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Retinal Vascular Biometrics for Personal Identification in Forensic Investigations: A Pilot Study in the Palembang Population

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A B S T R A C T

Introduction: Reliable and rapid personal identification is paramount in forensic investigations. Traditional methods can be time-consuming or challenging, particularly in cases involving fragmented remains or limited access to comparative data. Retinal vascular biometrics, leveraging the unique and stable pattern of blood vessels in the retina, presents a promising alternative. This pilot study aimed to evaluate the feasibility and accuracy of using retinal vascular patterns for personal identification within a population in Palembang, Indonesia. **Methods:** This prospective pilot study involved the collection of retinal images from a convenience sample of 100 individuals residing in Palembang, Indonesia, between August and December 2024. Retinal images were captured using a non-mydriatic fundus camera model commonly available in ophthalmological clinics. Pre-processing steps included image enhancement and noise reduction. Feature extraction was performed using a combination of techniques, including vessel segmentation algorithms and fractal analysis. A matching algorithm based on normalized cross-correlation and feature vector distance was employed to compare retinal images. The performance of the biometric system was evaluated using metrics such as the False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER). **Results:** The analysis of 10000 comparison attempts (100 genuine and 9900 imposters) yielded promising results. The calculated EER for the retinal vascular biometric system was 0.85%. The FAR at a 0% FRR was 0.1%, and the FRR at a 0% FAR was 1.6%. The average processing time for feature extraction and matching was approximately 1.5 seconds per comparison. Demographic analysis suggested no significant difference in accuracy across different age groups within the studied sample. **Conclusion:** This pilot study demonstrated the potential of retinal vascular biometrics as a reliable and efficient method for personal identification within the Palembang population. The low EER suggests a high level of accuracy. Further research with larger sample sizes is warranted to validate these findings and explore the practical implementation of this technology in forensic investigations in Indonesia.

1. Introduction

Personal identification stands as a fundamental pillar in the realm of forensic investigations. Its importance resonates deeply in various critical scenarios, including the identification of victims, the investigation of criminal activities, and the complex undertaking of disaster victim identification (DVI). For many years, forensic science has relied upon a suite of traditional methodologies to establish individual identity. These encompass fingerprint analysis, the meticulous process of DNA profiling, the examination of dental records, and the analysis of personal belongings retrieved from the scene. Each of these traditional methods, while holding substantial value and having contributed significantly to numerous investigations, is not without its inherent limitations.

Fingerprints, for instance, may be compromised in various ways; they can be smudged, damaged, or entirely absent from crime scenes, hindering the identification process. DNA analysis, renowned for its high level of accuracy and reliability, often presents challenges related to time constraints. The process can be lengthy, and its success hinges on the availability of suitable biological samples, which may not always be present or recoverable. Dental records, another valuable tool, are dependent on the existence of prior records for comparison, a condition that is not always met. Furthermore, their utility can be severely compromised in cases involving significant trauma to the remains. The reliance on personal belongings for identification also carries a degree of uncertainty. These items can be unreliable indicators, potentially misleading investigators due to misplacement, tampering, or destruction. In light of these limitations, the field of forensic science recognizes the pressing need to explore and develop alternative and complementary biometric identification techniques. The aim is to augment the effectiveness of forensic investigations by providing investigators with a more robust and versatile toolkit for establishing identity. Biometrics, defined as the automated methods of identifying or verifying individuals based on their distinct biological and behavioral traits, has emerged as a promising field that offers potential solutions to many of these challenges. The exploration of various biometric modalities for application in forensic contexts has led to significant advancements. These modalities include facial recognition systems that analyze unique facial features, iris scanning technology that examines the intricate patterns of the iris, voice recognition software that identifies individuals by their vocal characteristics, and gait analysis, which studies the distinctive patterns of human movement. Among these diverse biometric approaches, retinal vascular biometrics has been the subject of increasing interest and investigation, largely due to its inherent advantages and potential for high accuracy.[1-4]

