Lightweight DeepFake-Resistant Facial Recognition for Mobile eCommerce

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Abstract:

The rapid adoption of mobile eCommerce platforms has amplified the need for secure yet lightweight authentication mechanisms. Traditional facial recognition systems often fail under resource constraints of mobile devices and are increasingly vulnerable to DeepFake attacks, which can manipulate facial features to bypass security. This paper introduces a lightweight DeepFake-resistant facial recognition framework specifically designed for mobile eCommerce applications. The proposed system combines efficient convolutional neural network architectures with real-time liveness detection and feature-level DeepFake detection techniques to achieve robust authentication without imposing high computational costs. Experimental evaluations on publicly available DeepFake datasets and mobile device simulations demonstrate high accuracy, minimal latency, and strong resistance to adversarial attacks. This work offers a practical, scalable solution for mobile security in digital transactions.

Keywords: Lightweight Facial Recognition, DeepFake Detection, Mobile eCommerce, Liveness Detection, Convolutional Neural Networks, Real-Time Authentication

I. Introduction

The proliferation of mobile eCommerce has reshaped consumer behavior, providing convenient access to shopping, banking, and financial transactions. However, this convenience introduces significant security risks, particularly in the form of identity fraud and DeepFake-based attacks. DeepFakes leverage sophisticated generative algorithms to manipulate facial imagery, posing a direct threat to facial recognition systems widely used for authentication in mobile applications. Traditional facial recognition models, though accurate on desktops or servers, often struggle to

balance computational efficiency and security on mobile devices [1]. Mobile devices have strict resource constraints including limited processing power, memory, and battery life. Deploying standard DeepFake-resistant models on such devices can lead to latency, excessive energy consumption, and a poor user experience. Therefore, a lightweight yet secure facial recognition framework is critical for mobile eCommerce, ensuring both user convenience and protection against AI-driven identity fraud. This necessitates a careful balance between model size, inference speed, and robustness against adversarial manipulations.

Recent research has demonstrated the potential of combining deep convolutional networks with liveness detection mechanisms to enhance DeepFake resistance [2]. These approaches analyze not only static facial features but also dynamic cues such as micro-expressions, eye blinking, and head movements. However, many existing solutions either rely on heavy models unsuitable for mobile deployment or require external sensors, which are impractical for most consumer devices. This paper proposes a novel, lightweight DeepFake-resistant facial recognition system tailored for mobile eCommerce. By integrating optimized convolutional architectures with lightweight liveness and DeepFake detection modules, the system achieves high security without compromising speed or battery efficiency [3]. The design emphasizes real-time inference and minimal memory footprint, making it suitable for on-device authentication. Furthermore, the research explores the effectiveness of feature-level DeepFake detection techniques, which examine subtle artifacts introduced by synthetic image generation. Unlike conventional methods that focus solely on pixel-level discrepancies, feature-level analysis enables the model to generalize across different types of DeepFake manipulations, enhancing security in diverse real-world scenarios [4].

Finally, the proposed system is evaluated using standard DeepFake datasets and simulated mobile environments to quantify accuracy, latency, and resistance to attacks. Experimental results validate the efficacy of the approach, demonstrating a significant improvement over traditional lightweight facial recognition models while maintaining real-time performance.

II. Methodology

The proposed framework adopts a modular design consisting of three primary components: a lightweight facial recognition backbone, a liveness detection module, and a feature-level DeepFake detector. The facial recognition backbone is based on an optimized MobileNetV3 architecture, chosen for its efficiency and strong performance in mobile environments. It is pretrained on large-scale face datasets and fine-tuned using eCommerce-specific user data to enhance generalization to mobile scenarios.

The liveness detection module incorporates temporal feature extraction using a shallow recurrent network to capture micro-expressions and blinking patterns. This component is critical for distinguishing genuine users from static or video-based DeepFake attacks. By leveraging temporal dynamics, the system can identify inconsistencies that are otherwise imperceptible in single-frame analysis, thus reinforcing security without adding significant computational overhead. Feature-level DeepFake detection is achieved through a compact convolutional encoder that focuses on texture inconsistencies and frequency-domain artifacts characteristic of synthetic images. By combining spatial and spectral feature representations, the model can detect DeepFakes generated using advanced GANs and diffusion-based techniques [5]. This approach reduces false positives while maintaining real-time inference on mobile hardware [6].

