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Touchless Fingerprint Recognition in the Post-COVID Era: A Machine-Learning-Centric Review of Features, Matching, Classification and Security

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Abstract
Touchless fingerprint recognition removes physical contact from fingerprint capture through cameras or other optical sensors while computationally recovering ridge information. COVID-19 did not create the technology, but it made the hygiene and shared-surface limitations of contact-based biometrics more visible. This review emphasizes acquisition, segmentation, enhancement, pose normalization, features, matching, classification and presentation-attack detection (PAD). Reported work shows a wide performance range: HOG + SVM reached 100% in one touchless classification experiment, while HOG + decision tree reached 67%; transfer learning, Siamese learning and hybrid generative approaches have reported results above 93% on their respective datasets. These values are not a common benchmark. Compared with face, iris and voice, touchless fingerprint offers a useful balance of permanence, distinctiveness, mature infrastructure and hygienic capture, while challenges remain in pose, illumination, cross-sensor interoperability, spoof resistance, privacy, dataset diversity and edge efficiency.

Keyword: touchless fingerprint, contactless biometrics, machine learning, HOG, SVM, random forest, deep learning, liveness detection, COVID-19.

I. Introduction

Fingerprint biometrics remain attractive because friction-ridge patterns are distinctive and persistent, while contact-based databases, minutiae processing and matching algorithms are mature [1], [2]. Traditional sensors require a shared physical surface; dirt, moisture, pressure-induced deformation and latent impressions can reduce quality or acceptance [1], [3].

The post-COVID deployment problem is therefore twofold: remove unnecessary contact while preserving fingerprint identity information. Free-space imaging replaces platen deformation with a vision problem involving finger pose, perspective, scale, focus, illumination and background [1], [4]. This creates an important role for machine learning from fingertip segmentation through learned embeddings and calibrated decision logic [7], [8].

II. SYSTEM ARCHITECTURE

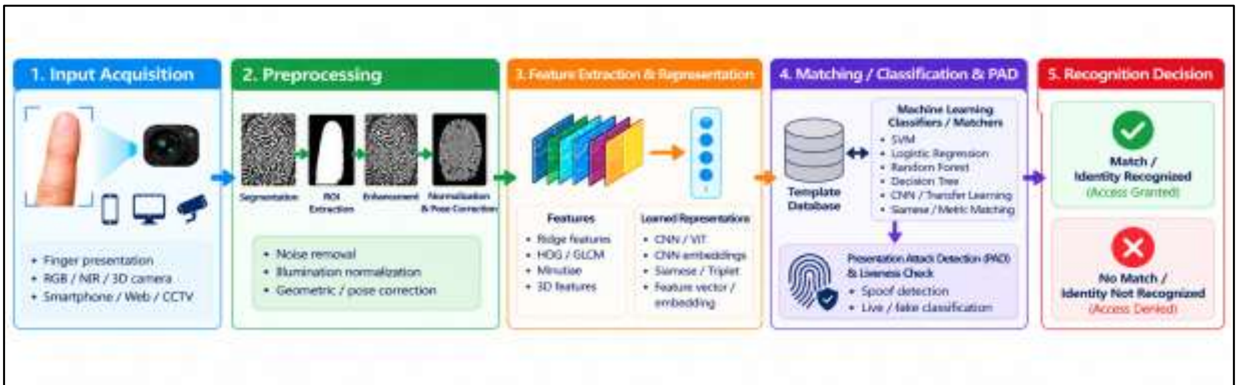

Fig. 1. Machine-learning-centric architecture for touchless fingerprint recognition.

