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Lightweight CNN with wavelet-attention for fingerprint liveness detection

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Abstract: Fingerprint authentication has been extensively employed as a biometric method in diverse applications, including smartphones and embedded systems. Despite its advantages, this technology is susceptible to spoofing attacks using materials such as gelatin, posing a significant security risk. Numerous solutions have been proposed, but deep learning-based approaches often face challenges due to their large model sizes, limiting deployment in resource-constrained environments. To address this issue, we developed a lightweight and efficient fingerprint liveness detection model by integrating wavelet-attention with inverted-bottleneck convolution. The proposed method balances computational efficiency with high accuracy, enabling its practical implementation on low-resource devices. The model was designed with only 874,000 parameters and a memory footprint of 4 MB, representing a significant reduction in size compared to conventional deep learning models. The use of wavelet-attention enhances feature extraction by focusing on multi-scale spatial details crucial for distinguishing live and spoof fingerprints. Extensive experiments were conducted on the LivDet dataset and a custom dataset, encompassing fingerprints captured from multiple sensors. The results demonstrated robust performance, achieving an average classification error (ACE) of 2.27 across various sensors, which is competitive with state-of-the-art methods. Additionally, the model exhibited consistent performance in scenarios with limited computational resources, highlighting its efficiency and scalability. These findings suggest that the proposed approach is a viable solution for enhancing the reliability of fingerprint liveness detection, particularly in applications requiring lightweight and resource-efficient models.

Keywords: convolutional neural network, fingerprint liveness detection, lightweight architecture, wavelet-attention

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Introduction

Fingerprint recognition has emerged as a widely adopted authentication method in contemporary systems. This biometric approach has been integrated into numerous applications, ranging from smartphone devices to laptop computers, as a primary authentication mechanism [1]. The preference for fingerprint-based biometric security systems over alternative biological components—such as electrocardiograms, electroencephalograms, iris scans, and facial recognition—can be attributed to its comparatively straightforward authentication process. The widespread adoption of fingerprint authentication in digital systems has precipitated significant security and privacy concerns within the field of biometrics.

As with other authentication mechanisms, fingerprint-based systems introduce unique vulnerabilities to the security landscape. Of particular concern is the threat of fingerprint spoofing. Empirical studies have demonstrated that the success rate of fingerprint spoofing attacks can range from 68% to 100% [2]. These artificial fingerprints are typically fabricated using various material combinations, including gelatin and plastic molds [3]. The high efficacy of these forgery techniques underscores the critical need for advanced intelligent systems capable of robust liveness detection and fingerprint authenticity verification. There are already so many fingerprint liveness detection exist, ranging from a traditional digital image processing method to the use of deep learning.

The study presented in [4] conducts a comprehensive comparison of several texture feature descriptors, including Binarized Statistical Image Features (BSIF), Local Phase Quantization (LPQ), Weber Local Descriptor (WLD), Local Contrast Phase Descriptor (LCPD), and Rotation Invariant Co-occurrence among adjacent Local Binary Patterns (RicLBP). The findings indicate that the combination of LCPD and WLD enhances the effectiveness of fingerprint liveness detection. Meanwhile, other studies [5], [6], [7] and [8] have explored the synergy between fingerprint pore features, ridges and texture descriptors, demonstrating that integrating these complementary features can further boost the accuracy and reliability of liveness detection systems. Despite this promising approach, the performance of handcrafted features falls short compared to deep learning methods due to their lack of adaptability [9]. One of the first model to employ deep learning techniques in this context was introduced by [10], utilizing pre-trained convolutional neural networks (CNNs) to extract both CNN features and spatial features. The research is then followed by [11] and [12] where a ResNet architecture was combined with Transformer elements to enhance selectivity. By employing 830,000 parameters and multi-head attention layers, LFLDNet effectively extracts crucial information from fingerprint images.

