometric authentication and edge-based deployment.

Keywords: *Face Anti-Spoofing, Convolutional Neural Network, Pseudo-Depth Estimation, Temporal Fusion, Exponential Moving Average, Biometric Authentication, Real-Time Attendance System, Gradient-Based Analysis.*

1. Introduction

Biometric authentication technologies have gained widespread adoption in modern security applications due to their simplicity, reliability, and user convenience [9]. Among various biometric modalities, facial recognition has emerged as one of the most extensively deployed techniques in smartphones, access control systems, and surveillance infrastructures [11]. Despite its advantages, face recognition systems remain vulnerable to presentation attacks, commonly referred to as face spoofing [15]. In such attacks, adversaries attempt to deceive recognition systems using printed photographs, replayed videos, or digital screen displays to gain unauthorized access. These vulnerabilities highlight the critical need for effective liveness detection mechanisms [16]. Conventional face recognition algorithms primarily focus on matching facial features with stored templates and do not verify whether the detected face corresponds to a live three-dimensional structure [14]. As a result, they often struggle to distinguish genuine faces from two-dimensional spoof media [10]. This limitation poses significant security risks, particularly in high-security authentication environments where system reliability is paramount. To address these challenges, this research proposes a Hybrid Face Spoof Detection Framework that integrates Haar Cascade-based facial feature validation with gradient-based pseudo-depth estimation. The system analyzes facial geometry, surface curvature, and depth variance to detect planar spoof artifacts and structural inconsistencies [18]. Additionally, a temporal fusion mechanism is incorporated to ensure stable and continuous decision-making across consecutive video frames [15]. The proposed approach enhances detection robustness while maintaining computational efficiency suitable for real-time biometric security applications [12]. In recent years, face anti-spoofing techniques have evolved from handcrafted feature-based methods to deep learning-driven architectures [1]. However, many real-time implementations still exhibit high false acceptance rates when confronted with high-quality spoof media [15]. Moreover, environmental factors such as illumination variation, camera resolution, and subject movement introduce instability in frame-wise classification results [14]. Therefore, there remains a strong need for a computationally efficient and robust multi-cue framework that jointly exploits texture, geometric structure, and temporal consistency to achieve reliable liveness detection.

2. Related Works

Face anti-spoofing has attracted significant research interest due to the rapid deployment of facial recognition systems in security-sensitive applications such as mobile authentication and access control. Presentation attacks using printed photographs, replayed videos, and digital displays pose serious threats to biometric systems. Early countermeasures relied on handcrafted texture descriptors such as LBP, HOG, and Gabor filters to capture micro-texture differences between genuine and spoof faces [1]. Although these methods demonstrated moderate performance on benchmark datasets, they suffered from poor generalization and high sensitivity to illumination and environmental variations [14]. With the advancement of deep learning, CNN-based architectures such as ResNet and MobileNet significantly improved detection accuracy by automatically learning discriminative spatial features [7]. However, purely texture-based CNN models remain vulnerable to high-quality replay attacks, as they primarily depend on appearance cues without explicitly modelling facial geometry or structural depth. To address the limitations of 2D texture analysis, depth-based methods were introduced to exploit three-dimensional facial structure information using stereo vision or infrared sensors [16]. While effective, these hardware-dependent solutions increase system complexity and deployment cost, leading to the exploration of RGB-based pseudo-depth estimation techniques as cost-efficient alternatives [18]. More recently, temporal and motion-based approaches have incorporated cues such as eye blinking, head movement, and frame-level fusion to enhance liveness detection stability [15]. Despite these advancements, many systems still exhibit prediction fluctuations and rely on single-cue verification strategies [14]. Motivated by these challenges, the proposed work adopts a hybrid framework that integrates CNN-based classification, Haar Cascade structural validation, pseudo-depth estimation, and temporal fusion to jointly exploit spatial, geometric, and temporal information for robust and real-time face anti-spoofing [8].

