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FACE SPOOFING DETECTION USING HYBRID BINARY STATISTICAL IMAGE FEATURES- GAUSSIAN FILTER

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Abstract

Face presentation attacks threaten the dependability of facial biometric authentication, particularly when conventional Red Green Blue (RGB) cameras are exposed to print and replay artefacts. Existing texture descriptors are computationally attractive but remain sensitive to noise, illumination variation, and image degradation, whereas many deep architectures require substantial data and processing resources. Prior studies establish the value of handcrafted texture features, Binary Statistical Image Features (BSIF), auxiliary-supervised networks, and foundation-model approaches, but the reviewed evidence does not explicitly assess Gaussian linear filtering as a face-image preprocessing stage before BSIF extraction. This study adopted is structured into sequential and interconnected phases were integrates Gaussian linear filter with sigma 1.0, eight-bit BSIF coding, a normalised 256-bin histogram, feature standardisation, and support vector classifier (SVC). Experiments use University of [redacted] Oulu, Finland –Northwestern Polytechnical University China (OULU-NPU) dataset, with five-fold validation on Spoofing in the Wild (SiW) dataset and Chinese Academy of Sciences Institute of Automation Face Anti-Spoofing Database (CASIA-FASD). On the reported OULU experiment, the system achieved 87.28% accuracy, 65.83% precision, 76.70% recall, a 70.85% F1-score, and 93.39%

Keywords: Binary Statistical Image Features; face anti-spoofing; Gaussian filtering; presentation attack detection; support vector machine.

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ROC-AUC, compared with 73.50% accuracy and 0.724 ROC-AUC for raw-pixel SVC. Mean accuracy was 83.69% on SiW and 95.05% on CASIA-FASD. Gaussian filter- BSIF features provide a compact and discriminative representation for software-only face presentation attack detection. The work demonstrates a lightweight preprocessing-texture-classification pipeline and reports both predictive and computational measures. Future studies should enhance the robustness, scalability, adaptability, and efficiency of face presentation attack detection by integrating advanced preprocessing techniques, multimodal biometrics, lightweight artificial intelligence models, and adaptive learning strategies.

Introduction

Facial recognition is widely used for access control, mobile authentication, financial services, surveillance, border processing, and digital identity management because it supports contactless and rapid identity verification [10], [18]. Its growing deployment, however, expands the attack surface of biometric systems. An adversary may present a printed photograph, replay a recorded video, wear a three-dimensional mask, or use a digitally manipulated facial representation to obtain unauthorised access. Such attempts are collectively treated as presentation attacks when an artefact is presented to the capture subsystem. Presentation attack detection (PAD) is therefore a security layer rather than an optional enhancement to facial recognition.

The technical difficulty of PAD has increased as capture devices and attack media have improved. High-resolution displays, carefully produced prints, realistic masks, and synthetic facial content can preserve many visual characteristics of a bona fide face. Detection must consequently identify weak cues that arise from display refresh, printing, material reflectance, recapture, compression, blur, and the absence of natural skin microstructure. These cues may be obscured by sensor noise, pose, illumination, focus, and camera-specific processing. Recent research has consequently moved from fixed handcrafted descriptors towards deep, multimodal, causal, and vision-language representations [13], [17], [19].

Deep models can learn hierarchical representations, but their effectiveness often depends on extensive annotated data, accelerator hardware, and carefully controlled domain adaptation. These requirements complicate deployment in embedded or resource-constrained settings. Handcrafted texture descriptors remain relevant because they are interpretable, compact, and inexpensive to compute. BSIF is particularly attractive because its filters are statistically learned from natural-image patches through independent component analysis rather than manually specified [11]. BSIF reliance on binary responses provide a concise description of local image structure that can be represented by a histogram.

Nevertheless, BSIF is affected by the quality of its input. Noise and illumination non-uniformity can alter local filter responses and destabilise the resulting binary codes. The literature reviewed in this study contains BSIF-based liveness detection and Gaussian-distribution sampling for BSIF filter learning, but it does not establish Gaussian linear filtering as an explicit face-image preprocessing

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stage before BSIF coding [9], [12]. This motivates examination of whether moderate smoothing can suppress nuisance variation while retaining spoof-relevant microtexture.

