# On Wrist Vein Recognition For Human Biometrics

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***Abstract*—Human biometric recognition has always been of interest to researchers. This biometric recognition can broadly be classified into physiological and behavioral recognition based on the modality being considered. The former covers face, fingerprint, palm vein, palmprint and the latter covers gait, keystroke and more. Within the physiological set, vein recognition methods like palm vein, finger vein and wrist vein recognition are attracting more attention due to their subcutaneous nature. Veins being subcutaneous contributes to the possibility of developing contactless biometric systems which is essential in a post COVID-19 pandemic era. In vein recognition, palm vein and finger vein methods have been extensively reviewed and researched. However, there is very limited information on wrist vein recognition. This limits exploring the full potential of wrist vein recognition. In this paper we systematically review recent relevant research on wrist vein recognition and highlight its advantages and disadvantages. Wrist vein images are easier to capture and process when compared to other vascular biometric images. This conducted literature review revealed that wrist vein recognition is promising when used in conjunction with deep learning methods and can be successfully used in designing contactless wrist biometric systems. This study would aid future research and application of wrist vein biometric systems.**

## I. Introduction

The popularity of human biometric recognition systems has increased significantly in recent years. This is due to the ease of use and better security as compared to traditional security measures such as keys, passwords and personal identification numbers (PINs). Biometrics have an advantage over the above mentioned methods. They are mainly because the features used for recognition in biometrics are physiological or behavioural [1] [2]. Again, commercially successful biometric recognition systems use the face, fingerprint and palmprint extrinsic modalities [3]. The intrinsic modalities such as vein biometric recognition has not been well researched significantly compared to their extrinsic counterparts. Intrinsic modalities, more specifically veins, are much harder for impersonators to spoof [4], are mostly invisible by the human eye, are unique to each person [5] and do not naturally change over time. However, except in face recognition, most of these biometric systems require the user to touch the sensor or the image capturing device [6]. This is where vein biometrics have a further advantage over other methods. Vein biometrics can be broadly classified into palm vein [2], finger vein [7] and wrist vein [8]. Sufficient research has been done on palm and finger vein whereas there is little investigation into wrist vein biometrics and its potential. More so, the requirement to have contactless biometric systems has increased due to the COVID-19 pandemic since the technology eliminates hygiene concerns and makes the capturing process more comfortable for the user. This ensures social distancing which is key to decelerate the spread of the virus.

Fig. 1 shows the general structure of a complete wrist vein recognition system. In general, wrist vein recognition involves capturing images of wrist vein patterns and comparing them with a known database of patterns to determine if the user is a genuine user or an imposter. When the comparison is one-to-one, it is verification, and when the comparison is one to $n$, then it is identification of the person. The complete system of wrist vein biometrics can be broken down into four stages as shown in Fig. 1. The very first stage is image acquisition. Here an acquisition device as such as sensor or camera is used to capture the wrist vein image of a person contactlessly. The quality of this image is often dependant on the acquisition device and needs to be improved. This is when the pre-processing stage becomes relevant. It is the process of improving the quality of the image and contrast between skin and vein and there are multiple approaches to do this [9]. The next stage is feature extraction. It is the stage where features from the pre-processed image are extracted to a meaningful format. Once features from the images are acquired then the user can be registered into the system by just storing the features. Be it for authentication or recognition the feature storage method is similar. The features which is the biometric modality can be stored as is or by encoding it in some format [10]. The last and the final stage is the decision making stage. It is the process of comparing the captured wrist vein features with the known database of wrist vein features to determine whether the user is an imposter or genuine user. There are many methods used for decision making and is an active field of research with more methods preferring the use of deep learning [11].

The primary purpose of this paper is to systematically review the most recent and relevant literature that talks about wrist vein recognition. It also highlights the available wrist vein databases, the approaches used for decision making along with its advantages and disadvantages. This systematic review would help stimulate future research into wrist vein recognition which is promising for effective contactless human biometric recognition systems.

