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PALM VEIN RECOGNITION BY ARTIFICIAL NEURAL NETWORK

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Master's Thesis

Supervisor

Prof. Dr. Osman Nuri UÇAN

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The thesis titled PALM VEIN RECOGNITION BY ARTIFICIAL NEURAL NETWORK prepared by SURA AHMED JABER and submitted on 16/12/2022 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Sura Ahmed Jaber JABER

Signature

DEDICATION

First, I thank God Almighty for my success.

I thank the University of Altınbaş and my career institution for giving me the opportunity to complete my education and get acquainted with the state of Turkey and its citizens. My father is my support, my strength and my companion. My beloved husband, the man who trusted me, walked with me, and helped me to the end. My children who bore with me travel and alienation. My child, Amir, who accompanied me in my first steps, was a fetus in my womb. To my Turkish friends. To all who asked about me and stood by me. I dedicate this research to you and say with gratitude, thank you.

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ABSTRACT

PALM VEIN RECOGNITION BY USING ARTIFICIAL NEURAL NETWORK

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After the great development in various fields of life, especially in technology, various methods have appeared recently to classify biometrics with artificial intelligence, such as fingerprint, eye print and palm vein fingerprint, where several methods were used to distinguish and met with great success. In this paper, we will classify the palm venous fingerprint of a Tongji dataset data set consisting of 3000 images distributed over 300 people for each person 10 images. This system went through three stages, the first stage was to obtain the area of interest and the pre-processing of the image, where in this stage a part of the palm was cut out to be processed after filtering it using Gauusian low filter converting the image to binary image, then the image pre-processing where the image was passed by the histogram equalization to get a clearer image and stronger features. The second stage is extracting features from the resulting image, where the Linear Discriminant Analysis was used for the purpose of extracting features, The classification was done using several algorithms, and we adopted the algorithm that gave the highest percentage. Three algorithms for machine learning and an algorithm for an artificial neural network were used in this research. Multilayer Perceptron Neural Network Classifier achieved 100%, while the rest of the algorithms, the result was 99%.

Keywords: Palm Vein, Artificial Neural Network, LDA, MLP, Machine Learning.

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ABBREVIATIONS

AI	:	Artificial Intelligence
NIR	:	Near Infrared
ROI	:	Region Of Interest
LED	:	Light Emitting Diode
SIFT	:	Scale Invariant Feature Transform
LBP	:	Local Binary Pattern
LDP	:	Local Directional Pattern
EER	:	Equal Error Rate
PCA	:	Principle Component Analysis
DCT	:	Discrete Cosine Transform
CNN	:	Convolutional Neural Network
LDA	:	Linear Discriminant Analysis
ANN	:	Artificial Neural Network
MLP	:	Multilayer Perceptron
RF	:	Random Forest

1. THE PREVIOUS STUDIES

1.1 INTRODUCTION

Palm vein discrimination is one of the modern vital ways to distinguish between humans, and because the veins of the palm are not visible and they cannot be manipulated or changed, and each person has his own map of veins that is not similar to others, so it is considered one of the correct ways to distinguish and the blood vessels are detected using near infrared devices (NlR). However, the other methods such as Token-based recognition or knowledge based recognition and the way of identify them have become useless and effective at the present time for the development of ideas and the growth of the human mind. (Jain et al., 2004)

ln such cases, more sophisticated techniques such as biometrics are required and can be more effective than other techniques.

ln this working paper, we will present research that deals with distinguishing the previous palm veins for various databases and in different ways to treat them.

1.2 GET A PALM VEIN IMAGE

Four processes make up the method for recognizing palm veins: "palm vein capture, area of interest (ROl), feature extraction, and feature matching." (Solimanv et al., 2012) according to figure 1. Picture of a palm vein is being collected for image collection. A portion of the palm vein photos are used during preprocessing to extract features.

The preprocessed veins of the palm are used to provide useful features for feature extract. A database maintains registered templates and a matcher analyzes two aspects of the palm veins.

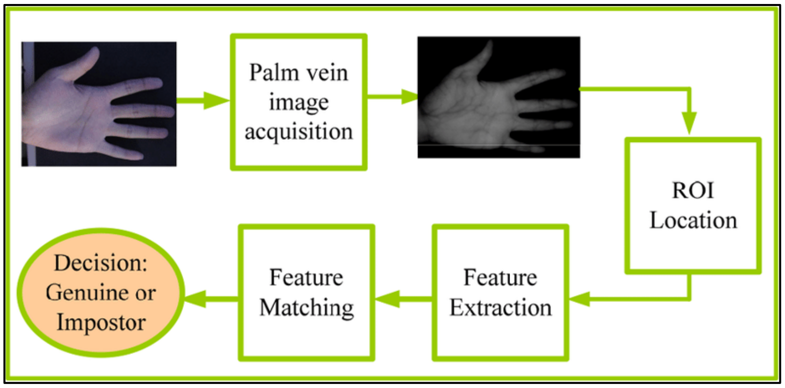


Figure 1.1: Diagram outlining the key stages for palm vein recognition

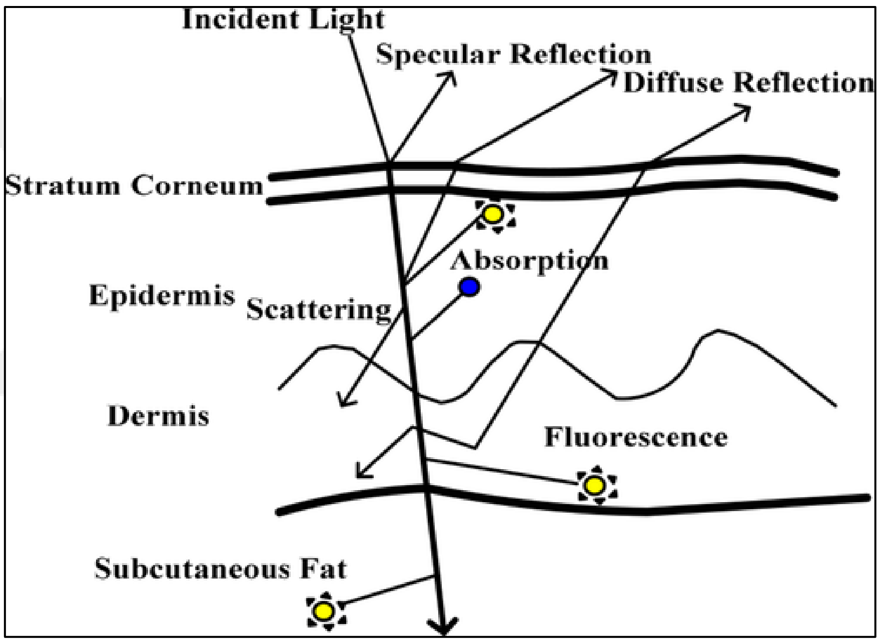


Figure 1.2: Diagram demonstrating how light travels through the skin's layers[1]

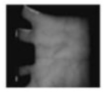
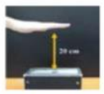
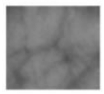
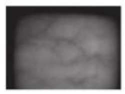
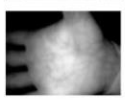
In the image acquisition stage, the image can be used in dataset acquired by CCD were used. In ROI stage we take the important part in palm vein image and leave the remaining unimportant parts. This important part is called ROI. Which includes several stages: remove noise, remove, block, extract boundaries, define joints and define the area by drawing a rectangle around it. Then come the stage of image Enhancement, which also includes several stages then comes the stage of improving the image, which also includes several stages. Then comes the stage of segmentation, which also includes several stages. With feature extraction, palm veins that have already been treated provide a high level of quality criteria. How palm and element are contrasted as electronic races The generated template data set's fragmentation is logged.

1.3 PUBIIC PAIM VEIN DATASET

Taking pictures is the basis for recognition. We will compare the devices for obtaining palm veins through some features such as the shape of the device, the corresponding image, the type of camera, as well as the type of paper . (Kang & Wu, 2014)(Yan et al., 2015) employed a 940 nm active infrared illumination and a multispectral camera (AD-080GE) for the palm vein database. Wang (R. Wang et al., 2014) captures a picture of a palm vein using an NlR charge-coupled CDD camera, an 850nm light-emitting diode, an LED, and an infrared light source. Based on a CDD camera and an NlR active light source, the polyU database was created.(Sierro et al., 2015) Another palm vein picture utilizing the same CDD camera has been proposed, but this time the light source is different and uses three separate wavelengths: blue, far red, and infrared. Whereas the infrared and far red colors primarily display the vein, the blue rays emphasize the skin's structure.(De Santis et al., 2017) Another palm vein picture utilizing the same CDD camera has been proposed, but this time the light source is different and uses three separate wavelengths: blue, far red, and infrared. Whereas the infrared and far red colors primarily display the vein, the blue rays emphasize the skin's structure.While Wang (Y. Wang et al., 2018) obtained accurate information by using a 3D image of the palm vein, the camera used JAl CV-M50lR 1/2 near infrared is expensive, amounting to 3000 dollars. (J. G. Wang et al., 2008)Jen-Chun Lee (J. C. Lee, 2012) and Yen-Po Lee (Y. P. Lee, 2015) also used a modified CCD camera - the $1,500 Sony XC711. The complete system of FUJlSTU palm vein extraction costs $5000. (Cao et al., 2016) Therefore, the researcher has to conduct a test between NlR and FlR to choose the most suitable light source.

The most suitable wavelengths for the light source are 850 and 950 nm and the use of infrared NlR (Dong et al., 2017).

Table 1.1: Comparing several methods and equipment for capturing palm veins

Literature	Capture device	Sample of imaging	Camera type	Light source	Image method
Zhang et al.[6]			CCD camera	A set of infrared light source	reflection
Zhang and Hu [7]			CCD NIR camera (JAI AD-080 CL 1/3'')	850nm LED arrays	reflection
Gohk and Andrew[8]			Webcam	880nm to 920 nm infrared LEDs	reflection
Greitans et al.[9]			CCD camera	850nm IR LEDs	reflection
Kabacinski and Kowalski[10]			low-cost USB camera	880nm IR LED	reflection
Han and Lee[11]			CCD camera (Sony XC711)	LED infrared light peaks at 750nm	reflection
Tome and Marcel[12]			CCD camera (Sony ICX618)	940nm LEDs	reflection
Cao et al.[16]			infrared night-vision camera (Zmodo zp-ibh13)	850nm LEDs	transmission
Ladoux[13]			CCD camera	LEDs 850nm	reflection
Cancian et al.[14]			NIR camera	850 ± 30nm LED	reflection
Dandawate and Inamdar [17]			CCD camera	Near IR LED's (SFH4550) 850nm Matrix	transmission
Sierro et al.[15]			CCD camera (IEEE 1394 Sony ICX618)	940 nm NIR LEDs	reflection

1.4 PREPROCESSING

The accuracy of the vein discrimination system is thought to be a function of the caliber of the pre-processing procedures, and it serves as the foundation for extracting characteristics and matching them. The area of interest is an imperative step in preprocessing with regard to image optimization, filtering, and other steps. The area of interest includes steps: palm vein flexion, hand and finger contour extraction, identification of key points, coordination system organization, file extraction aiming sides, and normalization.

Zhou and Kumar (Y. Zhou & A. Kumar, 2011a) based on finding the ROl by measuring the distance between the index, middle, ring, and little fingers, then identifying the ROl by looking for any minimums that would match the estimated value.

Lee(Anderson & Parrish, 1981) located ROl Two points (P1 and P2) and one distance determine the location. The ROl is situated below P1 and P2 at a distance of one-sixth of the length of p1 and p2, as shown in the image. P1 stands for (the point between the little finger and the finger ring), while P2 indicates the valley point among the middle finger and the index finger.

Kang and Wu (Yan et al., 2015) Finding the midpoints of the index and little fingers and the valley points on each side of the little finger, p1 and p2, respectively, and using them as a reference point will boost the ROl.

