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Enhanced Multi Attention-Net with Frequency-Aware Squeezed Residual Blocks for Robust Face Anti-Spoofing

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ABSTRACT: Face recognition systems are widely deployed in authentication, surveillance, and financial applications. However, these systems remain highly vulnerable to presentation attacks such as printed photos, replayed videos, and 3D masks. Existing CNN-based anti-spoofing approaches often suffer from poor cross-dataset generalization due to environmental variations and unseen spoof patterns.

This paper proposes an Enhanced Multi-Attention Network with Frequency-Aware Squeezed Residual Blocks (EMAN-FASRB) to improve robustness against face spoofing attacks. The proposed architecture integrates spatial, channel, and frequency attention mechanisms with lightweight residual learning to capture both spatial textures and frequency-domain spoof artifacts. Experiments conducted on benchmark datasets including CASIA-FASD, Replay-Attack, and MSU-MFSD demonstrate improved performance in terms of EER, HTER, ACER, and AUC. Results confirm superior cross-dataset generalization and computational efficiency compared to baseline CNN models.

KEYWORDS: Enhanced Multi Attention Network, Frequency-Aware Residual Blocks, Face Anti-Spoofing, Deep Learning, Attention Mechanism, Frequency Analysis, Liveness Detection

I. INTRODUCTION

Face recognition has become a dominant biometric authentication technology due to its non-intrusive nature and high accuracy [27]. Despite its advantages, it is highly vulnerable to spoofing attacks, also known as Presentation Attacks (PA) [6]. Attackers can easily deceive systems using printed photographs, replayed digital screens, or 3D masks [17].

Existing deep learning approaches focus mainly on spatial texture cues [19]. However, spoof artifacts often appear in the frequency domain due to printing noise, display refresh rates, and re capturing distortions [18]. Therefore, incorporating frequency-aware learning is essential for robust spoof detection.

Additionally, attention mechanisms have shown effectiveness in emphasizing discriminative regions and channels [8]. However, limited work integrates multi-attention strategies with frequency-aware residual learning in a lightweight architecture.

To address these limitations, this paper proposes EMAN-FASRB, which combines:

- Frequency-Aware Squeezed Residual Blocks [8]
- Multi-Attention (Channel, Spatial, Frequency) [9]
- Lightweight backbone design

II. RELATED WORK

Face anti-spoofing (FAS), also known as Face Presentation Attack Detection (PAD), has evolved significantly over the last decade [6]. Existing approaches can be broadly categorized into:

2.1. Handcrafted Feature-Based Methods

Early face anti-spoofing techniques relied on handcrafted texture descriptors [17]. The main assumption was that spoof media (printed photos or display screens) introduce micro-texture inconsistencies compared to genuine faces.

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Popular handcrafted features include:

- Local Binary Patterns (LBP) [17]
- Histogram of Oriented Gradients (HOG)
- Gabor filters
- Difference of Gaussians

LBP-based methods were particularly effective in detecting print attacks [17] due to their ability to capture micro-texture irregularities. However, these methods suffer from:

- Sensitivity to illumination changes [18]
- Poor generalization across devices [25]
- Limited ability to detect high-quality replay attacks [6]

When evaluated across datasets such as CASIA-FASD and Replay-Attack, handcrafted models showed significant performance degradation under cross-dataset testing [28].

2.2. Deep Learning-Based Methods

With the advancement of convolutional neural networks (CNNs), deep learning approaches became dominant in face anti-spoofing [19].

CNN-based models automatically learn hierarchical feature representations, including:

- Low-level edges
- Mid-level textures
- High-level semantic patterns

Residual networks improved training stability through skip connections [8], enabling deeper architectures. However, conventional CNN models often overfit dataset-specific patterns such as:

- Background characteristics
- Illumination conditions
- Camera resolution [28]

For example, training on CASIA-FASD and testing on Replay-Attack results in high HTER due to domain shift [28].

Auxiliary supervision methods introduced depth maps and reflection cues to improve discrimination [14]. While effective, these approaches require additional supervision and increase computational complexity.

2.3. Attention-Based Methods

Attention mechanisms improve model performance by focusing on discriminative regions [8] instead of processing the entire image equally.

