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SURVEY

Contactless Palmprint Recognition System: A Survey

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ABSTRACT Information systems in organizations traditionally require users to remember their secret pins or (passwords), token, card number, or both to confirm their identities. However, the technological trend has been moving towards personal identification based on individual behavioural attributes (such as gaits, signature, and voice) or physiological attributes (such as palmprint, fingerprint, face, iris, or ear). These attributes (biometrics) offer many advantages over knowledge and possession-based approaches. For example, palmprint images have rich, unique features for reliable human identification, and it has received significant attention due to their stability, reliability, uniqueness, and non-intrusiveness. This paper provides an overview and evaluation of contactless palmprint recognition system, the state-of-the-art performance of existing studies, different types of ''Region of Interest'' (ROI) extraction algorithms, feature extraction, and matching algorithms. Finally, the findings obtained are presented and discussed.

INDEX TERMS Biometrics, information system, palmprint images, region of interest.

I. INTRODUCTION

A biometric authentication effectively recognizes a person's identification with high confidence [1]–[3]. Recent study interest has been required by palmprint recognition, an emerging technique in biometrics systems. Researchers have been looking at constructing such systems in a contactless approach to make the palmprint. Thus, there are two categories of palmprint capture techniques: contact-based and contactless-based. However, human users have expressed much justifiable opposition to contact-based acquisition strategies. However, this has had a detrimental effect on the advancement of palmprint recognition. As a result of these failures, contactless palmprint recognition has been developed to increase user-friendly and hygienic and safeguard user privacy [4]–[7]. Thus, this paper provides an overview and evaluation of the contactless palmprint recognition system, the state-of-the-art performance of existing works, different types of ''Region of Interest'' (ROI) extraction algorithms, feature extraction, and matching algorithms.

This work discusses the theoretical background of biometric recognition, contactless palmprint as a biometric, and the concept of on-device intelligence. Several related works are also discussed to highlight the state-of-the-art techniques related to these research areas. The following are some of the significant challenges in respect of palmprint biometrics in the literature: its pose and Illumination affect the layouts and visibility of palm lines; detecting the contactless palmprint region of interest (ROI) due to the different orientations of the presented palm is challenging; current palmprint processing

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is off the device; and due to costs, most of the devices are equipped with limited memory [8]–[11].

By the eighteenth century, pin-making was already a popular topic of conversation. The Wealth of Nations is unique as it connects pin-making to the division of labour. Adams Smith finds that the pin-unusual maker's trade has been split into various strange trades [12]. The Wealth of Nations pin factory has a straightforward internal structure. The labourers, similar to their jobs, are replaceable. As the study progresses, a well-researched conclusion emerges [13]. Figure 1 shows a pinhole camera imaging a distant point. This tale led to the invention of the plane mirror several millenniums ago, at the start of the bronze era. The Greeks later invented a mechanism for gazing through a mirror, convex mirrors, and glass burning [12], [14].

About 1500 years later, the pinhole camera was devised and invented by Alhazen (Ibn Al-Haytham) [14]; nobody could explain why the image was inverted, as shown in Figure 1. Della Porta [15] re-invented the pinhole camera around 1600 [14]. Della Porta's camera consisted of a big dark room with a large hole in one of the walls, as shown in figure 2. He also used optics to expand the hole and produce a brighter image. The pinhole camera has advantages over lens optics [14].

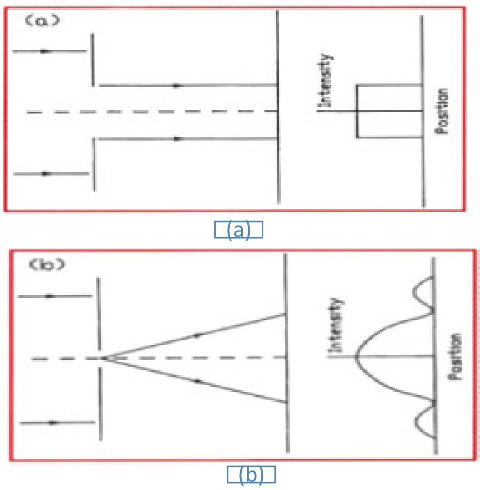


FIGURE 1. Pinhole camera imaging a distant point (a) Large pinhole geometrical optics (b) Small pinhole, far-field diffraction [14].

The pinhole camera was initially made using photographic film, but with the decline of film photography and the advent of digital cameras, the activity was converted for use with a digital camera, producing satisfactory excellent results [13]. Figure 3 shows the different devices used after the advent of digital cameras. With the widespread use of palmprint recognition and the extensive availability of cameras, a person's palmprint images are highly likely to be captured by various devices [16]. Technology is constantly evolving, and there is an increasing demand for improved security and privacy in our daily lives. Biometric approaches are a current and effective solution to achieve these technological security aims [17]. Today, people use various online services related

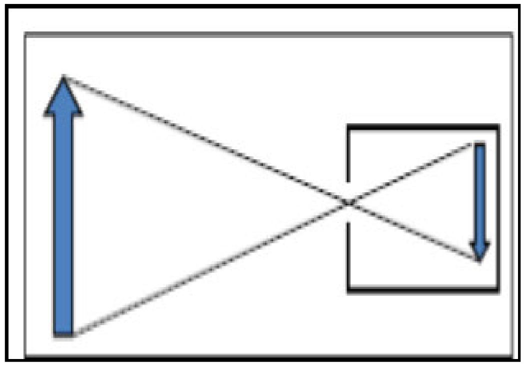


FIGURE 2. Ray diagram for a pinhole camera [13].

FIGURE 3. Different devices (a) Digital Camera (b) Smartphone [16].

to telecommunications advancements, social media, smart devices, and small IoT devices [18]. Thus, behavioural and physiological data can be employed for biometric recognition validation. Signatures, keystrokes, and gait are examples of behavioural features. Face, iris, ear, fingerprint, and palmprint are physiological qualities. Because of their uniqueness, behavioural and physiological biometrics are used in biometric applications [19].

Biometric scanning is a method of verifying identity by exploiting humans' unique physical or biological traits. The demand for information is increasing, and we need it now. Mobile and digital devices have become a lifeline for many people. Computers, tablets, smartphones, and other computing devices are no longer merely for communication; they have evolved into mobile workplaces with access to many resources. We must continue to secure ourselves and protect personal documents such as passports and driver's licenses and actions such as cash withdrawals and acquiring easier and safer access to facilities.

Traditional authentication solutions based on a username and password are no longer adequate for today's identity needs. As a result, more straightforward, dependable, and secure authentication techniques are required [20]. On the other hand, Biometric systems are vulnerable to various attacks, including image-level attacks. Here, the attackers

TABLE 1. Performance of the various biometric sensing system.

Factor	Fingerprint	Face	Hand Geometry	Iris	Palm Vein	Palmprint
	Biometric Sensing System					
Accuracy	High	Low	Medium	High	High	High
Ease of use	High	Medium	High	Medium	Medium	Medium
Cost	Low	Medium	Medium	High	High	High
Privacy	High	High	Medium	High	Low	Medium
Distinctiveness	High	Low	Medium	High	High	High
Error Causing Factor	Age	Occlusion	Injury	Eye Angle	Illness	Age
Barrier to Universality	Worn Ridges	Plastic Surgery	Hand Impairment	Visual Impairment	Ageing	Worn Prints

devise a method of fabricating phoney biometric photos that can easily fool the systems, which are then utilized to impersonate legitimate users [18]. As a result, there are two sorts of attacks: reconstruction attack (RA) and presentation attack (PA) [21]. The ''similarity'' of RA and PA is considered, but ''naturalness'' is often ignored. ''Similarity'' refers to the distance metric between two biometric templates. A real user's biometric image and a forged biometric image generate two biometric templates in image-level attacks. Once the ''similarity'' is fulfilled, i.e. successful impersonation of the authentic user, the image-level assault is successful. However, ''naturalness'' refers to a state in which a counterfeited image appears natural, implying that there should be no strong noise or unnatural appearance in the image. As a result, when an image appears natural rather than counterfeited, it is counterfeited; for example, if the image has strong noise or a noise-like appearance, it is counterfeited. As a result, any image lacking in naturalness can be immediately spotted and countered [22]. Biometrics can be safe guarded against all these types of assaults. Biometrics is a method of automatically identifying an individual based on their physical or behavioural characteristics. Fingerprints, palm prints, face, hand, and iris are a few examples. Security of computer systems, access to doors (entry), government IDs, banking and other financial transactions, online banking, policing, health, retail sales, and support services are only a few biometrics applications [11]. Because a person's inherent traits cannot be taken away, neglected, fashioned, or stolen, biometric recognition has shown to be a viable and widely accepted method of authenticating their identity [23].