Lee (J. C. Lee, 2012) determined the location of the ROl in a similar way to (Y. Zhou & A. Kumar, 2011b),(Zhou & Kumar, 2010) However, it was rectangular where the valley points p1 (between the little and ring fingers) and p2 (between the middle and index fingers) were selected, and via two important points an area is established. Rectangular shape with C1, C2, C3, and C4 as the area of interest The lines C1C2 and C1C3 are vertical and C1C3 = 2 × C1C2 The reason (Dandawate & Inamdar, 2015) the reason to use this technique for ROl extraction is that it guarantees that all extracted ROls correspond to the same area of the picture. Iee (J. C. Lee, 2012) eliminates the drawback of the ROl finding technique without employing docking devices. That’s show in figure (1.3).

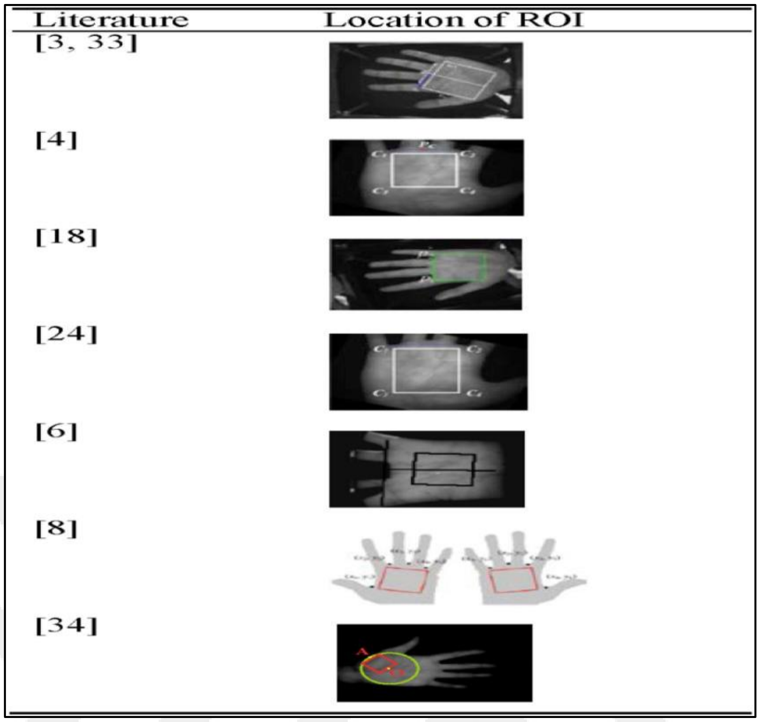


Figure 1.3: Technique of ROI palm vein

1.5 FEATURE FOR EXTRACTION AND MATCHING

As illustrated in Table 3, the region of interest, which is the area that can be handled and worked on, is situated among the index finger and the pulp, with the lnternet situated among the ring finger and the little finger.

As illustrated in Table 3, the region of interest is the manageable and workable area that is situated amongst the index finger and the core, along with the lnternet, amongst the ring finger and the little finger. Rectangular cross-sectional areas were adopted to obtain the characteristics of the shape. The square area is easier to manage segment properties. While circular and elliptical regions can be added to that, it is simpler to deal with rotation and its difference.

The palm vein was recognized in 1991 for the first time, as it was proven that the palm vein is highly safe in identifying humans as it cannot be genetically copied or modified (Sierro et al., 2015) . Because the sensor is not directly linked to the blood flowing in the palm veins, which is, it is not susceptible to water, heat, dust, muck, oil, plastic gloves, etc., makes palm vein identification feasible

1.6 RECOGNITION OF PAIM VEIN FUSION

Big data, mistake rate, and inability to record caused difficulties for the only system for recognizing palm veins.

One of the most crucial solutions to these issues is biometrics. The system's performance is significantly enhanced by the multi-scale integration. combining more individual biometrics to improve system performance (Lin & Tai, 2016). Wang et al. presented a technique for identifying palm veins using the Iappelcian palm, which would allow a person's identity to be revealed by combining their palm vein and handprint images. (P. Li et al., 2014). Whil e Toh (Toh et al., 2006)suggested a system that combined the palmar vein and its tissue surface wrinkle to verify personal identity.

Kay-Wood used a complex two-tree wavelet transformation, palm vein fusion treatment and palm print fusion. Nayar and others (Nayar et al., 2016) The advantage of merging the palm of the hand and the composite fingerprint and its use in the ways of using the different features. Partial matching of the palm print by repeating the matching to reach the fine details, When the greatest curvature is utilized to extract the vein pattern and the coarse-to-fine matching approach is used. Deshpande et al (Deshpande et al., 2016)

The Wave decomposition approach was used to retrieve the palm print's finer characteristics. The same filtering method was used to retrieve palm print profiles. ln this case, the filter was spun in 12 different ways, and a different tool was used for each kind of detection.Yang and Shams (X. Yang & Sun, 2016) extracted palm vein fingerprints with LBP with canonical correlation and CCA analysis and matching. A common method for assessing the linear connection between two data sets is the CCA.. Trabelsi (R. B. Trabelsi et al., 2015) merged palm vein and palm print in the levels that were highlighted. Circular differences and statistical directional pattern descriptors are among the characteristics they extract.Nikisins et al. (Nikisins et al., 2015) introduce the vein and crease combination on the palm. ln the palm vein and palm screase feature extraction stages, a features descriptor called a vector histogram is proposed. Gupta et al. (Gupta et al., 2014) propose amulti,modal biometrics system using face modality combine with,palm print and palm vein modality. The propose methodology, used a local statistical methods in which defined blocks of the distinct cosine transformed (DCT) constant is used to calculate

Feature vectors were created from the standard deviations and saved. The distances between feature vectors are used for matching. Tekade and Shende (Tekade & Shende, 2018)employ three different modalities: palm vein, facial, and finger prints. Each modality's feature extraction is carried out using a distinct algorithm. For the extraction of facial features, the LBP algorithm was utilized. Palm and vein feature extractions are done using discrete wavelet transforms, while finger print feature extractions are done using the minutiae approach. The fusion of feature levels follows that. Leng et al.(Leng et al., 2013) palm veins and prints were combined to identify people. Conjugate 2D Palm Hash Codes is a fusion strategy created using photographs of the palm's veins, print, and 2DPalm hash codes.Michael et al. (Michael et al., 2010) The features of the palm, print, and vein were represented as bit strings. The palm print and palm vein modalities' matching scores are combined using an SVM as the fusion technique.Sanchit et al. (C. Yang et al., 2020) introduced a multimodal system that combines biometric data from the hand's palm and dorsal veins at the scoring levels. For the extraction of texture characteristics, a 2D Gabor filter is used. ln matching, the Hamming distances were used. Fuksis et al. (Fuksis et al., 2011)We demonstrate how the statistical data about bio-codes generated by employing bio hash methods helps to enhance bio-code comparison algorithms and get a reduced EER. Ramalho et al. (Ramalho et al., 2011)palm print, finger surfaces, hand geometry, and palm vein were all utilized to identify people. Orthogonal lines ordinal features, competitive codes, and palm-code are used in the feature extraction stages to extract features from the palm print, finger surfaces, and palm vein. ln order to implement secure template storage systems that combine cryptographic hash functions and error-correcting codes, the outputs of the features were then translated to binary. Throughout the system architectures. ln order to cut down on the amount of time needed for identification searches, the hand geometry's data banks were used.Gusain et al. (Gusain et al., 2018)fusedface, iris and palm vein together. Samoil et al. (Samoil et al., 2014) provided sparkle access to information including palm prints, hand forms, finger joint positions, and vein patterns via the utilization of the RGB, depth, and NlR spectral ranges.Michael et al. (Michael et al., 2012) utilised five features for fusion recognitions, including hands geometry, palmprints, palmar knuckle prints, palm veins, and fingers vein. They created their own data bank with 136 individuals. Bio-modals fusion and multi-modals fusion were evaluated using SVM-RBFs, FW-SVM-RBFs, Fuzzy-Weighted (FW)-Sum rules, and Sum rules. When many features are combined, zero EER is possible. The detections and acquisitions of palm vein fusion and other biometrics were among the fascinating research opportunities compared in this work. The literature's primary objective(Lumini & Nanni, 2017).ls to analyze different technique of evidence fusion applies in the biometric fields. lt gives good advices about the synthesis of biometric.

Table 1.2: Overview of feature and matching method in the field of palm vein recognition

Literature	Matching method	Feature extraction method	Database			Performance
			DB name	palms	samples	
(K. S. Wu et al., 2013)	normalized hamming distance	directional filter bank to extract line- based feature	Self-built	256	20	EER = 0.518%
(Raut & Humbe, 2016)	Euclidean distance	corner point detection	PolyU [29]	100	6	CRR = 95%
(Wirayuda, 2015)	weighted Euclidean distance	minutiae features	CASIA V1.0 [28] (left hands)	100	6	CRR = 90.87%
(Y. Zhou & A. Kumar, 2011b)	hamming distance	neighborhood matching radon	CASIA V1.0	200	6	EER = 0.51%
	hamming distance	transform (NMRT)	PolyU	500	12	EER = 0.44%
		hessian phase	CASIA V1.0	200	6	EER = 0.004%
			PolyU	500	12	EER = 0.43%
(Piciucco et al., 2018)	score-level fusion	local binary pattern and local derivative pattern	self-built	86	12	EER = 1.74%
	cosine similarity measure	local tetra patterns	PUT Vein database	100	12	EER = 0%
(X. Yang & Sun, 2016)	LBP	maximal principal curvature (MPC) algorithm and k-means method	CASIA V1.0 (left hands)	100	6	EER = 1.965%
(Mirmohamadsadeghi & Drygajlo, 2014)	histogram intersection	LBP	CASIA V1.0	100	6	CRR = 93.20%
		LDP				CRR = 97.00%
(Akbar et al., 2016)	histogram intersection	LDP	CASIA V1.0	100	6	CRR = 98.3%

Table 1.2: Overview of feature and matching method in the field of palm vein recognition 'Tables Continued'

	Chi-square distance	mutual foreground LBP	CASIA V1.0 (left hands)	100	6	EER = 2.53%
	Chi-square distance + SVM score fusion					EER = 0.267%
(Yan et al., 2015)	Chi-square distance	mutual foreground local directional texture pattern	CASIA V1.0	100	6	CRR = 95%
(Tome & Marcel, 2015)	histogram intersection	LBP	VERA Palmvein [12]	220	10	EER = 3.75%
(Mirmohamadsadeghi & Drygajlo, 2014)	cosine distance	LBP rotation invariant	CASIA V1.0	200	6	CRR = 96%
						EER = 11.7%
(Fronitasari & Gunawan, 2017)	probabilistic neural network	modified of the LBP	CASIA V1.0	50	10	CRR = 96.6%
	(PNN)			80	10	CRR = 92.75%
(Yazdani & Andani, 2017)	SVM and KNN	estimate of wavelet coefficient with autoregressive model	PolyU	50	6	EER = 0.7%
(X. Wu & Zhang, 2006)	hamming distance	multiscale filtering	Self-built	24	6	EER = 4.00%
(Savitha & Ramegowda, 2017)	normalised hamming distance	adaptive gabor filter	Self-built	207	20	EER = 0.44%
(Cancian et al., 2017)	Hellinger distance	2D Gabor filters	Self-built	24	3	EER = 1.84%
(Han & Lee, 2012)	normalised hamming distance	VeinCode	Self-built	207	20	CRR = 99.38%
(Ma et al., 2017)	minimum normalised hamming distance	adaptive 2D Gabor filter	CASIA V1.0	200	6	EER = 0.12%
(Boubchir et al., 2018)	Jaccard distance	competitive coding (2D log Gabor filter)	PolyU	500	12	CRR = 99.5%

Table 1.2: Overview of feature and matching method in the field of palm vein recognition 'Tables Continued'

