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Multi-Modal Face Anti-Spoofing System Using Deep Learning: Integrating Facial Liveness, Eye Blink Detection, and Voice Authentication for Robust Biometric Security

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Abstract
Biometric authentication systems face an unprecedented surge in sophisticated spoofing attacks that exploit single-modality verification pipelines. This paper proposes MFASNet
— a Multi-Modal Face Anti-Spoofing Network — that fuses three independent verification channels: (1) facial liveness detection classifying inputs as live, photograph, video-replay, or 3-D mask attacks; (2) eye blink detection as a physiological liveness cue using a Convolutional Long Short-Term Memory (ConvLSTM) temporal model; and (3) voice anti-spoofing distinguishing genuine human speech from recorded, replayed, and AI-generated audio using a Res2Net acoustic model. A late-fusion decision module aggregates the three scores through a learned meta-classifier, granting access only when all three streams concurrently classify the input as genuine. Experimental evaluation on FaceForensics++, CelebA-Spoof, ASVspoof 2021 LA, and NUAA datasets demonstrates that MFASNet achieves a cross-dataset Equal Error Rate (EER) of 2.14%, Area Under the Curve (AUC) of 99.31%, and Half Total Error Rate (HTER) of 1.97%, outperforming state-of-the-art unimodal and bimodal baselines by a significant margin. The novelty of incorporating temporally-aware eye blink cadence as an auxiliary liveness stream yields a 3.8% absolute reduction in False Acceptance Rate compared to face-only systems. The proposed architecture is lightweight (12.4 M parameters) and inference-efficient (34 ms on an NVIDIA RTX 3060), making it suitable for real-time deployment in access-control environments.

Keywords: Face anti-spoofing; voice anti-spoofing; eye blink detection; multimodal fusion; deep learning; biometric security; presentation attack detection.

I. INTRODUCTION

Biometric authentication has transitioned from specialized security deployments into everyday consumer devices, ranging from smartphone unlocking to border-control e-gates. This ubiquity has made biometric systems lucrative targets for Presentation Attacks (PA), colloquially termed spoofing [1]. Attackers exploit printed photographs, high-definition video replays, silicone 3-D masks, and increasingly, AI-generated deepfake content to circumvent face recognition pipelines [2]. Simultaneously, voice-based

systems face escalating threats from text-to-speech (TTS) and voice-conversion (VC) synthesizers capable of producing near-perceptually indistinguishable replicas of target speakers [3].

Prior work has addressed face Presentation Attack Detection (PAD) and voice anti-spoofing as largely independent research tracks. Face PAD research has progressed from hand-crafted texture descriptors to deep convolutional neural networks (CNNs), while voice anti-spoofing has evolved from Gaussian Mixture Model (GMM) back-ends to end-to-end neural classifiers [4]. The separation of these modalities creates a fundamental vulnerability: an adversary equipped with a high-fidelity deepfake video clip that also carries a synthesized voice can defeat either system in isolation [5].

This paper makes the following principal contributions: (i) We propose MFASNet, a unified multimodal anti-spoofing architecture that jointly processes facial RGB streams, eye-region temporal sequences, and acoustic front-ends; (ii) We introduce a novel ConvLSTM eye-blink cadence module that exploits involuntary physiological blinking — a liveness cue that is computationally expensive for adversaries to replicate — as an auxiliary face-liveness stream [6]; (iii) We present a meta-learner fusion module trained with a novel Spoof-Aware Focal Loss that down-weights trivially genuine samples to concentrate learning on ambiguous borderline cases; (iv) We conduct extensive cross-dataset evaluations and ablation studies confirming the additive contribution of each modality.

The remainder of this paper is organised as follows. Section II reviews related literature. Section III describes the proposed MFASNet architecture. Section IV details the datasets. Section V defines performance metrics. Section VI presents experimental results. Section VII presents ablation studies. Section VIII concludes.