However, while these deep learning approaches, including LFLDNet, demonstrate significant improvements in feature extraction and selectivity, they often come with substantial computational costs. The complexity of models like ResNet combined with Transformers requires considerable processing power and memory, making them less suitable for resource-constrained environments. This trade-off between performance and efficiency remains a challenge in the application of deep learning for liveness detection systems. One model that caught our attention for its lightweight nature is FLDNet [13]. FLDNet, a dense model, exhibits a remarkably low misclassification rate of just 2%, coupled with a relatively small number of parameters. Previous studies have demonstrated that incorporating attention layers in deep learning models can significantly reduce the parameter count without sacrificing performance [9], [10]. However, dense models like FLDNet face limitations compared to alternatives such as wavelet-attention and convolutional models. Dense models generally struggle with efficiently capturing spatial hierarchies and multi-scale features, which are critical for robust liveness detection. In contrast, wavelet-attention, which integrates wavelet transforms with attention mechanisms, allows the model to more effectively extract critical features by considering spatial scale variations, while convolutional layers excel at learning localized patterns.

To produce a lightweight and effective model, we employ an attention mechanism inspired by [11], utilizing wavelet-attention due to its proven superiority over conventional attention methods. This approach enables more efficient capture of fine details in image data while comprehensively addressing spatial scale variations. Additionally, we incorporate channel-wise convolution to further reduce the number of parameters without sacrificing the model's ability to extract critical features. By combining wavelet-attention with this convolutional technique, our model achieves enhanced efficiency and accuracy in liveness detection.

Methodology

Architectural Design

This research aims to develop a lightweight fingerprint liveness detection model with a compact architecture and high accuracy, specifically optimized for deployment in resource-constrained environments. The study was divided into three key phases: Our proposed model extends the MobileNetV2 architecture [14], incorporating a novel attention mechanism. Leveraging the Inverted Bottleneck block from MobileNetV2, we maintain a lightweight model suitable for resource-constrained environments. The comprehensive architecture is illustrated in Figure 1. The model is structured into three distinct stages, each designated for specific tasks. The initial stage, termed the "feet," processes high-level features from the input image, efficiently extracting information and rapidly reducing the image size.

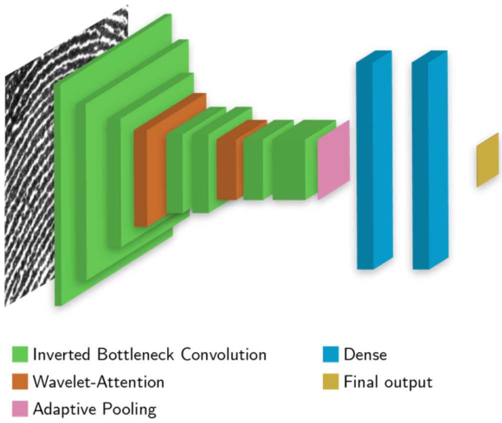

Figure 1. The proposed model architecture

The subsequent stage, referred to as "the body", focuses on intermediate feature extraction and transformation. This stage employs the Wavelet-Attention mechanism, enhancing the model's ability to capture and refine intricate details. By leveraging wavelet transforms, the body stage effectively balances computational efficiency with feature richness, ensuring robust performance across diverse input variations. This design allows for detailed feature representation while maintaining the model's overall efficiency. The final stage, termed "the head," is dedicated to final feature aggregation and classification.

This stage consists of two Inverted Bottleneck layers, which further refine the features extracted from the previous stages. Following these layers, an adaptive pooling layer is employed to ensure a consistent output size, regardless of the input dimensions. The output is then flattened and passed through a linear layer, which performs the final classification. This structured approach ensures that the model effectively integrates features at multiple scales, culminating in a robust and accurate classification output. The overall detail of the proposed architecture can be seen through Figure 1 and Table 1.

Table 1. Proposed model layer detail

Stage	Layer	Kernel Size/Expansion Factor/Stride	Output Shape (W, H, C)
Feet	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(112, 112, 32)
	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(56, 56, 64)
	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(28, 28, 72)
Body	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(28, 28, 72)
	Wavelet-Attention	-	(28, 28, 72)
	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(14, 14, 92)
	Wavelet-Attention	-	(14, 14, 92)
Head	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(14, 14, 216)
	Inverted Bottleneck	$(1 \times 1), (3 \times 3)/1/2$	(14, 14, 216)
	Adaptive Average Pool	-	(1, 1, 216)
	Flatten	-	(32, 16)
	Linear	1	(32, 1)

Wavelet-Attention Mechanism

The wavelet-attention mechanism employed in this model draws inspiration from [15]. Consider an image I with dimensions $M \times N$. As I represents a digital signal, it can be decomposed into multiple sub-bands wavelets w using the discrete wavelet transform (DWT) with a specific wavelet family γ, as expressed in Equation (1). This decomposition yields in a series of sub-band coefficients that encapsulate various frequency components of the original image. Specifically, w_{ll} represents approximate image details, meanwhile w_{lh}, w_{hl} and w_{hh} represent image details.