(Ladoux et al., 2009)	Euclidian distance	SIFT	Self-built	24	60	EER = 0.14%
(Kang et al., 2014)	RootSIFT matching + LBP-based mismatching removal	RootSIFT	CASIA V1.0	200	6	EER = 0.996%
	RootSIFT matching + LBP-based mismatching removal		Self-built	210	6	EER = 3.112%
(Yunanto et al., 2017)	Euclidean distance	DCT and k-PCA	CASIA V1.0 (left hands)	100	6	CRR = 99.989%
(Setiawan & Yuniarno, 2018)	learning vector quantisation	phase symmetric	Self-built	47	10	CRR = 94%
(Rizki et al., 2016)	cosine similarity	two-dimensional linear discriminant	CASIA V1.0 (left hands)	100	6	EER = 8%
(Y. P. Lee, 2015)	minimum distance classifier	modified (2D) 2 LDA	Self-built	207	20	CRR = 99.41%
(Perwira et al., 2014)	PNN	PCA	CASIA V1.0	200	6	CRR = 84%
(Al-jaberi & Al-juboori, 2021)	AlexNet	CNN	CASIA	100	6	CRR=96%

the related work for used dataset Tongji is show in table

Table 1.3: Related work for tongji dataset

Refs.	Method	Accuracy
F. Ahmad (Ahmad et al., 2020)	Wave Atom Transform (WAT) based palm-vein recognition scheme	EER=0%
Felix Olanrewaju Babalol (Babalola et al., 2021)	fusion of texture-based and CNN-based methods	100%
Jiashu Lou, Jie zou, Baohua Wang (Lou & Wang, 2022)	Multi-task Loss Function and Attention Layer	98.89%
M. Rajalakshmi (Rajalakshmi & Annapurani Panaiyappan, 2022)	Adapt-HKFCT segmentation and feature-based chaos integrated deep neural networks	98.3%
John Prakash Veigas (Veigas & Kumari M, 2022)	CNN model inspired by Alex-net	99.98%
Selma Trabelsi2 • Djamel Samai2 • Fadi Dornaika1,3,4 Abdelmalik Taleb-Ahmed (S. Trabelsi et al., 2022)	Identification systems using deep learning and feature selection methods	EER= 0.53% ROR=97.85%

Table 1.3: Related work for tongji dataset 'Tables Continued'

Dexing Zhong (Zhong & Zhu, 2019)	extract discriminative features and CNN classification	99.43%
Mengwen Li (M. Li et al., 2022)	principal component analysis network	EER=0.06
Xuefeng Du , Dexing Zhong , Huikai Shao (Du et al., 2019)	CNN	96.9%
Huikai Shao (Shao et al., 2021)	Meta-Siamese Network	99.991%
Angelo Genovese(Genovese et al., 2019)	PalmNet is a new method of applying Gabor filters in a CNN	99.8% EER=0.16

2. THE THEORETICAL PART

2.1 INTRODUCTION

In this chapter We will discuss the theoretical part of the research, which includes image purification processes to obtain a clear vein using the processes that this chapter will deal with in detail and the processes by which the palm veins will be recognized.

2.2 IMAGE PROCESSING

Is a method for improving the image and improving the appearance of the image or extracting information that can be dealt with and used by performing operations on it. And processing the image consists of small units called pixels, where the pixel is transformed into a number for each pixel called the image elements, and the imaging device maintains a number or a group of numbers that describe the characteristics of the pixels such as color, intensity, brightness , which represents the intersection of rows with columns (Ruslau et al., 2020)and depending on the color system User like HIs, RGB, HSV, Gray scale.

Image processing is a technique for improving images obtained by cameras, satellite vehicles, ships and planes, as well as images captured in our daily lives. In image processing, contrast techniques have advanced in the past four or five decades, and technology has developed in improving images, due to the strong personality and advanced devices such as computers, large memory, graphic applications, and many others.

(Gonzalez & Woods, 2018) Image processing is used in many applications, including :

a. Recognition Faces

b. Distinguishing between people through fingerprints, palm veins, and others

c. Estimation and classification of age

d. Recognize

2.3 PALM VEIN APPROACH

2.3.1 Tongji Data Set

ln this database, a device was used that contains a CCD camera (JAl AD-80 GE), a white LED light source, a lens, a power source for light, and an industrial computer. The lens and the hole size is 230 mm * 230 mm where a touch screen is installed with a thin LCD screen, where the user can use it with ease and in Figure.1 the shape of the device used.

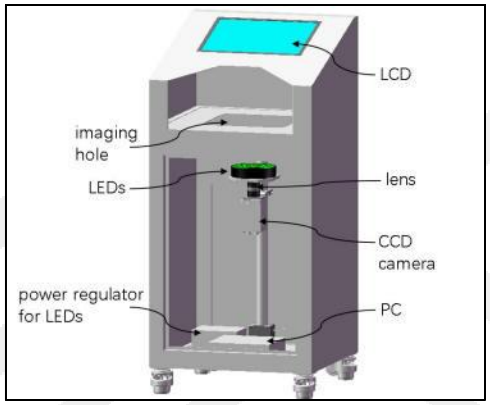


Figure 2.1: The shape of the device used

lmage samples were collected from 300 individuals, divided into 192 males and 108 females, 352 of whom ranged in age from 20 to 30, and the rest were between 30 and 50 years old.

Samples were taken in two separate sessions, the duration between the two sessions is an average of 61 days. ln each session 10 photos were taken for each palm. This rule contains 1200 photos taken from 600 different palms. (Zhang et al., 2017).

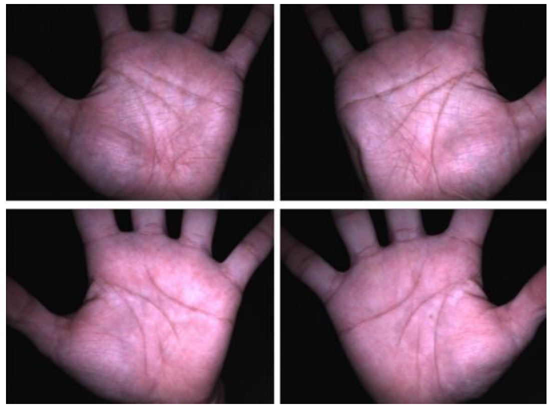


Figure 2.2: Four contactless palm print

2.4 PREPROCESSING PALM VEIN

Pre-processing is the basic stage in the biometrics system, and the main goal of pre-processing is to improve and enhance some of the features of the images or remove unwanted impurities in the image. Because of the invisible veins in some images, we will perform some steps to obtain contrast for the veins. In “Tongji dataset “ the image are clear and you need to: histogram equalization.

Histogram equalization: is a way to configure a file through the spatial area with a unified pixel distribution. This means that the file is settled and consistently extended to its ease of use and its effective easily. The graph is widely used as a variation in a group of applications with radar signal and medical images as an example. But there is one defect that can be adjusted brightness immediately after being processed. This is due to the frequency runway and its flatness of the equivalence in the graph. This strategy is increasing contrast in many images, especially when data represents the image of an image at a contiguous value of contrast. Figure 2.4 The modification works on the distribution of intensity on the graph to be accurate, and this allows low local contrast. The graph is through the publication of the most common and effective intensity values. Therefore, the cumulative distribution function has an interest in computing graph equivalent. (Ali et al., 2017)as shown in the equation.

$$\mathrm{cdf}(x) = \sum_{i=1}^{x} h(i) \tag{2.1}$$

Where (x) is a gray value , (h) is histogram of image.

$$T[\text{pixel}] = \mathrm{round}\left(\left(\frac{\mathrm{cdf}(x)-\mathrm{cdf}(x)_{max}}{E*F-\mathrm{cdf}(x)_{min}}\right) * (L-1)\right) \tag{2.2}$$

Cdf(x)min is the cumulative distribution function's minimum value.

E * F: Columns and rows of images, L: Gray levels. (used =256).

Algorithm (2.1): The Histogram Equalization Algorithm
Input: Palm vein image $\boldsymbol{FGray}$ with gray levels from 0 to 255 Output: palm vein image in enhanced intensity ,$\boldsymbol{F}$Enhanced
BEGIN - Get size of $\boldsymbol{FGray}$: E* F, gray level (0 - 255) , Build a (G1 matrix) with size (256) and start with a 0. - Scanning each pixel in the image and increasing the related element of the matrix to create the image's histogram. G1 [gray-val (pixel)] = G1 [gray-val (pixel)] + 1 - Get the function of cumulative distribution, as shown in the equation (2.2). - Use the formula of general histogram equalization to calculate the new value. as shown in the equation (2.3 - Replace (original) gray values with (new) gray values to create a new Image: $ImgNew$[E][F] = T1 [$Imgold$ [E][F]] END

2.5 FEATURE EXTRACTION METHODS

Feature extraction Is an important requirement in many applications and operations that must be performed frequently In image processing and computer vision .Image retrieval, pattern recognition, object detection, machine learning and bioinformatics .Feature extraction is used to extract the special features present In a data set (image, text, audio) that are used to describe and perform the data (Salau & Jain, 2019).Steps to extract the palm vein recognition feature where the system consists of reducing the large amounts of resources that are described .Feature extraction is a technique to reduce the palm vein data set by extracting the characteristics that can be used to Identify them and extracting the palm vein from the input Image (Oloyede et al., 2020)

Intuitively, if the algorithm input data is too large for processing and it Is expected to be a lot of data and little information, then the data Is transformed into a set of representation related to the features and low (such as the feature vector) and feature extraction FE is the process of converting the input data Into a set of features.

Features .Approach when you use feature extraction correctly, this process extracts basic information from the Input data to complete the discrimination operations by using a little representation of the data instead of using a huge amount of information.

Pattern recognition Is one of the important fields In the future in image processing sciences, face recognition, bank deposit, reading postal address, extracting data from checks, identifying people, document authentication, registration, data entry and text recognition, signature recognition.

The main goal of patterns is to take the input and assign It correctly to the potential output class, and the class recognition, characterization of objects, and recognition of people must be strong enough to prevent the creation of symbols for the same object.

Features can be divided Into two categories: (Kumar & Bhatia, 2014)

a. Local features: These features are generally geometric (number of end points, joints, concave and convex parts)

b. Global features: which are usually statistical (fixed moments) or topological .Focusing on feature extraction Is of great importance because it has a noticeable Impact on the effectiveness and strength of recognition systems .Linear discriminant analysis (LDA) has been studied in machine learning, statistics and pattern recognition in a wide range as LDA can be considered as a distinct file in Fisher Linear FLD as it is designed to work best to extract distinct features from two or more layers .Its implementation of LDA was kept in a small Image database to overcome the limitations of PCA and was accomplished by projecting an image onto the vein space via PCA. A pure procedure was done to classify the LDA data of face vector files in the best implicit space to distinguish between classes. (Singh et al., 2012).

In addition, LDA was compared with the LDA feature area to determine the autolysis associated with the appropriate matrix, given all data first .LDA features should be updated incrementally by selecting incoming samples .LDA requires joint implementation and early submission of all samples .When all data and Inputs are not available, this data Is classified as a stream .LDA feature extraction must be able to extract LDA features rather than executing an algorithm on whole data.

In addition, LDA can be used in a range of studies such as text recognition, face recognition, bioinformatics, and other recognition methods.

LDA orientation determination reduces high-dimensionality speaker vectors of many classes to the feature space of low vectors, allowing the feature to successfully separate separations of vectors from other vectors from feature vectors .As In (C.-N. Li et al., 2021)(Lahaw et al., 2018)

$$\mu_{cj} = \frac{1}{N_j} \sum_{k=1}^{N_j} X_k \tag{2.3}$$

$$\mu = \frac{1}{M} \sum_{i=1}^{M} X_K \tag{2.4}$$

$$S_B = \sum_{j=1}^{c} \left(\mu_{C_j} - \mu\right) \left(\mu_{c_j} - \mu\right)^T \tag{2.5}$$

$$S_W = \sum_{j=1}^{c} \sum_{k=1}^{N_j} \left(\chi_{k_j} - \mu_{C_j}\right) \left(\chi_{k_j} - \mu_{C_j}\right)^T \tag{2.6}$$

Where (μ) is overall mean,(M) a set of all Palm images,and μCj is the mean,of classCj . By increasing,between-class scatter "SB" and,decreasing the within-class,scatter "SW", the target of LDA is discover ('Wopt')) an optimal, projection. W is the optimal projection,which,satisfies,the equation:

$$W = S_W^{-1} S_B \tag{2.7}$$

$$W_{opt} = \arg\max_w \left|\frac{WTSBW}{WTSWW}\right| \tag{2.8}$$

Eigenvectors and engine, value of $W = S_W^{-1} S_B$ S B must be,solved to,complete optimization. For palm vein projection, we employed a first K eingenvectors in the collection, All the LDA step are detailed in Algorithm:

Algorithm(2.2): Linear Discriminant Analysis LDA

Input: Palm vein image

Output :feature Vector

Begin

- Read palm vein image
- Using Equation (2.3), find average value for each classes
- Calculate the total, mean to all dataset, Using equation (2.4)
- Using equation (2.4) To get the between-class matrix SB (M×M).
- Using Equation (2.6) to get the within -class matrix SW (M×M).
- In Equation (2.7), also known as Fisher's criterion, is used to calculate the transformation matrix (W) of the LDA approach.