Fig. 1. Simple flow of the touchless fingerprint recognition system. The figure presents the overall processing flow of a touchless fingerprint recognition system in five sequential stages. First, the fingerprint is acquired without physical contact using an RGB, NIR, or 3D camera. The acquired image is then

preprocessed through operations such as segmentation, ROI extraction, enhancement, normalization, and pose correction to improve fingerprint quality and consistency. Next, discriminative fingerprint features are extracted and represented using extracted features or learned approaches. These representations are subsequently used for matching or classification, with presentation-attack detection (PAD) and liveness checking incorporated to improve authentication security. Finally, the system produces an recognition decision, resulting in either a match (access granted) or no match (access denied). TipSegNet reported 0.999 segmentation accuracy and 0.987 mean IoU on its evaluation data [7], while MCLFIQ addresses mobile contactless image quality [8]. Preprocessing may include denoising, contrast correction, illumination normalization, geometric correction and pose compensation.

III. FEATURES, REPRESENTATIONS AND MATCHING

Touchless capture requires representations that tolerate scale, perspective, rotation and illumination differences. Level-1 ridge flow describes global structure; Level-2 minutiae capture ridge endings and bifurcations; Level-3 contours retain finer ridge detail. HOG and GLCM offer lightweight engineered features, whereas CNN, transformer, Siamese and triplet models learn more invariant representations. Matching may be descriptor-based, minutiae-based, classifier-based or learned metric matching [9], [10].

Table 1. Feature comparison

Representation	Use	Strength	Limitation
Ridge flow / L1	Global pattern	Fast	Low specificity alone
Minutiae / L2	Verification	Mature matching	Quality sensitive
Ridge contours / L3	Fine detail	Rich local shape	Needs resolution
HOG / GLCM	Classical ML	Low compute	Normalization dependent
CNN / ViT	Deep embedding	Learns invariance	Needs data/compute
Siamese / Triplet	Metric learning	Robust similarity	Training sensitive

Contactless-to-contact matching is especially difficult because the contact image contains elastic deformation while a finger photo does not. Pose correction and unwarping can therefore be more important than simply changing the matcher. One study reported contactless-to-contact EER as low as 1.46% for an enhancement configuration [9]. Triplet-GAN matching also targets low-resolution and rotation robustness [10].

IV. CLASSIFIERS AND REPORTED RESULTS

Classical ML is useful when features are compact and engineered well. Velapure and Kshirsagar reported 100% with HOG + SVM, 67% with HOG + decision tree, 43.40% with pattern + SVM, and 21.80% with pattern + decision tree [19]. Their LR-versus-RF study states that HOG + LR classifier showed superior performance in contactless fingerprint recognition [20].

Deep learning reduces manual feature engineering. VGG-16 with enhancement reached 93% test accuracy on an IIT-Bombay touchless database [11]; Xception with RGB/Laplacian reached 93.5% on 2,143 images from 175 subjects [12]; a Siamese network reported 98.68% for thumb verification [13]; and a CapsNet/PCA/dual-cross-GAN approach reported 99.51% and 99.13% on two datasets [14]. Rachel and Devarasan reported 94.07% for DOA-SVM and 98.00% for the strongest hybrid configuration [16]. These values are task- and dataset-dependent.

Table 2. Comparison of different Fingerprint recognition methods

Method	Family	Task / data	Reported result
Pattern + DT	Classical ML	Touchless classification	21.80%
Pattern + SVM	Classical ML	Touchless classification	43.40%
HOG + DT	Classical ML	Touchless classification	67.00%
HOG + SVM	Classical ML	Touchless classification	100%
VGG-16 + enhancement	Transfer learning	200 subjects	93% test
Xception + RGB/Laplacian	Deep learning	175 subjects	93.5%
Siamese network	Metric learning	Thumb verification	98.68%
CapsNet + PCA + GAN	Hybrid deep model	Two datasets	99.51 / 99.13%
DOA-SVM / FCM-DOA-SVM	Hybrid ML	Contactless authentication	94.07 / 98.00%