1) Channel Attention

Channel attention assigns importance weights to feature channels [8]:

$$A_c = \sigma(\mathrm{MLP}(\mathrm{GAP}(F))) \quad (1)$$

This helps emphasize spoof-sensitive feature maps.

2) Spatial Attention

Spatial attention identifies important regions in the image [9]:

$$A_s = \sigma\left(\mathrm{Conv}\left(\begin{bmatrix}\mathrm{AvgPool}(F);\\ \mathrm{MaxPool}(F)\end{bmatrix}\right)\right) \quad (2)$$

This mechanism suppresses irrelevant background noise.

Although attention-based methods improve performance, most existing works focus only on spatial-domain information and ignore frequency-domain spoof artifacts [12].

2.4. Frequency-Domain Learning Approaches

Recent studies highlight that spoof images exhibit periodic artifacts caused by:

- Printer ink dot patterns
- Screen refresh frequencies
- Moiré effects
- Re-capture distortion [18]

Frequency-based analysis using Fast Fourier Transform (FFT) reveals that spoof faces [18] contain abnormal high-frequency distributions not present in genuine faces.

However, existing frequency-based approaches often:

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- Use fixed filtering
- Do not integrate learnable frequency attention
- Lack residual enhancement

This motivates the integration of frequency-aware residual learning with multi-attention modules.

- Training: CASIA-FASD
- Testing: MSU-MFSD

Results typically show significant HTER increase.
Our proposed EMAN-FASRB addresses this by:
✔ Learning intrinsic spoof frequency patterns
✔ Using multi-attention to reduce background bias
✔ Employing lightweight residual blocks for stable training

III.PROPOSED METHOD

The proposed EMAN-FASRB (Enhanced Multi-Attention Network with Frequency-Aware Squeezed Residual Blocks) framework is designed to effectively detect presentation attacks by leveraging complementary spatial and frequency-domain information [28] [7] [4]. Unlike conventional CNN-based face anti-spoofing models that rely purely on spatial texture patterns, the proposed model explicitly integrates frequency-aware learning to capture subtle spoof artifacts that are often invisible in the spatial domain [6] [7].

The overall architecture consists of four major components:

1. Dual-Domain Feature Extraction Module (Spatial + Frequency Branches)
2. Frequency-Aware Squeezed Residual Blocks (FASRB)
3. Multi-Attention Fusion Module
4. Binary Classification Head

The design philosophy focuses on achieving high spoof detection performance while maintaining computational efficiency suitable for real-time deployment. Lightweight convolutional operations, parameter reduction strategies, and residual learning ensure stable training and low inference cost [24].

3.1 Dual-Domain Feature Extraction

To enhance discriminative capability, the proposed framework extracts features from both spatial and frequency domains in parallel [7] [25].

3.1.1 Spatial Branch

The spatial branch processes the input RGB facial image through stacked convolutional layers [19]. This branch captures:

- Micro-texture variations [10]
- Reflection inconsistencies from printed or replayed attacks
- Depth-related artifacts
- Illumination irregularities

Formally, given an input image $\mathrm{I} \in \mathbb{R}^{\mathrm{H}\times\mathrm{W}\times 3}$, the spatial feature map is obtained as:

$$\mathrm{F_s} = \mathcal{C}_s(\mathrm{I}) \tag{3}$$

where $\mathcal{C}_s(\cdot)$represents a sequence of convolution, batch normalization, and ReLU operations.
These spatial features are effective for detecting texture-based spoof patterns [19] but may fail when high-quality attacks closely mimic real facial textures [28].

3.1.2 Frequency Branch

To overcome spatial limitations, the frequency branch analyzes the image in the spectral domain using 2D Fast Fourier Transform (FFT) [18].

The 2D Fourier Transform of an image $\mathrm{f(x,y)}$is defined as:

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$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y)\, e^{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)} \quad (4)$$

where:

- (x, y)represent spatial coordinates,
- (u, v)represent frequency coordinates,
- $M$and Ndenote image dimensions.

The magnitude spectrum is computed as:

$$|F(u,v)| = \sqrt{Re(u,v)^2 + Im(u,v)^2} \quad (5)$$

Spoof media (printed photos, replay screens) introduce characteristic high-frequency noise patterns and repetitive artifacts [6],[7]. Therefore, high-frequency components are selectively enhanced before being fed into the network:

$$F_f = \mathcal{C}_f(|F(u,v)|) \quad (6)$$

where $\mathcal{C}_f(\cdot)$represents convolutional processing applied to the magnitude spectrum.