- The Eigen values (λ) are calculated, as well as the Eigen vectors (V) of W.
- Sorting eigenvalues by their corresponding Eigen values in decrement order. As a lower-dimensional space Vk, the first (k) Eigen vectors are used.
- As in Equation (2.8), apply each original sample (X) to the LDA's lower dimensional space.
- Return the feature vectors

END

2.6 MACHINE LEARNING

Machine learning is one of the most widely used technologies. The Internet has changed people's lives and the way they run their businesses over the course of a century and a half, while predictive analytics and machine learning have transformed society once again by turning data into positive predictions . (Bhavitha et al., 2017)

Machine learning is the study of automated systems for learning to make accurate predictions based on previous observations, broadly defined as any computing process based on logical and binary operations that learns from a set of situations. The point of machine learning is to classify expressions basic enough for human understanding. Where the machine must be simulated with human thinking in order to make a decision.

ML is a way of designing computer systems to learn and gain experience automatically.

One of the most basic applications of machine learning is data mining. While researching or in some situations trying to build relationships between different features. And since humans are prone to error in solving some problems, machine learning has been successfully applied to these problems, and this led to the improvement of the machine's design and the increase in the efficiency of the system. The same feature set was used to represent each instance in a data set used by the device using learning techniques

There are three types of features: intermittent, binary and continuous.

These technologies can be classified into three main types

Moderated, Unsupervised, and Enhanced.(Goh et al., 2021)

a. ML Supervised

A method for learning the function of training data, consisting of pairs of inputs (sometimes vectors) and desired outputs. The output of the function A can be a continuous value (regression) You can predict the entry of the class (which is called class) with the classification. After seeing questions about training, the supervised learner must predict a function value for each of the input objects. In classification and regression, learning uses examples called X and Y to predict their relationship.

b. Unsupervised learning algorithms, which do not require data to be named by the expert, unlike supervised learning algorithms. Unsupervised learning algorithms take opaque features from the input data and classify them using rules they have taught themselves without human intervention, which is why we often use these models to identify unknown and hidden relationships in the data. It is a difficult process where data is left unlabeled in order to identify their distributions.

c. Reinforcement Learning: Reinforcement learning uses algorithms only training data to detect if it is true or false, unlike supervised learning which uses labeled data. Where this type is trained using supervised learning and instead of having a large set of classified data, which interacts with the environment and through this interaction it is positively or negatively met, and this reinforces the behavior of the system by providing it with the name. Exploration and exploitation are phrases that are often mentioned in these algorithms to refer to work that produces the greatest reward**.**

2.6.1 Machine Learning Algorithms

Classification of machine learning algorithms is very important when it comes to pattern recognition systems, identifying a shape and belonging to any category. The main objective of classification is to assign models to previously unknown classes based on descriptions as parameters. In the classification process, a crossover is selected, where one section is used for selection and sections N-1 for training with each iteration. There is a set of prediction algorithms and machine learning classifications as shown in Figure(2.3) . We will include a few of them in this section in detail.

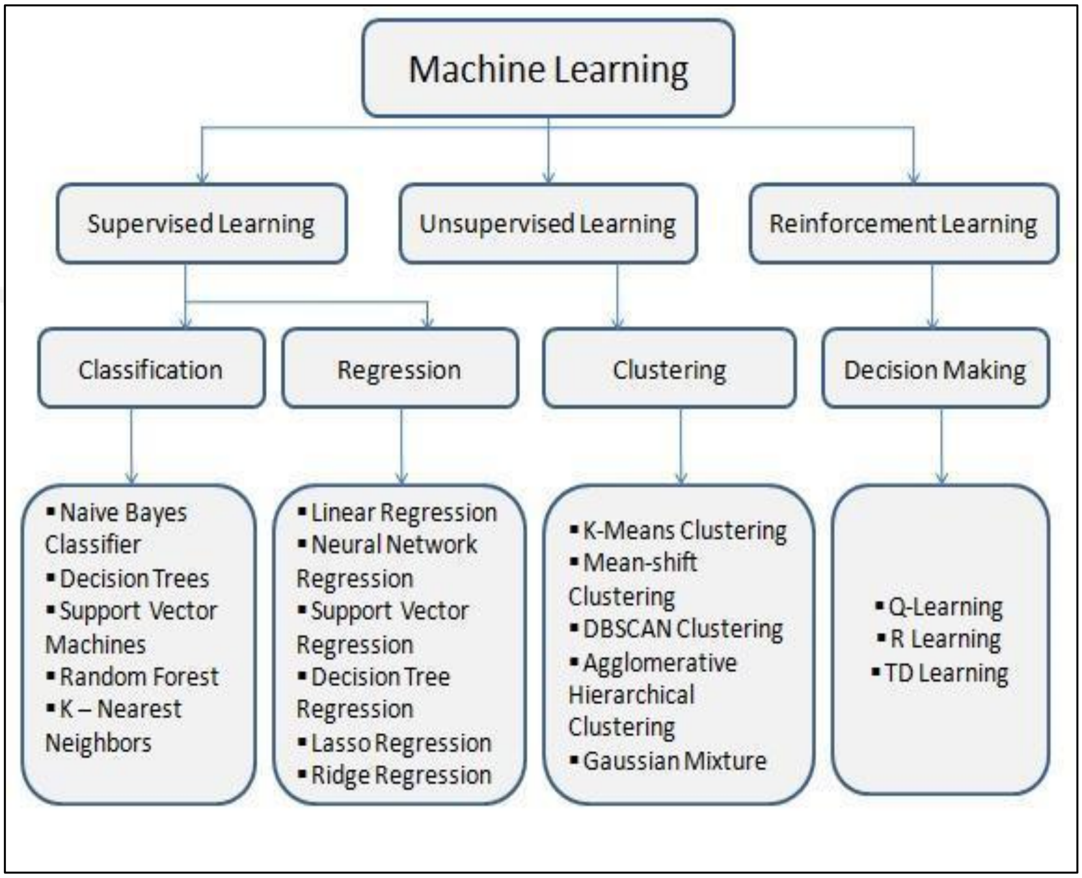


Figure 2.3: Type of machine learning

i. Naiva Bayes Classifier

A classifier that arises from a set of possibilities by calculating the frequency and combinations of values for a set of data. The Naiva Bayes classification is a probabilistic model that uses common probability classes and terms to estimate the probabilities of the Naiva Bayes classes.

The measurable features are independent. It calculates the class probability and the conditional probability distribution for a particular class based on the feature values using the values of standard probability distribution methods for the purpose of knowing the characteristic values of training and the relative frequencies of different classes. (Sen et al., 2020)

Its importance is that it separates the evaluation of one feature from the evaluation of the features of the rest. Bayes classifiers assign the most likely class by its feature vector to a specific example and have been shown to be effective in a range of applications such as text classification, system performance management, and medical diagnostics.

We will present the work of this classification as follows:

Give the probability P (Cn) for each class C n training set and show the prior probability of classifying the trait V j into C n and that the classification used is to find this as shown in the equation:

$$\frac{P(v_1 \wedge v_2 \ldots\ldots v_l | c_n) P(c_n)}{P(v_1 \wedge v_2 \ldots \ldots . v_l | c_n)} \tag{2.9}$$

The purpose of classification is to determine the best type of image. The algorithm shows the work of this type

Algorithm (2.3) Naive Bayes (NB)
Input: Read the daraset Out put:the accuracy of NB (evaluation matrices)
BEGIN - Split the data set into two parts: training and research. - P(Ci) = For every class in the training set, calculate frequency and probability. - P(Fi) = Using classlable, calculate frequency and likelihood for every feature in the entire dataset. - For every Fi in the Feature Set - BFi= get the probability value for a feature from the training set (Fi) - Bfi (C) = calculate the probability (C) - Apply equation (2.10) - Next Fi

- Class = class that has the maximal posterior probabilities..
- Return evaluation matrices

END

ii. K-Nearest Neighbour KNN:

It is one of the most common learning algorithms for pattern recognition, as it is considered one of the supervised algorithms. But the KNN is weak and lazy because there is no training phase, but it performs well when all the data have the same scale. Because of the ease of use of KNN, this made it one of the most popular classification tools in file number requests. When classifying a sample S i as an example, the searches start with the neighbors K using the vector feature for a certain distance and then the algorithm will vote on the neighbors based on their labels where the sample object will be classified into a group with the neighbors of the same classification (Aziz et al., 2020).

In the KNN algorithm, a set of distance measures is used, the best of which are:

Euclidean $$D(p,q) = \sqrt{\sum_{i=1}^{k}((p_i - q_i))^2} \tag{2.10}$$

Manhattan $$D(p,q) = \sum_{i=1}^{k}|p_i - q_i| \tag{2.11}$$

P,q vector space, the algorithm show KNN classifier.

Algorithm (2.*4*) of KNN (K_Nearest Nieghbour)
Input :feature vector, initialize the,(K) **Out put**: evaluation matrices of KNN
BEGIN - Choose the nearest-neighbor sample K - Calculate distance between sample in testing set, Using training equation. - Choose K that are nearest.

- Calculate the max value based on this class.
- Locate class label.
- Return evaluation matrices.

END

iii. Random forest (RF)

It is an easy supervised learning method in which a forest of trees is built for forecasting and decision making. In order to choose the best random subsets of features, the FL algorithm creates a file with a large number of trees (Tasneem et al., 2021) and in this case the trees are as columns. The name random forest is a term referring to decision trees whose nodes are defined in a pre-processing stage. The best feature in the random set is chosen after many trees have been built, so a random forest is formed for these trees used in classifying the new samples based on the input vectors. There are many benefits to using the random forest algorithm

i. Classification and regression task.

ii.The ability to deal with missing values.

iii. Dealing with big data that has high dimensions. (Shah et al., 2020), and we will explain the idea through the following figure:

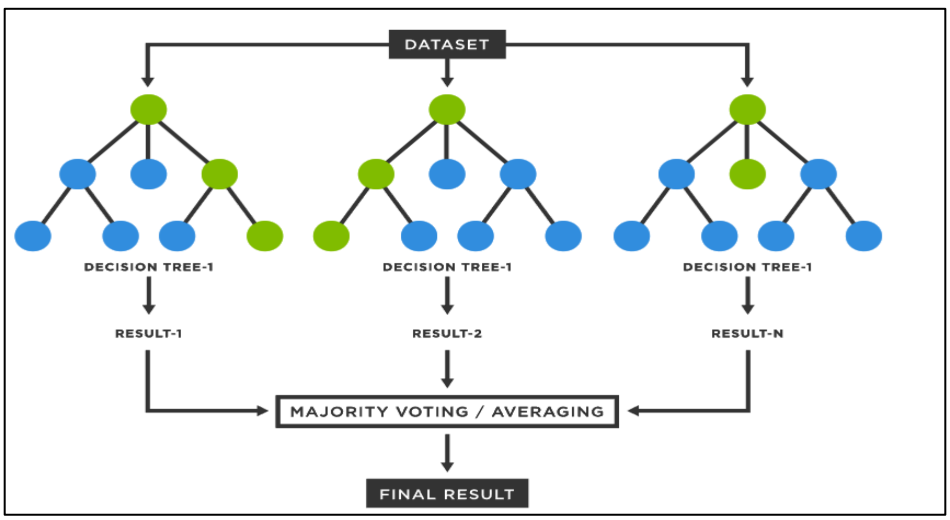


Figure 2.4: Random forest

That algorithm show the steps of Random Forest classifier

Algorithm (2.5) of Random Forest
Input: Feature Vectors **Out put:** Evaluation matrices
BEGIN - Select feature K randomly from a total of feature (m). - Compute the node (n) from (K) features by best-split point. - Split the node from daughter by using best-split. - Repeat step 1 - 3 until reach (I) the number of node reach. - Make a forest by repeating steps 1 to 4 for a (n) number of times, resulting in a (n) number of trees. - Define the class label. - Return Evaluation matrices END

iv. Decision Tree

lt is a technique that can be used to solve regression and classification problems and it is a more supervised technique to solve classification problems as it is classified in the form of a tree, the inner nodes represent the features of the data set, the branches are the databases while each sheet represents the result.

ln a decision tree there are two nodes, the decision node and the leaf node. Where the decision contract is used to make any decision and contains multiple branches, while the paper contract considers the results of those decisions and does not have any other branches. lt is called the decision tree because it is like any other tree that starts from the root and branches off to the branches to form what looks like the original tree.

ln a decision tree, it starts to predict the category of the given data set, where the algorithm starts from the root nodes of the tree. Then the algorithm again compares the attribute value with the attribute value of the child nodes and moves further until it reaches the sheets.(Somvanshi et al., 2016)

2.7ARTIFICIAL NEURAL NETWORK

This network consists of inputs, a hidden layer or more of neurons that are in the form of nodes or units, often a layer, two, or even three. And a final layer of the resulting neurons is linked by lines of communication associated with a number called (weight), and by adjusting these weights, learning takes place in the neural network. (Ayşe & Berberler, 2017) (Negnevitsky & Intelligence, 2005)Figure (2.3) show architecture of ANN.