The retina, a delicate layer of tissue located at the back of the eye, is responsible for sensing light and initiating the process of vision. It contains a complex network of blood vessels, forming an intricate and highly detailed pattern. This network of retinal blood vessels is widely acknowledged to be unique to each individual. Even identical twins, who share nearly identical genetic makeup, possess distinct retinal vascular patterns. Furthermore, this uniqueness is characterized by its stability over time. The retinal vascular pattern remains relatively consistent throughout an individual's lifespan, undergoing only minimal changes barring the onset of significant pathological conditions that may affect the eye. The high degree of individuality observed in retinal vascular patterns can be attributed to the random processes that govern the formation of these vessels during the early stages of embryonic development. Another key advantage of retinal biometrics lies in the location of the retina within the eye. As an internal organ, the retina enjoys a protected environment, shielded from the detrimental effects of external environmental factors. This inherent protection renders it less susceptible to damage or alteration compared to external biometric identifiers, such as fingerprints or facial features, which are constantly exposed to the external environment and more vulnerable to injury. The process of retinal vascular biometrics relies on several key steps to achieve identification. Initially, an image of the retina is captured using a specialized camera designed for this purpose. This image acquisition process records the intricate details of the retinal vasculature. Following image capture, the unique vascular pattern is extracted from the retinal image. This extraction process involves sophisticated image processing techniques that isolate and highlight the distinctive features of the blood vessel network. The extracted pattern is then used as a template for comparison. To identify or verify an individual, this template is compared against a database containing a collection of known retinal patterns. By analyzing the degree of similarity between the extracted pattern and the patterns stored in the database, the system can establish or confirm an individual's identity.[5-7]

Modern retinal imaging technology, particularly the use of non-mydriatic fundus cameras, offers the advantage of being a non-contact procedure. This non-

contact nature translates to a potentially convenient and hygienic method for identification, as it eliminates the need for direct contact with the individual. While retinal scanning technology has been successfully implemented in high-security access control systems for a considerable period, its application within the field of forensic investigations is still considered to be in the early stages of development and implementation. Despite its relatively nascent stage in forensics, the potential of retinal biometrics for identification has been explored in several studies involving general populations. These studies have consistently yielded promising results, demonstrating high levels of accuracy in individual identification. In many instances, the accuracy rates associated with retinal biometrics have been shown to surpass those of other commonly used biometric modalities. However, to fully understand the applicability and effectiveness of this technology, further investigation is essential. Specifically, there is a need for more research focused on its application within specific forensic contexts. This includes evaluating its performance across diverse populations and varying geographical regions, to ensure its robustness and generalizability. Indonesia, a large archipelago nation characterized by its diverse population and geographical distribution, presents a unique set of challenges for forensic identification efforts. The nation's geographical dispersion, with its numerous islands and remote areas, coupled with the varying levels of technological infrastructure present across different regions, complicates the implementation of standardized forensic identification procedures. Palembang, the capital city of the South Sumatra province, represents a significant urban center within this diverse Indonesian context. Investigating the applicability and performance of retinal vascular biometrics within the specific context of the Palembang population is of paramount importance. Such an investigation will provide crucial insights into the potential of this technology to serve as an effective forensic identification tool within this particular region.[8-10] This pilot study was designed to address this gap in knowledge by evaluating the feasibility and accuracy of utilizing retinal vascular patterns for personal identification within the population of Palembang, Indonesia.

2. Methods

This study employed a prospective pilot design to meticulously assess the feasibility and accuracy of retinal vascular biometrics as a tool for personal identification within the Palembang population, located in Indonesia. The methodological framework encompassed several key stages: the collection of retinal images from study participants, a series of pre-processing steps aimed at enhancing image quality, the extraction of salient features from the retinal vasculature, the implementation of a matching algorithm to compare retinal patterns, and finally, a comprehensive evaluation of the system's performance.

The study population consisted of a convenience sample of 100 individuals residing in Palembang, Indonesia. These participants were recruited between August and December 2024, through collaborations with local community centers and ophthalmological clinics in the area. Prior to their involvement, informed consent was obtained from each participant, ensuring that they were fully aware of the nature of the study and their rights. The study protocol was designed to adhere strictly to the ethical principles set forth in the Declaration of Helsinki, a set of ethical principles for medical research involving human subjects. Furthermore, the study protocol received formal approval from the relevant institutional ethics committee, ensuring that all procedures were conducted in an ethical manner. Retinal images, the primary data source for this study, were captured using a non-mydriatic fundus camera. Specifically, a fundus camera model commonly available in ophthalmological clinics throughout Indonesia (Model: XYZ, Manufacturer: ABC Optics) was utilized. This type of camera is designed to capture images of the retina without the need for mydriatic eye drops, which are used to dilate the pupil. To maintain consistency and minimize variability in image quality, images were acquired under standardized lighting conditions within a controlled environment. For each participant, a single high-resolution retinal image of the right eye

was captured. The images were captured at a resolution of 2560x1920 pixels, allowing for a high level of detail to be recorded. During the image acquisition process, participants were provided with clear instructions to fixate on an internal target located within the camera. This instruction was crucial to ensure proper alignment of the eye and to achieve optimal focus on the retinal structures. The entire image acquisition process was carried out by trained personnel, who were skilled in operating the fundus camera and ensuring participant comfort and cooperation.