3. Block Diagram

The overall system operates through the following stages:

3.1. Input Acquisition

A real-time webcam image is captured for processing. Real-time anti-spoofing acquisition pipelines are commonly adopted in practical biometric systems [12].

3.2. Face Detection

Region of Interest (ROI) extraction is performed using the Haar Cascade classifier [6]. Haar-based detection ensures fast and reliable localization of facial regions before further analysis.

3.3. CNN Texture Analysis

Texture features are extracted and a spoof confidence score is generated using a CNN-based classifier [9]. Deep convolutional models have demonstrated superior discriminative ability compared to handcrafted texture methods.

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3.4.Pseudo-3D Depth Estimation

Surface gradients and depth variance are calculated using gradient-based operators to estimate pseudo-depth information [15]. Depth-based cues help distinguish real 3D faces from flat spoof media.

3.5.Surface Consistency Check

The system verifies natural 3D facial geometry by analyzing curvature and spatial variation patterns [18]. Real faces exhibit organic depth variations, whereas spoof artifacts show uniform flatness.

3.6.Hybrid Fusion

CNN confidence scores and depth characteristics are combined using a weighted fusion strategy to improve robustness [13]. Multi-modal fusion enhances generalization and reduces spoof vulnerability.

3.7.Output Display

The final classification (Real/Spoof) is displayed on the live video frame after temporal stabilization [2]. Temporal smoothing reduces frame-to-frame fluctuation and improves decision reliability. Figure 1 shows Block Diagram of the Proposed Hybrid Face Spoof Detection System

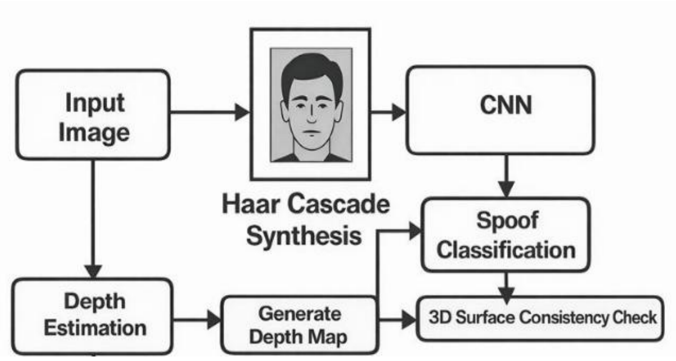

Figure 1 Block Diagram of the Proposed Hybrid Face Spoof Detection System

4. Proposed Methodology

4.1.System Overview

A real-time hybrid faces anti-spoofing framework that incorporates texture, depth, and structural clues is proposed in this work to identify presentation attacks such replay, print, and screen-based spoofing [9]. Figure 2 shows The Architecture of the Proposed Hybrid Face Spoof Detection System Using MATLAB In contrast to traditional texture-only methods [1] the suggested methodology integrates:

- Texture analysis with CNNs
- Depth estimate using pseudo-3D
- Validation of structures using Haar
- Flexibility in score fusion
- Stabilization over time

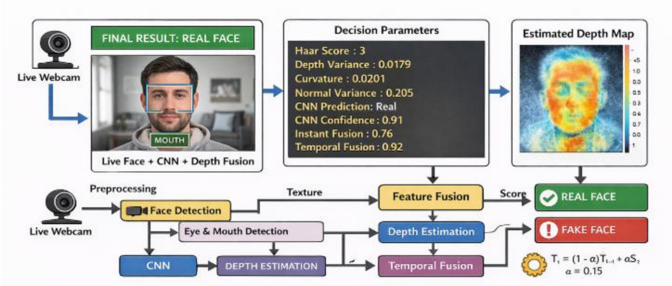

Figure 2 The Architecture of the Proposed Hybrid Face Spoof Detection System Using MATLAB