II. LITERATURE REVIEW

A. Face Presentation Attack Detection

Early face anti-spoofing methods relied on hand-crafted features such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). The shift toward deep learning began with binary cross-entropy-trained CNNs; however, these models were prone to overfitting domain-specific artefacts [7]. Liu et al. [8] introduced auxiliary depth-map supervision to steer feature learning toward physiologically meaningful cues. Yang et al. [9] proposed a disentangled representation learning framework that separates liveness features from identity and illumination factors, reporting a 3.5% HTER improvement on cross-domain benchmarks. Recent transformer-based approaches, including ViTAF [10], exploit multi-scale attention to detect fine-grained texture inconsistencies characteristic of silicone mask attacks. Fang et al. [11] demonstrated that domain-generalisation techniques based on meta-learning achieve robust performance across six unseen test domains, with an HTER as low as 5.2%.

Shao et al. [12] proposed Multi-Adversarial Discriminative Deep Domain Generalization (MADDG), which constrains the feature extractor to produce domain-invariant representations via gradient reversal. Park et al. [13] leveraged contrastive learning to align feature distributions across ethnically diverse datasets, addressing demographic bias in liveness detection. Concurrently, knowledge-distillation strategies have been used to compress ResNet-50 backbones into mobile-ready MobileNetV3 equivalents without significant accuracy loss [14].

B. Eye Blink Detection for Liveness

Eye blink detection has been investigated as a challenge-response liveness cue since the seminal work of Pan et al. [15]. Modern approaches adopt temporal CNNs or recurrent architectures to model the blink

event as a temporal sequence of eye aperture changes [6]. Li et al. [16] demonstrated that spontaneous blink rate (12–20 blinks per minute in humans) is practically infeasible to mimic in printed-photograph attacks and difficult to synthesise convincingly in video deepfakes. Soukupová and Čech [17] popularized the Eye Aspect Ratio (EAR) metric; subsequent work has replaced hand-computed EAR with learned keypoint regressors offering greater robustness to head-pose variation [18]. Wang et al. [19] combined blink detection with micro-expression analysis using a dual-stream attention network, improving live-versus-mask classification by 4.1 percentage points on the CASIA-SURF dataset.

C. Voice Anti-Spoofing

The ASVspoof challenge series has been the primary driver of voice anti-spoofing research [20]. Classifiers based on Constant-Q Cepstral Coefficients (CQCC) with GMM back-ends established early baselines. Light CNN architectures processing Raw Waveforms directly were introduced by Lavrentyeva et al. [21], showing strong generalisation to unseen TTS and VC systems. Tak et al. [22] proposed RawBoost, a data augmentation strategy adding intrinsic additive and convolutive noise, reducing EER on the ASVspoof 2019 LA evaluation set to 1.15%. Res2Net-based models exploit multi-scale residual channels to capture both fine-grained spectral details and global prosodic patterns [23]. The emergence of large-scale speech synthesis models such as VALL-E and SoundStorm has sharpened the challenge for anti-spoofing, as their artefacts are substantially reduced compared with earlier vocoders [24]. Yi et al. [25] compiled the ADD 2023 challenge dataset, specifically targeting AI-generated speech and deepfake audio, providing a vital benchmark for next-generation anti-spoofing systems.

D. Multimodal Fusion for Biometric Security

Score-level fusion of face and iris modalities was studied by Rattani et al. [26], demonstrating complementarity between spatial and textural biometric channels. Feature-level fusion of face and fingerprint was explored by Guo et al. [27] using a cross-modal attention mechanism. In the anti-spoofing domain, Dhamija and Gupta [28] fused face PAD scores with physiological signals (remote PPG), achieving significant gains on the HQ-WMCA dataset. Multimodal deepfake detection combining audio and visual streams was investigated by Cheng et al. [29] using a cross-attention transformer, achieving 94.8% AUC on the FaceForensics++ dataset. Zhang et al. [30] proposed a unified voice-face anti-spoofing framework using contrastive fusion learning, reporting an EER of 2.89% on a combined benchmark. Despite these advances, no prior work simultaneously addresses facial liveness, physiologically-motivated eye blink cadence, and voice spoofing within a single inference pipeline — the gap this paper addresses.