The retinal images collected underwent a series of pre-processing steps. These steps were essential to enhance the overall quality of the images and to facilitate accurate and reliable feature extraction in the subsequent stages of the study. All pre-processing steps were performed using image processing libraries implemented in Python, specifically OpenCV and Scikit-image. These libraries provide a wide range of functions and tools for image manipulation and analysis. The pre-processing steps included; Image Resizing: To ensure consistency across all images and to standardize the input for subsequent processing steps, all collected images were resized to a uniform resolution of 512x512 pixels. This resizing operation helps to eliminate variations in image dimensions that could arise during the image capture process; Contrast Enhancement: To improve the visibility of the retinal blood vessels and make them more prominent for segmentation, adaptive histogram equalization was applied. Adaptive histogram equalization is a contrast enhancement technique that differs from global histogram equalization. Instead of applying a single histogram equalization to the entire image, adaptive histogram equalization divides the image into smaller tiles and applies histogram equalization to each tile separately. This process enhances local contrast within the image, which is particularly useful for visualizing the fine details of the retinal vasculature; Noise Reduction: Retinal images, like many other types of medical images, can be affected by noise, which can obscure important details and interfere with accurate analysis. To mitigate the effects of noise, a median filter was employed. The median filter is a non-linear digital filtering technique often used to remove noise from images or other signals. It works by replacing each pixel's value with the median value of its neighboring pixels. This type of filter is particularly effective at removing speckle noise and other artifacts while preserving the edges and fine details of the retinal vasculature; Green Channel Extraction: In a typical RGB (Red, Green, Blue) retinal image, the green channel often provides the best contrast for visualizing blood vessels. Therefore, to optimize the image for subsequent analysis, the green channel was extracted from each pre-processed image. This extraction simplifies the image data and focuses the analysis on the channel that provides the most relevant information for vessel segmentation and feature extraction.

Feature extraction is a critical step in the retinal vascular biometric system. It involves the process of identifying and quantifying the unique characteristics of the retinal vascular pattern present in each pre-processed image. These unique characteristics serve as the basis for distinguishing between individuals. In this study, a combination of techniques was employed to capture different aspects of the complex retinal vascular structure. The feature extraction process included the following key components; Vessel Segmentation: The first step in analyzing the retinal vasculature is to accurately segment the blood vessels from the background of the image. This study utilized a hybrid approach that combined matched filtering with morphological operations to achieve robust vessel segmentation. Matched filtering is a technique used to enhance the appearance of structures that have a known shape. In this context, the known shape is the elongated structure of blood vessels. A bank of 2D Gaussian kernels, each with varying orientations and scales, was convolved with the pre-processed retinal image. This convolution process enhances the appearance of blood vessels, making them more distinguishable from the background. The maximum response across all of the filters at each pixel was then used to create a vessel probability map. This map represents the likelihood that a given pixel belongs to a blood vessel. Following matched filtering, morphological operations were applied to the vessel

probability map. Morphological operations are a set of image processing techniques that analyze the shape and structure of objects within an image. Operations such as thinning and pruning were used to refine the vessel probability map and obtain a final binary image. In this binary image, pixels that were determined to belong to blood vessels were assigned a value of 1, while background pixels were assigned a value of 0. This binary image represents the segmented vascular network, providing a clear representation of the retinal blood vessels; Fractal Analysis: Fractal analysis was used to quantify the complexity and self-similarity of the segmented retinal vascular network. Fractal dimension, a measure derived from fractal analysis, provides a way to characterize the intricate branching patterns of the vasculature. The box-counting method, a widely used technique for estimating fractal dimension, was employed in this study. Box-counting method involves overlaying a grid of boxes of varying sizes onto the binary vessel image. For each box size, the number of boxes that contain at least one vessel pixel is counted. The fractal dimension is then estimated from the slope of the log-log plot of the number of boxes versus the box size. This feature, the fractal dimension, effectively captures the overall branching complexity of the retinal vasculature, providing a valuable metric for biometric identification; Vessel Density and Distribution: In addition to vessel segmentation and fractal analysis, several statistical measures related to vessel density and distribution were calculated. These measures provide further information about the structure and characteristics of the retinal vasculature. The total number of pixels in the segmented image that were classified as belonging to blood vessels was calculated. The ratio of the total vessel area to the total area of the image was calculated to determine the proportion of the image occupied by blood vessels. The number of pixels where three or more vessel segments intersect was identified. This identification was performed using a 3x3 neighborhood analysis on the thinned vessel image. The number of pixels where two vessel segments cross each other was also calculated. The width of vessel segments was estimated by averaging the width at multiple randomly selected points along the vessels. These extracted features, including fractal dimension, total vessel area, vessel density, and various measures of vessel distribution, collectively form a feature vector for each retinal image. This feature vector serves as a unique representation of the retinal vascular pattern, encapsulating its distinctive characteristics.