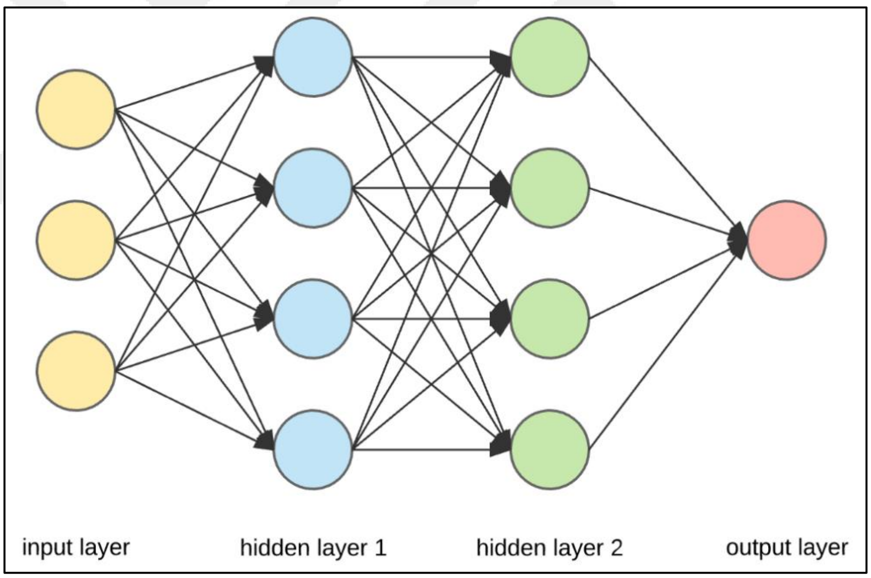


Figure 2.5: Architecture of ANN

It can also be defined as a programmed system to model what happens in the human brain. They can be classified according to the learning method of the network and are classified into three categories:

a. Supervised Learning: It is the process of giving the values assumed to be obtained in the outputs of the network in response to the sample data given to the inputs in the network training, meaning that the input data of the network is matched with the output data obtained from these inputs where the outputs of the problem are learned.

In supervised learning, it attempts to reduce the difference between the results obtained and the expected results, where the difference is accepted as the error rate, and the test is done continuously to reduce this rate and obtain the required accuracy. Figure 2 shows the structure of this type.

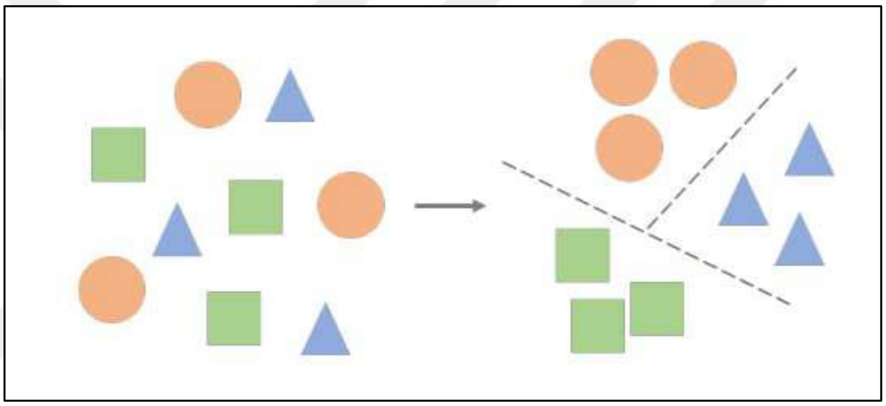


Figure 2.6: Structure of supervised ANN classifier

b. Unsupervised learning: Examples are given to the neural learner, which represents the input, as the network learns the data samples given to it on its own, which represents the input and obtains the output values. That is why in this learning algorithm the classification is done according to certain attributes using uncertain data.(Elmas, 2003) figure (2.5) architecture of unsupervised learning.

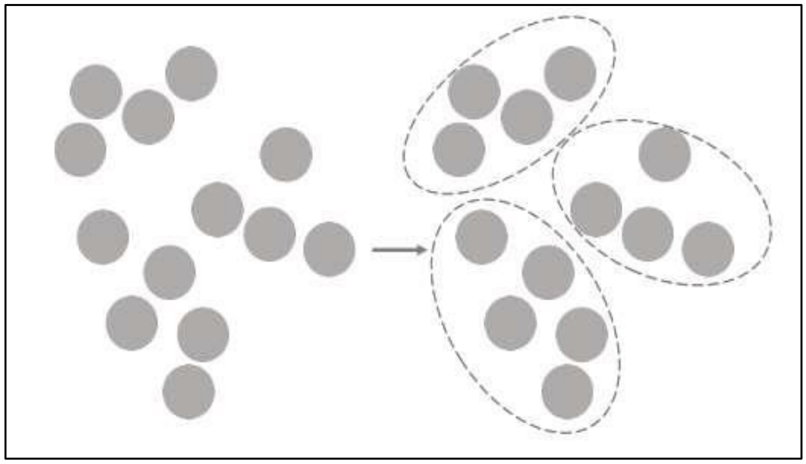


Figure 2.7: Architecture of unsupervised learning

c. Reinforcement Learning: In this type a different structure is used than supervised and unsupervised learning in which learning is by trial and error and follows up on feedback from the agent's experiences and actions.(Elmas, 2003) That is, in this learning, the corresponding inputs and output values are not provided, nor are they given to the network directly. Figure (2-6) show architecture of this type.

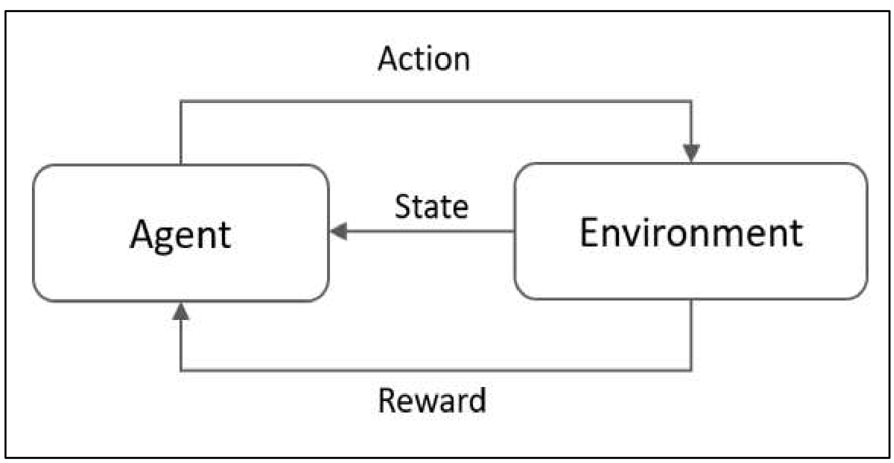


Figure 2.8: Architecture of Reinforcement Learning

2.8 PERFORMANCE MEASURE

Several metrics can be used in the system and are designed for evaluating system performance

a. Precision: It is the result of dividing the number of true positives by an integer number of positive cases and false positives (for example, the model defines accurately as positive but in fact negative, such as people who are classified as criminals but they are not), as the ratio of the true positive to the sum of expectations is known as Precision. It is expressed mathematically as:

$$Precision = \frac{TP}{TP+FP} \tag{2.12}$$

TP: True Positive

FP: False Positive

b. Recall: The ability to determine the relevance of each example in the data set, describing the percentage of data points that the model claims are actually relevant. The ratio of the number of correct predictions and correct observations is expressed mathematically:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2.13}$$

TP: True Positive

FN: False Negative

c. F-measure: Is the weighted cross-sectional average of accuracy and recall. When and This rating scale is when the data set is unbalanced. The F measure is used to evaluate the performance of the model if the stratified distribution is unbalanced. As a more serious note, the higher the F-measurement value, the better the results. Mathematically:

$$\text{F}_1 = \frac{1}{\frac{1}{\text{Recall}}+\frac{1}{\text{Precision}}} = 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{2.14}$$

d. Accuracy: The ratio of correct predictions to the total observations known to be accurate. The accuracy of the model is best if and only if we have a similar data set that the values of FP and FN are approximately equal. Accuracy in many unbalanced data sets is not the best measurement, so F-measure will be better. The precision can be expressed mathematically as:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{2.15}$$

TN: True Negative

FP: False Positive

3. THE PROPOSED SYSTEM DESIGN

3.1 INTRODUCTION

In this chapter, a comprehensive description of the palm vein recognition system is presented with the steps that were followed in the description scheme and all the processes used in this system in addition to the algorithms and description of each step.

3.2 SUGGESTED SYSTEM DESIGN

The process of classifying images at the present time is extremely important and is more prevalent in the field of security and discrimination. Where the process of classifying the pictures of the palm veins of people is one of the important processes of discrimination and security in our time because of the fame it has gained and the guarantee that it is not tampered with.

And because the design process is important because it shows how the system works and explains exactly the processes and steps involved, it does not show the result.

The Identification System classifies people based on their palm veins, which are known and important biometric features.

Chart (3.1) explains the scheme of the system for identifying people through the image of the palm vein.