The novelty of our research lies in our distinctive utilization of these sub-bands. We concatenate each of these wavelets to construct a comprehensive feature map.

$$DWT_{\gamma}(I) = \{w_{ll}, w_{lh}, w_{hl}, w_{hh}\} \quad (1)$$

$$I_m = \sum_{i=0}^{4} c_i w_i \quad (2)$$

$$O = I \bowtie (\sigma(I_m)) \quad (3)$$

Unlike [15], which discards the w_{hh} sub-band due to the belief that it contains only noise, our approach leverages a weighted sum of all sub-bands, as expressed in Equation (2). In Equation (2), I_m represents the resulting feature map, w_i denotes the sub-band coefficients and c_i are the corresponding weights assigned to each sub-band. This method ensures that our model effectively harnesses the complete frequency information, thereby enhancing feature extraction and overall performance. Sigmoid activation function is then applied to the weighted sum and since the concatenation process of feature maps produced a downsampled vector, we perform bilinear interpolation to upsample the vector back to its original size and perform multiplication between image I and activated feature map $I \bowtie (\sigma(I_m))$ as expressed in Equation (3). Overall, the complete process of wavelet-attention blocks is illustrated in Figure 2.

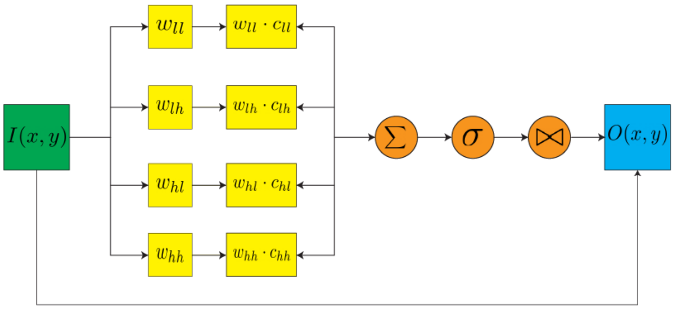

Figure 2. Visualization of wavelet-attention mechanism

By incorporating this attention mechanism, we enhance the network's ability to adaptively weight different regions and scales of the input, leading to improved feature representation and ultimately better performance in various computer vision tasks. The bilinear interpolation step ensures that the attention map aligns properly with the original input dimensions, maintaining spatial coherence throughout the network. This approach not only improves the model's efficiency in processing complex visual information but also contributes to its interpretability, as the attention maps can be visualized to gain insights into the network's decision-making process.

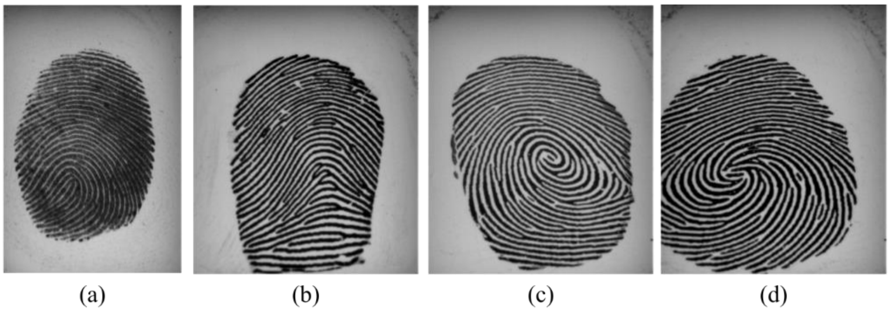

Figure 3. Representative samples from the dataset. From left to right: (a) Real fingerprint, and (b), (c), (d) are spoof fingerprints created using different materials: wood glue, latex, and gelatin, respectively.