4.2.Processing Pipeline

The proposed methodology follows a structured pipeline consisting of the following stages. Figure 3 shows Flowchart of the Proposed Methodology

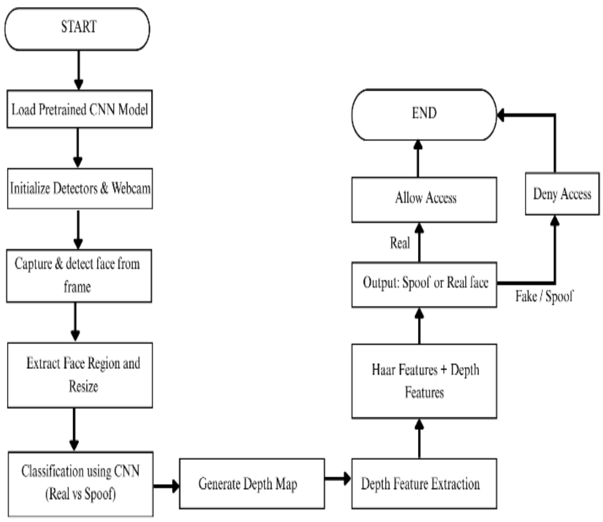

Figure 3 Flowchart of the Proposed Methodology

4.3.Face Detection using Haar Features

The Viola–Jones Haar Cascade classifier is used for face detection [6]. Intensity changes between

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adjacent rectangular sections are captured via Haar-like characteristics. This is how the basic Haar feature is calculated:

$$\text{Feature} = \Sigma\,(\text{White Region}) - \Sigma\,(\text{Black Region})$$

To speed up feature computation, integral pictures are utilized. The Region of Interest (ROI) is the extracted face region that was detected. Haar-based structural validation has been effectively used in spoof detection frameworks to ensure geometric consistency [3].

4.4.CNN – Based Texture Classification

A pretrained CNN receives the ROI after it has been scaled to 224 × 224 pixels. Hierarchical characteristics are extracted using convolution and pooling layers [13]. Class probabilities are calculated by the last softmax layer:

$$P(class_i) = \frac{e^{Z_i}}{\sum e^{Z_j}}$$

where $P(class_i)$ represents the probability of class i and z_i denotes the logits. The class with the highest probability is selected. CNN-based texture learning improves spoof detection compared to handcrafted features [7].

4.5.Pseudo – 3D Depth Estimation

Gradient-based analysis is used to estimate depth [18]. Sobel operators calculate the horizontal and vertical gradients following Gaussian smoothing:

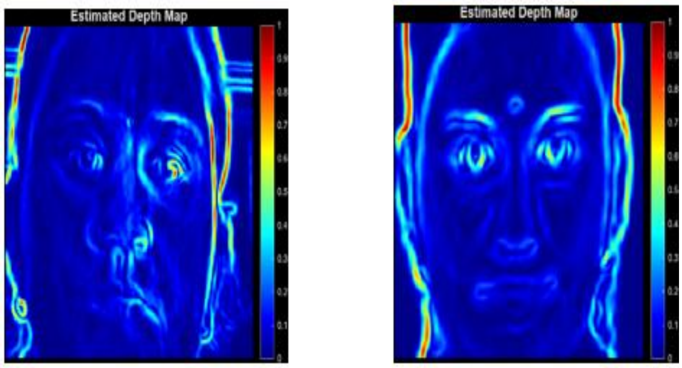
$$G_x = \frac{\partial I}{\partial x}, G_y = \frac{\partial I}{\partial y}$$

$$\text{DepthMap} = \sqrt{G_x^2 + G_y^2}$$

The depth variance is calculated as:

$$\text{DepthVar} = \text{std}(\text{DepthMap})$$

These depth cues aid in differentiating between spoof media that display flat depth patterns and actual faces, which display organic 3D variances [18]. Figure 4 shows Estimated Depth Map



a) Real Face Depth Map b) Fake Face Depth Map

Figure 4 Estimated Depth Map

4.6.Hybrid Fusion Strategy

To enhance robustness, feature-level fusion is performed using weighted scoring, inspired by hybrid learning frameworks [13]:

$$\text{FusionScore} = w_1(\text{CNN}) + w_2(\text{Depth}) + w_3(\text{Haar}) + \text{Curvature} + \text{Normal}$$