Biometric-based systems provide the following advantages over knowledge-based or token-based authentication systems [24]:

a) Uniqueness: the characteristics of biometrics are unique and peculiar to an individual, making it distinctive in identifying a person in a unique form.
b) Convenient: Biometric use is more convenient since the user will not carry any token for authentication or have any secret information in his/her memory. Therefore, users cannot lose, misplace or forget their physiological or behavioural traits.
c) Hard to forge: The biometrics characteristics are hard to forge, but the spoofing technique can be used to attack it. Hence, more than one biometric trait is used to reduce the forgery chances massively.
d) Requires Physical Presence: Live biometric sample is captured during authentication by the biometric system.

Table 1 shows the performance of the various biometric sensing systems.

Palmprint has received much interest in studies because of its appealing properties, including high accuracy, stability, reliability, distinctiveness, non-intrusiveness, ease of ''use,'' and privacy. As a result, various imaging technologies are needed to acquire evidence-based biometric traits. Each biometric system is made up of the following.

i. Image acquisition module: The biometric image trait is obtained and transmitted to the system for further processing.
ii. The preprocessing module removes unwanted noise and blur and performs smoothing and segmentation.
iii. Feature attraction module: this does image processing by extracting the key elements from the captured image.
iv. Matching module: to obtain a match score, the image of the extracted features is compared to the images contained in the template.
v. Decision module: this is where the decision to validate or reject the identification claimed on the match score is made [25]. A biometric system functions in one of two modes: verification or identification.

Biometric sensors and processing systems are potent instruments for verifying and identifying individuals. The biometric feature, which cannot be shared or fabricated, exhibits a strong relationship to an individual based on their identification [26]. As security concerns become more prevalent, demand for biometric capacity also grows. Services that demand high degrees of data security and authentication rely on convenient biometric security. However, biometric security to identify and authenticate an individual based on their physical or behavioural characteristics is expanding rapidly [27]. Biometric data is collected from a person, a feature set is extracted from the data, and the feature set is compared to the database's template set. Biometric technology can be used in two modes: verification and identification.

Figure 4 a typical biometric system's generic design at the end of the procedure, the person is identified using the extracted feature.

Images are visible line features in contact-based palmprints. The principal lines, also known as the heart line, headline, and lifeline, are an individual's largest and longest permanent lines. The wrinkles are the other lines that are shorter and thinner. The texture-based images, which are low-resolution images, are also important features of the contact-based palmprint. The images in contact-based biometrics are captured using scanners and pegs, which has the following drawbacks:

i) Users' palms are constantly in contact with the sensor, which is unsanitary, especially with the present COVID-19 pandemic and other health concerns.
ii) Acquisition flexibility and convenience are harmed by user acceptance and repair procedures.

In some nations, placing hands on devices touched by the opposite sex is frowned upon.

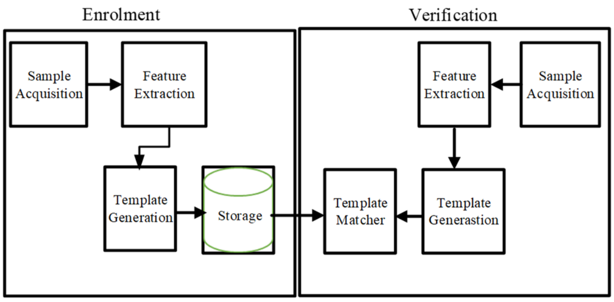
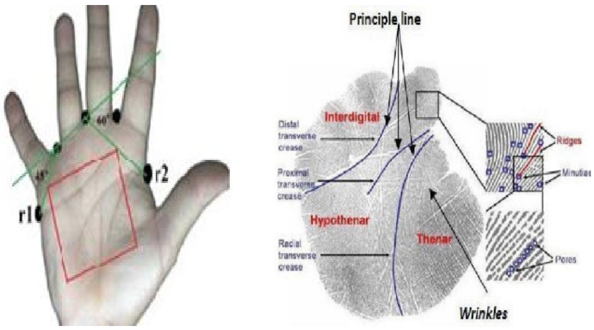


FIGURE 4. A generic architecture of typical biometric systems [26].

Images in contactless palmprint biometrics, on the other hand, are frequently distorted by translations, scaling, rotations, and illuminations and are prone to noise. Also, because the lines and textures are the most important aspects of contactless-based palmprints, they are low-resolution images. Therefore, additional features are derived from the images to improve palmprint recognition accuracy [28]. We can also use a collaborative representative and a subspace learning approach [29], [30]. Furthermore, due to the influence of rotation, scale, luminance, and variances in the translation of the images, features with high resilience are useful for contactless palmprint recognition [28]. As a result, images are acquired using several sensors in an uncontrolled environment with variations in scales, illuminations, rotations, and translations due to hand movement.

II. LITERATURE REVIEW

In image processing, biometrics technology has become an important application and is getting more popular daily. Today researchers dwell more on improving this area because, in security, biometrics is very important. It then became helpful in analyzing many security cases, which gave many researchers the strong will to do more in developing the field. Also, biometric technology plays a very important role in security and commercial, civil, and industrial project designs by incorporating recognition and identification of human beings in their designs. This work discusses the theoretical background of biometric recognition, contactless



(a) (b)

FIGURE 5. Palmprint images (a) Palmprint [19] (b) Palmprint image; principal lines, ridges, and palm valley [31].

palmprint as a biometric, and the concept of on-device intelligence. Several related works are also discussed to highlight the state-of-the-art techniques related to these research areas.

The human palm is the flat region of the hand below the fingers visibly marked by principal lines similar to fingerprints. As presented in Figure 5, its unique features include ridges and valleys patterns, minutiae, and pores visible in high resolution [32]. Palm print information is another widely used method of identifying individuals. According to studies, the hand groove pattern and arteries can be used to identify individuals accurately. Different features of a person's palmprint, including geometric features, principal lines, and wrinkles, produce distinct and unique patterns. These techniques are employed in biometrics and the identification of individuals. In terms of vascular location, palmprints have numerous features and a set of distinguishing features that can be used for identification [33]. The palmprint features are considered reliable for personal recognition systems desiring high usability, execution speed, user acceptance, and reduced acquisition cost. Palmprint recognition systems have been deployed for access control, law enforcement and forensic analysis systems, to mention a few [34].

Hitherto, biometrics usage has been accepted as an authentication system due to its unique identification based on physiological or behavioural traits. The physiological traits include Palmprint, Fingerprint, Face or Eye, while behavioural traits include Voice, Signature, or Gait. Therefore, the biometric authentication system's robustness can be judged by how variations due to physiological or pathological conditions are caused. Thus, we need to consider the permanence trait factor; hence ageing is a parameter causing muscle atrophy, reduced ability or loss of elasticity in the biometric system [35].

Many reviews work on different modalities as it affects ageing on different characteristics of biometrics has been done, authors rated the biometric templates in accordance with the variance caused due to ageing over time. Their review was centred on how ageing affects the face, fingerprint, voice, and iris used to develop robust biometric authentication systems.

FIGURE 6. Face images displaying ageing which have been caused due to variations [35].

a) Face Ageing: Recently, face trait has been investigated for biometric reasons. Even though ageing affects the facial features directly between childhood and adulthood, other factors such as external environmental factors affect the face texture. However, the major problem is for the claimed user to be recognized by the biometric system [36], proposes a generative statistical model that simulates the ageing effects to recognize faces at any time. However, ...(Biswast *et al.*,2008) propose a coherence feature which is a discriminative approach by using second-order polynomial and model refining considering the individual lifestyle. As age progresses, there is a drift of feature vectors due to the ageing of the face, as shown in Figure 6.

b) Fingerprint Ageing: Fingerprints as biometrics has been widely accepted for biometric verification. Studies have shown that the error rate increases for older people in analyzing the impact of ageing on fingerprint biometrics. According to the experimental evaluation by [38], the biometric recognition efficiency is affected as age progresses due to fingerprint deterioration. Two reasons that affect fingerprints were cited in their study:
   i. There is elasticity loss of the skin due to ageing, which makes poor contact with the scanner.
   ii. When there are injuries on the fingers, this causes direct damage to the fingers. Figure 7 shows the variations in the fingerprints due to ageing.

c) Iris Ageing: The dataset was divided into four short to long-duration sets. They then reported a 50% FRR using the veriEye method. Figure 8 shows the changes in Iris due to ageing. Iris ageing is regarded as part of the body less affected by within-person variation. In their work, Bowyer *et al.*, 2008) revealed that some eye diseases affect the iris part of the eyes, decreasing the authentication system's accuracy. In their work, [39], investigated the impact of ageing on Iris using a 644 Iris images dataset.

d) Voice Ageing: Ageing is a major cause of the non-recognition of an individual in a biometric system. Physiological changes, environmental factors and

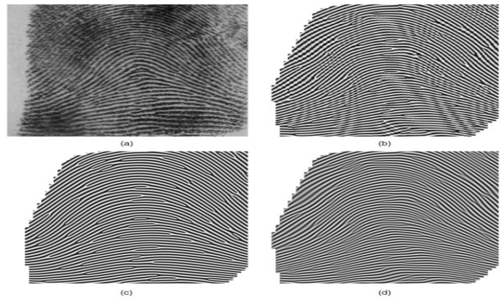


FIGURE 7. Variation can be seen in the fingerprint due to the impact of ageing [35].