Dataset

The dataset utilized in this study is derived from the LivDet (Liveness Detection) Fingerprint Competitions held in 2009 [16], 2011 [17], 2013 [18] and 2015 [19]. This comprehensive dataset encompasses two primary categories: "genuine" and "fake" fingerprints. The "fake" fingerprint samples were obtained using various sensor technologies, which evolved and improved with each competition year, providing a diverse and challenging set of spoof attempts to analyze. The dataset's composition reflects the advancement in both fingerprint acquisition technologies and spoofing techniques over the years.

The "genuine" category consists of real fingerprints collected under controlled conditions, while the "fake" category includes a wide array of artificial fingerprints created using materials such as gelatin, silicone, and play-doh, among others. Figure 3 illustrates representative samples from the dataset, including one genuine fingerprint and several fake samples produced using different spoofing materials. Table 1 provides a detailed breakdown of the total number of genuine and fake fingerprint samples used in this study. It is important to note that the initial dimensions of the fingerprint images vary significantly across the dataset. This variation is due to the different sensors used in each competition year and the specific acquisition protocols followed. The 2009 competition used 3 different sensors, while both 2011 and 2013 used 4 sensors each, resulting in a diverse dataset with varying image sizes and characteristics. The distribution of the fingerprint samples can be seen in Table 2.

Table 2. Distribution of fingerprint samples in LivDet competitions (2009-2015)

Year	Total Genuine Samples	Total Fake Samples	Total Samples
2009	5,493	550	10,993
2011	8,012	7,835	15,847
2013	8,874	8,629	17,503
2015	13,459	15,968	29,427

Implementation Details

The model was trained for a minimum of 10 epochs using the Adam optimizer with AMSGrad. The initial learning rate was set to 1×10^{-4} with mini-batches of 32 images. A *ReduceLROnPlateau* scheduler was implemented, reducing the learning rate by a factor of 0.1 after 2 epochs without improvement in validation performance.Training was conducted on two hardware configurations: a Google Colab environment with NVIDIA V100 GPU and a Lenovo X270 laptop (Intel Core i5-7200U, 8GB RAM). This dual-platform training approach was employed to assess the model's performance under varying computational constraints, relevant for both cloud-based and edge computing scenarios in computer vision applications.

For performance evaluation, we adopt common metrics used in fingerprint liveness detection, including FERRLive, FERRFake and Average Classification Error (ACE) [19]. FERRLive is defined as the percentage of live fingerprints that are incorrectly classified as fake, while FERRFake denotes the percentage of fake fingerprints misclassified as live. The ACE value reflects the average of these two errors, offering a balanced measure of overall classification performance. Let $n(y_l)$ and $n(y_f)$ denote the number of ground-truth live and fake fingerprint samples respectively. Let $n(\hat{y}_l)$ and $n(\hat{y}_f)$ be the number of fake samples misclassified as live. The evaluation metrics are computed as follows:

$$FERR_{live} = \frac{n(\hat{y}_l \neq y_l)}{n(y_l)} \times 100\% \tag{4}$$

$$FERR_{fake} = \frac{n(\hat{y}_f \neq y_f)}{n(y_f)} \times 100\% \tag{5}$$

$$ACE = \frac{FERR_{live} + FERR_{fake}}{2} \times 100\% \tag{6}$$

It is important to note that all reported error rates are expressed in percentage format (0–100%), not as normalized fractions between 0 and 1. Therefore, ACE values greater than 1 are valid and represent percentage error, not normalized error.

Results and Discussions

Results

The experimental results underscore that our proposed model, which incorporates a custom wavelet-attention mechanism, achieves performance competitive with state-of-the-art methods. As detailed in Table 3, the model's performance varies across different sensor types and data years. Notably, it attains an ACE of 1.716% with the CrossMatch sensor, demonstrating its effectiveness in this context, while a higher ACE of 2.198% is observed with the DigitalPersona sensor, suggesting areas for further optimization.