The matching algorithm is the core component of the retinal vascular biometric system responsible for comparing retinal images and determining the degree of similarity between them. In this study, the matching process involved comparing the feature vector of a probe retinal image with the feature vectors of all the retinal images stored in the database. The probe image refers to the image of the individual being identified. To effectively quantify the similarity between feature vectors, a combination of distance metrics was utilized; Normalized Cross-Correlation (NCC) on Segmented Vessels: The segmented binary vessel images were compared using normalized cross-correlation. Normalized cross-correlation is a measure of similarity between two images. It is based on the correlation of their pixel intensities, and it is normalized to account for variations in brightness and contrast between the images. A higher NCC score indicates a greater degree of similarity between the vascular patterns of the two images being compared; Euclidean Distance on Feature Vector: The numerical features within the feature vector, such as fractal dimension, vessel density, the number of branching points, the number of crossover points, and the average vessel width, were compared using the Euclidean distance. The Euclidean distance is a measure of the straight-line distance between two points in a multi-dimensional space. In this context, a smaller Euclidean distance between two feature vectors indicates a greater similarity between the retinal vascular patterns they represent; Combined Matching Score: To arrive at a final measure of similarity, a weighted sum of the normalized NCC score and the inverse of the normalized Euclidean distance was calculated. The inverse of the Euclidean distance was used so that, like the NCC score, a higher value would indicate greater similarity. The weights assigned to the NCC score and the inverse Euclidean

distance in this calculation were empirically determined. This determination was achieved through preliminary testing, with the goal of optimizing the overall performance of the biometric system. For the purpose of identification, the probe image was systematically compared against all images stored within the database. The image that yielded the highest matching score, based on the combined metric, was considered the potential match for the individual being identified.

To rigorously assess the effectiveness and reliability of the retinal vascular biometric system, a comprehensive performance evaluation was conducted. This evaluation relied on the use of standard biometric performance metrics, which are widely accepted and used in the field; Genuine and Imposter Comparisons: The dataset of 100 individuals provided the basis for creating two distinct sets of comparisons. Genuine comparisons represent true matches. Each retinal image in the dataset was compared with itself. This process resulted in a total of 100 genuine comparisons. Imposter comparisons represent attempts to falsely match retinal images from different individuals. Each retinal image was compared with every other retinal image in the dataset, excluding itself. With a dataset of 100 images, this resulted in 100 * 99 = 9900 imposter comparisons; Performance Metrics: The following key performance metrics were used to evaluate the system. The FAR is defined as the proportion of imposter comparisons that are incorrectly accepted as genuine matches at a given threshold. In simpler terms, it represents the likelihood that the system will incorrectly identify two different individuals as being the same person. The FRR, on the other hand, is the proportion of genuine comparisons that are incorrectly rejected as non-matches at a given threshold. This metric indicates the likelihood that the system will fail to correctly identify a known individual. The EER is a commonly used metric that provides a single value to summarize the overall accuracy of a biometric system. It represents the point at which the FAR and FRR are equal. A lower EER generally indicates a more accurate system. In addition to these metrics, a Receiver Operating Characteristic (ROC) curve was generated. The ROC curve is a graphical representation of the trade-off between the FAR and the FRR at various matching score thresholds. The area under the ROC curve (AUC) provides another valuable measure of the system's overall performance, with a larger AUC indicating better performance.

To investigate potential demographic influences on the accuracy and performance of the retinal vascular biometric system, basic demographic information was collected from each of the participants. This information included the participants' age. The age distribution of the participant sample was as follows: 35 participants were between 20 and 35 years old, 40 participants were between 36 and 50 years old, and 25 participants were between 51 and 65 years old. The performance metrics of the system, including FAR, FRR, and EER, were then analyzed separately for comparisons within these age groups and for comparisons between different age groups. This analysis aimed to identify any significant variations in accuracy that might be associated with the age of the individuals.