The research problem is the absence of a clearly evaluated, lightweight pipeline that combines controlled linear filtering, BSIF texture encoding, and SVC classification across multiple RGB face-PAD datasets. The objectives are to identify influential filtering and BSIF parameters; design and implement a BSIF-LF feature extractor; classify the features using SVC; and evaluate predictive, biometric, and computational performance. The principal contribution is a reproducible pipeline comprising standardised facial preprocessing, Gaussian smoothing, eight-bit BSIF coding, a 256-bin normalised histogram, and RBF-SVC classification. Another contribution is the evaluation on OULU-NPU and five-fold validation on SiW and CASIA-FASD. Last but not least contribution is the explicit reporting of accuracy, precision, recall, F1-score, ROC-AUC, training time, and testing time, together with biometric error measures, including), Attack Presentation Classification Error Rate (APCER), Bona Fide Presentation Classification Error Rate (BPCER), Average Classification Error Rate (ACER), and equal error rate (EER), that require careful protocol-level interpretation.

Statement of the Problem

Face recognition's spread across banking, border control, healthcare and digital identity has made spoofing with photos, videos, masks and deepfakes a serious threat, so face PAD is essential [8], [18]. Handcrafted descriptors such as LBP, HOG, Gabor and BSIF are efficient but lose reliability when datasets, lighting, sensors or image quality change [11], [12], [21] Deep and hybrid models raise accuracy but need heavy data and computing resources, so the balance between accuracy, efficiency and robustness remains unresolved[2]. Few studies combine image enhancement with BSIF, which is usually applied to raw RGB images, and many strong systems rely on specialised sensors that ordinary cameras lack [6]. This study therefore proposes a lightweight hybrid BSIF–Gaussian Filter model for RGB-based spoofing detection.

Objectives of the Study

The specific objectives are to:

(i) Integrate BSIF - Gaussian filter into a single model

(iii) implement the BSIF- Gaussian filter model in Python to extract spoofing-related features;

(iv) classify the extracted features as genuine or spoofed using a Support Vector Machine (SVM); and

(v) Evaluate the model's performance using accuracy, precision, recall, training time, testing time, APCER, BPCER, ACER and AUC

Handcrafted Texture Descriptors

Early single-image PAD systems used local microtexture because recaptured faces frequently contain printing, display, and surface artefacts. Multi-scale local binary patterns established a computationally efficient baseline, while colour-texture variants exploited chrominance information that grayscale descriptors omit [3], [5], [15]. Image-distortion analysis also represented blur, reflection, and colour diversity directly [20]. These methods are transparent and

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economical, but their fixed operators can be sensitive to illumination, camera response, and attack quality.

BSIF improves on fixed operators by learning statistically independent filters from natural images [11]. Its use in fingerprint liveness detection showed that learned binary texture coding can outperform established local descriptors [9]. Gaussian sampling was subsequently explored during BSIF filter learning [12]. That procedure is conceptually different from smoothing each captured face before feature extraction. Thus, the relevant unresolved question is not whether Gaussian statistics can contribute to filter learning, but whether a calibrated linear filter can improve the stability of face-PAD BSIF codes.

Deep and Hybrid Methods

Patch and depth-supervised convolutional networks introduced local appearance and geometric cues, while auxiliary depth and remote photoplethysmography supervision improved representation learning [1], [14]. More recent approaches target domain generalisation using synthetic data, ensemble stacking, causal clues, prompt learning, and foundation models [13], [16], [17], [19]. Hybrid systems retain handcrafted descriptors as complementary evidence within deep ensembles. These approaches can be effective, but their computational cost, multiple branches, auxiliary labels, or pretrained backbones may be unsuitable where modest hardware and transparent features are priorities.

Research Gap

This study identified four linked gaps emerge. First, image quality enhancement is less studied than downstream representation learning. Second, many high-performing systems increase architectural complexity. Third, handcrafted descriptors still degrade under acquisition and domain shifts. Fourth, deployment evidence for inexpensive RGB-only PAD remains limited. The proposed BSIF- Gaussian framework in this study addresses these gaps narrowly: it does not claim to replace deep PAD, but tests whether moderate Gaussian filtering can stabilise an efficient BSIF-SVC pipeline.