## II. Methodology

In this section we discuss the process involved in different stages of wrist vein recognition that was introduced in section I. The various steps involved in wrist vein recognition are

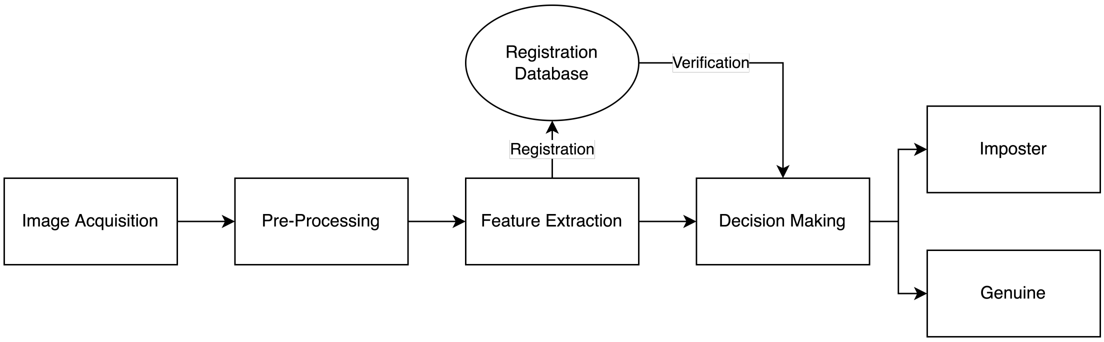


Fig. 1: Wrist Vein Verification System Flowchart

common to that of other vascular biometrics methods like palm vein and finger vein. It is important to understand the working of every stage to best appreciate the research trend and identify the research gaps that can contribute in development of wrist vein recognition systems.

### A. Image Acquisition

Here we talk about the first stage of the recognition system. Veins are subcutaneous in nature making them not visible and cannot be captured in normal light setting [12]. Infrared light (IR) can be used to see the veins with the help of a infrared camera. The two common methods of doing this is using far-infrared and near-infrared imaging. Recent studies show that near infrared imaging is successful for vein visualization in medical applications [13]–[15]. This is the reason that we investigated further into near-infrared methods in contrast to far-infrared imaging. Near-infrared (NIR) light has a wavelength lying between 700 nm to 1400 nm and is invisible to the human eye. More importantly, it is absorbed by the hemoglobin used to carry oxygen in the blood. Veins are used to carry blood back to the heart so hemoglobin found here will be deoxygenated. When veins are imaged under NIR light by a NIR camera, which is a camera capable of capturing light found in the NIR wavelength range, they will appear darker than the surrounding skin due to the light being absorbed by the hemoglobin flowing through the veins [16]. The rate at which the hemoglobin absorbs NIR light greatly depends on the wavelength of the NIR light and whether the hemoglobin is oxygenated. Experimentally, we were able to ascertain that deoxygenated hemoglobin, which is found in the veins, absorb NIR light the best at a wavelength of 760 nm. Oxygenated and deoxygenated hemoglobin also absorb NIR light with a wavelength of 800 nm at equal rates. This further confirmed our survey conclusions from [17]–[20].

Most consumer cameras are fitted with IR-cut filters to prevent capturing IR light that can distort the colours of the image and make it appear unnatural-looking. To capture images of the wrist under NIR light, the IR-cut filter can be removed from a consumer camera or a special purpose camera developed specifically for capturing IR light can be used. An IR-pass filter is generally used to **only** capture IR light and block out any visible light wavelengths. The image capturing setup can be of two types, namely, reflection of IR light based and transmission of IR light based. Both these methods are commonly used for palm and finger vein recognition and literature suggests that reflection of IR light method is more effective [2]. Based on the information from the literature we prototyped such a setup for wrist vein recognition. The setup we used is shown in Fig.2. The image sensor shown as CCD camera here is a Nikon D7500 IR conversion camera from Life-pixel[1], which is a modified camera where the IR filter has been removed to capture the vein images.