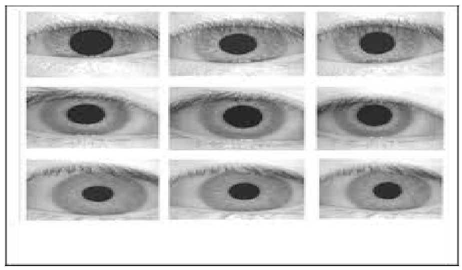


FIGURE 8. Sample shows the changes caused due to ageing in the iris [35].

emotional variations are some of the challenges an individual faces as age progresses. The rate of speech, pitch etc., are also affected by ageing. The longitudinal analysis of the voice data was carried out for about 30-40 years [40]. But [41], in their work, proposed using relevant parameters to report 90% accuracy when classifying the voice of three different age groups. Figures 9(a) and (b) show the variations in the voice due to ageing and ageing as it affects speech pitch rate, respectively.

e) Signature: The characteristics of the signature as it concerns individuals show a likelihood of an individual's signature changing with age. Data were collected from middle to elderly individuals to analyse and check the effect of ageing on their handwriting. The data set consists of 51 individuals, of which 25 subjects have the same writing style. Since ageing is a continuous changing process, inter or intra variations were brought into the technique used to characterize the individual. Figure 10 shows the changes in signature due to ageing.

III. PALMPRINT RECOGNITION SYSTEM

As shown in Figure 11, Palmprint recognition systems usually consist of six different processing stages or modules: image acquisition, image preprocessing, region of interest (ROI) extraction, feature extraction, matching/classification palmprint, and decision making. Details of each module are provided in the following sections.

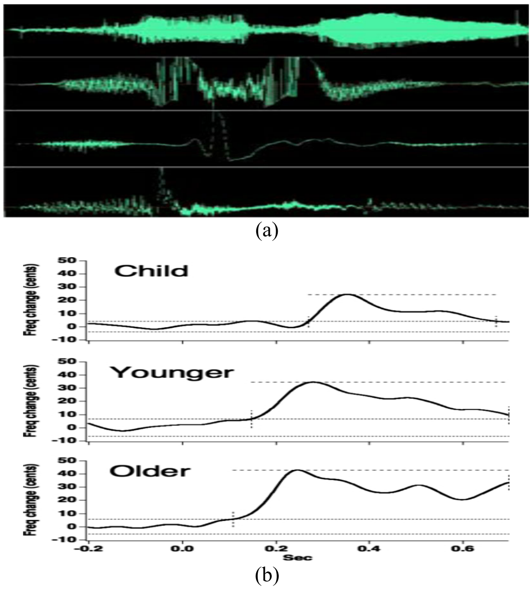


FIGURE 9. Variation in the voice due to ageing (a)Variation in the voice of two subjects due to ageing [35] (b) Ageing affects the pitch rate of speech [42].

FIGURE 10. Variation in the signature speed [35].

There are two types of palmprint recognition systems - Contact-Based Palmprint and Contactless palmprint; based on contact with the acquisition device.

A. CONTACT-BASED PALMPRINT RECOGNITION SYSTEMS

This method usually requires a fixed palm position on the sensor screen to acquire stable images. The images are acquired using scanners with pegs for hand placement. The constrained acquisition mode enhances the accurate extraction of the region of interest (ROI) and, consequently, the system's overall performance [19]. However, contact-based systems have the following disadvantages: [18], [43], [44].

i. Hygiene: Direct contact with the sensor makes the user susceptible to infectious diseases.
ii. User Convenience: The acquisition process is not flexible and can reduce wide acceptance.
iii. Image Quality: The sensors' surface can be easily contaminated by harsh or dirty outdoor environments. Thus, the acquired palmprint images' quality is likely to be degraded.

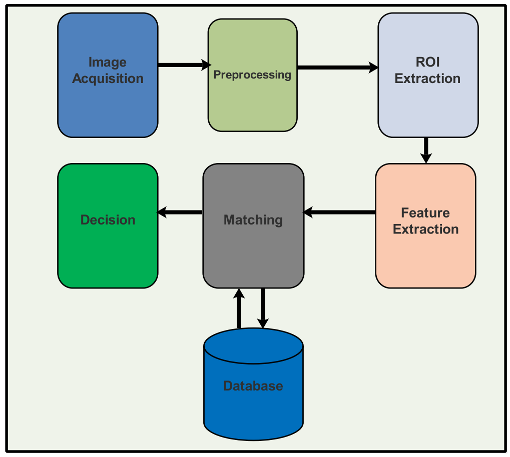


FIGURE 11. Stages involved in palmprint recognition system [45].

iv. Surface Contamination: Some acquisition systems' contact sensors' surface is easily contaminated due to harsh, dirty, and outdoor environments. Thus, the acquired palmprint images' quality is likely to be degraded.
v. Cultural Resistance: In some countries, there is resistance to placing hands-on devices touched by the opposite sex users [46].

B. CONTACTLESS PALMPRINT RECOGNITION SYSTEMS

This method acquires images in a less-constrained manner. Image acquisition can be achieved with four different types of sensors: Colour Charge Couple based (CCD-based), digital camera, digital scanner, and video camera. The CCD-based palmprint scanner usually captures high-quality palmprint images, enhancing the development of a robust recognition algorithm. Furthermore, image acquisition based on digital scanners and video cameras does not use pegs for hand placement. Also, the images are collected in an uncontrolled environment with a variant on rotations, scales, illuminations, and translations due to the hand movement [47]. A summary of the various capturing devices for contact-based and contactless palmprint images is provided in Figure 12.

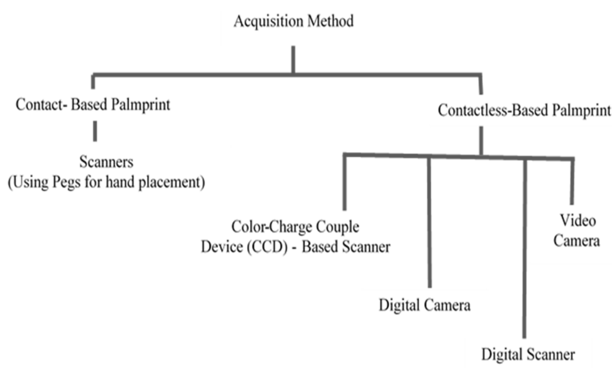


FIGURE 12. Palmprint acquisition methods and devices.

TABLE 2. Publicly available palmprint image database.

References	Existing Dataset	Demographic Details of Subjects and Ethnic Race	No of subjects	No of images
[29], [48], [49]	Poly U Palmprint image database	195 Males, 55 Females, 20 – 60 years Asians and Americans	250	6000
[50]–[52][53]	IITD image database	12 – 57years Asians and a few Africans	312	3220
[47], [50][54]	CASIA Image database	Asians, Africans and Americans	312	5502
[49], [55]–[57]	Multispectral palmprint image database	Asians	250	6000
[9]	Tongji palmprint database	Caucasians	300	1200
[58]	Poly U 3D	Asians and few Africans	200	8000
[33]	7.	Asians and Americans	190	11,076
[59]	GPDS	Spanish whites	100	1000
[60]	THUPALMLAB	Asians and Few Africans	80	2040
[61]	XJTU-UP	Caucasians	100	30,000
[44]	Poly U M_B	Asians 20-60years	250	6000
[47]	Poly U 2D/3D	Asians and White Americans 18-50years	177	3,540

TABLE 3. Palmprint acquisition devices and properties.

Sensor Types	Sensor Resolution (MP)	Image Produced	Apparent Features	References
Digital Camera	2.74 3 – 6 8 – 10	Low-quality images	Images collected are with variance in palmprint and can be distorted due to hand movement.	[28], [62][24], [63]
Digital scanner	15.6 12.5 13.2	Distorted images due to contact with the scanner	Due to the scanning time. It is not suitable for real-time applications.	[64], [65]
Video Camera	12 5 12	Low-quality images	Images collected with variance in palmprint are distorted due to hand movement.	[48], [53], [66]

IV. CONTACTLESS PALMPRINT IMAGE ACQUISITION DEVICES AND DATABASES

Numerous publicly available database has been released to facilitate the development and deployment of contactless palmprint recognition technology, as detailed in Table 2. The data acquisition method determines the algorithm/techniques that will be applied in the subsequent stages of the palmprint recognition system and, consequently, the system's performance [28]. Table 3 presents some contactless palmprint acquisition devices, highlighting device types, sensor properties, and image quality.