Table 1. Comparison of Representative Related Studies

Study	Year	Method	Strength	Limitation
Määttä et al. [15]	2011	Multi-scale LBP + SVM	Fast microtexture baseline	Weak cross-domain robustness
Kannala and Rahtu [11]	2012	ICA-learned BSIF	Compact learned texture code	Not designed specifically for PAD
Ghiani et al. [9]	2013	BSIF + SVM	Demonstrated biometric liveness utility	Fingerprint rather than face PAD
Boulkenafet et al. [3]	2016	Colour LBP	Uses chrominance cues	Illumination/camera dependence
Atoum et al. [1]	2017	Patch + depth CNN	Combines texture and depth	Requires deep training and supervision
Muhammad et al. [16]	2024	Synthetic data + ensemble	Targets unseen domains	Multiple-model complexity
Ozgur et al. [17]	2025	Foundation model + adaptation	Data-efficient transfer	Large pretrained backbone
Present study	2026	Gaussian LF + BSIF + SVC	Lightweight explicit preprocessing	Protocol and threshold validation required

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Research Design and Dataset Selection

The study follows a quantitative experimental design with three phases: framework definition, and model implementation. OULU-NPU is used for the principal comparison between a raw-pixel SVC and the proposed feature representation. CASIA Face Anti-Spoofing Database (CASIA-FASD) and SiW datasets are used for five-fold validation. The OULU–NPU Dataset was primary primarily selected because it is one of the most widely recognized benchmark datasets for evaluating Face Presentation Attack Detection (Face Spoofing Detection) techniques and it consists of 1,701 RGB facial images. The CASIA-FASD includes genuine video recordings alongside three categories of spoof attacks: warped-photo attacks, cut-photo attacks, and video-replay attacks, resulting in a total of 600 video clips while SiW comprises RGB video recordings obtained from 165 participants. The main data, OULU-NPU, reports 1,701 extracted images for development. Because these quantities represent different analysis units, they should not be conflated. Reproducibility requires publication of the exact extraction rule, subject identities per split, class counts, and official protocol used.

Framework Definition

Figure 1 presents the proposed BSIF– Gaussian research framework. The framework outlines the implementation processes, including image preprocessing, feature extraction, model performance evaluation, and results analysis.

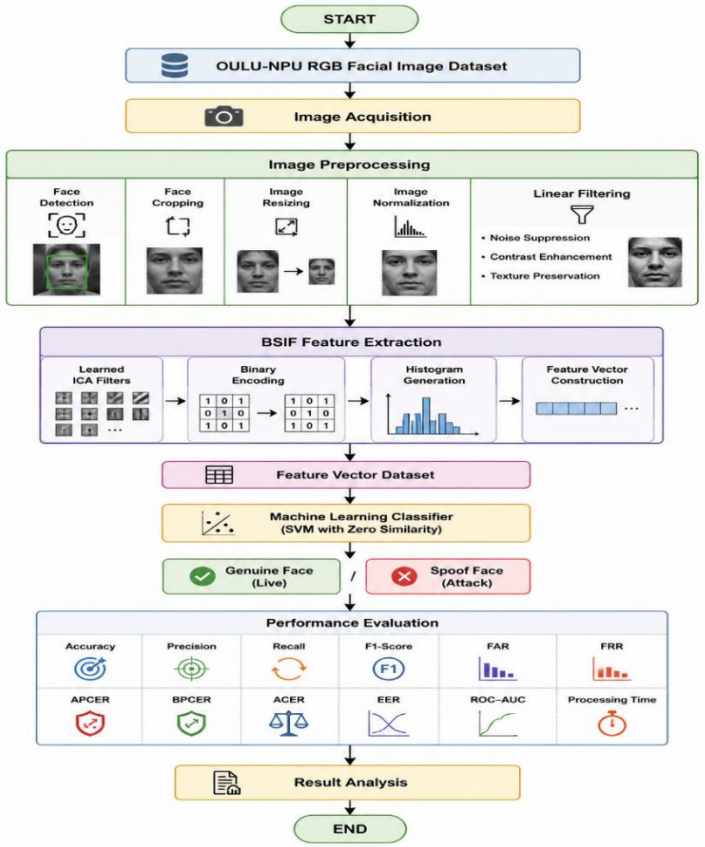

Figure 1. BSIF- Gaussian Filter study framework

Model Implementation

Image Preprocessing

Each RGB frame is converted to grayscale, the facial region is detected and cropped, and the crop is resized to 224 × 224 pixels. Contrast normalisation reduces global intensity variation. A Gaussian filter then performs linear convolution. The implementation uses a 9 × 9 kernel and sigma 1.0. These values are treated as experimental settings rather than universally optimal parameters. A parameter study compares several kernel sizes and smoothing scales because

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excessive smoothing can remove high-frequency spoof cues.