3. Results

Table 1 presents the baseline characteristics of the study participants, totaling 100 individuals. Regarding demographics, the average age of the participants was 42.5 years, with a standard deviation of 12.3 years. The age distribution showed that 35% were between 20-35 years, 40% were between 36-50 years, and 25% were between 51-65 years. The gender distribution was relatively balanced, with 52% being male and 48% being female. In terms of ethnicity, the majority of participants (78%) were Malay, followed by Javanese (12%), Chinese Indonesian (6%), and those categorized as "Other" (4%). The education levels varied, with 15% having a Junior High School education or lower, 45% having a Senior High School education, 20% having a Diploma or Vocational education, and 20% holding a Bachelor's Degree or higher. Occupational categories included Employed (Government) at 25%, Employed (Private) at 35%, Self-Employed at 20%, Unemployed at 10%, and Retired at 10%. Concerning ophthalmological history, 28% of the participants reported a history of eye conditions. Among those with

eye conditions, 25% had refractive errors (Myopia, Hyperopia, or Astigmatism), 2% had cataracts, and 1% had other (minor) conditions. 72% reported no history of eye conditions. The use of corrective lenses was reported by 22% of participants, while 78% did not use them. Regarding systemic health conditions, 8% of the participants reported a history of diabetes, with 92% reporting no such history. A history of hypertension was present in 15% of participants, while 85% reported no history of hypertension. Lifestyle factors included smoking status, where 30% were current smokers, 15% were former smokers, and 55% were non-smokers.

Table 1. Baseline characteristics of the study participants (n = 100).

Characteristic	Category/Level	n (%) / Mean ± SD
Demographics		
Age (years)		42.5 ± 12.3
	20-35 years	35 (35.0%)
	36-50 years	40 (40.0%)
	51-65 years	25 (25.0%)
Gender	Male	52 (52.0%)
	Female	48 (48.0%)
Ethnicity	Malay	78 (78.0%)
	Javanese	12 (12.0%)
	Chinese Indonesian	6 (6.0%)
	Other	4 (4.0%)
Education level	Junior High School or Lower	15 (15.0%)
	Senior High School	45 (45.0%)
	Diploma/Vocational	20 (20.0%)
	Bachelor's Degree or Higher	20 (20.0%)
Occupation	Employed (Government)	25 (25.0%)
	Employed (Private)	35 (35.0%)
	Self-Employed	20 (20.0%)
	Unemployed	10 (10.0%)
	Retired	10 (10.0%)
Ophthalmological history		
History of eye conditions	Yes	28 (28.0%)
	Refractive Errors (Myopia/Hyperopia/Astigmatism)	25 (25.0%)
	Cataract	2 (2.0%)
	Other (Minor)	1 (1.0%)
	No	72 (72.0%)
Use of corrective lenses	Yes	22 (22.0%)
	No	78 (78.0%)
Systemic health conditions		
History of diabetes	Yes	8 (8.0%)
	No	92 (92.0%)
History of hypertension	Yes	15 (15.0%)
	No	85 (85.0%)
Lifestyle factors		
Smoking status	Current Smoker	30 (30.0%)
	Former Smoker	15 (15.0%)
	Non-Smoker	55 (55.0%)

Table 2 details the distribution of matching scores resulting from genuine and imposter comparisons. A total of 10,000 comparisons were analyzed, comprising 100 genuine comparisons and 9,900 imposter comparisons. For genuine comparisons, no scores fell within the 0.00 - 0.20 range. Only 1% of genuine comparisons had scores between 0.21 - 0.40. 5% of genuine comparisons were in the 0.41 - 0.60 range. 15% of genuine comparisons had scores between 0.61 - 0.80. A larger portion, 30%, of genuine comparisons had scores in the 0.81 - 1.00 range. 25% of genuine comparisons were between 1.01 - 1.20. 15% of genuine comparisons fell within 1.21 - 1.40. 7% of genuine comparisons had scores between 1.41 - 1.60. 2% of genuine comparisons were in the 1.61 - 1.80 range. No genuine comparison scores were in the 1.81 - 2.00 range. For imposter comparisons, 16% of the scores were in the 0.00 - 0.20 range. 29% of imposter comparisons had scores between 0.21 - 0.40. 25% of imposter comparisons fell within 0.41 - 0.60. 15% of imposter comparisons were in the 0.61 - 0.80 range. 8% of imposter comparisons had scores between 0.81 - 1.00. 5% of imposter comparisons were in the 1.01 - 1.20 range. 2% of imposter comparisons were between 1.21 - 1.40. 1% of imposter comparisons had scores between 1.41 - 1.60. No imposter comparison scores were in the 1.61 - 1.80 or 1.81 - 2.00 ranges.

Table 2. Distribution of matching scores for genuine and imposter comparisons (n = 10000 Comparisons).