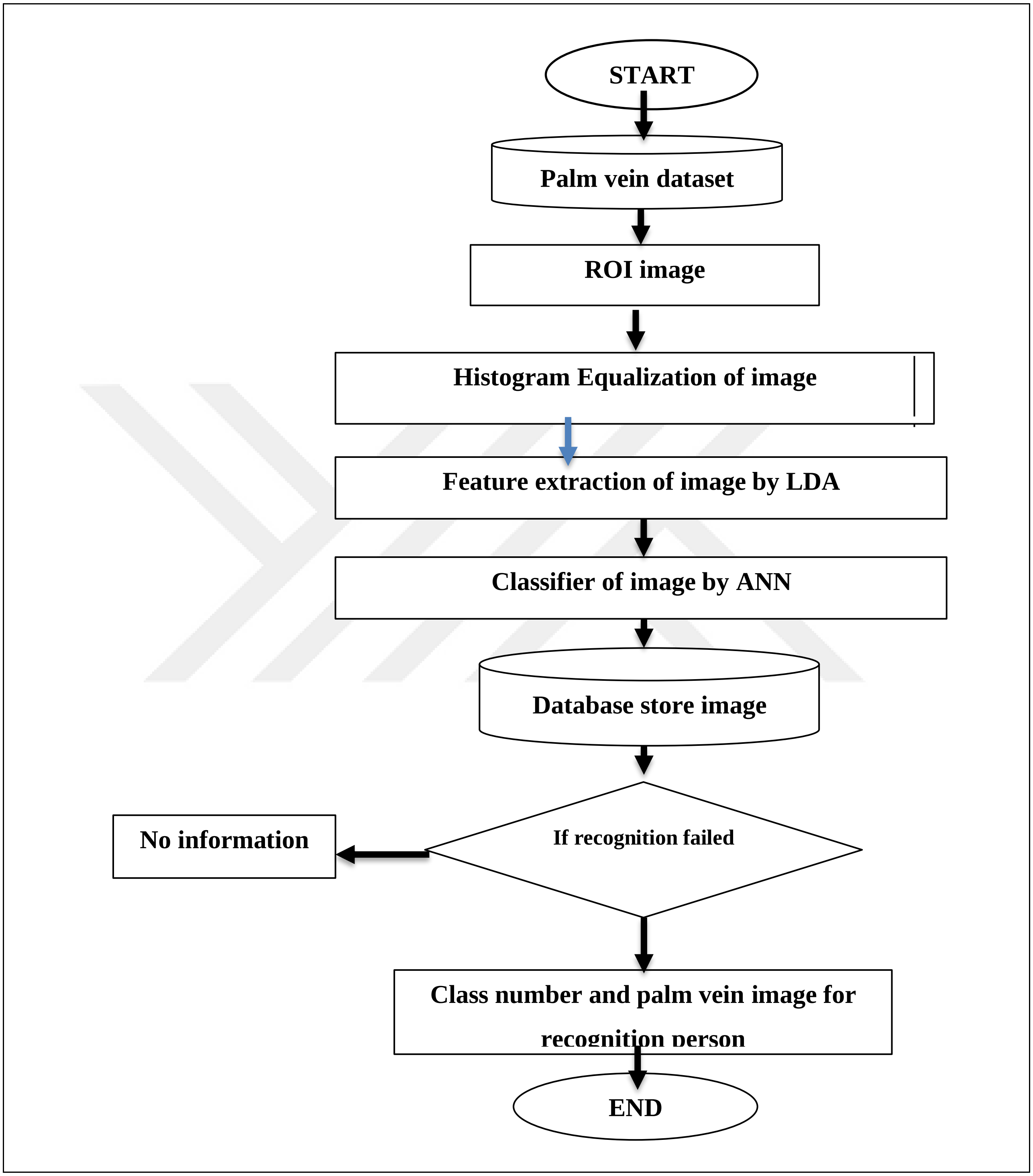


Chart 3.1: Explains the scheme of the system

3.3 SUGGESTED METHODOLOGY

The proposed methodology includes four parts, which are as follows: data preparation, pre-processing, feature extraction, classification and feature extraction.

Part one:

It includes collecting and dividing data for examination and training, as the database of palm vein images consists of 300 people, and each person has 10 samples. We collected all 10 photos of the palm in one file, and so on for the rest of the other 299 samples.

Part two:

Includes finding the region of interest and making a histogram equalization to increase the clarity of the image and distribute the intensity of whiteness on the image.

Part three:

Feature extraction palm vein image by using LDA algorithm.

Part four:

Classification palm vein image by artificial neural network.

3.3.1 Region of Interest

The ROI is extracted by defining the alignment points shown in Figure 5 and since there are geometric transformations it is necessary to align the palm images.

It is done by finding the coordinates for each image in a suitable manner, where the ROI can be cropped from the original image based on these coordinates. The ROI finding algorithm is taken from Which has been applied for contact-based handprinting.

Looking at the palm image, We find the boundaries of the gaps of the two fingers (the gap between the index finger and the middle finger and the gap between the ring finger and the little finger) and is referred to as X 1 and X 2, and the space between them is the x-axis of the coordinate system. The point between X1 and X2 is referred to as O and is considered the point of origin. Then a line is drawn from the origin perpendicular to the line X 1 and X 2 representing the Y axis where c1 X1 X2 is determined parallel to the X axis and away from O. It is assumed that this line intersects with the palm groin at points O1 and O2, then a square area with sides C 2 O1 O2 is drawn, symmetrical with the axis C3 O1 O2 away from the x-axis. It is cropped to get a square area of size N * N.

The Region of interest palm vein image shown in figure (3.1)

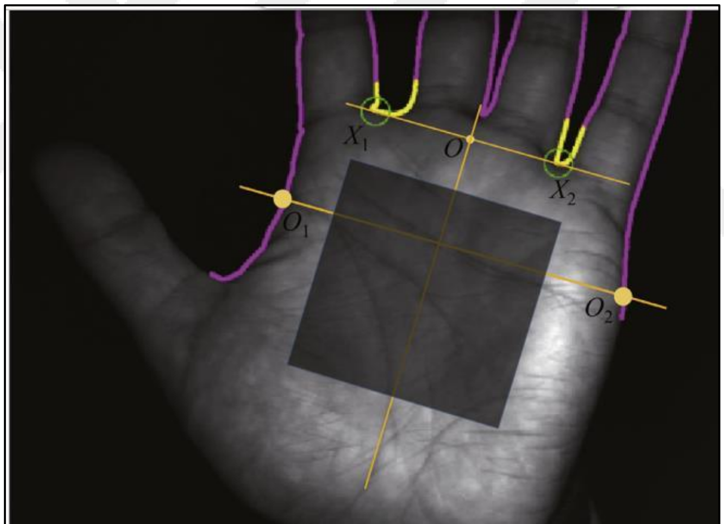


Fig. 5. Illustration for the proposed ROI extraction approach.

Figure 3.1: Illustration for proposed ROI extraction

Algorithm (3.1) ROI extraction from a contactless palmprint image
Input: A palmprint image **output: The ROI sub-image R**
BEGIN - Low-pass filter I using a Gaussian filter and then convert it to a binary image B; - From B, extract boundaries of two finger gaps (as illustrated in Fig. (3-1)). - Get the tangent line of the gap boundaries and the tangent points are X1 and X2; - X1X2 is taken as the X-axis and the midpoint of X1X2 is taken as the origin O; - A line passing through O and perpendicular to X-axis is the Y-axis; - A line being c1|X1X2| far away from O and parallel to X-axis intersects the palm contour at passing O1 and O2; - A square region S of side length c2|O1O2|, being symmetric with respect to Y-axis and c2|O1O2| far away from X-axis is extracted; - S is normalized to the size N × N and the result is taken as R END

3.3.2 Histogram Equalization

It is a technique for correcting the distribution of gray levels in the image and thus correcting the histogram based on transforming the cumulative distribution function and thus increasing the general contrast of the image. For example, in the figure() the gray areas are distributed excessively within the palm region, and the contrast is at a low level that prevents the clarification of the veins, so extracting the features will be very difficult, so we used the graph equation to increase the contrast and clarify the veins. Where the treatment is shown in Figure ( ), where it shows that the histogram equalization showed the variance of the veins of the palm, and this leads to showing the venous tissue, which shows more points of features.

3.4 FEATURE EXTRACTION BY LDA ALGORITHM

Feature reduction is achieved using Linear Discriminative Analysis (LDA). LDA is a popular feature reduction method as it provides well separated classes that are reliable for classification. In the second chapter, we explained the Linear Distribution Algorithm with its equations and algorithm, and the following is the result of passing the image of the palm vein with LDA equations.

a b c

Figure 3.2: Images from feature extraction stage (a) sample palm vein image from class no 1 (b) the global mean for the palm vein images (c) The LDA palm vein for image (a) that is used in classification.

3.5 CLASSIFICATION BY MACHINE LEARNING

In this part, we used machine learning to classify the palm veins and in order to show good results. After several experiments, we used three learning algorithms and we passed through them the output of images from feature extraction. These algorithms are in order:

a. Gaussian Naïve Bayes (Gaussian NB): When working with continuous data, an assumption often taken is that the continuous values associated with each class are distributed according to a normal (or Gaussian) distribution. The likelihood of the features is assumed to be

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i-\mu_{y)}}{2\sigma_y^2}\right) \quad (3.1)$$

b. Random Forest: It is considered a supervised learning method, and it is considered a fairly easy classification, and it is similar to a decision tree in the nature of its work.

c. Decision tree: It is a learning method that can be used to solve regression and classification problems, as it is classified in the form of a tree and in which the internal nodes represent the features of the data set, which is explained in the second chapter two.

3.6 CLASSIFICATION BY MLP NEURAL NETWORKS

Multilayer Perceptron (MLP) :

It is a class of fully connected frontal artificial neural network where the ANN is forward facing, or refers to the network consisting of multiple layers of cognition.(Hastie et al., 2009)

MLP consists of at least three layers of nodes: the input layer, the hidden layer, and the output layer. All ganglia are neurons that use a non-linear activation function, except for the input nodes. It works with a supervised learning method called backpropagation for training (Rosenblatt, 1961)(宮本健司, 1988) Perhaps what distinguishes MLP from the linear cognition is its multiple layers and the ability to distinguish non-linearly separable data.(Cybenko, 1989).

$$\varepsilon(n) = \frac{1}{2}\sum_j e_j^2\,(n) \quad (3.2)$$

the change in each weight by using gradient descent

$$\Delta w_{ji}(n) = -\eta \frac{\partial\varepsilon(n)}{\partial_{vj}(n)} y_i(n) \quad (3.3)$$

Where y_i is the product of the previous neuron, η the learning rate for determining weights is determined when they converge quickly without vibrations, The derivative to be computed depends on the induced local field vj It is easy to prove for the output node, since the derivative can be simplified to

$$-\frac{\partial\ \varepsilon(n)}{\partial v_j(n)} = e_j(n)\emptyset'\left(v_j(n)\right)\sum\nolimits_k -\frac{\partial \varepsilon(n)}{\partial_{vj}(n)}\omega_{kj}\,(n) \tag{3.4}$$

The change in the nodes weights depends on the$k$ nodes, which represents the output layer and which changes the weights of the hidden layer. The weights of the output layer change according to the derivative of the activation function, so it represents an inverse spread of the activation function.(Simon Haykin, n.d.) figure (3-3) show MLP.

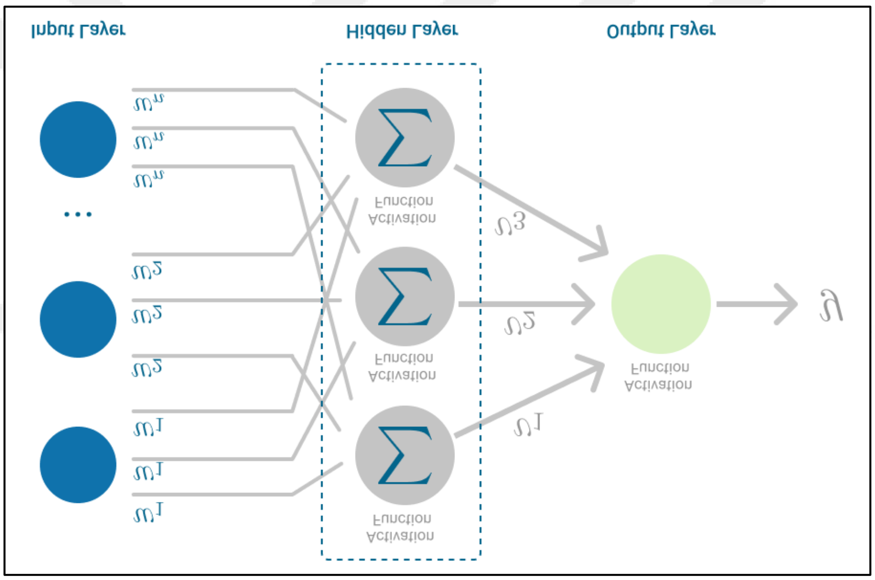


Figure 3.3: MLP of ANN

4.THE EXPERIMENTAL RESULTS AND EVALUATION

4.1 INTRODUCTION

In this chapter, the experimental results of palm vein recognition using LDA algorithm and Multilayer Perceptron classifier, which we were exposed to in the third chapter, will be presented using detailed steps that concern the image of the palm vein. But first, we will show the environment in which the program was worked and implemented from the programming language environment and the specifications of the work computer, and we will display the results of each step with pictures and tables.

4.2 DESCRIPTION OF THE SYSTEM IMPLEMENTATION ENVIRONMENT

This description is important in knowing the characteristics and features of the system and the programming languages in which it was implemented in order to take a general idea of evaluating the behavior and performance of the proposed system with a full description of the system and the work environment and the programming languages that are used to implement this system.

i. Programming language: Python 3.6 version under IDLE.
ii. Java 8 the version 8.2 under the NETBEANS IDE.
iii. The proposed system has been implemented and worked on Device

a. Dell laptop Processor Intel(R) Core(TM) i7-6820HQ CPU @ 2.70GHz 2.70 GHz.
b. Installed RAM 16.0 GB (15.9 GB usable).
c. Screen card NVIDIA Quadro M1200 8GB
d. Hard SSD 512 GB.
e. Operating system Windows 10, System type 64-bit , x64-based processor.