A. PALMPRINT IMAGE PREPROCESSING METHOD

Image preprocessing is accomplished by removing the noise and smoothing the boundary region in the required image before extracting salient features from the palm print images. Figure13 illustrates the preprocessing module of the palmprint recognition system involving three necessary steps: palm images binarisation, hand and or fingers contour extraction, and key points detection.

The steps available in preprocessing contactless palmprint are as follows

i) Palm images binarization/hand and or fingers contour extraction: Palm Images binarization and hand/or fingers contour extraction and hand and or fingers contour extraction. There is a similarity in all preprocessing algorithms [9], [25], [28], [32], [48], [59], [67], [68]

ii) Key point detection: It has several various implementation approaches, which include:

(a) Tangent-based approach: It is reliant on a very short boundary around the finger's bottom edge. It is robust to inadequate fingering and ring presence: All intersections represent the two focal points for the coordination framework [45], [58], [60], [69]–[72].

(b) Bisector-based approach: It builds lines using two points finger boundaries of gravity, and the midpoint of its starting point and endpoints with intersection considered a critical point [2], [22], [46], [51], [72], [73].

(c) Finger-based approach: The edge points can be found from the inputted pegs coordinates, and Line profiles were extracted and decomposed. Then the edge points were found from the transformed signal [48], [57], [74], [75].

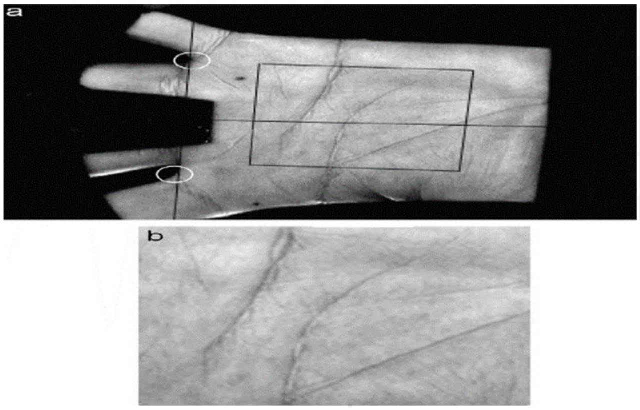


FIGURE 13. Preprocessing Illustration (a) Key points based on the boundary (b) Central parts for feature extraction [55].

B. REGION OF INTEREST (ROI) EXTRACTION METHOD

ROI extraction is carried out before the feature extraction stage. It is the process that can either be a square or circular shape, and the points that match the palm's internal structure and contain enough information to represent the palmprint are presented. The region extracted across all palmprint images is either a portion of the palm cropped at a fixed size or the entire palm. Besides, different ROI methods depend on the database of choice. ROI Techniques can be divided into four practical approaches, as shown in Figure 14:

The various ROI approaches are briefly described here:

i. Bottom-up-feature-based: This method target features wherein lighting, or pose, have varying conditions and are used in detection procedures [18], [48], [68], [76].
ii. Top-down knowledge-based: This approach controls the false positive situations since it deals with the object of interest [44], [56], [61], [77].
iii. Template Matching Approach: This approach represents the global object image by using parts and the possibility for detection. [21], [60], [78], [79].
iv. Appearance-based Approach: This method undertakes learning models from the training collection of images which are then used for detection [18], [80]–[82].

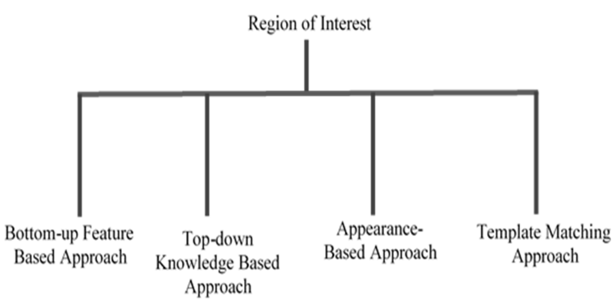


FIGURE 14. Methods of region of interest (ROI) extraction.

C. PALMPRINT FEATURE EXTRACTION METHOD

Feature extraction is extracting the biometrical values that uniquely describe an individual. It is also a crucial phase in the biometric system recognition process. The extraction step of features helps identify the most critical characteristics in the input images that can be used for classification [83].

Palmprint feature extraction methods are broadly divided into three, namely: holistic-based, local feature-based, and hybrid methods [25], [84]. In the holistic-based method, palmprint images are treated as an image with a vector of high dimension and used as the feature vector for palmprint classification or matching. In feature-based extraction, salient features such as lines, texture features, and edges are extracted from palm print images. To boost recognition accuracy, the hybrid technique integrates holistic and local feature-based features. [46], [76]. Numerous palmprint approaches for extracting and matching features have been proposed due to the increased interest in low-resolution palmprint recognition. Figure 15 highlights the palmprint feature extraction methods.

1) HOLISTIC-BASED FEATURE EXTRACTION

The holistic feature-extractor or matcher uses the real palm print image as input, creating two main issues: the holistic representation of palmprint images and the design classifiers. The holistic palm print feature is divided into subspace methods, spectral representation, and invariant moment. The algorithm related to the holistic approach is summarised in Table 4

a) Subspace method: The palm print images usually have a higher dimension than the training samples, which can be classified as a small sample size (SSS) problem. In the unattended/supervised area, many ideas have been given for mapping a palm print image from original data space to lower-dimensional feature space, including vector/tensor and linear/nonlinear subspace approaches [85]. An ab-initio linear non-supervised approach called principal component analysis (PCA) was applied to extract the holistic vectors. [76], [86], [87], while various unsupervised approaches, such as independent component analysis ICA) and locality preserving projection (LPP), have been used to recognize palmprints [10], [24], [53]. However, supervised methods are generally more efficient when resolving issues with recognition. Hence, the need to find a collection of discriminating vectors transforming the original data into a low-dimensional feature space has attracted research interest. Using supervised subspace approaches to solve the SSS problem consists of algorithm-based and transform-based strategies. An alternative formalization of LDA in an algorithm-based strategy is to solve the SSS problem [64], [71], [80], [88], [89]. Hence, in a transform-based method like PCA+LDA, the original picture data is first converted into a lower-dimensional subspace, and then LDA is used to extract the feature. [90].

Nonlinear subspace approaches for palmprint recognition have been used in the recent decade. Palmprint features have also been extracted using kernel subspace methods such as kernel PCA (KPCA) and kernel Fisher

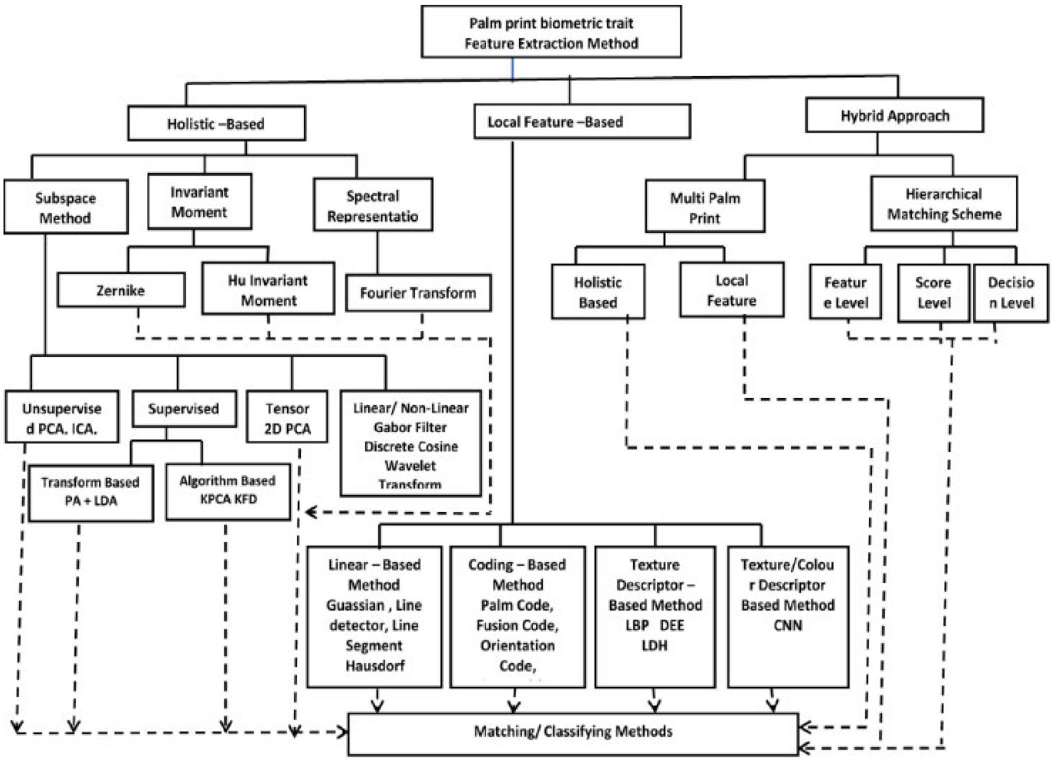


FIGURE 15. Palmprint feature extraction methods.