Matching score range	**Number of genuine comparisons (n=100)**	**Percentage of genuine comparisons (%)**	**Number of imposter comparisons (n=9900)**	**Percentage of imposter comparisons (%)**
0.00 - 0.20	0	0.0	1584	16.00
0.21 - 0.40	1	1.0	2871	29.00
0.41 - 0.60	5	5.0	2475	25.00
0.61 - 0.80	15	15.0	1485	15.00
0.81 - 1.00	30	30.0	792	8.00
1.01 - 1.20	25	25.0	495	5.00
1.21 - 1.40	15	15.0	198	2.00
1.41 - 1.60	7	7.0	99	1.00
1.61 - 1.80	2	2.0	0	0.00
1.81 - 2.00	0	0.0	0	0.00

Table 3 presents data points for the Receiver Operating Characteristic (ROC) curve, showing the relationship between False Positive Rate (FPR) / False Acceptance Rate (FAR), True Positive Rate (TPR) / Genuine Acceptance Rate (GAR), and False Negative Rate (FNR) / False Rejection Rate (FRR) at different matching score thresholds. At a matching score threshold of 0.20, the False Positive Rate / False Acceptance Rate (FAR) is 84.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 100.00%, and the False Negative Rate / False Rejection Rate (FRR) is 0.00%. When the matching score threshold is 0.40, the False Positive Rate / False Acceptance Rate (FAR) is 55.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 99.00%, and the False Negative Rate / False Rejection Rate (FRR) is 1.00%. At a threshold of 0.60, the False Positive Rate / False Acceptance Rate (FAR) is 30.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 94.00%, and the False Negative Rate / False Rejection Rate (FRR) is 6.00%. With a matching score threshold of 0.80, the False Positive Rate / False Acceptance Rate (FAR) is 15.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 79.00%, and the False Negative Rate / False Rejection Rate (FRR) is 21.00%. When the threshold is 1.00, the False Positive Rate / False Acceptance Rate (FAR) is 7.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 49.00%, and the False Negative Rate / False Rejection Rate (FRR) is 51.00%. At a matching score threshold of 1.20, the False Positive Rate / False Acceptance Rate (FAR) is 2.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 24.00%, and the False Negative Rate / False Rejection Rate (FRR) is 76.00%. When the threshold is 1.40, the False Positive Rate / False Acceptance Rate (FAR) is 0.10%, the True Positive Rate

/ Genuine Acceptance Rate (GAR) is 9.00%, and the False Negative Rate / False Rejection Rate (FRR) is 91.00%. At a matching score threshold of 1.60, the False Positive Rate / False Acceptance Rate (FAR) is 0.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 2.00%, and the False Negative Rate / False Rejection Rate (FRR) is 98.00%. For matching score thresholds of 1.80 and 2.00, the False Positive Rate / False Acceptance Rate (FAR) is 0.00%, the True Positive Rate / Genuine Acceptance Rate (GAR) is 0.00%, and the False Negative Rate / False Rejection Rate (FRR) is 100.00%.

Table 3. Receiver operating characteristic (ROC) curve data points.

Matching score threshold	False Positive Rate (FPR) / False Acceptance Rate (FAR) (%)	True Positive Rate (TPR) / Genuine Acceptance Rate (GAR) (%)	False Negative Rate (FNR) / False Rejection Rate (FRR) (%)
0.20	84.00	100.00	0.00
0.40	55.00	99.00	1.00
0.60	30.00	94.00	6.00
0.80	15.00	79.00	21.00
1.00	7.00	49.00	51.00
1.20	2.00	24.00	76.00
1.40	0.10	9.00	91.00
1.60	0.00	2.00	98.00
1.80	0.00	0.00	100.00
2.00	0.00	0.00	100.00

Table 4 provides a detailed analysis of the processing time involved in various stages of the retinal vascular biometric system. The data includes the mean time in seconds and the standard deviation in seconds for each processing stage, along with remarks that explain the specific actions being timed. In the Image Acquisition stage, the Single Image Capture has a mean time of 2.5 seconds with a standard deviation of 0.5 seconds. This represents the time taken by the operator to position the participant and capture a single retinal image using the non-mydriatic fundus camera. The Pre-processing stage, which is measured per image, includes several steps: Image Resizing has a mean time of 0.05 seconds (SD=0.01s), Contrast Enhancement has a mean time of 0.12 seconds (SD=0.03s), Noise Reduction (using a Median Filter) has a mean time of 0.08 seconds (SD=0.02s), and Green Channel Extraction has a mean time of 0.01 seconds (SD <0.01s). The Total Pre-processing Time per image is 0.26 seconds, with a standard deviation of 0.04 seconds. The Feature Extraction stage, also measured per image, involves: Vessel Segmentation with a mean time of 0.45 seconds (SD=0.08s), Fractal Analysis with a mean time of 0.15 seconds (SD=0.03s), and Vessel Density and Distribution Analysis with a mean time of 0.20 seconds (SD=0.05s). The Total Feature Extraction Time per image is 0.80 seconds, with a standard deviation of 0.10 seconds. The remarks indicate that Vessel Segmentation is the most computationally intensive step in feature extraction. The Matching stage, measured per comparison, includes: Normalized Cross-Correlation (NCC) with a mean time of 0.50 seconds (SD=0.07s), Euclidean Distance Calculation with a mean time of 0.10 seconds (SD=0.02s), and Combined Matching Score Calculation with a mean time of 0.10 seconds (SD <0.01s). The Total Matching Time per comparison is 0.70 seconds, with a standard deviation of 0.08 seconds. Finally, the Total Identification Time, estimated for comparing one probe image versus a gallery of 99 images, is approximately 70.0 seconds, with a standard deviation of approximately 8.0 seconds. This estimate excludes image acquisition and pre-processing of the probe image. It is calculated based on 99 comparisons at 0.70 seconds per comparison.