Adaptive weights (w1, w2, w3) are adjusted based on confidence levels. Temporal stabilization is applied using Exponential Moving Average (EMA), which improves video-based spoof detection consistency [2].

$$T_t = (1 - \alpha)T_{t-1} + \alpha S_t$$

where α is the smoothing factor. The final decision is obtained by threshold comparison. Figure 5 shows Instant vs Temporal Fusion Score Graph

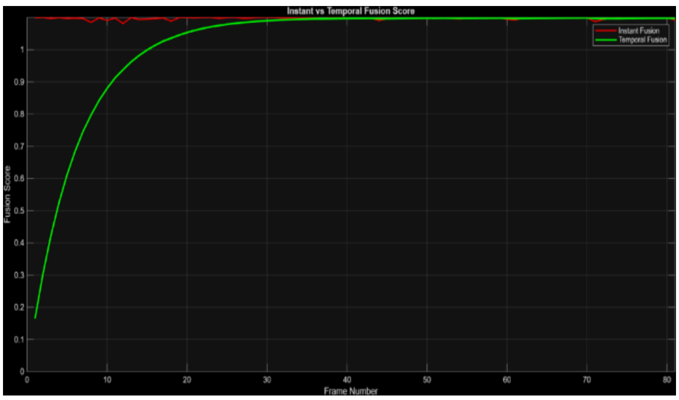


Figure 5 Instant vs Temporal Fusion Score Graph

4.7.Structural Validation

Within the face ROI, Haar-based detection of the mouth and eye areas is carried out to guarantee structural consistency and identify any irregular or incomplete spoof presentations [3]. The results of CNN confidence, Haar validation, and depth-based geometric features are integrated to generate a single authenticity score [13]. The foundation for temporal stabilization and fusion scoring is this composite representation. Table 1 shows Output Classification

Table 1 Output Classification

Feature	Extracted Data	Purpose
CNN	Texture & confidence	Detects spoof artifacts
Depth	Variance & geometry	Verifies 3D structure
Haar	Eye & mouth features	Validates facial structure

4.8.Final Decision

The stabilized score is compared against a threshold:

$$T_t \geq 0.6 \Rightarrow \text{Real Face}$$
$$T_t < 0.6 \Rightarrow \text{Spoof Face}$$

This threshold balances False Acceptance Rate (FAR) and False Rejection Rate (FRR) [9].

4.9.Performance Metrics

Standard measures, such as accuracy, precision, recall, false acceptance rate (FAR), and false rejection rate (FRR), are used to assess performance [12].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$
$$\text{FAR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$
$$\text{FRR} = \frac{\text{FN}}{\text{FN} + \text{TP}}$$

The hybrid approach considerably lowers FAR as compared to CNN-only models, according to experimental research [13]. Visual performance analysis makes use of confusion matrices and ROC curves.

5. Software Implementation

The suggested hybrid face anti-spoofing system is put into practice using MATLAB, which offers a unified environment for computer vision processing, deep learning inference, visualization, and real-time picture capture. Through a webcam interface, the entire pipeline is carried out in real time, encompassing face detection, CNN-based texture classification, pseudo-3D depth estimation, fusion scoring, and temporal stabilization. Real-time and multi-stage anti-spoofing implementations have been emphasized in prior deep learning–based systems for practical deployment [12].