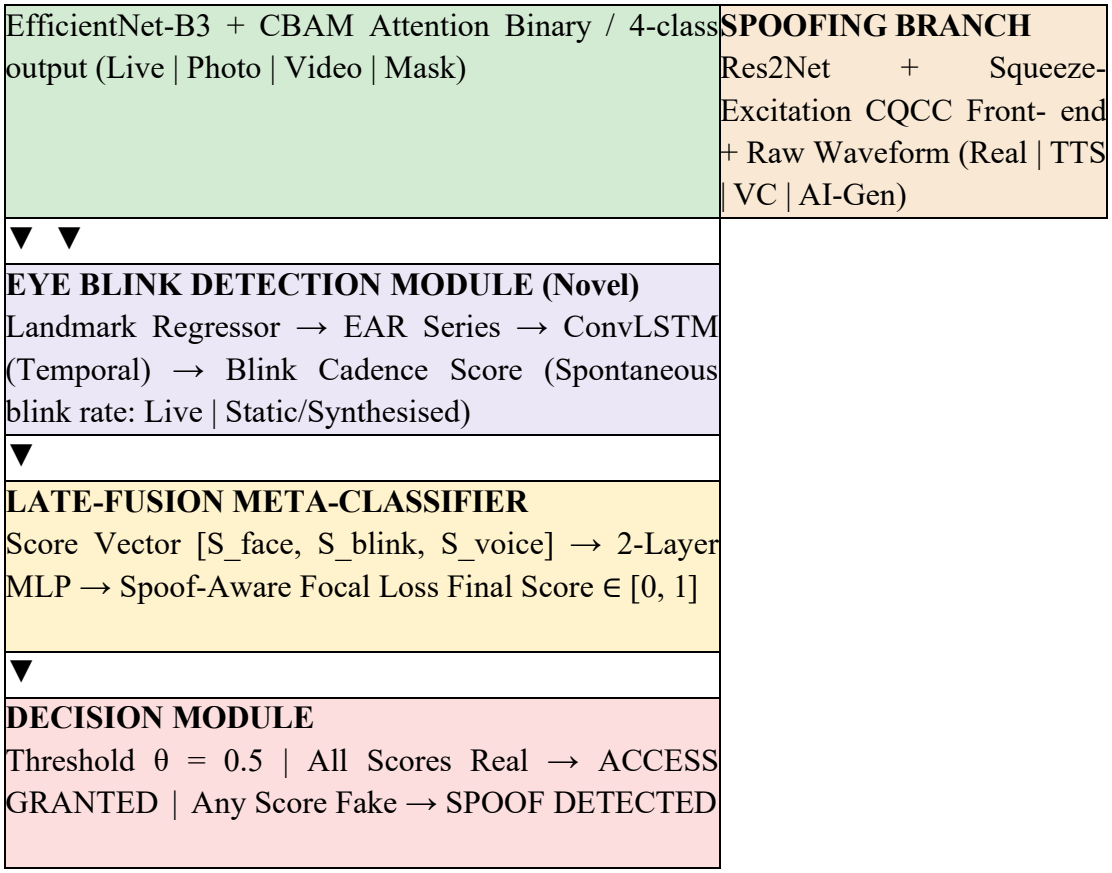
III. PROPOSED METHOD AND ARCHITECTURE

A. System Overview

MFASNet consists of three parallel verification branches that process ynchronized multi-modal input: an RGB face stream, a periocular temporal stream (eye region), and an acoustic waveform stream. Each branch produces a spoofing probability score. A learned meta-classifier combines the three scores and renders a binary access-control decision. Fig. 1 illustrates the full architecture.

