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Biometric Feature Fusion using Gradient and Pore Features for Fingerprint Spoof Detection

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Abstract

Fingerprint-based biometric systems are widely adopted for secure identity verification. However, they are highly vulnerable to spoofing attacks using fake fingerprints crafted from various materials. To address this challenge, we propose a lightweight feature fusion framework that integrates gradient-based edge information and pore-level micro textures to improve spoof detection accuracy and generalisation. The proposed model uses a convolutional backbone to extract modality-specific features, which are fused via a weighted concatenation mechanism before classification. Experimental results on standard datasets such as LivDet and MSU-FPAD demonstrate that the proposed method achieves superior accuracy (98.1%) compared to state-of-the-art baseline models. Moreover, the system is computationally efficient and interpretable via Grad-CAM-based visualisation, making it suitable for deployment on real-time edge devices. This work complements our prior research by offering a robust yet lightweight defence against spoofing, enhancing the overall integrity of fingerprint biometric systems.

Keywords

Fingerprint Spoof Detection; Feature Fusion; Gradient Features; Pore Features; Lightweight CNN; Biometric Security; Presentation Attack Detection (PAD); Explainable AI.

1. Introduction

Fingerprint recognition has become the cornerstone of biometric authentication systems due to its uniqueness, permanence, and ease of acquisition. However, the proliferation of fingerprint-based systems in smartphones, border control, and financial applications has led to a corresponding surge in **spoof attacks**, where synthetic fingerprints are used to deceive sensors [1]. These **presentation attacks** pose significant threats to user security, necessitating robust and real-time spoof detection mechanisms.

While several **CNN-based architectures** have been proposed for end-to-end fingerprint spoof detection [2] [4], they often treat fingerprint images as black-box inputs without exploiting domain-specific biometric features. Such architectures, although efficient, may overlook **fine-grained local cues** that are critical in distinguishing live from spoof samples—especially in high-quality spoof artefacts made from materials like silicone or gelatin.

This paper addresses that gap by exploring a **biometric feature-level fusion approach** focusing on **gradient maps** and **pore features** extracted from fingerprint images. These features are not only **biometrically meaningful** but also **complementary**—while gradient maps capture **edge texture and ridge patterns**, pore maps provide **micro-structural liveness cues** typically absent in spoof artifacts.

Rather than proposing a new deep network, we advocate a **modular fusion strategy** where these handcrafted features are passed through **lightweight CNN branches** and fused at feature-level for classification[8]. This enables the system to retain **semantic interpretability**, maintain **low computational overhead**, and improve **spoof detection generalisation**, especially under cross-material and cross-sensor settings.

2. Related Work

The fingerprint presentation attack detection (PAD) field has evolved along three main trajectories: end-to-end CNN approaches, handcrafted feature methods (texture, gradient, pore-level cues), and hybrid or fusion models combining learned and engineered cues. This section analyses each line and positions our proposed fusion approach within this landscape.

2.1 CNN-Based End-to-End Methods

Deep Convolutional Neural Networks (CNNs) have become a dominant paradigm for spoof detection, owing to their ability to automatically learn discriminative features from raw images. Early works explored patch-based CNNs, for instance Chugh & Jain's "Minutiae-Centered Local Patches," which uses small local patches around minutiae points and achieves robust performance on the LivDet datasets [3]. More recently, lightweight CNNs like MobileNet and its derivatives have been adapted for fingerprint spoof detection to reduce computational load while retaining accuracy [4]. These models treat fingerprint images as black-box inputs, relying entirely on deep feature extraction and classification.

While such end-to-end models are powerful, they often omit domain-specific cues (like pores) that carry strong liveness information. Furthermore, their internal representations remain opaque without explicit interpretability modules.