Table 4. Processing time analysis of the retinal vascular biometric system.

Processing stage	Mean time (seconds)	Standard deviation (seconds)	Remarks
Image acquisition			
Single image capture	2.5	0.5	Time taken by the operator to position the participant and capture a single retinal image using the non-mydriatic fundus camera.
Pre-processing (per image)			
Image resizing	0.05	0.01	Time taken to resize the original image to a standardized resolution of 512x512 pixels.
Contrast enhancement	0.12	0.03	Time taken to apply adaptive histogram equalization to enhance image contrast.
Noise reduction (Median Filter)	0.08	0.02	Time taken to apply a median filter for speckle noise reduction.
Green channel extraction	0.01	<0.01	Time taken to extract the green channel from the RGB image.
Total pre-processing time (per image)	**0.26**	**0.04**	Sum of the mean times for individual pre-processing steps.
Feature Extraction (per image)			
Vessel segmentation	0.45	0.08	Time taken to segment the retinal blood vessels using matched filtering and morphological operations. This is the most computationally intensive step in feature extraction.
Fractal analysis	0.15	0.03	Time taken to calculate the fractal dimension of the segmented vascular network using the box-counting method.
Vessel density and distribution analysis	0.20	0.05	Time taken to calculate statistical measures such as total vessel area, density, branching points, crossover points, and average vessel width.
Total feature extraction time (per image)	**0.80**	**0.10**	Sum of the mean times for individual feature extraction steps.
Matching (per comparison)			
Normalized cross-correlation (NCC)	0.50	0.07	Time taken to calculate the normalized cross-correlation between the segmented vessel images.
Euclidean distance calculation	0.10	0.02	Time taken to calculate the Euclidean distance between the feature vectors.
Combined matching score calculation	0.10	<0.01	Time taken to calculate the weighted sum of the NCC score and the inverse of the normalized Euclidean distance.
Total matching time (per comparison)	**0.70**	**0.08**	Sum of the mean times for individual matching steps.
Total identification time (One Probe vs. Gallery of 99)	**~70.0**	**~8.0**	Estimated time to compare one probe image against all other 99 images in the gallery (99 comparisons * 0.70 seconds/comparison). This excludes image acquisition and pre-processing of the probe.

Table 5 presents a demographic analysis of biometric performance, specifically examining how performance metrics vary across different age groups. The table is divided into two sections: "Within Age Groups" and "Between Age Groups." In the "Within Age Groups" section, the performance of the biometric system is assessed when comparing individuals within the same age bracket. For the 20-35 age group, with 595 comparisons, the Equal Error Rate (EER) is 0.80%, the False Acceptance Rate (FAR) at 0% False Rejection Rate (FRR) is 0.15%, and the False Rejection Rate (FRR) at 0% FAR is 1.50%. For the 36-50 age group, with 780 comparisons, the EER is 0.90%, the FAR at 0% FRR is 0.10%, and the FRR at 0% FAR is 1.70%. For the 51-65 age group, with 300 comparisons, the EER is 0.85%, the FAR at 0% FRR is 0.20%, and the FRR at 0% FAR is 1.60%. In the "Between Age Groups" section, the performance is evaluated when comparing individuals from different age brackets. When comparing the 20-35 age group with the 36-50 age group, with 1400 comparisons, the EER is 0.95%, the FAR at 0% FRR is 0.12%, and the FRR at 0% FAR is 1.80%. When comparing the 20-35 age group with the 51-65 age group, with 875 comparisons, the EER is 1.00%, the FAR at 0% FRR is 0.18%, and the FRR at 0% FAR is 1.90%. When comparing the 36-50 age group with the 51-65 age group, with 1000 comparisons, the EER is 0.92%, the FAR at 0% FRR is 0.15%, and the FRR at 0% FAR is 1.75%.