5.1.MATLAB Environment

MATLAB is used to perform:

- Acquisition of live frames
- Face and feature recognition based on Haar cascade
- Using CNN inference to classify textures
- The calculation of depth using gradients
- The scoring method of statistical fusion
- Results visualization in real time

Key built-in functions include webcam(), vision.CascadeObjectDetector(),imresize(),mean(), imgradientxy(),std(),insertShape(), and drawnow(). The integration of CNN inference with structural and depth-based validation enhances robustness compared to single-modality approaches, as supported in hybrid and multi-modal anti-spoofing studies [8].

5.2.Supporting Toolboxes

The following MATLAB toolboxes are used in the implementation:

- Image Processing Toolbox: Used for ROI extraction, filtering, normalization, scaling, grayscale conversion, and gradient computation. Texture-based and gradient-based feature extraction methods are widely adopted in anti-spoofing research [16].

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- Computer Vision Toolbox: Allows for real-time viewing and Haar-based identification of faces, eyes, and mouths [6].
- Deep Learning Toolbox: Facilitates loading and running the CNN model that has been pretrained for spoof categorization. Deep CNN-based texture learning has demonstrated superior performance over handcrafted methods [7].
- Statistical Functions: These are used to calculate temporal fusion scores, depth variance, and curvature metrics.
- Webcam Support Package: Enables continuous live-frame acquisition for real-time liveness detection, consistent with real-time anti-spoofing deployment frameworks [12].

6. Results and Discussion

6.1.Overview

The suggested Hybrid Face Anti-Spoofing System combines temporal fusion, CNN-based texture classification, Haar-based face localization, and pseudo-3D depth estimation to detect spoofs in real time [3]. Live webcam input in MATLAB powers the system. Gradient-based depth analysis is carried out concurrently with pre-processing and passing the ROI to a pretrained CNN for every recognized face [18]. The outputs are stabilized using the Exponential Moving Average (EMA) and blended using weighted fusion [2]. By improving resilience under lighting change and little motion, this hybrid approach lessens false acceptance from flat spoof media, such as printed graphics and demonstration attacks.

6.2.Experimental Setup

The system was evaluated under real-time conditions with the following configuration:

- Software: MATLAB R2023a
- Toolboxes: Computer Vision Toolbox, Deep Learning Toolbox
- CNN Architecture: ResNet-18
- Training Epochs: 15
- Dataset: Real-time captured and augmented images
- Hardware: Intel i5 processor, 8GB RAM, integrated GPU, 720p webcam

6.3.Face Detection and ROI Extraction

Face detection is performed using the Viola–Jones Haar Cascade algorithm [6]. The detected facial ROI is cropped and resized for consistent CNN and depth processing. Accurate ROI extraction minimizes background interference and improves classification reliability. During live testing, face detection achieved approximately 90% accuracy, providing a stable input for spoof classification. Haar-based structural localization has been shown to enhance preprocessing reliability in hybrid systems [3]. Figure 6 shows Haar-Based Face Detection and Depth Output