Table 3. Performance comparison of our model compared to existing methods on LivDet 2015 dataset

Method	ACE's Score on LivDet2015 Test Dataset (%)				
	Biometrika	**CrossMatch**	**Digital Persona**	**GreenBit**	**Average**
DRN	6.24	3.46	6.8	4.77	5.32
fPADNet	4.1	0.3	8.5	1.4	3.58
FLDNet	2.34	1.54	2.58	0.56	1.76
Our model	**2.55**	**1.71**	**2.98**	**2.47**	**2.27**

Despite an average ACE of 2.274%, which slightly exceeds the state-of-the-art benchmark of 1.38, the efficiency of the proposed model remains noteworthy. With only 874,000 parameters and a total size of 4 MB, the model effectively balances performance and computational efficiency. However, the observed ACE can largely be attributed to architectural choices made to achieve such lightweight efficiency. Speicifically, the use of single-level wavelet decomposition and static weighting significantly simplifies the network and reduce computational complexity. It also limits the model's ability to extract complex, multi-scale features essential for robust fingerprint liveness detection. This trade-off is consistent with recent findings in the literature. For instance, research done by [20] demonstrated that lightweight architecture relying on simplified decomposition techniques often struggle to capture fine-grained details, leading to higher error rates.

Similarly, [21] reported that while static weighting schemes provide computational advantages, they frequently hinder a model's adaptability to the inherent variability in real-world data. Moreover, the performance discrepancies observed between CrossMatch and DigitalPersona sensors highlight the challenges posed by sensor heterogeneity, a factor that [22] found to significantly impact detection outcomes in multi-sensor systems.In resource-constrained scenarios, an ACE value of 2.274 remains within an acceptable range, aligning with trends observed in lightweight architectures optimized for real-time applications. Future research should focus on incorporating advanced multi-level decomposition techniques and adaptive weighting strategies to enhance the model's representational capacity while preserving its computational efficiency.

While existing methods have largely focused on traditional convolutional architectures or transformer-based models, the proposed wavelet-attention framework offers a promising direction for enhancing both feature extraction and computational efficiency. This pioneering approach lays the foundation for future advancements in biometric security, encouraging further exploration into hybrid architectures that leverage wavelet-based transformations alongside dynamic attention mechanisms to improve adaptability and robustness in real-world applications.

Ablation Studies

We conducted an ablation study to assess the efficacy of our proposed wavelet-attention layer by comparing it to a baseline model using standard pooling operations. The experimental results, summarized in Figure 4, provide strong empirical evidence demonstrating the superiority of wavelet-attention across multiple fingerprint datasets. Specifically, our model achieved an error rate of 2.550 on the Biometrika dataset, compared to 3.025 for the baseline model, reflecting a 15.7% reduction. Similar improvements were observed for the CrossMatch dataset (1.710 vs. 2.227, 23.2% reduction), the Digital Persona dataset (2.980 vs. 4.495, 33.7% reduction), and the GreenBit dataset (2.470 vs. 3.751, 34.2% reduction). These consistent performance gains across diverse fingerprint sensors underscore the robustness and generalizability of our approach.

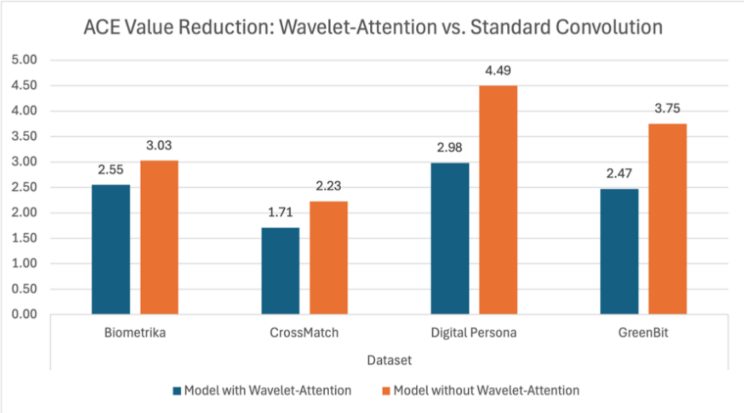

Figure 4. ACE Score comparisons between proposed wavelet-attention convolution and standard convolution

The justification for these improvements lies in the ability of the wavelet-attention layer to efficiently extract and retain both global and local spatial information while mitigating unnecessary redundancy. Unlike conventional convolutional layers, which apply fixed-size filters across the image and tend to lose high-frequency details, wavelet-based transformations decompose input features into multiple frequency components, preserving fine-grained structures crucial for distinguishing live and spoofed fingerprints.