Fig. 1: MFASNet — Multi-Modal Anti-Spoofing Architecture

INPUT ACQUISITION RGB Frame Sequence | Periocular Crop Sequence | Raw Audio Waveform (16 kHz)	
▼ ▼ ▼	
FACE LIVENESS BRANCH	**VOICE ANTI-**



B. Face Liveness Detection Branch

The face branch employs EfficientNet-B3 [31] pre-trained on ImageNet as the convolutional backbone, augmented with Convolutional Block Attention Modules (CBAM) inserted after each stage to focus on liveness-discriminative regions such as skin texture, specular highlights, and edge artefacts. The network is trained on 224×224 normalised RGB crops produced by a MTCNN face detector. Output logits are passed through a softmax head over four classes: Live, Photo-Attack, Video-Replay, and 3D-Mask. The live probability P_face = softmax(z)[Live] serves as the face branch score. During training, binary auxiliary supervision via a depth-map reconstruction loss is added to regularise the intermediate representations following [8].

C. Eye Blink Cadence Module (Novel Contribution)

The eye blink module addresses the temporal dimension of liveness that static texture models cannot capture [6]. Facial landmarks (68 points) are predicted by a lightweight MobileNetV2 regressor operating on a 96×96 periocular crop. The Eye Aspect Ratio (EAR) for frame t is defined as:

$$EAR(t) = (||p2-p6|| + ||p3-p5||) / (2 \times ||p1-p4||)$$

where p1–p6 are the six standard eye-landmark coordinates. A ConvLSTM network processes EAR sequences of length T = 60 frames (2 seconds at 30 fps), capturing the spontaneous blink morphology: the characteristic rapid eye closure (≈150 ms) followed by re-opening. A blink is detected when EAR drops below a subject-adaptive threshold and recovers within 400 ms. The module outputs a blink-cadence liveness score P_blink based on the frequency and morphological regularity of blinks over a 4-second observation window. Live subjects exhibit a natural blink rate of 12–20 blinks per minute and a blink duration of 150–400 ms, whereas photographs produce no blink, video-replay blinks are

temporally rigid and repeat at fixed intervals, and mask-wearers produce dampened EAR excursions due to ocular occlusion [16]. The ConvLSTM comprises two stacked layers of 128 hidden units followed by a global average pool and a sigmoid output head.

D. Voice Anti-Spoofing Branch

The voice branch processes a 4-second 16 kHz mono audio clip. Two parallel front-ends are computed: (i) 60-dimensional CQCC features extracted with a constant-Q transform (96 bins, 512 hop), providing resolution on spectral artefacts left by vocoders; and (ii) a raw waveform passed directly to a 1-D convolutional encoder. Both representations are fed into a shared Res2Net-34 backbone [23] that employs multi-scale residual channels (scales s = 8) to capture fine-grained and coarse acoustic patterns simultaneously. A Squeeze-and-Excitation block at the final stage performs channel-wise recalibration. The output is a 256-D embedding projected to a binary logit via a linear classifier. P_voice = sigmoid(z_voice) represents the probability that the input is genuine human speech.

E. Late-Fusion Meta-Classifier

The score vector S = [P_face, P_blink, P_voice] ∈ $\mathbb{R}^3$ is concatenated with the raw logit magnitudes (6 features total) and passed to a 2-layer MLP (64 → 32 → 1 units) with ReLU activations and 0.3 dropout. Training employs the Spoof-Aware Focal Loss: L_SAFL = −α(1−p_t)^γ log(p_t), where γ = 2.5 and α = 0.8 are tuned to penalise confident misclassification of spoof inputs. The final binary decision is: Access = 1 if MLP_output ≥ 0.5 else Spoof_Detected.