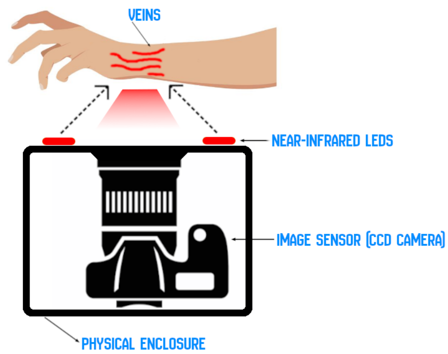


Fig. 2: Wrist Vein Recognition System Hardware

Fig. 3 shows a general design of a wrist vein recognition scanner. Here the user holds their wrist above a camera mounted facing upwards towards their wrist. NIR light LEDs are mounted around the camera and are used to illuminate the wrist surface with NIR light. This light is absorbed by the hemoglobin in the blood flowing through the wrist veins, while it is reflected back to the camera sensor on the surrounding skin, which then captures image(s). These images

[1]Life-pixel converted cameras: https://www.lifepixel.com/shop/converted-cameras/nikon-converted-cameras/nikon-d7500-camera-and-conversion

| Name | Participants | Wrists | Samples | Sessions | Total | Camera | NIR Wavelength |
|---|---|---|---|---|---|---|---|
| PUT [21] | 50 | 2 | 4 | 3 | 1200 | N/A | N/A |
| Singapore [22] | 150 | 2 | 3 | N/A | 900 | Hitachi KP-F2A | 850 nm |
| FYO [8] | 160 | 2 | 2 | 1 [2] | 640 | 1/3 inch infrared CMOS | N/A |
| UC3M [23] | 121 | 1 | 5 | N/A | 605 | DM 21BU054 | 880 nm |
| UC3M-CV1 [24] | 50 | 2 | 6 | 2 | 1200 | Logitech HD Webcam C525 | 850 nm |
| UC3M-CV2 [25] | 50 | 2 | 6 | 2 | 1200 | Xiaomi Pocophone F1, Xiaomi Mi 8 | 960 nm |
| Kurban et al. [26] | 17 | 2 | 3 | N/A | 102 | 5MP mobile phone | No NIR |
| Pascual et al. [27] | 30 | 2 | 6 | N/A | 360 | DM 21BU054 | 880 nm |
| Fernández et al. [28] | 30 | 1 | 4 | 1 | 120 | CCD Camera | 880 nm |

TABLE I: Recent Wrist Vein Image Databases

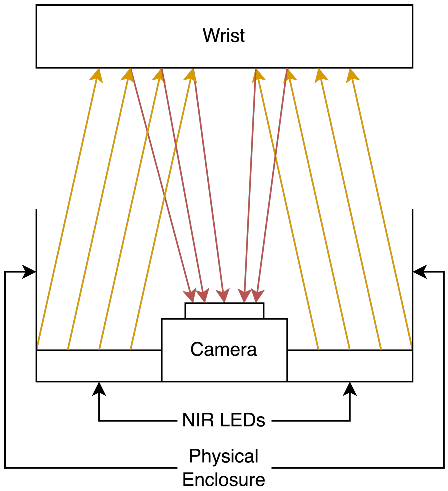


Fig. 3: Design of a Wrist Vein Recognition Scanner

will show the skin illuminated, while the veins will appear darker due to the lack of NIR light reflection.

### *B. Pre-Processing and Feature Extraction*

Fig. 4 shows an example captured wrist vein image (left), its pre-processed form (middle) and feature extracted form (right). The captured vein pattern images are not ready for feature extraction immediately. They are usually noisy and lack contrast between the vein and skin, contain regions not used for recognition (surrounding skin, free air) and the translation, rotation and scale of the veins can vary between images in reference to the image frame [29]. Various traditional image enhancement techniques can be used to reduce the noise in the image, such as Gaussian, median and averaging filters [30]. Histogram-based approaches are common for increasing the contrast between the veins and the surrounding skin [31]. Deriving the region of interest used for wrist vein recognition can be done by hardware and software approaches. Using a physical jig to hold the wrist in place is the simplest solution, as the image can be cropped at the same factor for every image, however this negates the benefits of a contactless recognition system as the user must place their wrist on a physical surface. Various algorithmic approaches have been attempted in literature which will be discussed further in later sections. Once pre-processed, feature extraction is performed to convert the input vein pattern image into a numerical set of features that represent the vein pattern. Texture-based feature extraction methods have been the most commonly used in literature [32], [33]. Once derived, these features can be stored in a vein pattern database or compared with another set of features. This has been elaborated further in section II-C.