TABLE 4. Holistic-based palmprint recognition approach.

REFERENCE	APPROACH	DESCRIPTION
	Holistic Feature Extraction A. Subspace Method	
[50], [63], [65], [76][27], [94]	-Unsupervised linear method	Application of PCA and other unsupervised subspace methods
[69]	- Supervised linear method	PCA+LDA on raw data
[24], [92]	- Kernel method	Applications of kernel PCA and kernel fisher discriminant
[95], [54]	Transform domain subspace method	Subspace methods in the transform domains
[6], [8]	B. Invariant Moment	Zernike moments And Hu Invariant moment
[81]	C. Spectral Representation Wavelet Signature	Global statistical signatures in the wavelet domain
[25], [86]	Correlation filter Classifier Design	Advanced correlation filter
[16] [35] [36][77][96]	A. Nearest Neighbour	Extensively adapted in palmprint recognition
[57]	B. Support Vector Machine (SVM)	SVM with Gaussian Kernel

discriminant (KFD) [91], [92]. Multiple learning, a class of nonlinear dimensionality reduction algorithms with similar linear and kernel formalizations, has recently showed a good prospect in palmprint recognition [49], [57], [93].

The subspace method's performance can be enhanced further by using the image transform. After this, the transform coefficients may be effectively used to recognize palmprint and robust variability within the class. Again, the function transforms coefficients that may be omitted from subsequent processing operations, thus effectively reducing overall data dimensionality. Therefore, in the transform domains, the subspace methods techniques such as Fourier transforms are applied [95]. Gabor [92]; discrete cosine [66] and wavelet transform [74].

a) Invariant Moment-Based Feature Extraction: General information of images can be captured by image moments where rotation, scale-invariant properties, and translation are found in image recognition applications. With Zernike and Hu invariant moments, palmprint feature representation has witnessed a few feature descriptors being developed for it [20], [92], [97]
b) Spectral Representation Feature Extraction: Using image transformation and a set of frequency features, the Palmprint image can be transformed into its Fourier frequency transformation domain. This can be extracted, or palmprint discriminative features can be designed and characterized in the frequency domain by a correlation classifier [6], [57], [89]. These references proposed angular radial energy information for palmprint image into wavelet domain, then extract to characterize the directional context characteristics of palmprint are set of global statistical signatures [66] in their work proposed training advanced correlation filter each palm. In addition, multiple correlation filters per class have been proposed to improve the accuracy of palmprint recognition [6]. Another form of the correlation process, other than the correlation filter, is known as phase-only matching [75].
c) Classification-based Feature Extraction: In palmprint recognition, it is common that the number of valuable samples of each class is lower than the number of classes' characteristics. Hence, each palm has only one training age. Where these parameters are considered, the hyper-parameters of sophisticated classifiers are challenging to estimate; therefore, adopted widely is the nearest neighbour classifier [58], [72], [76], [98], [99].

Classification methods such as neural networks and support vector machines (SVM) were used in palmprint recognition in a similar way [25], adopted SVM with Gaussian Kernel and dual-tree complex wavelet features for the palmprint classification. In [93], recognition of backpropagation is a challenging multiclass problem for neural networks on a large scale with backpropagation. In [18], [79], the palmprint recognition task is decomposed using the modular neural network into a succession of two-class subproblems of varying sizes and similarities. Other neural networks have been proposed to authentic the palmprint; hierarchical neural networks and probabilistic neural networks are two examples of neural network bases [17], [56].

2) LOCAL FEATURE-BASED APPROACH

Palmprint recognition has two local characteristics: ridges and creases- which can be extracted from both low and high-resolution palmprint images. Each type of local palmprint feature has its own strengths and limitations, which are briefly introduced, while Table 5 summarises the local feature-based approach algorithm

i. Principal lines: have good governance and are usually the product of excellent permanence genetic effects essential in palmprint images. Nonetheless, because the principal lines of twins are identical, the distinguishability of the principal lines is minimal.
ii. Wrinkles: Only for a few months or years is it stable. As a result, wrinkles do not have the same level of permanence as minutiae. Principal lines and wrinkles are difficult to recover from a crime scene, and no latent full matching procedures have been devised for them, making them less effective in latent recognition. Still, the low-resolution palmprint image is rich in details about the wrinkles. High performance online palmprint recognition system can be developed Combing principal line and wrinkle features [24], [72], [100]–[102].
iii. 3D structure: 3D information on palm surface acquisition is more challenging than a representation of a 2D palmprint. Although 3D palmprint recognition is resistant to false palmprint attacks, it can be used with

TABLE 5. Local feature based palmprint recognition approach.

Reference	Approach	Description
[74]	A derivative of a Gaussian	Gaussian derivatives with different directions in the first and second order
[96]	Wide line detector	Location extraction and palm line width information
[19]	Line segment Hausdorff distance	Line segment Hausdorff distance application
[105]	Palm Code	2D-Gabor filter responses phase coding
[48]	Fusion Code	2D-Gabor filter responses phase calling with the maximum magnitude
[10]	Orientation Code	Palm lines orientation information coding
[9], [49]	Text Descriptor	Local binary pattern DCT coefficient coding

TABLE 6. Comparison of palmprint template matching methods based on complexity and template size.

Palmprint Template Matching	Computational Method	Memory Utilization	Template Size
Holistic Methods			
Subspace method	Low	Medium	Medium
Invariant moment	Medium	Low	Low
Spectral representation	High	High	Medium
Local Feature-based			
Line-based	High	Medium	Medium
Coding-based	Medium	Low	Low
Texture descriptor	Medium	Medium	Medium
Hybrid Method			
Multiple Palmprint Representation	High	High	High
Hierarchical Matching Scheme	Low	Medium	High

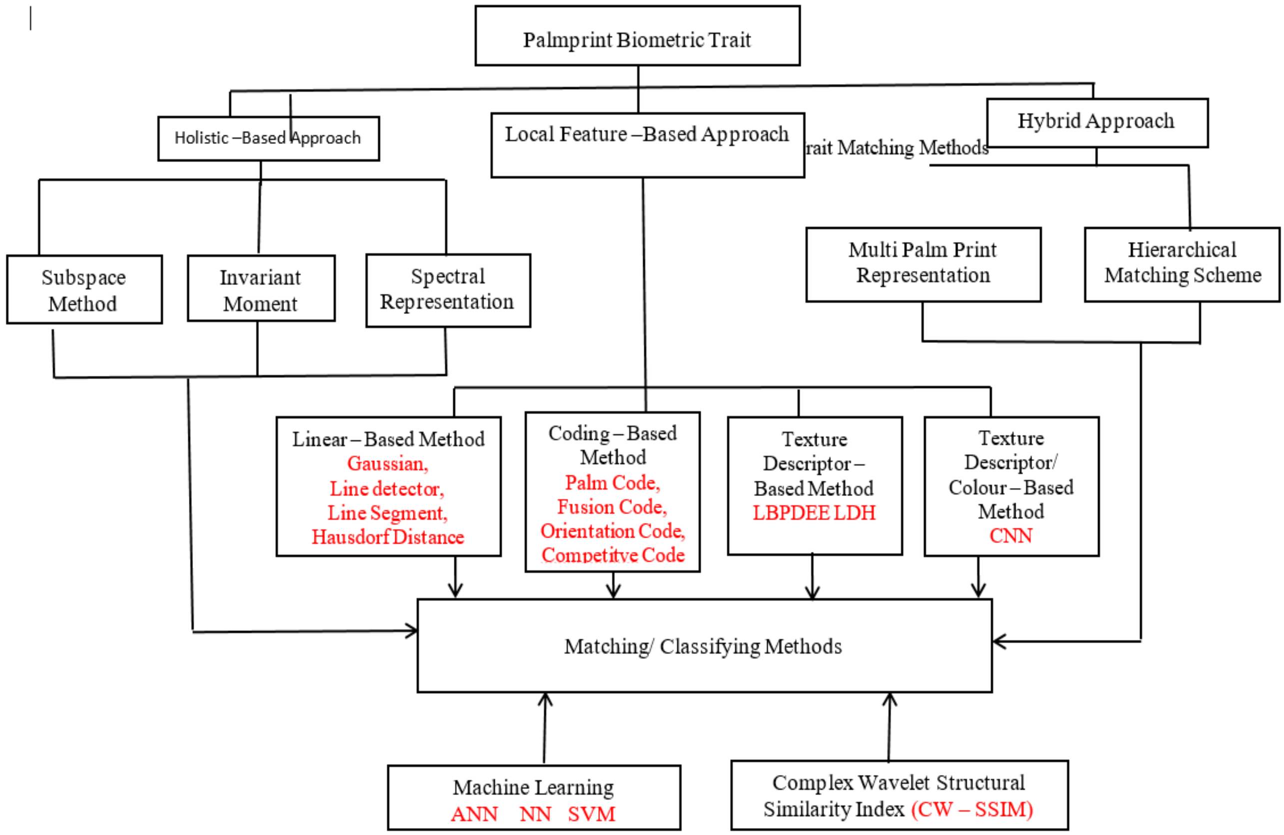


FIGURE 16. Palmprint biometric trait matching methods.