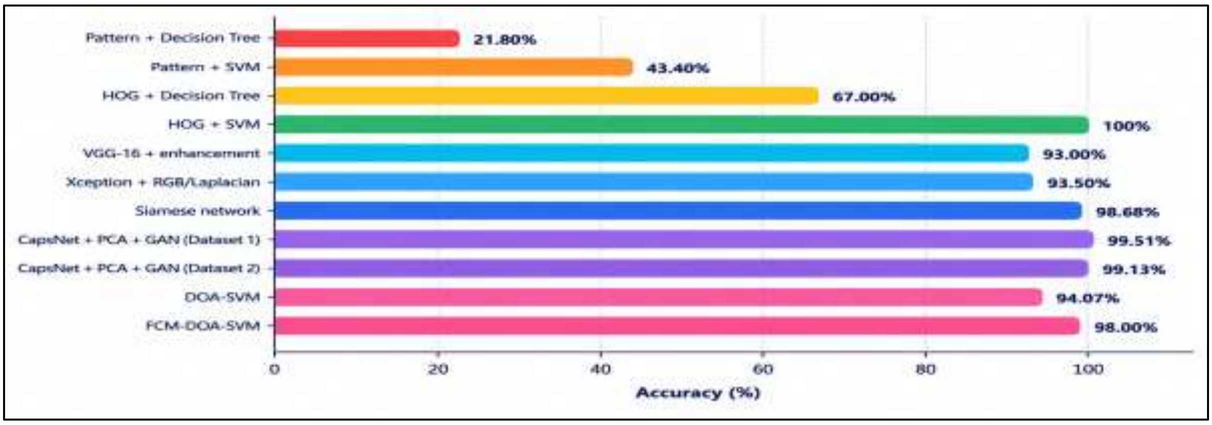

Fig. 2. Reported recognition-accuracy comparison and histogram; results come from different datasets and tasks.

V. WHY TOUCHLESS FINGERPRINT IS ATTRACTIVE AFTER COVID-19

Touchless fingerprint combines a mature, persistent biometric trait with hygienic acquisition. The user does not need to repeatedly press a common platen, so direct shared-surface contact is reduced [3], [5]. This is especially useful in hospitals, airports, workplaces, kiosks, financial terminals and public-access environments. Importantly, the advantage is not that fingerprint is universally better than other traits; it is that the acquisition method changes while the underlying identity signal stays familiar and highly distinctive.

- Permanence and distinctiveness: ridge patterns are highly distinctive and persistent [1].
- Mature ecosystem: existing fingerprint databases and matching logic provide a migration path from contact systems [1], [2].
- Hygiene: free-space capture removes the need to place the finger on a shared surface [3], [5].
- Face-independent operation: useful when masks, occlusion, pose or appearance changes reduce face reliability [4].
- Less behavioral dependence than voice: fingerprint morphology is not strongly altered by acoustic noise, microphone variation or temporary speech changes [4].
- Flexible hardware: RGB, NIR and 3D sensing can support mobile and edge deployments [5], [6].
- Multimodal fallback: fingerprint can be fused with face, iris or palm when one modality has poor quality [4].

VI. FINGERPRINT VS. FACE, IRIS AND VOICE

Face has the lowest user effort but is exposed to masks, pose, lighting, aging and heightened privacy sensitivity. Iris is extremely distinctive and stable, but acquisition often demands tighter imaging and illumination control. Voice is naturally remote and convenient, but it is strongly influenced by noise, microphone quality, health, language and replay or synthesis. Touchless fingerprint sits between them: acquisition is slightly more deliberate than face/voice, but the identity trait is persistent, compatible with mature fingerprint infrastructure, and no physical platen is required [4].