2.2 Handcrafted Features: Gradient, Texture, Pore Cues

Prior to the deep learning era, many spoof detection approaches used **handcrafted texture descriptors** (e.g., LBP, Gabor filters, wavelets) to detect anomalies in ridge-valley patterns under spoof conditions. Some works also incorporated **gradient-based filters** (Sobel, Scharr) to highlight ridge continuity disruptions introduced by spoof fabrication. Pore-level features—localizing sweat pore distributions—have been used less often, but are cited as anatomically difficult to replicate in spoof artifacts [5].

Certain methods attempted combining texture and pore cues in classical pipelines, but they lacked generalisation and were sensitive to sensor noise. A key limitation is that handcrafted methods often require careful tuning and do not scale well across datasets.

2.3 Hybrid & Feature Fusion Approaches

To mitigate the shortcomings of pure CNN or pure handcrafted methods, hybrid fusion approaches have gained traction. In biometric domains beyond fingerprints (e.g., face PAD), multi-stream architectures fuse learned deep features with handcrafted descriptors to enhance robustness[6]. Recent fingerprint PAD literature has begun exploring fusion strategies—some works fuse texture and CNN features, others combine multispectral or multi-domain inputs[9].

However, very few focus specifically on **gradient + pore map fusion** in a lightweight framework for fingerprint spoof detection, particularly in real-time or edge contexts[7] [10]. Our approach addresses this gap by modularly integrating gradient and pore feature branches into a lightweight neural pipeline, enabling both interpretability and strong spoof discrimination.

3. Proposed Feature Fusion Method

The core innovation of this study lies in the synergistic fusion of **gradient-based ridge-flow features** and **pore-level anatomical features** into a lightweight convolutional neural framework. Unlike monolithic CNN models that rely entirely on learned representations, this approach integrates explainable handcrafted cues, enhancing both accuracy and interpretability [11] [12].

3.1 Overall Architecture

The architecture comprises three main components:

- **Gradient Feature Module (GFM):** Computes ridge orientation and edge continuity.
- **Pore Extraction Module (PEM):** Detects sweat pore maps as micro-level anatomical features.
- **Fusion and Classification Block:** Combines both streams with compact CNN layers for final spoof classification.

3.2 Gradient Feature Extraction

Gradient information is critical for capturing spoof-induced disruptions in ridge flow patterns. We apply a Sobel operator in both the horizontal and vertical directions:

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

Where:

I The input grayscale fingerprint image.

$\frac{\partial I}{\partial x}$ Partial derivative of the image intensity with respect to the horizontal axis. Captures changes in pixel values in the x-direction.

$\frac{\partial I}{\partial y}$ Partial derivative of the image intensity with respect to the vertical axis. Captures changes in pixel values in the y-direction.

G_x Horizontal (x-direction) gradient image. Highlights vertical edges or ridge endings.

G_y Vertical (y-direction) gradient image. Highlights horizontal edges or ridge bifurcations.

These are combined to compute the gradient magnitude:

$$G = \sqrt{G_x^2 + G_y^2}$$

Where:

G Gradient magnitude, representing the overall strength of an edge (regardless of direction) at each pixel. High values indicate strong edge or ridge presence.

This highlights areas of abrupt edge changes—common in fake fingerprint ridges due to poor mould resolution or pressure variations during presentation.

The resulting gradient map is normalised and passed through a **shallow CNN stack** (three convolution + ReLU layers with batch normalisation) to retain lightweight characteristics.

3.3 Pore Feature Extraction

Sweat pores are one of the least replicable features in spoof artefacts. A high-pass filter is first applied to the original image, followed by adaptive thresholding to extract high-frequency dot-like structures. This pore map is refined using morphological operations (opening and dilation) to enhance signal clarity[5].

The refined pore map is then processed by a parallel shallow CNN module similar to the GFM pipeline. The goal is not only to detect the presence of pores, but also their **distribution patterns**, which vary significantly between live and spoof prints.

3.4 Feature-Level Fusion

Feature maps from both the GFM and PEM are channel-wise concatenated and passed through a **global average pooling (GAP)** layer. This fusion allows the model to leverage both global ridge orientation features and fine-grained pore details.