2D features to render robust palmprint recognition and a highly accurate system [47], [69].

iv. Multispectral features: Features obtained with various wavelength/resolution/sensors spectrum utilize multispectral palmprint recognition for authentication personally [18], [46], [56].

v. Minutiae: Detailed research into minutiae's distinctive and enduring essence has been conducted in palmprint and fingerprint recognition. Palmprint images with 500dpi minutiae feature essential for latent palmprint recognition can be extracted.

vi. Level 3 features: all dimensional permanent ridge attributes are included here. Examples include pores, edge contour line shape, incipient ridges, warts, scars, and ride path deviation [103]. Level 3 traits are important in latent recognition, as just 20 to 40 pores are required to determine a person's identity [44], [74]. Currently, most level 3 feature acquisition, extraction, and matching techniques are aimed at identifying fingerprints.

The local feature-based approach can be described as follows.

a) Linear-Based Method: A Gaussian second-order derivative to describe line magnitude was used by [74], and the Gaussian first-order derivatives to determine the line's location. The output is obtained by merging all directional line detection results, with camp code being utilized for encoding. Extracting palm lines' position and width information [61] suggested a large line detector using a nonlinear isotropic filter. Two-stage filtering also applies to the detection of palm lines [48]. Local line matching is a different focus in the line-based system, where two-line images are matched and produce a score. Thus, the number of line pixels in the same place as two-line images is calculated using the standard matching methodology. The performance of the system is due to many unavoidable factors, e.g. translation, rotation, and deformation of the palmprint images, which is unsatisfactory [86] proposed dilation of template line image before matching and [6] used line segment Hausdorff distance to indicate the matching score of two-line image value.

b) Coding-Based Method: The coding-based method encodes a bank of filters that responds to a bitwise code. With the representation of the bitwise function properties, motivated by Daugman's [48] iris code has a coding-based method with a lower memory requirement, and quick matching speed was effective in the representation and matching of palmprints. It should be noted that a palm code method which encodes

TABLE 7. Selected contactless palmprint recognition systems.

z	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
1.	[107]	Hand images database	Gaussian filter and Laplacian filter	Competitive Hand valley detection (CHVD)	Finite Random Transform (FRT) and Simple directional coding method	Support vector machine and radial basis kernel (BRF)	EER-1.94
2.	[108]	Multispectral palmprint database	Gabor filters		2D Gabor features (Comp Code) 3D Features (Surface curvature map)	2D Matcher (Angular Matching) 3D Matcher (Local correlation Matching)	EER-0.022
3.	[109]	IITD database and GPDS-CL1 database	Histogram equalization	SIFT	SIFT and OLOF	Modified scale-invariant feature transform (MSIFT)	EER-0.21, 0.17, 0.57
4.	[110]	Personal database	Gaussian filter and morphological filter	Competitive Hand Valley Detection (CHVD)	Directional coding and relative measurement	Hamming distance and Euclidean distance	EER-0.12
5.	[109][111]	Personal database	Otsu Threshold	Valley point detection	DCT Transform Orthogonal line Ordinal Features (OLOF) and Modified Scale-invariant feature Transform (MSIFT)	Least square support vector Machines (LS.SVM) & Euclidean distance	EER-0.21
6.	[112]	Personal database	Tracking algorithm and local-ridge-enhancement (LRE) technique	Competitive Hand Valley Detection (CHVD)	Directional coding	Hamming distance	EER —0.21
7.	[113]	Multimedia University database.	Skin-color thresholding and triple-perpendicular directional translation residual (TPDTR)	Valley point detection based on TPDTR	Edge detection	Palm code	EER—0.025
8.	[114]	Poly U Palmprint Database	Block dominant orientation code (BDOC)	Block-based Histogram of Oriented Gradient (BHOG)	Block dominant orientation code (BDOC) and Block-based Histogram of oriented gradient (BHOG)	Hamming distance and Hierarchical classifier	EER-0.074
9.	[115]	Poly U and IITD Palmprint databases	Not specified	Not specified	Modified finite Random Transform (MFRAT)	Robust line orientation code (RLOC)	EER-0.0334
10.	[116]	Personal database	Histogram equalization and Median filtering	Active contour without edges with Haar wavelet	SURF descriptor	Support vector machine	Avg F1: 0.9009 Avg Acc:0.9486 Avg Prec: 0.9602
11.	[48]	Poly U IITD Palmprint database Multispectral Database	Binarisation	Bank of Half Gabor Filters	Bank of Half Gabor Filters	Double half orientation codes	EER—0.0139

TABLE 7. ***(Continued.)*** **Selected contactless palmprint recognition systems.**

S/N	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
12.	[29]		Low-Rank Representation (LRR)		Modified-Finite Random Transform (MFRAT) and LRR	Low-Rank Representation (LRR) with Principal Line Distance (PLD) (LRR-PLD)	
13.	[95]	FBKS-DB Knuckle database	Canny edge detection	Edge-map Image	Angular geometric analysis method and discrete curvelet transform	Euclidean distance	EER—0.30
14.	[117]	Personal database	Morphological technique And Gaussian filter	Geodesic active contour (GAC)	Shape factor	Hydrophobicity classification (HC)	Avg F1: 0.8600 Avg Acc: 0.8429
15.	[56]	Multispectral Palmprint database	Fast and Adaptive bi-dimensional empirical mode decomposition (FABEMD)	Fast and Adaptive bi-dimensional empirical mode decomposition (FABEMD)	Illumination tensor-based machine learning	Tensor-based machine learning	FAR—97.9
16.	[98]				Sparse Representation Based Classification (SRC)	Collaborative Representation Based Classification with Regularized Least Square (C-RLC)	FRR- 99.15%
17.	[97]	Poly U	Active appearance model (AAM)	Valley point detection	Gabor-based kernel fisher discriminant analysis (KFDA)	Cosine Mahalanobis (COSMAH)	EER-0.154
18.	[77]	IITD Poly U and CASIA databases	Soft-Shifted Triplet Loss (SSTL)	Soft-Shifted Triplet Loss (SSTL)	Convolutional network (CNN) and Fast R-CNN	Residual feature network (RFN) and soft-shifted triplet loss function	EER- 1.17
19.	[118]	Tongji University Contactless Palmprint dataset	Inception-ResNet v1	Inception-Resnet v1	Modified inception ResNet VI network	Euclidean distance & Support Vector machine	EER-2.74
20.	[105]	HKPU IITD	Nearest Neighbor Interpolation	Chartfield's CNN using transfer learning approach	CNN with pre-trained architecture	Support vector machine (SVM) K-Nearest Neighbor (KNN) And Random Forest (RF)	0.0125 0.0156 0.0625
21.	[69]	Poly U 3-D Palmprint database	Phase Shifting Algorithm	Not specified	Mean Curvature Image with a revised Gabor filter	Binary code list	EER-0.19998
22.	[32]	Poly U Multispectral Dataset	2d Principal component analysis	Random subspace method	2D Linear discriminant analysis (2DLDA)	Nearest Neighbor	Execution Time: 0.06s
23.	[89]		Gaussian Filter		Gabor Filter Discriminative Competitive Code	Index using Discriminative Competitive Code - Based Method	EER -0.0334
24.	[119]		Circular Gabor Contrast Enhancement and Global Based Illumination		Masked SIFT	Selective matching using Euclidean Distance	