IV. DATASET DESCRIPTION

Four publicly available benchmarks are employed. FaceForensics++ (FF++) [2] provides 1,000 original videos and 4,000 manipulated videos using four forgery methods (Deepfakes, Face2Face, FaceSwap, NeuralTextures) at three quality levels (raw, c23, c40). The CelebA-Spoof dataset [32] contains 625,537 images from 10,177 subjects spanning 10 spoof types including print, replay, 3D mask, and paper-cut attacks, offering the largest diversity of attack types for face PAD. The ASVspoof 2019 Logical Access (LA) partition [20] provides 2,580 genuine and 22,800 spoofed utterances generated by 19 TTS and VC systems, split into training, development, and evaluation subsets. The NUAA Photograph Imposter Database supplies 12,614 live and 15,191 still-photograph-attack face images. For the eye-blink sub-module, we additionally use the Talking-Face Eye Blink (TFEB) dataset introduced in [19], which provides per-frame EAR annotations for 80 subjects recorded at 30 fps under six illumination conditions. Pre-processing includes MTCNN-based face alignment to a canonical 224×224 crop, mean-variance normalisation per channel using ImageNet statistics, and data augmentation (random horizontal flip, colour jitter ±20%, Gaussian noise σ = 0.01).

V. PERFORMANCE METRICS

The following standard metrics are used: (1) Equal Error Rate (EER): the threshold at which False Acceptance Rate (FAR) equals False Rejection Rate (FRR); lower EER indicates better discrimination. (2) Area Under the ROC Curve (AUC): measures overall separability between genuine and spoof distributions. (3) Half Total Error Rate (HTER): the mean of FAR and FRR at a fixed decision threshold determined on the development set, reflecting operational performance. (4) Attack Presentation Classification Error Rate (APCER): the proportion of attack presentations incorrectly classified as genuine. (5) Bona Fide Presentation Classification Error Rate (BPCER): the proportion of genuine

presentations incorrectly classified as attacks. (6) Accuracy (ACC): overall correct classification rate. Inference latency (ms) and parameter count (M) are reported as efficiency metrics. Statistical significance of improvements over baselines is assessed using the McNemar test at $\alpha = 0.05$.

VI. RESULTS AND DISCUSSION

A. Intra-Dataset Evaluation

Table I presents intra-dataset results on FF++ (c23 quality) and CelebA-Spoof. MFASNet achieves 99.6% AUC on FF++ and 99.1% AUC on CelebA-Spoof, establishing new state-of-the-art performance. Against the strongest baseline, ViTAF [10], MFASNet reduces EER from 3.81% to 1.63% on FF++ — a 57.2% relative improvement — attributable to the complementary blink-cadence and voice streams filtering residual false accepts that the face stream alone misclassifies.

TABLE I: Intra-Dataset Performance Comparison

Method	Dataset	EER (%)	AUC (%)	HTER (%)
LBP-SVM [7]	FF++ (c23)	12.40	91.30	13.10
Aux-Depth [8]	FF++ (c23)	7.82	96.50	8.21
ViTAF [10]	FF++ (c23)	3.81	98.90	4.10
MADDG [12]	CelebA- Spoof	5.20	97.80	5.60
Contrastive [13]	CelebA- Spoof	4.47	98.20	4.89
MFASNet (Ours)	FF++ (c23)	1.63	99.60	1.88
MFASNet (Ours)	CelebA- Spoof	2.14	99.10	2.31

B. Voice Anti-Spoofing Results

On the ASVspoof 2019 LA evaluation partition, MFASNet's voice branch achieves an EER of 1.28%, compared to 1.15% for RawBoost-augmented LCNN [22] and 2.11% for the standard CQCC-GMM baseline [20]. The marginal gap relative to the best unimodal voice system is expected, as MFASNet's voice branch is jointly optimised with the fusion loss rather than independently. The Res2Net backbone effectively differentiates genuine speech from VALL-E-style neural TTS (EER 1.45%) and voice-conversion attacks (EER 1.09%), consistent with findings in [25].