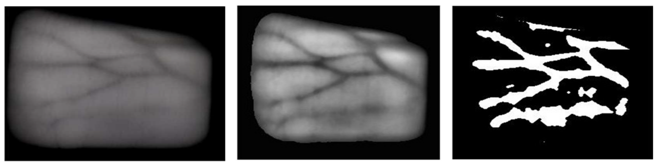

Fig. 4: Wrist Vein Example Images - Left: Original Image, Middle: Pre-processed Image, Right: Feature Extracted Image [34]

### *C. Decision Making*

Once the features have been extracted from the image, they can be compared to the features stored in the database. This can be a one to one comparison or a one to many comparison depending on the type of recognition. Typically the distance between these two feature sets is calculated using a commonly used distance algorithm such as the Euclidean or Manhattan distances [35]. One method to decide if the subject under consideration is a genuine or imposter user is simple thresholding.

Literature suggests that deep neural networks are a new field being explored in wrist vein recognition which can encompass the pre-processing, feature extraction and decision making processes to provide an end-to-end wrist vein recognition system [25], [36]–[38].

### *D. Wrist Vein Databases*

The quality of the database is critical to the development of the algorithms used in the pre-processing, feature extraction and decision making stages of a wrist vein recognition system. A few databases have been collected as part of recent research to be applied for the development of wrist vein recognition systems. These databases have been summarised in Table I for ready reference.

The main parameters include the number of participants, number of samples, number of sessions, camera used and the NIR wavelength utilised. Wrist vein is a relatively unexplored research area where the databases tend to be small compared to other vein modalities such as palm and finger vein. This is one of the primary purpose of this paper, where we review the databases and the methods to accelerate the research that uses wrist vein as a modality. Capturing multiple samples over multiple sessions is also crucial to capture the differences in ambient lighting and if the wrist changes over time. Images from different cameras or illuminated under different NIR light wavelengths will also cause the image to differ in quality and contrast as mentioned in [38].

## III. Review of Literature

In this section a systematic literature review for wrist vein recognition systems that have been implemented until date has been presented. Table II summarizes the recent and relevant vein recognition research.

### *A. Performance Parameters*

The performance of wrist vein biometric system depends on the output quality of every stage mentioned in Section II. This can be measured qualitatively on the basis of the output of the pre-processing and feature extraction stage by analyzing the visual quality of the images. However, it is important to also quantify the quality/performance of the system using some metric. This can be done in the pre-processing or feature extraction stage directly on the images or by measuring the recognition performance using some metric in the decision making stage.

In Table II, it can be seen that the accuracy has been reported using some standard common metrics. Here, we briefly describe these metrics and their relevance for the sake of completeness so that the reader can interpret the review in its complete sense.

Based on the literature reviewed, a few quantifiable metrics such as Equal Error Rate (EER), Root Mean Square Error (RMSE), Accuracy, False Match Rate (FMR) and False Non-Match Rate (FNMR) are used. In this paper, to compare the performance of different methods quantitatively, we have used the above mentioned metrics. The primary focus is only on wrist vein recognition methods but they have also been contrasted with very few relevant finger vein methods due to the limited availability of wrist vein recognition literature. The overall performance of the wrist vein biometric system is presented in terms of EER, the lower the value of EER the better is the system performance [39]. RMSE is the square root of the difference between the value obtained and the value obtained during the training of the network [40]. FMR and FNMR demonstrate the probability of an imposter attempt being incorrectly accepted as a genuine match and the probability of a genuine attempt fails to match respectively in the decision making stage [41]. Accuracy is obtained by calculating the number of correct image data recognition images [42].