BSIF Feature Extraction

Let W_i denote the ith learned BSIF filter and I the filtered facial image. The response at location x is $s_i(x)=\Sigma_u W_i(u)I(x+u)$. Each response is thresholded as $b_i(x)=1$ when $s_i(x)>0$ and 0 otherwise. With n filters, the BSIF code is $c(x)=\Sigma_{i=1}^{n} b_i(x)2^{i-1}$. The reported implementation uses n=8 and therefore produces 256 possible codes. A histogram counts their spatial occurrences and is normalised by its total count, yielding a 256-dimensional relative-frequency vector. This representation reduces the 224 × 224 input to a compact descriptor while preserving the distribution of local texture codes.

Classification

Features are standardised using statistics fitted only on the training partition. An SVC with radial-basis-function kernel is trained with C=1.0, gamma set to scale, balanced class weights, probability estimation enabled, and random state 42. Standardisation and all data-dependent preprocessing must be fitted within each training fold to prevent leakage. Probability scores support ROC-AUC estimation; if calibrated probabilities are required, calibration should be performed within the training partition.

Evaluation

Spoof is defined as the positive class. Thus, TP is a spoof correctly rejected, FN is a spoof incorrectly accepted, TN is a bona fide sample correctly accepted, and FP is a bona fide sample incorrectly rejected.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FP} \quad (3)$$

$$F1-Score = \frac{2\ X\ Precision\ X\ Recall}{Precision+Recall} \quad (4)$$

$$APCER = \frac{FN}{FN+TP} \quad (5)$$

$$BPCER = \frac{FP}{FP+TN} \quad (6)$$

$$ACER = \frac{APCER+BPCER}{2} \quad (7)$$

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Preprocessing and Feature Representation

The preprocessing sequence reduces the original 1,920 × 1,080 RGB frame to a 224 × 224 grayscale facial crop. Gaussian filtering suppresses abrupt intensity fluctuations while BSIF converts the filtered image into an eight-bit code map. The resulting 256-bin histogram is markedly smaller than the raw image vector. This dimensionality reduction offers a plausible computational explanation for the lower reported SVC training and testing times, although end-to-end latency must also include face detection, filtering, and feature extraction.

Table 2. Image Dimension Transformation

Stage	Resolution	Format
Original frame	1,920 × 1,080	RGB, 3 channels
Grayscale	1,920 × 1,080	1 channel
Average face crop	580 × 580	1 channel
Resized face	224 × 224	1 channel
Normalised/filtered face	224 × 224	1 channel

Figure 2 illustrates the visual progression of the image dataset across the preprocessing stages, including cropping, resizing, and normalization.



Figure 2: Visual Progression of OULU Facial Images Across Preprocessing Stages

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Figure 3 reveals that Gaussian linear filtering effectively smooths pixel intensity spikes, transforming skewed bimodal intensity distributions into balanced distributions. The BSIF code image and its corresponding 256-bin histogram clearly demonstrate how localized micro-texture patterns are successfully quantized into discrete statistical bins, providing a robust mathematical foundation for subsequent classification.