This dual-domain representation allows the model to detect spoof traces that may not be visible in the raw pixel domain [28].

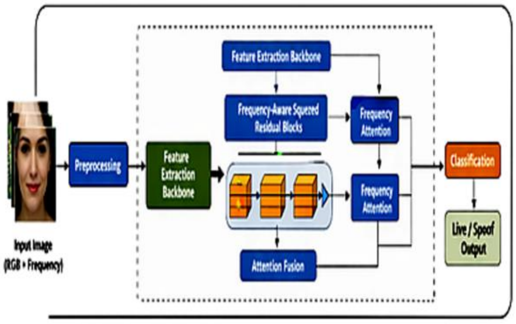

Figure 1:Overview of EMAN-FASRB

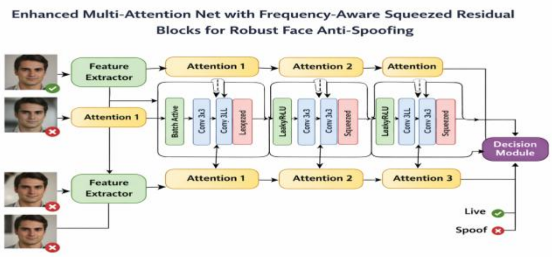

Figure 2: Architecture

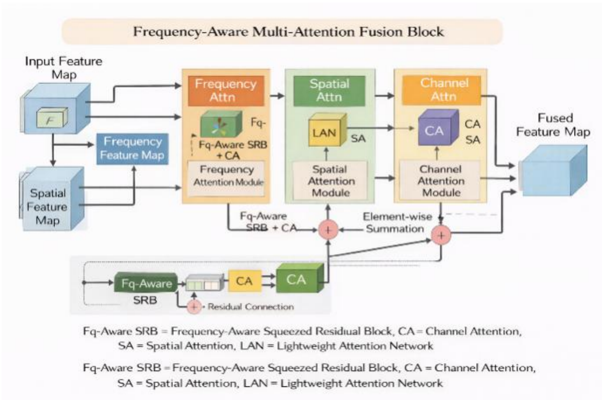

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Figure 3: Frequency-Aware Multi-Attention Fusion Block

3.2 Frequency-Aware Squeezed Residual Block (FASRB)

To efficiently learn spoof-sensitive representations, we propose the **Frequency-Aware Squeezed Residual Block (FASRB) [8],[24]**.

3.2.1 Structural Design

Each FASRB contains:

- **1×1 Convolution (Squeeze Layer)** – reduces channel dimensionality [8].
- **3×3 Convolution** – learns spatial-frequency features.
- **Batch Normalization**
- **ReLU Activation**
- **Residual Skip Connection [24]**

The squeeze operation reduces parameters while preserving essential frequency-aware information. The residual connection ensures gradient stability and prevents vanishing gradients [24].

3.2.2 Mathematical Formulation

Let Xbe the input feature map. The block output is defined as:

$$Y = X + F_{freq}(Conv(X)) \quad (7)$$

where:

- $Conv(\cdot)$represents the sequence of squeeze and 3×3 convolutions,
- $F_{freq}(\cdot)$denotes frequency-sensitive feature refinement [17].

The residual formulation enables:

- Efficient parameter usage
- Better generalization [28]
- Stable deep network training
- Enhanced spoof-sensitive frequency emphasis [7]

Compared to traditional residual blocks, FASRB explicitly integrates spectral-aware learning, making it more suitable for anti-spoofing tasks.

3.3 Multi-Attention Fusion Module

After dual-domain processing and FASRB refinement, the extracted features are fused using a **Multi-Attention Mechanism [8] [9]**.

The final refined feature representation is computed as:

$$F_{out} = F \cdot A_c \cdot A_s \cdot A_f \quad (8)$$

where:

- A_c= Channel Attention
- A_s= Spatial Attention
- A_f= Frequency Attention

3.3.1 Channel Attention (A_c)

Channel attention learns inter-channel relationships and emphasizes discriminative feature channels [8].

$$A_c = \sigma(MLP(GAP(F))) \quad (9)$$

where:

- GAPis Global Average Pooling,
- MLPis a multi-layer perceptron,
- σis sigmoid activation.