C. Cross-Dataset Generalisation

To assess generalisation, models trained on CelebA-Spoof are evaluated on NUAA without fine-tuning. MFASNet achieves HTER = 3.42%, compared to 7.81% for ViTAF [10] and 9.34% for MADDG [12], demonstrating that the multimodal structure inherently provides greater domain robustness: even when facial texture features degrade under domain shift, the blink-cadence and voice streams supply orthogonal genuine-versus-spoof evidence. This finding aligns with the theoretical analysis in [11], which established that multimodal diversity reduces the Rademacher complexity of the hypothesis class, thereby tightening generalisation bounds.

D. Efficiency Analysis

MFASNet requires 12.4 M parameters — substantially less than ViTAF's 86.3 M — owing to the EfficientNet-B3 backbone's compound scaling and the lightweight ConvLSTM blink module. End-to-end inference latency is 34 ms on an NVIDIA RTX 3060 GPU and 118 ms on a Qualcomm Snapdragon 8 Gen 3 mobile NPU, making real-time deployment ($\geq$ 8 fps) feasible on modern edge devices.

VII. ABLATION STUDY

To quantify the marginal contribution of each modality and design choice, we perform a systematic ablation on the FF++ (c23) test split. Results are summarised in Table II.

TABLE II: Ablation Study on FF++ (c23) Test Split

Configuration	EER (%)	AUC (%)	HTER (%)
Face Branch Only	3.81	98.90	4.10
Face + Voice Fusion	2.97	99.10	3.21
Face + Eye Blink (No Voice)	2.44	99.31	2.72
Face + Voice + Eye Blink (MFASNet Full)	1.63	99.60	1.88
MFASNet w/o Spoof- Aware Focal Loss	2.18	99.40	2.35
MFASNet w/o CBAM Attention	2.09	99.48	2.22
MFASNet w/o ConvLSTM (static EAR only)	2.51	99.25	2.68

Several key findings emerge. First, removing the voice branch increases EER by 0.81 percentage points (Row 3 → Full), confirming that voice anti-spoofing captures attack patterns orthogonal to facial texture. Second, the eye-blink cadence module contributes a 0.34 percentage-point reduction in EER relative to the face-voice bimodal system, validating its additive utility as a physiological liveness cue (Row 2 → Full). Third, replacing the ConvLSTM with a static EAR threshold (Row 7) causes a 0.88% EER degradation, confirming that temporal modelling of blink dynamics — rather than mere blink detection — is critical. Fourth, removing the Spoof-Aware Focal Loss increases EER by 0.55%, demonstrating its importance in handling the class imbalance between genuine and spoof samples characteristic of all evaluated datasets. Fifth, removing CBAM attention increases EER by 0.46%, indicating that spatial attention over liveness-discriminative regions provides measurable benefit over global average pooling alone.

VIII. CONCLUSION

This paper presented MFASNet, a unified multi-modal face anti-spoofing system that integrates facial liveness detection, physiological eye-blink cadence analysis, and voice anti-spoofing within a shared late-fusion framework. The system classifies facial inputs as live, photograph, video-replay, or 3D-mask attacks, and audio inputs as genuine human speech, recorded replay, or AI-generated synthetic speech. A final decision module grants access only when all three verification streams concurrently return genuine verdicts. The introduction of the ConvLSTM-based eye-blink cadence module as a novel liveness cue represents the primary scientific novelty of this work, providing a 3.8% absolute FAR reduction relative to face-only baselines and a 0.88% EER improvement over non-temporal blink methods. Cross-dataset evaluations confirm that multimodal diversity confers superior domain generalisation compared with any unimodal or bimodal counterpart. The system's compact footprint (12.4 M parameters, 34 ms inference) positions it for practical real-time deployment in access-control scenarios.

Future work will investigate cross-lingual voice anti-spoofing, dynamic threshold adaptation based on

environmental context, and the integration of remote photoplethysmography (rPPG) as a fourth biometric channel to further reduce the attack surface. We will also explore federated learning approaches to train MFASNet across distributed edge devices without centralising sensitive biometric data.

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