### *B. Systematic Review of Literature*

In [43], Das et al. propose using Adaptive Histogram Equalisation (AHE) and Discrete Meyer wavelength for pre-processing, combined with Dense Local Binary Pattern (D-LBP) for feature extraction and multiple Support Vector Machine (SVM) variants for classification, achieving an EER of 0.79% with LibSVM. However, the system was only tested on one dataset, the PUT dataset. This limits the generalization of the design on other wider databases and does not indicate if the method could be applied for the development of a contactless wrist vein vascular biometric system. In [44], Abed et al. compares the usage of Principal Component Analysis (PCA) with Linear Discriminant Analysis (LDA) for feature reduction, an optional process where extracted features are reduced in number. Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gaussian filtering are used for pre-processing of the acquired images and Gabor filtering is used for feature extraction. Euclidean distance combined with simple thresholding is used for classification. PCA helped in achieving highest accuracy of 93.33%, while LCA observed an accuracy of 91.33%. Again, only a small, private dataset was used to validate the techniques, with only 50 participants and 2400 wrist images. This limits the generalization possibility of the technology. Raghavendra et al. introduces a low-cost wrist vein imaging system in [45]. A monochromatic Complementary Metal Oxide Semiconductor (CMOS) camera capable of capturing NIR light is surrounded by Light Emitting Diode (LED)s with a wavelength of 940 nm. However, the system requires the use of hand pegs to stabilise the wrist and to keep it in frame, which negates the benefit of an otherwise contactless system. CLAHE is used to increase the contrast between vein and skin in the pre-processing stage. Two different local feature extraction methods and seven different global feature extraction methods are compared, with the Log-Gabor Sparse Representation Classifier (LG-SRC), a global feature extraction algorithm, providing the lowest EER = 1.63%. Again, a small private dataset of 50 participants and 100 wrist vein images was used to evaluate the system.

In [28], Fernández Clotet et al. introduces a low-cost wrist vein imaging system utilising a Charge-Coupled Device (CCD) camera. NIR LEDs with a wavelength of 880 nm are used to illuminate the wrist. The camera is mounted with a NIR band-pass filter with a pass-band of 700-1000 nm to prevent capturing visible light. The system requires the user to hold their wrist in a specific region as the image is cropped to the same size every time for ROI extraction. Scale Invariant Feature Transform (SIFT) is proposed for use in the feature extraction stage. Mean, median and standard deviation is used for majority voting with SIFT, achieving an EER = 7.2% with SIFT Mean.

[2]The FYO database was collected over two sessions separated by only 10 minutes.