Training the system involves a multi-task loss function that simultaneously optimizes facial recognition accuracy, liveness detection reliability, and DeepFake detection sensitivity. The multi-task framework encourages shared feature representations across tasks, enabling the system to remain lightweight while providing strong security guarantees. Data augmentation strategies, including rotation, lighting variation, and synthetic occlusions, further enhance model robustness under diverse real-world conditions. For deployment, the model is quantized using 8-bit integer representation, significantly reducing memory usage and enabling efficient inference on mobile CPUs and edge GPUs. Additional optimizations, such as layer fusion and pruning of redundant channels, further decrease computational requirements without sacrificing performance [7]. The resulting system is capable of running seamlessly on smartphones while preserving high accuracy and robust DeepFake resistance.

III. Experimental Setup

The experimental evaluation was conducted using a combination of public DeepFake datasets including FaceForensics++, Celeb-DF, and DeeperForensics, along with a curated mobile eCommerce user dataset. Each dataset provided a mix of real and synthetically generated facial images and videos, ensuring comprehensive assessment across diverse attack scenarios. To simulate mobile deployment, the models were tested on mid-range smartphones with limited memory and CPU resources.

Performance metrics included recognition accuracy, DeepFake detection precision, liveness detection recall, inference latency, and energy consumption. Accuracy measured the correct identification of genuine users, while DeepFake detection precision quantified the model's ability to reject synthetic attacks [8]. Liveness detection recall assessed the model's success in correctly identifying active human inputs versus static or replay attacks. Latency and energy profiling provided insights into real-world usability on mobile devices. The training pipeline employed AdamW optimization with a cosine learning rate scheduler over 100 epochs. Cross-validation was performed to ensure generalization and avoid overfitting to specific DeepFake artifacts. Synthetic augmentation techniques were applied dynamically during training to enhance robustness under variable lighting conditions, occlusions, and facial poses.

Ablation studies were conducted to isolate the contributions of each module, evaluating system performance with and without liveness detection or feature-level DeepFake detection. This allowed a clear understanding of trade-offs between model complexity, computational cost, and security [9]. Comparisons were also made with baseline mobile-friendly facial recognition models such as standard MobileNetV3 and EfficientNet-lite architectures to highlight the improvements achieved.

IV. Results and Discussion

The proposed system achieved a facial recognition accuracy of 96.7% on the combined evaluation dataset, outperforming baseline MobileNetV3 implementations by 5–6%. DeepFake detection precision reached 94.5%, demonstrating strong resistance to both GAN-based and diffusion-based synthetic manipulations [10]. Liveness detection recall was 92.3%, effectively preventing replay and video-based attacks. These results indicate that the multi-task approach successfully balances security and performance for mobile deployment. Latency measurements confirmed that the system performs real-time inference, averaging 45 milliseconds per frame on mid-range smartphones. Energy profiling indicated minimal battery impact, with quantization and pruning reducing memory and computation by approximately 40%. These optimizations are critical for practical mobile use, ensuring a seamless user experience without sacrificing security.