Furthermore, the integration of an attention mechanism amplifies these advantages by dynamically weighting relevant features at multiple scales, ensuring that key discriminatory patterns are emphasized while less informative regions are suppressed. This combination of wavelet decomposition and attention enables our model to capture both long-range dependencies and fine-scale details, enhancing its capacity to generalize across different sensor types. Additionally, recent studies [23] have demonstrated that adaptive wavelet pooling strategies improve classification accuracy by maintaining critical structural information while reducing computational overhead, further supporting the observed reductions in ACE values in our experiments.

Notably, the most significant performance gains were observed for the Digital Persona (33.7%) and GreenBit (34.2%) datasets, both of which have historically posed challenges due to their susceptibility to spoofing artifacts. This suggests that wavelet-attention is particularly effective in fingerprint authentication tasks where fine-scale textural variations play a crucial role in differentiating real from fake prints. Given the absence of prior work explicitly integrating wavelet-based processing with attention mechanisms for fingerprint liveness detection, our approach establishes a novel and promising direction for future research in biometric security. These findings highlight the potential of wavelet-attention as a fundamental building block for more robust and efficient fingerprint recognition systems, paving the way for further advancements in multi-scale feature learning and adaptive deep learning architectures.

Discussions

The results demonstrate that the incorporation of a custom wavelet-attention mechanism into our model effectively balances performance with computational efficiency. Although our model's average ACE of 2.27 is slightly higher than the benchmark of 1.38, it consistently performs well across a variety of sensor types, particularly achieving an ACE of 1.716 with the CrossMatch sensor. This performance, coupled with the model's compact architecture—boasting only 874,000 parameters and a 4 MB footprint—highlights its suitability for deployment in resource-constrained environments. In contrast to larger, more computationally intensive state-of-the-art models, our approach provides a compelling trade-off between accuracy and efficiency, a critical consideration for real-world applications.

Nonetheless, the discussion of our findings also brings to light several limitations inherent in the current design. The use of only a level 1 wavelet decomposition, while effective for reducing computational complexity, may restrict the model's ability to capture finer-scale features, which could be essential for handling more complex or variable biometric data. Additionally, the reliance on static weights for the wavelet components—implemented to avoid overfitting—limits the adaptability of the model. Experiments with learnable weights resulted in rapid overfitting, suggesting that a more nuanced approach to dynamic weighting is necessary to enhance generalization without compromising the model's stability.

Our model has a compact raw size of only 4.00 MB, without the application of any compression techniques such as pruning, quantization, or weight sharing. This baseline footprint demonstrates the efficiency of our architecture by design, and serves as a strong starting point for further optimization. Compared to existing models such as FLDNet (~1.9 MB, 0.48M parameters) and fPADNet (~1.2 MB, 308K parameters), our model offers a balanced trade-off between size and performance, particularly in terms of generalization across multiple sensors. Given that our 4 MB size is achieved without any post-training compression, there is significant room for further reduction if needed, making it highly practical for real-world applications with strict resource constraints. This positions our approach as not only accurate and robust, but also scalable and deployment-ready from the outset.

Looking forward, these observations provide a clear pathway for future improvements. Exploring multi-level decomposition techniques could enable the model to extract richer, hierarchical features, thereby potentially reducing the performance gap with the state-of-the-art. Moreover, developing adaptive weighting mechanisms that strike a balance between flexibility and regularization may mitigate the overfitting issues encountered during initial experiments. Such refinements could further bolster the model's robustness and applicability across diverse biometric datasets, ultimately advancing the field of biometric security by offering solutions that are both effective and computationally efficient.

Conclusion

In this work, we employed and refined the Wavelet-Attention Mechanism specifically for fingerprint liveness detection. Our experiments reveal that incorporating this mechanism leads to substantial performance gains. Evaluated on the LivDet 2015 dataset, our proposed model, which is notably lightweight, achieved an average ACE of 2.27 across all sensor types, ranking as the second-best model among state-of-the-art approaches. This highlights the effectiveness of wavelet-based attention mechanisms in enhancing liveness detection accuracy while maintaining a compact architecture.

Additionally, ablation studies show that our refinements lead to performance improvements ranging from 15.7% to 33.7%, further validating the benefits of our approach. Future work will focus on exploring the use of multilevel wavelet transforms instead of single-level ones to potentially enhance performance further. Another avenue for research includes developing a learnable wavelet family to optimize feature extraction capabilities

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