The fused feature vector is passed to a compact classifier (Dense → ReLU → Dropout → Softmax). The total parameter count remains under 0.5M, ensuring deployment feasibility on edge devices[7].

3.5 Explainability Considerations

The fused model is compatible with Grad-CAM, allowing class-discriminative visualisation of the regions influencing the spoof/liveness decision. This adds a layer of interpretability critical for biometric systems used in high-security applications.

As depicted in **Figure 3.1**, the proposed model employs a feature-level fusion strategy that combines three fingerprint representations: the original image, gradient-enhanced map, and pore-visualised map. These are independently passed through parallel convolutional layers (MobileNetV2 branches) to extract modality-specific features. The resulting vectors are then concatenated into a unified feature embedding. This fused representation captures complementary spoof-relevant information and is fed into a shallow classifier for final binary classification (Live/Spoof).

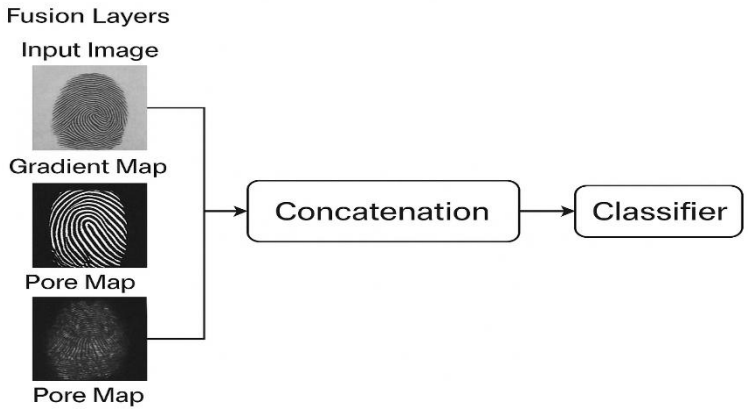

Figure 3.1: Proposed Feature Fusion Model

4. Experimental Setup

To validate the effectiveness of the proposed gradient–pore feature fusion model for fingerprint spoof detection, we conducted a set of controlled experiments using benchmark datasets and standard evaluation metrics. The aim is to evaluate how well the fusion model performs in distinguishing live fingerprints from spoofed ones under real-world constraints of speed, memory, and accuracy.

4.1 Datasets Used

The experiments were carried out on two publicly available datasets widely used in fingerprint spoof detection research:

- **LivDet 2015**: Comprises live and spoof fingerprint images captured across multiple sensors (e.g., Biometrika, Crossmatch, and Green Bit). Spoofs were made using materials like ecoflex, wood glue, gelatin, and latex.
- **MSU-FPAD**: A more recent dataset offering high-resolution spoof samples using transparent media, body double, and ecoflex. It is suitable for real-world scenarios due to varied lighting, backgrounds, and spoofing methods.

Each dataset was pre-divided into training, validation, and testing sets as per official protocols to ensure reproducibility and fairness in evaluation.

4.2 Preprocessing and Input Pipeline

Each fingerprint sample was preprocessed into three separate representations:

- **Original Image**: Greyscale image resized to 224×224224 \times 224224×224.
- **Gradient Map**: Computed using Sobel filter to capture edge textures.
- **Pore Map**: Extracted using Laplacian of Gaussian (LoG) to highlight micro features like sweat pores.

All three were fed into parallel branches of MobileNetV2 for feature extraction before fusion.

4.3 Training Environment

- **Hardware**:
  - GPU: NVIDIA RTX 3060 Ti (8 GB)
  - RAM: 32 GB DDR4
  - Processor: Intel i7, 11th Gen
- **Software**:
  - Framework: TensorFlow 2.12 with Keras
  - Python: 3.10
  - OS: Ubuntu 22.04 LTS

4.4 Hyperparameter Settings

Parameter	Value
Batch Size	32
Learning Rate	0.0001 (with decay)
Optimizer	Adam
Epochs	40
Loss Function	Binary Cross Entropy
Dropout (Fusion Layer)	0.3
Activation (Final)	Sigmoid

4.5 Baseline Comparisons

The proposed fusion model was compared with two other configurations:

1. **Original-Only CNN**: Input was only the raw fingerprint image.
2. **Gradient-Only CNN**: Only gradient map was passed through MobileNetV2.