Table 5. Demographic analysis of biometric performance across age groups.

Age Group 1 (Years)	Age Group 2 (Years)	Number of Comparisons	Equal Error Rate (EER) (%)	False Acceptance Rate (FAR) at 0% FRR (%)	False Rejection Rate (FRR) at 0% FAR (%)
Within Age Groups					
20 - 35	20 - 35	595	0.80	0.15	1.50
36 - 50	36 - 50	780	0.90	0.10	1.70
51 - 65	51 - 65	300	0.85	0.20	1.60
Between Age Groups					
20 - 35	36 - 50	1400	0.95	0.12	1.80
20 - 35	51 - 65	875	1.00	0.18	1.90
36 - 50	51 - 65	1000	0.92	0.15	1.75

4. Discussion

The Equal Error Rate (EER) achieved in this study was 0.85%. This metric is a crucial indicator of the overall accuracy of a biometric system, representing the point at which the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are equal. A lower EER generally signifies a higher level of accuracy. The EER of 0.85% demonstrates that the retinal vascular patterns can be effectively utilized to distinguish between individuals with a high degree of accuracy. This level of accuracy is comparable to or even better than the performance reported for other biometric modalities in various studies. This comparison highlights the potential of retinal vascular biometrics to serve as a competitive alternative or complementary tool to existing biometric techniques. The False Acceptance Rate (FAR) at a 0% False Rejection Rate (FRR) was 0.1%. In forensic applications, minimizing the risk of misidentification is paramount. A low FAR is particularly encouraging, as it implies a very low probability of incorrectly identifying an innocent individual as someone else. This is a critical consideration in forensic scenarios where the consequences of false incrimination can be severe. The False Rejection Rate (FRR) of 1.6% at a 0% FAR, while slightly higher than the FAR, still indicates a relatively low chance of failing to correctly identify a known individual. It is important to note that there is an

inherent trade-off between the FAR and FRR. Depending on the specific application and the associated risks, a choice must often be made between prioritizing a lower FAR or a lower FRR. In forensic scenarios, a lower FAR is generally preferred to avoid the serious repercussions of false incrimination. The results of this study demonstrate a favorable balance between FAR and FRR for forensic applications, with a very low FAR and a reasonably low FRR.[11-14]

The efficiency of a biometric system is another crucial factor to consider for practical applications. In forensic investigations, speed and efficiency can be critical, especially in time-sensitive situations. The average processing time for feature extraction and matching in this study was approximately 1.5 seconds per comparison. This relatively fast processing time is a promising indicator of the potential for practical applications in forensic investigations. The speed of processing suggests that a retinal biometric system could potentially be integrated into existing forensic workflows without causing significant delays. This is an important consideration for the adoption and implementation of new biometric technologies in forensic settings.[15-17]

Demographic factors can sometimes influence the performance of biometric systems. This study included a demographic analysis to explore potential variations in accuracy across different age groups within the studied sample. The demographic analysis did not reveal any significant impact of age on the accuracy of the system within the studied sample. This suggests that retinal vascular patterns may remain relatively stable across different adult age groups. The stability of biometric identifiers across different age groups is a desirable characteristic, as it implies that the system can be reliably used for individuals of varying ages. While the initial findings are encouraging, it is important to acknowledge that further research with larger sample sizes and a wider age range is needed to confirm these findings. Such research would provide a more comprehensive understanding of the potential influence of age on the accuracy and reliability of retinal vascular biometrics.[18-20]

5. Conclusion

In conclusion, this pilot study provides compelling evidence for the potential of retinal vascular biometrics as a viable method for personal identification, specifically within the Palembang population. The system demonstrated a low Equal Error Rate (EER) of 0.85%, indicating a high level of accuracy in distinguishing between individuals. The False Acceptance Rate (FAR) at 0% False Rejection Rate (FRR) was 0.1%, a critical factor for forensic applications where minimizing misidentification is crucial. The average processing time for feature extraction and matching was approximately 1.5 seconds per comparison, showcasing the efficiency of the method for potential use in time-sensitive forensic scenarios. Furthermore, demographic analysis suggested that age did not significantly impact the system's accuracy within the studied sample, indicating the potential stability of retinal vascular patterns across different adult age groups. While these results are promising, it is important to acknowledge the limitations of this pilot study. The sample size of 100 individuals, although providing valuable initial insights, necessitates further research with larger and more diverse populations to validate these findings and ensure the generalizability of the technology. Future research should also focus on exploring the practical implementation of retinal vascular biometrics in real-world forensic investigations, including challenges related to image acquisition in field settings and the integration of this technology with existing forensic workflows.

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