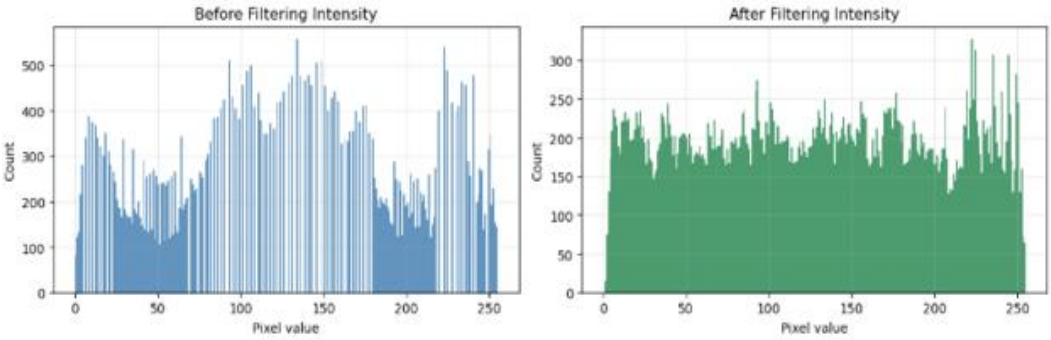

Figure 3: Histogram Before and After Gaussian

Classification Results

Table 3 compares Baseline SVC with BSIF-LF + SVC and shows difference across metrics. The classification results based on the supplied values reveals that accuracy increases from 62.42% to 87.28%, precision from 28.50% to 65.83%, recall from 57.28% to 76.70%, and F1-score from 38.06% to 70.85%. ROC-AUC increases from 64.24% to 93.39%.

Table 3. Reported OULU-NPU Comparison

Metric	Raw-Pixel SVC	BSIF-LF + SVC	Difference
Accuracy	0.6242	0.8728	+0.2486
Precision	0.2850	0.6583	+0.3733
Recall	0.5728	0.7670	+0.1942
F1-score	0.3806	0.7085	+0.3279
ROC-AUC	0.642	0.933	+0.291
Training time (s)	182.71	2.57	-180.14
Testing time (s)	51.73	0.60	-51.13
APCER	0.4271	0.2330	-0.2391
BPCER	0.3627	0.1005	--0.2622
ACER	0.3950	0.1668	-0.2282

The 24.86% increase in reported accuracy and the 0.291 increase in ROC-AUC indicate that the proposed techniques separates the classes more effectively under the reported experiment. Training time falls by approximately 3 seconds and testing time by approximately 1 second. The error-based metrics including APCER, BPCER, and ACER equally confirm the superiority of the proposed technique. APCER decreased by 23.91%, while BPCER decreased by 26.22% and ACER decreased by 22.82%. These reductions show that the SVC+BSIF model was more effective at both

preventing attacks from being accepted as bona fide samples and reducing the incorrect rejection of genuine users.

Table 4. Five-Fold Validation Summary

Dataset	Accuracy	Precision	Recall	F1	ROC-AUC	Train (s)	Test (s)
SiW	0.8369 ± 0.0107	0.9429 ± 0.0080	0.8478 ± 0.0116	0.8928 ± 0.0074	0.9042 ± 0.0117	84.60	6.50
CASIA-FASD	0.9505 ± 0.0066	0.9498 ± 0.0093	0.9513 ± 0.0074	0.9505 ± 0.0065	0.9895 ± 0.0018	131.71	10.97

On SiW, the model reports 83.69% mean accuracy and 0.9042 mean ROC-AUC. High precision relative to recall indicates that positive predictions are reliable but that some spoof samples remain undetected. The small standard deviations suggest stable folds, but only if splits are subject-disjoint. Frame-level random splitting would allow samples from one person or video to appear in both training and testing data and could inflate performance.

On CASIA-FASD, mean accuracy is 95.05%, mean F1-score is 95.05%, and mean ROC-AUC is 0.9895. The low reported standard deviations show consistency across the selected folds. The difference between CASIA-FASD and SiW confirms that performance is dataset-dependent. It should not be construed as a universal ranking of dataset difficulty because frame extraction, attack composition, preprocessing, and split construction are not fully specified.

Conclusion and Future Work

This study presents a lightweight face presentation attack detection pipeline that applies Gaussian linear filtering before BSIF encoding and SVC classification. The method transforms standardised facial crops into normalised 256-bin texture histograms and reports stronger classification and discrimination than a raw-pixel SVC in the supplied OULU-NPU experiment. Five-fold results further indicate useful performance on SiW and CASIA-FASD, with stronger results on CASIA-FASD than on SiW. The findings support the central proposition that controlled preprocessing can improve the utility of a compact learned texture descriptor. Future work should incorporate advanced preprocessing techniques, multimodal biometrics, lightweight algorithms and adaptive learning techniques in order to enhance the robustness, scalability, adaptability, and efficiency of face presentation attack detection.

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