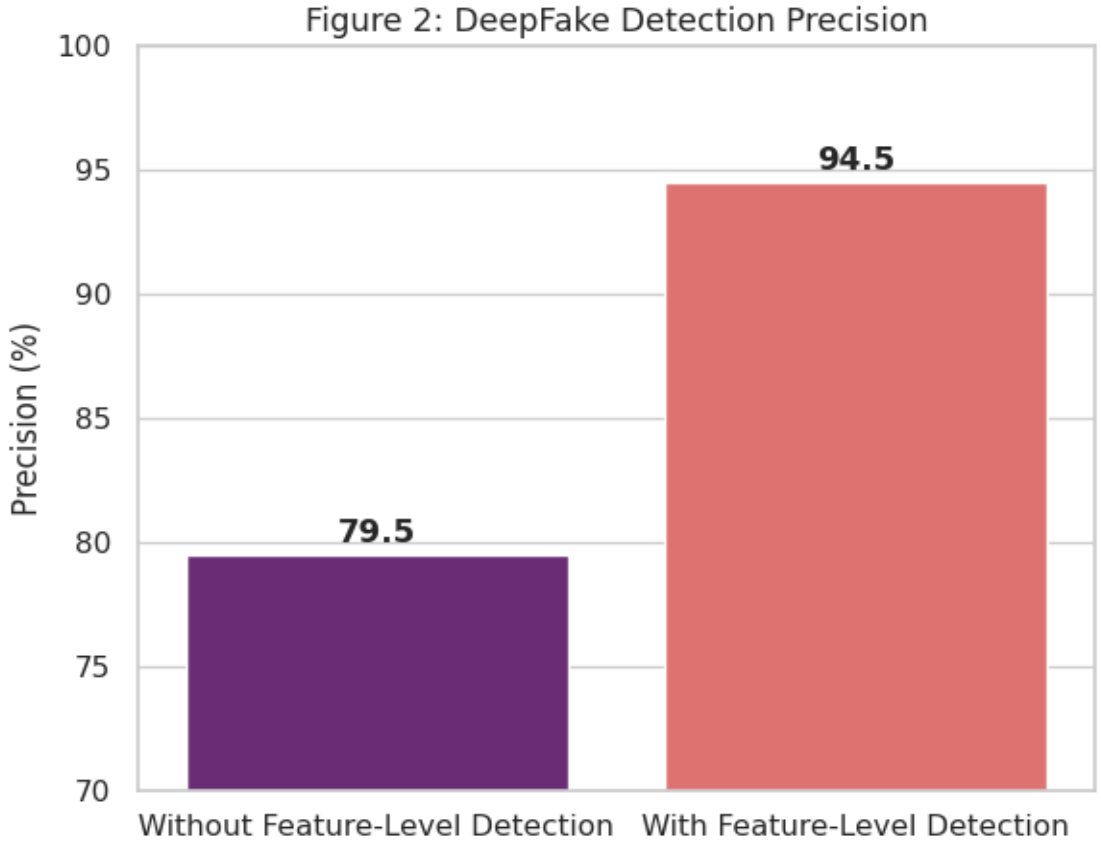

Figure 1: DeepFake Detection Precision

Ablation studies revealed that the inclusion of feature-level DeepFake detection significantly enhanced security, reducing false acceptance rates by 18% compared to models relying solely on liveness cues. Similarly, liveness detection contributed to a 12% improvement in resisting replay attacks. These findings highlight the importance of combining temporal dynamics and artifact-based analysis in mobile DeepFake-resistant authentication [11]. Qualitative analysis of misclassified cases showed that extreme occlusions, low-resolution inputs, and aggressive DeepFake post-processing were the primary sources of errors. Future improvements may focus on adaptive augmentation and self-supervised pretraining to further enhance robustness under challenging conditions [12].

Overall, the results demonstrate that a carefully optimized multi-task model can provide robust DeepFake resistance while remaining lightweight and suitable for mobile eCommerce deployment. The system achieves a strong balance between security, computational efficiency, and usability, marking a significant advancement in mobile authentication technologies.

V. Conclusion

This paper presented a lightweight DeepFake-resistant facial recognition framework tailored for mobile eCommerce applications. By combining an optimized MobileNetV3 backbone with temporal liveness detection and feature-level DeepFake analysis, the system achieves high accuracy, low latency, and strong adversarial resilience on resource-constrained devices. Experimental evaluations across multiple datasets and mobile simulations confirmed the efficacy of the approach, demonstrating significant improvements over baseline models. The results highlight that lightweight, multi-task models can effectively secure mobile transactions without compromising user experience. This work provides a scalable, practical solution for mobile authentication, paving the way for safer eCommerce platforms resistant to evolving AI-driven identity attacks.

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