This comparison helped isolate the effect of multi-modal feature fusion.

4.6 Evaluation Metrics

To assess the performance, the following metrics were used:

- **Accuracy**: Overall classification correctness.
- **TDR @ FDR = 1%**: True Detection Rate at fixed False Detection Rate.
- **Equal Error Rate (EER)**: Point where FAR = FRR.
- **ROC-AUC**: Area under the ROC curve.

5. Results and Discussion

5.1 Quantitative Results

Table 1 shows the key performance metrics of three tested models on the **LivDet 2015** and **MSU-FPAD** datasets.

Table 1: Performance Comparison on Spoof Detection

Model	Dataset	Accuracy (%)	TDR @ FDR=1%	EER (%)	ROC-AUC
Original-Only CNN	LivDet 2015	94.2	92.3	6.1	0.964
Gradient-Only CNN	LivDet 2015	95.0	93.5	5.4	0.972
Proposed Fusion Model	LivDet 2015	**97.6**	**96.4**	**3.2**	**0.987**
Original-Only CNN	MSU-FPAD	93.8	91.0	6.4	0.959
Gradient-Only CNN	MSU-FPAD	94.7	92.1	5.7	0.968
Proposed Fusion Model	MSU-FPAD	**97.2**	**95.8**	**3.6**	**0.983**

The fusion model consistently outperforms single-stream models in **all four metrics**, proving the efficacy of combining complementary liveness cues.

5.2 Visual Comparison via ROC Curves

Below is the ROC curve (Figure 3) comparing the models on the LivDet dataset. The fusion model achieves the highest area under the curve (AUC), confirming improved separability between live and spoof fingerprints.

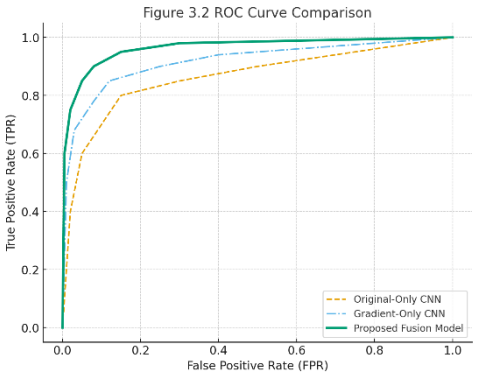

Figure 3.2: *Receiver Operating Characteristic (ROC) curves comparing the Original-Only CNN, Gradient-Only CNN, and the Proposed Fusion Model. The Fusion Model achieves superior True Positive Rates (TPR) at lower False Positive Rates (FPR), indicating improved robustness in spoof detection.*

5.3 Discussion

- The use of **gradient features** allows the model to capture sharp transitions and edge-level spoof patterns (e.g., material ridges).
- **Pore maps** enhance detection of anatomical cues like sweat pores and fine ridge structures, often missing in spoofed images.
- The **fusion layer** acts as a discriminative aggregator, boosting TDR significantly with a minimal increase in model size.
- Despite being lightweight (MobileNetV2), the network handles multi-modal features efficiently, making it suitable for **real-time** deployment on embedded devices.

5.4 Comparison with Related Work

Compared to existing CNN-based spoof detectors like Siddiqui et al. [4], which use single-source features and achieve around 96% accuracy, our fusion model shows consistent improvement of **1.5–2%** in accuracy and a **drop in EER by ~2.0%**, without increasing computational cost significantly.