TABLE 7. *(Continued.)* **Selected contactless palmprint recognition systems.**

S/N	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
25.	[71]	MS Poly U CASIA Tongji	Coordinate system	Coordinate System	Hybrid HOG-SGF Method (Histogram of Oriented Gradients) and (Steerable Gaussian Filter)	Optimized Auto-Encoder (AE) and Regularized Extreme Learning Machine (RELM)	EER- 0.0073 0.0113 0.0025 0.0040
26.	[46]	Poly U CASIA IITD	Digital Back End (DBE), 2D Discrete Wavelet Transform	Lifted Based Wavelet Transform	Dimensional Reduction (DR) method using Kernel Principal Component Analysis (KPCA)	Normalization and Covariance method	EER—0.00272
27.	[64]	MS Poly U	Gaussian filter	Valley point detection	NGist-based descriptor with AE	Regularised Extreme Learning Machine	Blue—0.0001 Green—0.0003 Red—0.0007 NIR—0.0017
28.	[62]	CASIA IITD REgimSfax Tunisia (REST) hand database and Tongji Contactless Palmprint dataset	Binary image using the Otsu threshold and Kirsch edge detector	Not specified	PalmNet-Gabor and PalmNet-GaborPCA	K-NN classifier based on the Euclidean Distance	EER - 0.72 EER - 0.52 EER - 4.50 EER - 0.16
29.	[120]	Personal	Top-hat Filter Morphological Technique	Active Contour Model and Valley Point Detection	Local Binary Pattern	Support Vector Machine (SVM) and K-Neural Network (KNN)	10-Fold Validation LBP +Sum- 100% LBP+ KNN- 100% Testing ACC: LBP+SVM- 100% LBP+ KNN- 100%
30.	[68]	Poly U	N. A	N. A	Pretrained MobileNetV2	Support Vector Machine (SVM)	Acc: 100%
31.	[9]	Poly U IITD Tongji CASIA	Segmented images from the dataset were provided	Valley point detection	Convolution Neural Network using AlexNet and VGG-16	PalmNet and GenderNet with BoostNet-Parallel and BoostNet Sequential	Acc: 95.16% Acc: 99.05% Acc:100%
32.	[27]	IITD MS Poly U PolyU PPDB	Cohort Information	Cohort Information	Local Binary Pattern (LBP) and Spiral Features (Moment Skewness and Kurtosis)	Hamming Distance, K-Nearest Neighbor (KNN) Classifier	EER –0.0026
33.	[19]	IITD	Median Filter	Edge Detector	2D Gabor and Principal Component Analysis (PCA)	Principal Component Analysis (PCA)	EER - 0.50%
34.	[25]	NA	Image enhancement and Image filtering	Valley point detection	Double orientation using structure based algorithm Statistics- based algorithm and Sub-space based algorithm	Machine learning and Deep learning	NA
35.	[21]	MSU Idiap Oulu CASIA	Dual-force Triplet- mining	Dual-force Triplet mining	Pretrained Multiple source feature extraction	Multiple-adversarial Discriminative Deep Domain Generalization	M&I to C HTER% 41.02 AUC% 64.33 HTER% 39.5 AUC% 65.10

TABLE 7. ***(Continued.)*** **Selected contactless palmprint recognition systems.**

S/N	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
36.	[86]	HK Poly U UST Hand Image	Discriminant Coding	Discriminant Orientation and Scale Feature Learning (DOSFL)	Multi-Orientation and Multi-Scale Discriminative Feature Learning (MOSDL)	Angular Distance	EER—0.342% 0.234%
37.	[102]	IITD	Hand Shape and Palmprint Texture	Convex Hull	Short Feature Vector	Texture based Template Method	Accuracy 74% 83% 77% 78%
38.	[54]	CASIA	Gaussian filter and binarisation	Localization and Isolation	Hough Transform and Sobel edge Detector	Machine learning Techniques -Neural Networks - SVM -Naïve Bias -K-NN	NN-0.968 SVM-0.950 NB-0.941 RF-0.879 KNN-0.921 -Tree-0.755 AdaBoost- 0.865
39.	[17]	CASIA	Hue Saturation Brightness (HSB) Skin Color Modelling and Denoising	Hue Saturation Brightness (HSB) Color Space	N. A	N. A	Accuracy 98.8%
40.	[121]	Personal	Image Gray Enhancement	Valley point detection	Gray Code and Log-Gabor Filter	Hamming Distance	AA-98.40% FAR- 1.60% FRR-0 EER-
41.	[72]	Poly U IITD CASIA	Deep Convolution Neural Networks (DCNNs)	Deep Convolution Neural Networks (DCNNs)	Deep Discriminative Feature Method (DDF)	Deep Discriminative Feature Method (DDF) with Collaborative Representative Based Classifier	EER ARR 0.021% 98.7% 0.005% 99.5%
42.	[59]	Poly U IITD GPDS CASIA	Low pass Gaussian filter	Valley point detection	Local discriminant direction binary pattern (LDDBP)	Local discriminant direction binary pattern (LDDBP) with double dominant direction (DDD) and Chi-Square distance	Time Taken: 0.0367 0.0423 0.0402 0.0787 0.0749 0.0768
43.	[63]	Poly U	NA	NA	Discrete Wavelet Transform Contourlet transform Curvelet and Ripplet-I Transform Principal Component Analysis Discrete Cosine Transform Local Binary Pattern	Artificial Neural Network Euclidean Distance Support Vector Machine Convolution Neural Network	Identifier Rate (IR): 44.912 44.912 44.912 44.795 44.795 44.795 84.444 84.211 83.626 83.392 82.924
44.	[101]	Tongji Poly U	Different Sizes of Mean Filters, Median Filters and Gaussian Filters,	Valley point detection	Deep Neural Networks (use of ResNet-20)	Large Margin Cosine Loss (LMCL) and Center Loss (C-LMCL)	EER- 0.26 0.125

TABLE 7. *(Continued.)* **Selected contactless palmprint recognition systems.**

S/N	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
45.	[8]	IITD CASIA Poly U	CNN for hand landmark detection	Spatial transformer with (ROI-Lanet) ROI Localization and Alignment Network	Feature Extraction and Recognition Network (FERnet) using CNN	Deep Learning Method	Rank-1 Rank-2 R4.14 97.53 98.98 99.55
46.	[72]	IITD CASIA GPDS Poly U	Salient and discriminative descriptor (SDD)	Salient and discriminative descriptor (SDD)	Salient and discriminative descriptor learning method	Nearest Neighbor and Euclidean distance	Running Time: 0.318
47.	[18]	Poly U	Genetic algorithm	Deep Convolution Generative Adversarial Network (DCGAN)	Coding-based method using Palm Code (PC) Fusion Code (FC) Competitive Code(CC) Ordinal Code(OC) Robust line orientation Code (RLOC) Binary orientation Co-occurrence vector (BOCV) Double orientation Code (DOC) Discriminate and Robust Competitive Code (DRCC)	Normalize Harming Distance	EER-23%
48.	[22]	Personal	Median filter and Morphological Technique	Distance Transformation	Hierarchical scheme consisting of Local and Global features	Minutiae-based Rigid Transformation Affine Transformation	EER-0.243%
49.	[60]	THUPALM-LAB	Median filter Histogram and Binarisation	Dilation of binary image and Extraction of ROI and Conversion to gray level	Statistical gray-level co-occurrence matrix (GLCM) algorithm.	Probablistic Neural Network (PNN)	0.040—0.0097 for 10% and 100% For 25%, 50% and 75%-- 0.009
50.	[72]	IITD CASIA PolyU GPDS	Binarisation	Valley point detection	Deep local convolution feature using DCNN transfer learning	Joint constrained least square regression (JCLSR)	Feature Time—33.05 (ms) Matching Time—0.131 (ms)
51.	[96]	CASIA and COEP (College of Engineering Pune)	Gaussian Filter, Binarisation and Canny Filter	Valley Point Detection and Euclidean Distance	Local Binary Pattern with Histogram	Decision Tree and K-Nearest Neighbor (KNN)	EER- 0.009
52.	[58]	Poly U 3D	Tan and Triggs Normalization Technique	Valley Point Detection	GIST descriptor with Principal Components and Linear Discriminant Analysis	Cosine Mahalanobis Distance	EER- 0.00% -- 0.081%

TABLE 7. *(Continued.)* **Selected contactless palmprint recognition systems.**

S/N	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
53.	[90]	Poly U	KAZE preprocessing method	Neighbor Tracing Algorithm	KAZE Feature Detection and Extraction Method	Nearest Neighbor and KAZE	Not Applicable
54.	[91]	Tongji University	Gabor Filter, Median Filter, Gaussian and Mean Filter	Cropped ROI Images From Dataset	Transfer Learning based on VGG16, Convolution Neural Network ConvNet	Machine Learning Model	EER Adaptive Gaussian-0.0383 Adaptive Mean-0.03111
55.	[82]	Personal	Adaptive filter and Speckle Reducing Anisotropic Diffusion (SRAD) filter with Morphological Technique SRAD and Derivative of Gaussian filter (DoG) with Morphological Technique SRAD filter and Bottom hat with Morphological Technique Median filter and Bottom hat with Morphological Technique	AND Operation and DILATE Operation	Curvature method	Normalized Score Differences with Mean and Standard Deviation Computed	EER—0.36%
56.	[44]	Poly U II Poly U M_B HFTU CS TJU-P Poly U 3D TJU-PU	Gaussian filter And Binarization	Valley point detection	Convolution Neural Network	Convolution Neural Network	Recogni-tion Rate: 97.66% 100% 98.51% 95.37% 99.25% 97.58%
57.	[61]	XJTU-UP Poly U Tongji	Gaussian filter and binarisation	Valley point detection	DDH	Deep Hashing Network	EER%-- 1.12 2.52 2.68 5.06
58.	[79]	IITD Iris IITD Palmprint Poly U	Weiner filter and Histogram Equalization	Valley point detection for palmprint and Adaptive mask for Iris	Haar decomposition and 2D Gabor fiters	Hamming distance and Bit Transition Code	EER% -- 1.6 – Iris 0.81-PolyU Palmprint 19.24 -- IITD
59.	[33]	Jilin University Dorsal Hand Vein 11K Dataset	Median filter and Thresholding	Prewit and Sobel edge detection method	Generative Adversarial Networks (GAN)	Deep forging based on CNN with Generator Classifier, Deep Learning GAN (DLGAN)	EER% -- 2.47 and 3.55
60	[93]	Sign Language Digits Datasets	Deep Learning Model	Deep Learning Model	Lightweight Convolution Neural Network and Mobile-NET-V2	Deep Learning and MobileNetV2 Model	Precision CNN MobileNet 1.0 1.0 1.0 1.0 1.0 0.98 0.97 1.0 1.0 0.98 0.93