| Contribution | Methods | Dataset(s) Used | Accuracy | Major Contributions |
|---|---|---|---|---|
| López-González et al. (2022) [46] | • **Pre-Processing:** ROI extraction, CLAHE, Gaussian, Median, and Average filters<br>• **Feature Extraction:** SIFT, Maximum Curvature (MC)<br>• Smartphone IR Camera | Custom (10 persons, 1000 images) | EER 1% (w/o QC) | Wrist vein recognition on a smartphone, Android app |
| Babalola et al. (2021) [47] | • **Pre-Processing:** ROI cropping, Histogram equalisation<br>• **Feature Extraction:** M-BSIF, Gabor Filter and Histogram of Gradient | • FYO dataset (160 persons, 1920 images)<br>• PUT dataset (50 persons, 1200 images) | • **FYO:** 93.92%<br>• **PUT:** 95.63% | Decision-level fusion of multiple feature descriptors |
| Garcia-Martin et al. (2020) [25] | • **Pre-Processing:** CLAHE, Gaussian, Median and Averaging filters<br>• **Feature Extraction:** SIFT, SURF, ORB<br>• **Classification:** BFM with hamming distance, FLANN with k-Nearest Neighbour. | UC3M-CV2 (50 persons, 2400 images) | EER 6.82% to 18.72% | Novel smartphone approach with production cameras, 2400 image dataset |
| Herbadji et al. (2019) [48] | • Multi-modal recognition system (wrist and palm)<br>• **Feature Extraction:** LPQ, LBP, BSIF, LTP<br>• **Classification:** t-norm score fusion | PUT dataset (50 persons, 1200 wrist images, 1200 palm images) | GAR 100% with FAR 0.01% | t-norm score fusion with multi-modal recognition system |
| Achban et al. (2019) [49] | • **Pre-Processing:** ROI cropping, AHE, filtering<br>• **Feature Extraction:** Local Line Binary Pattern (LLBP)<br>• **Classification:** Fuzzy k-Nearest Neighbour | Custom (50 persons, 600 images) | 96.50% | Feature extraction using LLBP and Fuzzy k-Nearest Neighbour |
| Nikisins et al. (2018) [50] | • **Pre-Processing:** Gaussian filter, ROI cropping via k-means++ clustering<br>• **Feature Extraction:** Maximum Curvature Points, Hessian-based algorithm<br>• **Classification:** Cross-correlation | PUT Dataset (50 persons, 1200 images) | EER 1.23% | Computationally efficient image translation and rotation compensation via cross-correlation |
| Mohamed et al. (2017) [34] | • **Pre-Processing:** CLAHE, Global Thresholding, Median and Average filter.<br>• **Feature Extraction:** SIFT<br>• **Classification:** 2D Correlation function | PUT Dataset (50 persons, 1200 images) | EER 3.2% to 4% | Modal fusion with Debois-Parade t-norm |
| Fernández Clotet et al. (2017) [28] | • **Pre-Processing:** ROI extraction, Gaussian Blur Filter<br>• **Feature Extraction:** SIFT<br>• **Classification:** SIFT | Custom (30 persons, 120 images) | EER = 0.072 | Proposed a compact system that can suit mobile environments, Using 4 vein images for enrollment and authentication |
| Raghavendra et al. (2016) [45] | • **Pre-Processing:** CLAHE<br>• **Feature Extraction:** MCP, Multi-scale match filter<br>• **Classification:** Sparse Representation Classifier | Custom (50 persons, 100 Images) | EER = 1.63% | Using 9 different feature extraction schemes |
| Abed et al. (2016) [44] | • **Pre-Processing:** CLAHE, Gaussian Filter<br>• **Feature Extraction:** Gabor Filter, LDA and PCA reduction<br>• **Classification:** Euclidean distance | PUT Dataset (50 persons, 1200 images) | 92.33% | Comparison of LDA and PCA for feature extraction |
| Kurban et al. (2016) [26] | • **Pre-Processing:** Low-pass Butterworth filter, unsharp masking<br>• **Feature Extraction, Classification:** Radial Basis Function, Multi-layer Perceptron, Support Vector Machine | Custom (34 persons, 102 images) | • **RBF**: 94.11%<br>• **MLP**: 94.11%<br>• **SVM**: 96.07% | Proposal and comparison of neural-network based approaches |
| Das et al. (2014) [43] | • **Pre-Processing:** Contrast-limited AHE, Discrete Meyer Wavelet<br>• **Feature Extraction:** Dense LBP<br>• **Classification:** Support Vector Machine | PUT Dataset (50 persons, 1200 images) | EER = 0.79% | Pre-processing utilising Adaptive Histogram Equalisation and Discrete Meyer Wavelet |

TABLE II: Systematic Review of Recent and Relevant Vein Recognition Methods

Local line binary pattern is proposed for use in feature extraction by Achban et al. in [49]. In [26], Kuraban et al. focuses on using neural network based wrist vein identification. Fast Fourier Transform (FFT) based low-pass filters, sharpen filter, and histogram equalization has been applied to the images to suppress background noise. Comparison of Radial basis function networks (RBF), Multi-layer perceptron (MLP), and Support vector machines (SVM) feature extraction methods has been carried out. SVM was found to have the highest success rate of 96.07% followed by MLP and RBF with 94.11% making a claim that an ordinary camera can be used for identification and authentication process.

In [34], Mohamed et al. investigates the use of SIFT based matching approach for feature extraction, which resulted in the EER being 0.072 when using 4 vein images for enrolment and authentication. A database of 120 wrist vein images from 30 participants was collected using the low cost capturing design developed. In [50], Nikisins et al. proposed the cross-correlation based comparison table of compensating both, rotation and translation, between the images in a computationally efficient way. It is proven to have a faster comparison rate compared to the equally performing brute-force approach, and is slower than the original cross-correlation based approach. The proposed system is capable of compensating for scale, translation and rotation between vein patterns in a computationally efficient way. To emphasize the wrist veins, a two-layer Hessian-based vein enhancement approach with adaptive brightness normalization is introduced, improving the connectivity and the stability of extracted vein patterns. The experiments on the publicly available PUT wrist vein database gives promising results with FNMR of 3.75% for FMR  0.1%. The main contribution of this paper is the cross-correlation based comparison principle which is capable of compensating both, translation and rotation between vein patterns in a computationally efficient manner. The introduced comparison algorithm requires only two cross-correlation operations in the Fourier domain to compensate for both translation and rotation, regardless of the number of observed angles. In contrast, in the classical approach, namely, cross-correlating with rotated templates, the number of cross-correlation operations is equal to the number of observed angles. The segmentation algorithm is Hessian-based producing a gray-scale vein pattern with a normalized intensity.