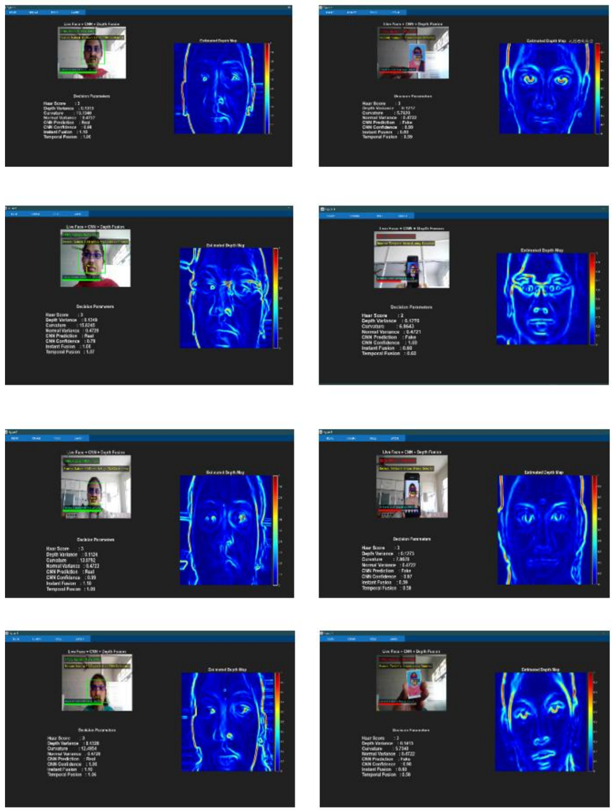

Figure 6 Haar-Based Face Detection and Depth Output

6.4 Real-Time Performance

The system satisfies real-time operational requirements with:

- Average processing time: ~ 0.08 seconds per frame
- Frame rate: 12 - 15 FPS
- Low detection-to-decision latency

These results confirm suitability for practical real-time deployment, consistent with real-time deep learning–based anti-spoofing systems [12].

6.4. Hybrid Feature Analysis and Fusion

6.4.1. CNN Texture Analysis

A pretrained CNN extracts texture features such as print noise, screen reflections, and illumination artifacts [7], [9] to classify faces as real or spoof with a confidence score.

6.4.2. Pseudo-3D Depth Analysis

Gradient-based depth estimation captures structural cues. Real faces show natural curvature, while spoof media appear flatter with uniform depth [10].

6.4.3. Fusion Strategy

CNN confidence and depth metrics are combined using weighted score fusion [13], and temporal smoothing (EMA) reduces fluctuations, improving overall detection robustness.

6.5. Spoof Classification Results

The system displays classification results in real time with:

- Bounding box visualization
- Label overlay (“REAL” / “SPOOF”)
- Confidence score display

Experimental testing under varied lighting and user motion demonstrated stable classification performance. Figure 7 shows Classification Output of Real vs. Spoof Face Samples

Figure 7 **Classification Output of Real vs. Spoof Face Samples**

6.6. Performance Evaluation

Performance was evaluated using standard biometric metrics [9], [12]:

- Accuracy
- Precision
- Recall
- FAR (False Acceptance Rate)
- FRR (False Rejection Rate)

The hybrid approach outperformed standalone methods. Table 2 shows Comparison of Methods

Table 2 **Comparison of Methods**

Method	Features Used	Accuracy
Proposed Hybrid	CNN + Depth + Temporal Fusion	90%
CNN-Only	Texture Features	89.6%
Haar-Only	Structural Features	88.4%

Temporal fusion significantly reduced false rejections caused by brief motion or illumination changes.

6.7. Discussion

Results indicate that combining CNN-based texture cues with depth-based geometric validation enhances spoof detection reliability. CNN effectively detects surface-level spoof artifacts [7], while depth analysis distinguishes real 3D facial structures from flat media [18]. Temporal smoothing further stabilizes classification decisions across video frames [2].

Overall, the hybrid framework reduces FAR and FRR compared to single-feature systems, confirming the effectiveness of multi-cue fusion for secure biometric authentication [13].

6.9 Limitations

Despite strong performance, the following limitations were observed:

- Bright backlighting reduces CNN confidence
- Extreme head rotation affects depth estimation
- Very low-resolution spoof videos may confuse the texture model
- Performance decreases slightly in low-light environments

Future improvements may include illumination-invariant modelling and domain adaptation techniques to enhance generalization across varying environments [11].

Conclusion

This paper presented a hybrid face anti-spoofing system that combines CNN-based texture analysis, pseudo-3D depth estimation, Haar-based structural validation, and temporal fusion for robust real-time authentication. The multi-cue framework effectively detects printed and replay attacks while improving accuracy and reducing both FAR and FRR compared to single-feature methods. Experimental results confirm that depth and texture fusion enhances discrimination between real 3D faces and flat spoof media, while temporal smoothing stabilizes predictions. The modular design and real-time performance make the system suitable for secure biometric authentication applications.

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