TABLE 7. *(Continued.)* **Selected contactless palmprint recognition systems.**

S/N	Reference	Database	Preprocessing Method	Region of Interest Extraction	Feature Extraction Method	Matching Method	Equal Error Rate
61.	[49]	Poly U CASIA	Sobel Filter with POP Hashing and A-POP Hashing	Double Orientation Encoding Method	Window-Based Feature Measurement	Orientation Field Code Hashing	FRR DBI:0.75 DB2 + DB3:4.11
62.	[6]	CASIA IITD GPDS	Local Binary Pattern	Edge Detector using Kirsch Operator	Direction Feature Method	Triple-Type Feature Descriptor	EER-0.0225
63.	[2]	XJTU-UP Tongji MDP IITD	Open sets are sampled	Multiple sets are sampled randomly	Deep metric learning based	Weighted based meta metric learning (W2ML)	EER% -- 2.97 3.27 1.91 3.35 2.42
64.	[53]	CASIA	Otsu Thresholding Algorithm	Valley Point Detection	Modified Local Binary Pattern Variance Algorithm (LBPV) and Laplacian of Gaussian (LoG)	Convolution Neural Network	EER- 0.5
65.	[7]	IITD-NIR CASIA-NIR SD-Poly U USM-PolyU	Sparse binary Codes for Recognition	Conversion of Binary codes of Each pixel into Real-value	Direction based feature matrix (DFM)	Chi-Square distance And Nearest Neighbor (NN)	Feature Score 0.033 0.026
66.	[3]	Poly U IITD CASIA GPDS PV_780 M_NIR REST	Complete Local Direction Features (CLDF)	Salient Convolution Different feature (SCDF)	Salient Complete Local direction Feature and Salient Convolution difference feature (SCDF)	Learning Complete and Discriminative Direction Pattern (LCDDP)	99.89 89.97 99.18 98.20 99.91 100.00 94.29
67.	[6]	CASIA IITD GPDS	LBP-like Texture descriptors	A3x3 local Neighborhood Pixel distance and Tcode encoding	Kirsh Operators	Matching score level Fusion with Tripple type matching score of feature descriptors	Accuracies: 72.30 64.56 70.75
68.	[1]	Tongji IITD DCPD	Skin-color-based segmentation and Designed Hardware based method for alignment	Valley points detection	CNN framework	Convolution Neural Network (CNN)	EER: 0.004 0.573 0.304
69.	[2]	XJTU-UP Tongji MPD IITD	Meta learning	ResNet 18	Metric learning based extractor	Weight based meta metric learning (W2ML)	EER: 2.97
70.	[5]	CASIA IITD GPDS TJI Poly U NIR PV_790	LPP-based method	discriminant palmprint method	Double Cohesion Learning based multiview and discriminant palmprint recognition method.	Support Vector Machine (SVM)	Accuracies: 98.43 93.93 99.76 99.44

as bitwise functions the filter response phase and convolved palmprint image with a 2D Gabor filter [25], [72]. Thus, there are correlations between different palm codes, which might cause the palm code's performance degradation. Reference [48] introduced a fusion code method convolving palmprint image of a bank of Gabor filters with different orientations encoding the maximum magnitude of the filter response process. A recent development in coding-based methods suggests that palm line orientation information is one of the most important features for personal identification [58], [105]; the three key topics in orientation coding are; coding scheme, filter design, and matching approaches. A bitwise feature representation was generated using the competitive coding scheme and matching two competitive codes using the angular distance [91].

c) Local Texture Descriptor: A palmprint image is divided into several small blocks by a typical local palmprint texture descriptor, and the mean, variance, power, or histogram of each block are then calculated as local characteristics [19], [66]. Local Binary Pattern (LBP) [76], a strong method of texture analysis, was successfully applied to face recognition through integration with AdaBoost [69], [95] performed palmprint image division into overlapped blocks to carry out calculations of the DCT coefficients of each block and formed a vector using its standard deviation. In addition, many texture descriptors have been adopted in palmprint recognition, such as local direction histogram and directional feature [28], [62].

3) HYBRID APPROACHES

The object of interest has been argued to have a human vision system using both holistic and promising hybrid approaches that are expected for palmprint recognition. Two main applications for hybrid approaches are palmprint recognition with good accuracy and rapid palmprint matching. For example, many feature-level, score-level and decision-level fusions are performed using holistic and local feature-based approaches to produce a multiple palmprint representation [51], [96]. Another highly significant application of hybrid approaches is quickly matching palmprints using a hierarchical method for coarse-to-fine matching [8]. Table 4 shows the hybrid palmprint recognition approach.

D. PALMPRINT TEMPLATE MATCHING METHODS

Matching shows the resemblance between data sets created by comparing the unfamiliar person's feature codes and those held in the system. Moreover, for a specific person's features, the score will be high and low for those who are different [90]. As earlier mentioned, feature extraction and matching are the most critical problems in palm print technology, which is equally grouped into holistic-based, feature-based and hybrid methods. Table 6 shows the various palmprint comparison methods, while Figure 16 shows the palm print matching/classification method.

V. EVALUATION AND SUMMARY OF CONTACTLESS PALMPRINT RECOGNITION AND EXISTING WORKS

Several palmprint recognition with extensive review of this work is presented in Table 7, highlighting the extraction area, preprocessing methods, feature extraction method,matching methods, and best accuracy. In addition, research works have been explored in contactless approach and the literatures are grouped as follows: (i) Holistic Based: [19], [29], [32], [46], [48], [59], [89], [92], [96], [106], [107], [111], [114], [119], [120]

(ii) Local feature Based: [3], [6], [25], [27], [58], [62], [63], [69], [71], [82], [108], [110], [113], [115], [118]

(iii) Hybrid Based: [5]–[7], [18], [22], [49], [54], [64], [72], [79], [86], [90], [95], [97], [101], [109]

(iv) Machine/Deep Learning: [1], [2], [8], [21], [33], [44], [53], [56], [60], [61], [68], [77], [91], [93], [100], [104], [112], [117]

VI. CONCLUSION

The key applications of palmprint recognition system include security; protecting personal information and documents such as identity documents, contracts and financial transactions), quick identification and unique recognition, access control; gaining access to premises made more accessible and safer, law enforcement and security profiling, forensic analysis

This survey presented identification technologies for traditional (knowledge or token-based) and state-of-the-art (biometric-based) authentication solutions with comparative advantages, drawbacks and restrictions. The vulnerability of these solutions to a variety of attacks is presented. The characteristics (similarity and natural) of RA and PA types of attacks. Various biometric sensing systems and their performances under different parameters are presented with palmprint identified as the most reliable. This work also showed the various imaging technologies needed to acquire evidence-based biometric traits while biometric sensors and processing systems are powerful tools. The theoretical foundation of biometric recognition, contactless palmprint biometrics, and the idea of on-device intelligence are all covered in this article. To illustrate the cutting-edge approaches used in these study fields, some related publications are also reviewed.

Compared to cloud computing, recent developments in edge computing have necessitated a paradigm shift in contactless palmprint biometrics. For example, the gadget collects data in the cloud and sends it to the cloud for knowledge and inference. Conversely, Inference processes are conducted locally on edge devices (which give ready use cases for contactless palmprint biometrics) (such as smartphones and other IoT gadgets). Furthermore, knowledge and inference at the edge could provide advantages such as faster reaction times due to fewer server trips, higher reliability, increased privacy and security, and better network capacity use. However, due to form factors or cost considerations, memory and energy resources are limited on edge devices and cannot be easily augmented. Thus, As a result, current and future research directions in this area will include increasing resources on the restricted edge device form-factor, developing more resource-efficient architecture, improving model training/inference on edge through novel software approaches, and a slew of other initiatives that will necessitate cross-cutting collaborations. A balanced palmprint dataset that goes across racial lines will also need to be curated, stored, and made available to the scientific community to reduce demographic bias.

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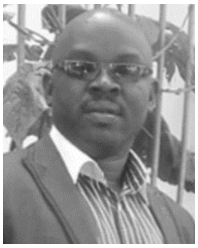

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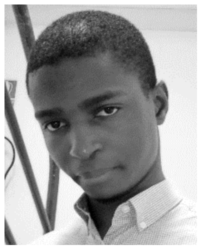

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