4.3 PALM VEIN DATA SET

In this data set was compiled by researchers Lin Zhanga, Lida Li a, Anqi Yanga , Ying Shena, Meng Yang at a School of Software Engineering in Tongji University, Collaborative Innovation Center of Intelligent New Energy Vehicle in Tongji University in China and School of Computer Science and Software Engineering in Shenzhen University, China

Using a device to obtain a fingerprint in a contactless manner. Where samples were collected from 300 people, and from each person 10 pictures of the right palm and 10 pictures of the left palm. In this study, we used only 10 images of the right palm of 300 people. figure (4-1) shows the small part of dataset.

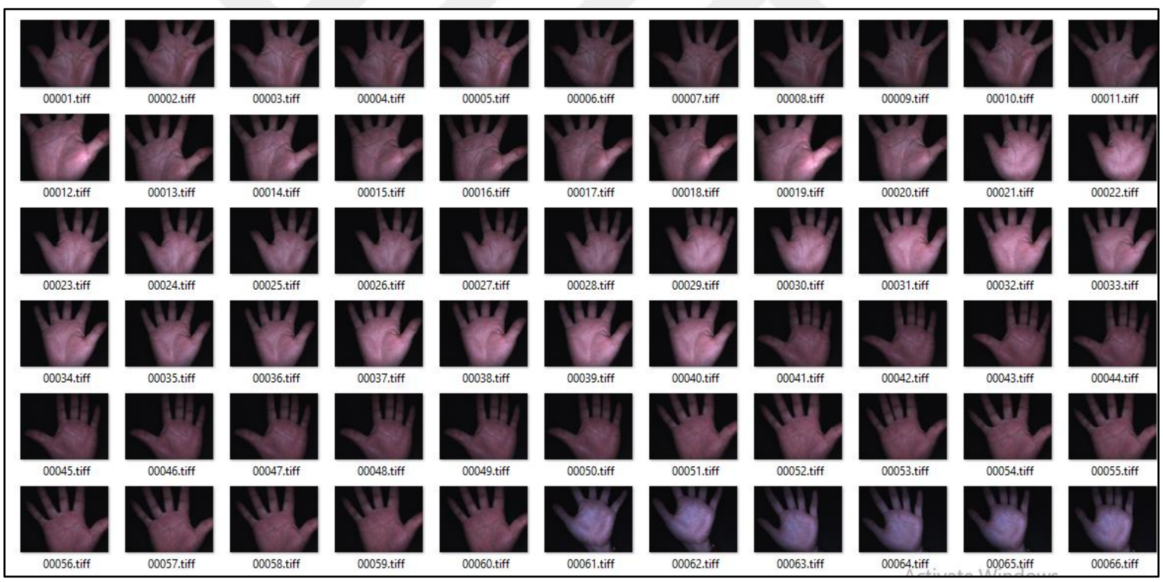


Figure 4.1: Small part of dataset

4.4 RESULT OF ROI IMAGE

Region of interest image is a way to crop an image to make its features visible and to get rid of areas we don't need. In the ROI technique, we identified points and through these points we drew a square to determine the cut part, but before that we filtered the image using gaussian low pass and then converted it to a binary image as shown in the algorithm (1-3) and the results appeared as in Figure (4- 2)

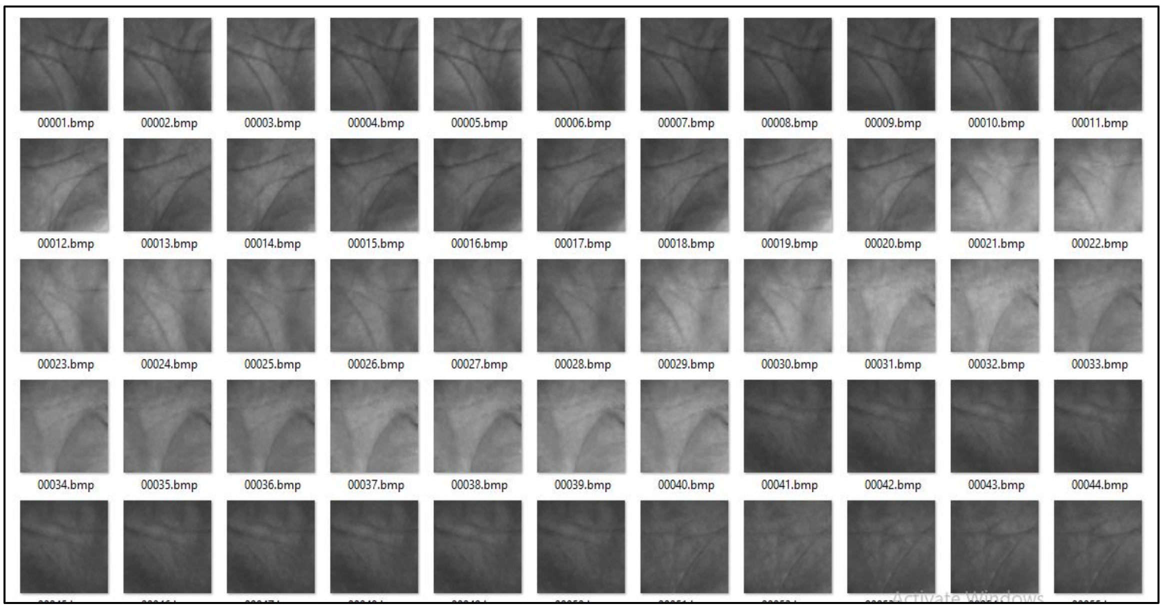
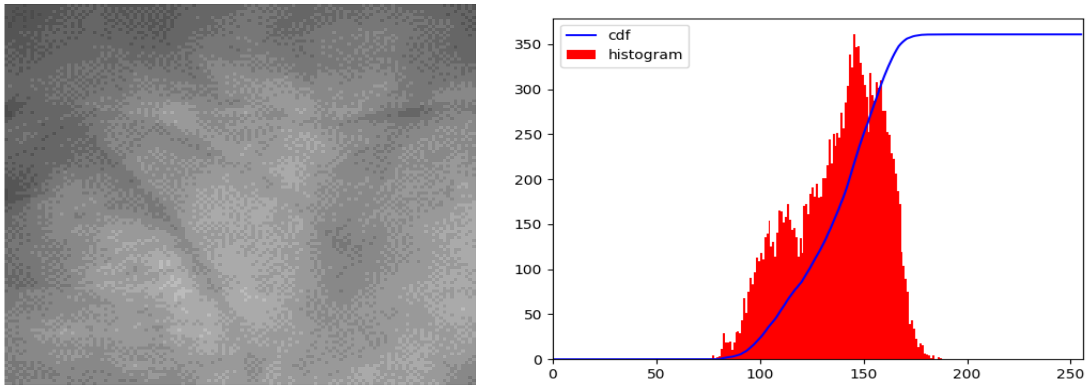


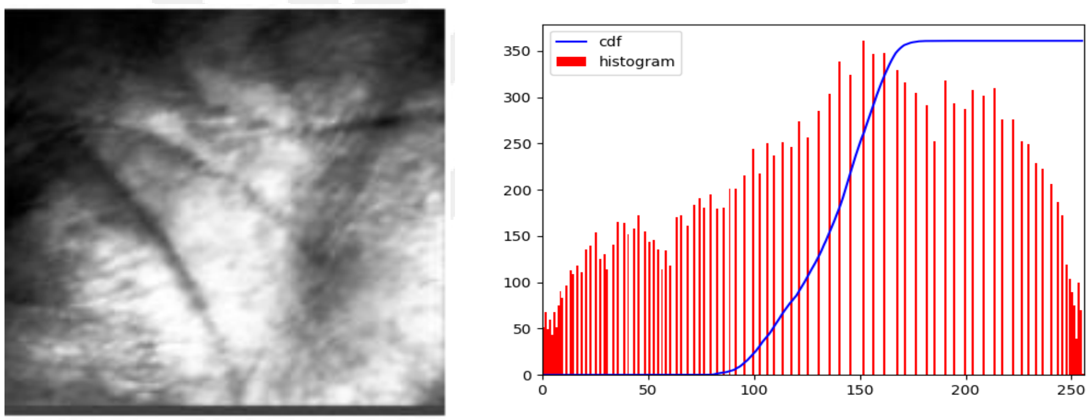
Figure 4.2: Result of region of interest of palm vein image

4.5 RESULT OF HISTOGRAM EQUALIZATION

Histogram equalization is a technique to increase the clarity of the image and highlight its features, where the histogram equation is applied to the image of the palm vein to make the image information more clear and this helps in the process of extracting features. in figure (4-3) show (a) the image before histogram equalization and (b) image after histogram equalization.



(a)



(b)

Figure 4.3: a- palm vein image before histogram equalization and histogram

b- palm vein image after histogram equalization and histogram

4.6 RESULT OF FEATURE EXTRACTION BY LINEAR DISCRIMINANT ANALYSIS LDA

The next step is feature extraction .the resulting of pre-processing of palm vein image is the input of feature extraction. We use Linear Discriminant Analysis (LDA) to feature extraction of palm vein image. The following is description of LDA shown in figure (4.4).