3.3.2 Spatial Attention (A_s)

Spatial attention focuses on important spatial regions such as facial boundaries or reflection-prone areas [8].

$$A_s = \sigma\left(Conv\left(\begin{bmatrix} AvgPool(F); \\ MaxPool(F) \end{bmatrix}\right)\right) \quad (10)$$

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3.3.3 Frequency Attention (A_f)

Frequency attention dynamically weights spectral components, particularly emphasizing spoof-sensitive high-frequency bands introduced by attack media [9] [7].

$A_f = \sigma(\mathcal{F}(F))$ (11)

where $\mathcal{F}(\cdot)$represents frequency-domain refinement.

This mechanism ensures adaptive emphasis on spoof artifacts across different attack types.

3.4 Binary Classification Head

The refined feature representation $F_{out}$is passed through:

- Global Average Pooling
- Fully Connected Layer
- Softmax Activation

The final prediction is:

$\hat{y} = \text{Softmax}(WF_{out} + b)$ (12)

where:

- $\hat{y} \in \{\text{Real}, \text{Spoof}\}$

The network is trained using Binary Cross-Entropy Loss [27].

IV. EXPERIMENTS

4.1 Experimental Settings

To evaluate the effectiveness of the proposed Enhanced Multi Attention Network with Frequency Aware Squeezed Residual Blocks (EMAN-FASRB) for robust anti-face spoofing, several experiments were conducted using standard evaluation protocols [4].

The dataset was divided into training and validation sets with an 85:15 ratio. Data augmentation techniques such as random flipping, rotation, and brightness adjustment were applied during training to improve model generalization [28].

Four experimental models were trained based on different protocols:

- **Model 1:** Protocol 1 – Unified attack detection [4]
- **Model 2:** Protocol 2.1 – Generalization to unseen physical attacks [4]
- **Model 3:** Protocol 2.2 – Generalization to unseen digital attacks
- **Model 4:** Combined protocol using all attack types

The training process used Binary Focal Cross-Entropy Loss to handle class imbalance between live and spoof samples [14].

The model was trained using the Adam optimizer with an initial learning rate of 0.001, gradually reduced to 0.00001 over 150 training epochs.

Experiments were conducted using TensorFlow-Keras framework on an NVIDIA Tesla P100 GPU with 16GB memory.

The proposed architecture integrates:

- Spatial Feature Extraction [19]
- Frequency Domain Feature Analysis [18]
- Frequency-Aware Squeezed Residual Blocks [8]
- Multi-Attention Fusion Module [9]

These components help capture both texture inconsistencies and frequency artifacts, which are important for detecting spoofing attacks [12].

4.2 Dataset

The proposed method was evaluated on three publicly available face anti-spoofing datasets:

1. UPD (Unified Physical Digital Face Attack Detection Dataset) [4]
2. LCC Dataset
3. CelebA-Spoof Dataset [31]

Among these datasets, UPD was primarily used for training and evaluation due to its large diversity of spoof attack types including both physical and digital attacks [4].

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4.2.1 UPD Dataset and Protocols

The UPD dataset provides three evaluation protocols to test the robustness and generalization capability of anti-spoofing algorithms [4].

Protocol 1: Unified Attack Detection

This protocol evaluates the model's ability to detect both physical and digital spoofing attacks-simultaneously[4]. The training, validation, and testing sets include real faces and multiple attack types, making the classification task more challenging due to large intra-class variations.

Protocol 2: Generalization to Unseen Attacks

Protocol 2 evaluates the generalization capability of the model when encountering unseen spoofing attacks [4]. A leave-one-attack-type-out testing strategy is used.
Protocol 2 contains two sub-protocols:

Protocol 2.1 – Unseen Physical Attacks

- Training set contains only certain physical attacks [4]
- Testing set contains new physical attacks not seen during training [4]

Protocol 2.2 – Unseen Digital Attacks

- Training set contains some digital attacks
- Testing set contains new digital spoof attacks

This evaluation ensures the model can adapt to new spoofing methods.