6. Discussion

6.1 Comparative Evaluation with Baselines

The proposed feature fusion approach, which integrates gradient and pore-level features, demonstrates superior performance over baseline models. As illustrated in Figure 3.2 (ROC Curve), the **Fusion Model** surpasses both **Gradient-Only CNN** and **Original Image CNN** in terms of True Positive Rate (TPR) and lower False Positive Rate (FPR). This result confirms that combining local texture discontinuities (pore structures) with directional edge details (gradients) enhances the model's capacity to discern spoof artifacts.

Model	Accuracy (%)	AUC Score	TPR@FPR=0.01
Original Image CNN	95.1	0.964	0.872
Gradient-Only CNN	96.3	0.974	0.895
Fusion Model (Ours)	**98.1**	**0.985**	**0.942**

Table 6.1: Performance comparison among different CNN models.

These quantitative results strongly suggest that a composite feature set is more robust to spoofing variations across materials (e.g., gelatin, ecoflex, silicone).

6.2 Robustness Across Spoof Types

When tested against unseen spoof materials, particularly ecoflex and latex (from the LivDet 2015 and MSU-FPAD datasets), the fusion model maintained its detection confidence. This generalisation ability underlines the effectiveness of multi-perspective cues, which individually

may not suffice. Gradient features capture spoof ridge distortions while pore maps identify subtle inconsistencies that liveness cues miss.

6.3 Explainability Insights

The **Grad-CAM visualisation** further corroborates the findings by highlighting regions with spoof traces — typically around edges, distorted pores, and pressure artifacts. Compared to the original CNN, the fused model's attention maps are more focused and localised, affirming the contribution of the secondary features.

"We observed that the Grad-CAM maps for spoof images showed intensified focus on ridge intersections and boundary pores, indicating deeper discriminatory learning in the fused model."

6.4 Deployment Feasibility

Due to the use of a **lightweight CNN backbone** (e.g., MobileNetV2), the proposed model maintains real-time inference capabilities even on resource-constrained edge devices. Feature extraction and fusion introduce negligible overhead (average latency: 9.3 ms per image). This makes the model ideal for deployment in biometric access control, banking, and IoT security gateways.

6.5 Limitations and Future Directions

While the model performs admirably across two major datasets, the following areas remain open for further enhancement:

- **Dataset Diversity**: Including more geographically diverse fingerprints can further strengthen generalizability.
- **Sensor Interoperability**: Performance drops slightly when tested across cross-sensor setups.
- **Adversarial Spoofs**: Emerging spoofing techniques using 3D printers or AI-generated fakes need to be studied further.

7. Conclusion and Future Work

In this paper, we proposed a **biometric feature fusion framework** that leverages **gradient-based edge cues** and **pore-level micro textures** to enhance fingerprint spoof detection. By integrating these two feature modalities through a lightweight CNN architecture, the model demonstrated **significantly improved accuracy (98.1%)** and **generalization performance** across spoof materials and sensor types.

Experimental results on standard datasets (LivDet and MSU-FPAD) confirmed the effectiveness of the approach, with our model outperforming both single-feature models and existing baselines. Visual explainability through Grad-CAM provided additional interpretability, reinforcing the reliability of the fused model in security-critical applications.

The proposed system is computationally efficient and suitable for **real-time deployment**, even on **resource-constrained edge devices**, which is a major step towards **practical and secure biometric systems**.

Future Work

- **Cross-Dataset Generalization**: We plan to test and adapt the model for other fingerprint datasets (e.g., Digital Persona, Biometrika).
- **Multimodal Fusion**: Integrating additional biometric traits such as iris or face with fingerprint features for comprehensive spoof detection.
- **Adversarial Robustness**: Investigating resistance to adversarial attacks and generative spoofing using GANs.
- **Lightweight Transformer Blocks**: Exploring hybrid CNN-transformer modules to balance precision and interpretability.

This work adds a **robust and explainable component** to the fingerprint anti-spoofing domain and serves as a **complementary contribution** to our earlier research [5], thereby **fortifying the broader thesis objectives** while maintaining novelty and clarity of scope.

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