In [46], López-González et al. have focused on using commercial smartphones with ordinary cameras as potential devices to improve the collectability and acceptability right in the acquisition stage. A recognition system has been developed along with an app showing the interface to acquire the image from the wrist named IRVeinViewer App. SIFT with pre and post processing stages are used in conjunction with standard signal processing methods to make a database of 1000 images from 20 wrists. The variability of the images acquired in different sessions under different ambient conditions are analyzed to see how they influence the recognition rates and the accuracy. The primary focus of this paper is on developing the app to exploit a simple smartphone camera to be used as an IR acquisition device which could conceptually be expanded to a design of smartphone based contactless wrist vein biometric system. Although the paper promises a good acquisition method, the accuracy of 1 is reported on the basis of a very small database and in no way can be generalized. The SIFT based matching approach is quite preliminary and its efficiency is reasonably questionable looking at the small number of images considered.

In [51], Xu et al. propose segmentation methods for vein images using U-Net and ResNet. This work is quite similar to the segmentation method proposed for palm vein images in [9]. The primary difference is that the deep residual network is used to replace the feature extraction part of the U-Net. Dilated convolution is used instead of traditional convolution that can increase the receptive field without pooling and can extract the information from the vein image better. Although the application is completely on finger vein, this approach was tested on a dummy wrist vein dataset and the images obtained were found to be useful to develop a contactless wrist vein recognition system. This is also indicative of how deep learning based segmentation and recognition methods are effective when compared with the traditional approaches. This means that with appropriate investigation into deep learning methods, robust end-to-end systems could be developed. In [52], Babalola et al. propose on of the first concrete wrist vein recognition systems that uses the fusion of multiple handcrafted methods. The handcrafted methods include texture-based feature descriptors, namely, multiple filters of Binarized Statistical Image Features (M-BSIF), 2D Gabor filter, and Histogram of Gradient Orientation by Decision-Level Fusion. The method was tested on 2 most common wrist vein databases, namely, the FYO and PUT wrist vein databases as seen in Table I. The method outperformed individual descriptors and achieved an accuracy of 95.63% on the FYO database and 93.92% on the PUT database. The main difference in this approach was the use of decision level fusion which suggests to be one of the factors contributing to the high accuracy. Again, they propose that their future research will be oriented towards the use of deep learning methods on use of wrist vein patterns for person verification which would then be extended to other vein modalities for cross validation. [25] proposes wrist vein biometric using smartphone. Here the authors have modified the image sensors on two commonly available smartphones to accommodate the application of vein recognition. Using this modification, they created a database of 2400 contactless infrared images from 2 wrists from 50 different subjects which are 25 females, 25 males resulting in 100 wrists in total collected in two separate sessions but different ambient light conditions. They then used SIFT, Speeded-Up Robust Features (SURF) and Oriented FAST and Rotated BRIEF (ORB) algorithms to perform matching and evaluate the results quantitatively in the decision making stage. The is one of the first successful smartphone based approach that has been applied on a wider database and appears to be promising. Our review indicates that the same acquisition method combined with deep learning approaches for segmentation and matching would achieve higher matching accuracy which would be the focus of our extended work after our detailed literature study.

## IV. Conclusion

This paper provides a comprehensive review on existing wrist vein recognition systems. The methods were assessed by bifurcating them into different stages, namely, image acquisition, pre-processing, feature extraction and decision making. Each stage has been reviewed highlighting how it affects the performance of the consecutive stage, in turn, affecting the overall performance of the wrist vein recognition system. Furthermore, we compare and contrast the conventional methods with deep learning based wrist vein methods. The literature shows that deep learning methods have significant improvement over the traditional wrist vein recognition methods. The paper presents the most recent advancement in the field of wrist vein recognition during the last decade and identifies precise limitations that need to be resolved to extend this method to become a commercially viable technology. This study is beneficial to all researchers aiming to investigate wrist vein recognition to develop a contactless wrist vein vascular biometric system.

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