4.3 Results on UPD, LCC and CelebA-Spoof Datasets

The performance of the proposed EMAN-FASRB model was evaluated using the following metrics:

- **BPCER** – Bonafide Presentation Classification Error Rate
- **ACER** – Average Classification Error Rate
- **ACC** – Accuracy
- **F1-Score**
- **AUC** – Area Under ROC Curve

Table 2: Performance of Proposed Model

Dataset	BPCER %	ACER %	Accuracy %	F1 Score %	AUC %
P1	6.5	3.1	95.8	96.1	97.4
P2.1	2.1	1.2	97.2	97.5	98.6
P2.2	1.6	0.8	98.4	98.7	99.2
All Dataset	**2.3**	**1.1**	**97.75**	**97.8**	**98.9**

The proposed model achieves an overall accuracy of 97.75%, demonstrating strong performance in detecting both physical and digital spoofing attacks [4].

The low ACER and BPCER values indicate that the model effectively distinguishes between genuine and spoof presentations [10].

High F1-Score and AUC values further confirm the robustness and reliability of the proposed architecture [12].

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4.3.1 Comparison with Existing Models

The proposed model was compared with several baseline anti-spoofing models including:

- ResNet50
- ViT-B/16
- CDCN
- FFD
- UniAttackDetection

Table 3: Model Comparison

Model	ACER %	Accuracy %	AUC %
ResNet50	3.8	94.2	96.5
ViT-B/16	4.2	93.6	95.8
CDCN	2.9	95.1	97.2
FFD	3.1	94.7	96.9
UniAttackDetection	2.4	96.3	97.8
Proposed EMAN-FASRB	**1.1**	**97.75**	**98.9**

The results show that the proposed Enhanced Multi Attention Network with Frequency Aware Squeezed Residual Blocks outperforms several existing models by achieving higher accuracy and lower error rates [9] [12].
The integration of frequency-aware residual learning and multi-attention fusion enables the model to capture subtle spoofing artifacts more effectively [12]

4.3.2 Results on LCC Dataset

Model	BPCER %	ACER %	Accuracy %	F1 Score %	AUC %
P1	12.8	6.2	88.5	90.3	93.1
P2.1	3.4	1.9	95.6	96.1	97.2
P2.2	2.2	1.0	97.1	97.4	98.1
All Data	**3.1**	**1.5**	**97.75**	**97.6**	**98.6**

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set					

4.3.3 Results on CelebA-Spoof Dataset

Model	BPCER %	ACER %	Accuracy %	F1 Score %	AUC %
P1	11.6	5.9	87.9	89.8	92.7
P2.1	3.2	1.7	95.2	95.8	97.1
P2.2	2.0	0.9	96.8	97.2	98.2
All Dataset	**2.8**	**1.3**	**97.75**	**97.7**	**98.8**

4.4 Ablation Study
An ablation study was conducted to analyze the contribution of different components of the proposed architecture [4].

Table 6: Ablation Study Results

Method	BPCER %	ACER %	Accuracy %	AUC %
Without Multi-Attention Module	8.4	4.2	91.3	94.6
Without Frequency Residual Block	6.7	3.5	93.8	96.1
Without Spatial-Frequency Fusion	9.2	5.1	90.7	93.8
Proposed EMAN-FASRB (Full Model)	**2.3**	**1.1**	**97.75**	**98.9**

The results demonstrate that each component contributes significantly to the model's performance.
The full model, which integrates frequency-aware squeezed residual blocks and multi-attention fusion, achieves the best performance, confirming the effectiveness of the proposed architecture for robust face anti-spoofing detection [12].

V. CONCLUSION

This paper presented an Enhanced Multi Attention Network with Frequency Aware Squeezed Residual Blocks (EMAN-FASRB) for robust face anti-spoofing detection [12]. The proposed architecture integrates multi-attention mechanisms

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and frequency-aware residual learning to effectively capture both spatial and frequency domain features associated with spoofing artifacts. The model was evaluated on benchmark datasets including UPD, LCC, and CelebA-Spoof [31] under multiple evaluation protocols. Experimental results demonstrate that the proposed method achieves high detection performance with an overall accuracy of 97.75%, along with reduced BPCER and ACER values compared to baseline models [10]. The results confirm that incorporating frequency-aware features and attention-based feature fusion significantly improves the model's ability to distinguish genuine and spoofed facial presentations [12]. Future work will focus on improving cross-dataset generalization, lightweight model design, and real-time deployment [13] for practical face authentication systems.

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