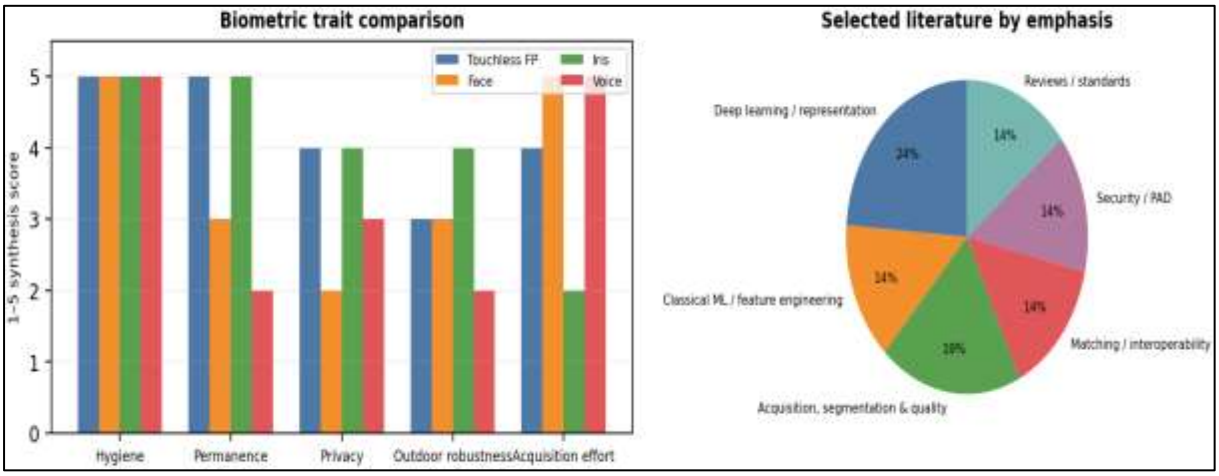

Fig. 3. Qualitative trait comparison and author-defined distribution of the selected literature by primary emphasis.

VII. CHALLENGES AND OPPORTUNITIES

Table 3. Challenges and opportunities comparison

Challenge	Opportunity
Pose, scale, focus, illumination	3D pose estimation, normalization and augmentation
Cross-sensor interoperability	Unwarping, domain adaptation and standardized capture [9], [22]
Low-quality finger images	Dedicated quality scoring and quality-aware matching [8]
Presentation attacks	PAD datasets, anti-spoofing and score fusion [21]
Dataset bias / limited diversity	Multi-device, multi-environment, multi-demographic benchmarks
Template privacy	Cancellable templates, on-device inference and federated learning
Edge latency	Quantization, pruning, distillation and early-exit models

VIII. RESEARCH GAPS AND FUTURE SCOPE

The field is transitioning from laboratory demonstrations toward deployable biometric infrastructure. The key gaps now extend beyond raw classifier accuracy:

- Cross-device interoperability: reliable matching should work across contactless cameras and legacy contact-based galleries [9], [22].
- Quality-aware decisions: quality scoring should estimate whether blur, pose, finger size or lighting makes a sample untrustworthy.
- Open-set PAD: systems must generalize to unseen print, screen, replay and synthetic attacks rather than only trained attack types [21].
- Large diverse benchmarks: datasets should span finger types, devices, distances, lighting, demographics and real-world user behavior.
- 3D-aware recognition: depth and multi-view capture can estimate finger pose and surface geometry explicitly [15].
- Self-supervised and foundation vision models: unlabeled pretraining may reduce annotation cost and improve cross-device transfer.
- Privacy-preserving biometric AI: template protection, cancellable representations, secure execution and federated learning can limit raw-image exposure.
- Edge-efficient inference: pruning, quantization, distillation and hardware-aware architecture design are essential for mobile/kiosk deployment.
- Explainable and calibrated matching: systems should expose quality, score confidence and failure reasons for audit and human review.
- Multimodal fallback and adaptive fusion: dynamically combine fingerprint with face or iris when the primary sample fails quality checks [4].

IX. Conclusion

Touchless fingerprint recognition is a practical evolution of fingerprint biometrics rather than a replacement for every other biometric. Its strongest value proposition is the combination of persistent fingerprint evidence, mature matching infrastructure and hygienic, camera-based acquisition. Machine learning is central because contactless capture introduces new variability in pose, geometry, illumination, quality and attack surface. The next research phase should prioritize cross-sensor generalization, robust PAD, privacy-preserving processing, efficient edge inference and reproducible benchmarks rather than isolated headline accuracy.

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