class	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a20	a21	a22
1	-62.6384	27.89537	58.98446	23.07678	10.2799	48.38281	43.31656	-28.6363	12.34901	-7.98344	0.292727	-14.945	37.10703	12.57012	8.211897	-1.27255	-23.5659	-62.8372	-19.0819	-15.2949	-0.99818	-39.8952
1	-63.8703	29.39899	55.49674	25.82226	10.4785	45.83264	45.14488	-24.7343	15.306	-4.5707	2.570981	-9.86358	36.44917	7.919818	12.09002	-0.70078	-23.9694	-58.3704	-14.0887	-19.5201	-3.77101	-36.419
1	-64.847	24.85396	75.43451	24.8767	11.58085	46.53754	48.77169	-24.4822	23.64599	-0.1225	-1.13786	-17.3026	38.23518	8.545657	9.389358	0.152701	-28.6137	-71.85	-26.2103	-21.0463	-8.21168	-31.935
1	-63.0718	34.64808	63.78164	25.44092	15.6184	47.97586	47.50329	-18.6267	21.44985	-7.75815	4.520903	-10.993	40.55594	6.543629	3.949506	-1.58349	-23.3615	-72.0933	-16.7776	-23.6365	-1.85197	-38.2821
1	-72.3441	29.47417	78.50908	41.85807	5.307967	53.90854	47.31924	-21.4765	22.17717	-12.9573	-2.25266	-14.7066	40.53508	10.46694	4.774183	-7.76993	-31.1372	-64.337	-29.776	-22.8873	-7.34942	-48.1155
1	-62.5387	23.80042	67.35448	30.34768	6.604989	53.19513	48.22949	-18.2835	20.4465	-12.4295	-3.98396	-11.7075	41.27584	10.88514	3.553399	-16.0313	-31.6147	-65.2482	-17.8745	-21.1639	-0.509	-43.8788
1	-67.6889	26.03334	65.65851	21.30648	6.18001	57.66455	51.39405	-34.0348	18.85018	-3.81244	0.252368	-15.6735	39.76105	6.53089	10.45583	-4.43528	-32.1835	-71.5564	-18.8838	-6.29272	-2.5598	-33.6288
1	-58.4864	19.22322	67.91192	21.94333	9.874034	55.37549	46.58618	-19.3501	16.18663	2.830317	11.77793	-10.818	43.26233	0.871792	4.082695	-1.6292	-26.9332	-74.616	-13.5374	-8.70895	-1.99354	-39.815
1	-69.8552	18.72855	61.6797	32.08595	8.877015	48.11246	46.51082	-21.954	18.78601	-9.99879	8.130538	-10.4491	43.54778	6.520342	10.71489	-4.26671	-20.6553	-64.6805	-22.8659	-20.1116	-4.7657	-27.7906
1	-72.3725	20.90956	64.20299	29.00549	4.00352	45.23652	44.72032	-20.4594	19.41384	-7.6116	8.945388	-22.4964	43.1819	4.223352	8.061397	-3.32392	-25.9112	-74.0777	-11.571	-21.1628	0.894153	-29.8993
10	28.39004	11.397	17.74922	-9.2935	-51.5646	-180.372	-66.1416	-63.1993	-198.4	55.78644	20.27144	-28.1774	19.88808	19.26077	-21.4308	-124.949	-67.4139	24.58547	-14.8683	-35.8941	-46.9513	95.43334
10	22.18472	10.96919	14.85091	-4.13801	-49.0242	-190.718	-70.0454	-63.8423	-216.289	68.25749	33.26442	-28.1449	19.87934	29.1038	-21.8984	-140.893	-65.9154	27.13725	-0.38457	-49.0865	-45.2687	94.89129
10	21.96222	-0.79833	24.7957	-5.52384	-43.2505	-197.467	-68.4639	-68.1157	-213.412	56.5526	35.88574	-26.2344	25.68954	15.43766	-29.6573	-146.034	-51.4938	36.42904	-12.5365	-48.295	-48.2331	99.21614
10	22.60865	9.209349	18.79039	-2.03494	-50.3024	-201.421	-76.7732	-66.2448	-233.517	69.97422	24.27109	-26.9122	23.83644	21.53802	-21.7327	-151.068	-68.4853	26.38391	-17.9121	-40.2785	-54.2051	95.29423
10	33.32039	7.511334	14.80953	-8.31908	-50.2472	-205.682	-72.2446	-79.8309	-233.501	80.05147	25.17334	-27.8341	21.3279	33.35931	-35.4105	-165.703	-72.5661	34.27819	-17.4229	-32.8898	-59.5615	99.10268
10	21.02568	14.72734	9.808873	-10.0051	-62.5759	-195.275	-68.5424	-64.2782	-227.189	54.88924	51.53242	-34.0249	27.90695	20.72496	-17.4857	-139.028	-71.9753	24.74075	-18.5292	-35.5458	-47.0748	86.97591
10	23.97775	4.766464	15.73358	-6.70925	-40.6274	-201.414	-77.449	-72.8518	-229.699	62.76233	18.96911	-14.6881	20.03016	19.64355	-29.2908	-162.904	-62.4793	33.98972	-20.9079	-42.3538	-53.676	98.71391
10	13.23707	11.56038	28.95771	2.593666	-43.468	-197.344	-68.04	-64.0291	-223.813	64.78725	20.21234	-27.4189	28.15421	26.33992	-17.6531	-148.588	-65.7624	36.3871	-9.22226	-34.1406	-62.2365	102.9902
10	13.08838	11.51326	18.56258	-18.727	-59.4724	-215.965	-77.4245	-74.3177	-236.171	68.12953	25.88485	-39.1668	35.34457	25.50658	-30.356	-154.646	-71.7545	28.90277	-9.70389	-41.5183	-51.4543	85.43735
10	23.86502	3.421199	21.49884	0.452615	-56.6336	-206.861	-75.6567	-64.876	-227.651	70.14214	28.7194	-20.1088	28.66623	27.44824	-20.2985	-158.608	-67.5509	38.41332	-9.80133	-44.1346	-45.1605	98.7012
100	92.07442	-21.8784	6.029401	52.50761	-2.8471	-7.83042	21.42685	-50.5546	42.79544	-40.2886	19.98287	67.44173	5.334232	-28.8697	-2.7112	4.012174	-6.1636	44.95526	-10.5575	-34.8469	-23.8002	10.04292
100	98.66603	-17.5002	15.13184	46.79498	11.32095	1.754908	18.20139	-44.6702	45.65503	-30.1662	13.52024	59.43066	-17.3983	-32.9287	-9.15618	0.991508	-2.68551	50.06723	6.244157	-42.119	-23.6567	4.986889
100	92.49415	-20.0472	19.00803	52.75724	17.88902	1.698855	18.37187	-52.0169	21.21281	-35.663	14.70516	54.96944	-4.46745	-29.7583	-14.4907	14.9689	10.05159	58.06809	1.022723	-49.2825	-9.02178	2.234239
100	75.34246	-4.78669	5.982276	48.91595	12.4956	11.51303	11.66459	-46.0475	25.02608	-24.421	9.02231	61.98857	0.376144	-22.8785	2.086123	13.93092	2.216082	39.6911	-7.63581	-41.2909	-13.7785	2.858812
100	73.25046	-22.8693	6.464124	51.88838	5.983468	4.163981	23.16374	-41.6435	17.78391	-32.5103	1.806892	46.67667	-5.18598	-21.4373	-13.9147	6.806529	-4.97793	44.54593	-0.0403	-36.8577	-7.32552	-2.93819
100	91.39563	-15.1861	8.967189	54.75519	17.26357	-4.22084	18.40447	-33.2249	35.16386	-41.6597	21.36303	61.28124	-12.1643	-26.4544	-1.38676	10.00915	3.73015	47.64849	2.310468	-54.0878	-24.2006	8.973594
100	95.49776	-19.2142	5.191835	48.86175	15.06004	-5.25835	12.66765	-55.9273	28.63354	-42.3571	7.141351	63.30063	-12.9205	-29.3578	-7.83827	16.9278	-7.97288	57.44944	-6.38143	-51.8614	0.733033	1.524027
100	88.98917	-14.1179	10.25919	44.85343	14.15507	-1.20791	28.11142	-48.6335	32.28898	-27.8315	10.29178	64.95345	-10.9232	-19.4521	-6.60652	2.047818	-7.92716	50.13441	-2.06881	-44.5126	-12.7035	5.681887

Figure 4.4: The result of LDA algorithm

4.7 RESULT OF CLASSIFICATION BY MACHINE LEARNING ALGORITHM AND MLP NEURAL NETWORK ALGORITHM

Classification is an essential feature. In this part, the result of LDA algorithm and machine learning algorithm and MLP algorithm show in table (4.1) .

Table 4.1: The excremental result

Methods	Precision	Recall	F-measure	Accuracy
Naïve Bayes +LDA	**0.99**	**0.98**	**0.98**	**0.98**
Random Forest +LDA	**0.99**	**0.99**	**0.99**	**0.99**
Decision Tree +LDA	**0.80**	**0.73**	**0.73**	**0.73**
MLP ANN +LDA	**1.00**	**1.00**	**1.00**	**1.00**

From the above table, we conclude that the best algorithm for palm vein recognition is using the Multilayer Perceptron.

4.8 PALM VEIN RECOGNITION SYSTEM IMPLEMENTATION

The execution program starts by reading the images from the database of 300 files, and inside each file 10 images of the palm vein It has to execute, which are 3000 images .the feature extraction by LDA algorithm is run and store the result in feature_lda.csv. Then we move to the implementation of the second file that performs the classification read from file feature_lda.csv then implement four algorithm that the result show in table (4.1).

5. CONCLUSIONS AND FUTURE WORK SUGGESTIONS

5.1 CONCLUSION

During the proposed work period, there are a number of conclusions that have been reached, depending on the practical reality, and they are summarized as follows:

a. Getting the image area of interest made it easy to work on the image and adjust it, especially after filtering the image.

b. Efficiency of recognition in the stage of pretreatment to get rid of defects and increase the clarity of the image in the image of the palm vein.

c. The enhanced image is much better than the original image with the degree of contrast. And the distribution of gray levels, and thus we obtained the edges and sharpness of the veins, and this helps in the next stage.

d. Also, the feature vector gives speed in decision-making and classification, which is what was adopted in this research, where the use of the LDA algorithm led to the extraction of good features of the image.

e. The machine learning classifier with LDA algorithm achieved 100% accuracy. Where LDA produced a clear contrast to the veins of the palm in the image.

f. The training time using the feature extraction algorithm achieved with three machine learning algorithm and MLP of ANN when using LDA is 5 minutes.

5.2 FUTURE CHALLENGES

The following is a set of recommendations that can be worked on and implemented in the future:

a. The proposed system can be used with another data set for the palm vein with less quality and more number.

b. The proposed system can be used to distinguish other biometrics such as iris, face and fingerprint.

c. The proposed system can be created as a mobile application and linked to the cloud.

d. Use other data sets of images in proposed system and compare the results.

REFERENCE

[1] Ahmad, F., Cheng, L.-M., & Khan, A. (2020). Lightweight and Privacy-Preserving Template Generation for Palm-Vein-Based Human Recognition. *IEEE Transactions on Information Forensics and Security*, *15*, 184–194. https://doi.org/10.1109/TIFS.2019.2917156

[2] Akbar, A. F., Wirayudha, T. A. B., & Sulistiyo, M. D. (2016). Palm vein biometric identification system using local derivative pattern. *2016 4th International Conference on Information and Communication Technology, ICoICT 2016*, 1–6. https://doi.org/10.1109/ICoICT.2016.7571956

[3] Ali, H., Lali, M. I., Nawaz, M. Z., Sharif, M., & Saleem, B. A. (2017). Symptom based automated detection of citrus diseases using color histogram and textural descriptors. *Computers and Electronics in Agriculture*, *138*, 92–104.

[4] Al-jaberi, A. S., & Al-juboori, A. M. (2021). Palm vein recognition based on convolution neural network. *Journal of Al-Qadisiyah for Computer Science and Mathematics*, *13*(3), Page-1.

[5] Anderson, R. R., & Parrish, J. A. (1981). The optics of human skin. *Journal of Investigative Dermatology*, *77*(1), 13–19. https://doi.org/10.1111/1523-1747.ep12479191

[6] Ayşe, A. R. I., & Berberler, M. E. (2017). Yapay sinir ağları ile tahmin ve sınıflandırma problemlerinin çözümü için arayüz tasarımı. *Acta Infologica*, *1*(2), 55–73.

[7] Aziz, S., Naqvi, S. Z. H., Khan, M. U., & Aslam, T. (2020). Electricity theft detection using empirical mode decomposition and K-nearest neighbors. *2020 International Conference on Emerging Trends in Smart Technologies (ICETST)*, 1–5.

[8] Babalola, F. O., Bitirim, Y., & Toygar, Ö. (2021). Palm vein recognition through fusion of texture-based and CNN-based methods. *Signal, Image and Video Processing*, *15*(3), 459–466.

[9] Bhavitha, B. K., Rodrigues, A. P., & Chiplunkar, N. N. (2017). Comparative study of machine learning techniques in sentimental analysis. *2017 International Conference on Inventive Communication and Computational Technologies (ICICCT)*, 216–221.

[10] Boubchir, L., Aberni, Y., & Daachi, B. (2018). Competitive Coding Scheme based on 2D Log-Gabor filter for Palm Vein Recognition. *2018 NASA/ESA Conference on Adaptive Hardware and Systems, AHS 2018*, 152–155. https://doi.org/10.1109/AHS.2018.8541451

[11] Cancian, P., Di Donato, G. W., Rana, V., & Santambrogio, M. D. (2017). An embedded Gabor-based palm vein recognition system. *2017 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI 2017*, 405–408. https://doi.org/10.1109/BHI.2017.7897291

[12] Cao, J., Shi, W., Salim, A., & Kilgore, P. (2016). MyPalmVein: A Palm Vein-Based Low-Cost Mobile Identification System for Wide Age Range. *Proceedings - 2016 IEEE 1st International Conference on Connected Health: Applications, Systems and Engineering Technologies, CHASE 2016*, 324–325. https://doi.org/10.1109/CHASE.2016.64

[13] Cybenko, G. (1989). Approximation by superpositions of a sigmoidal function. *Mathematics of Control, Signals and Systems*, *2*(4), 303–314.

[14] Dandawate, Y. H., & Inamdar, S. R. (2015). Fusion based Multimodal Biometric cryptosystem. *2015 International Conference on Industrial Instrumentation and Control, ICIC 2015*, 1484–1489. https://doi.org/10.1109/IIC.2015.7150984

[15] De Santis, M., Agnelli, S., Nardiello, D., & Iula, A. (2017). 3D ultrasound palm vein recognition through the centroid method for biometric purposes. *IEEE International Ultrasonics Symposium, IUS*, 1–4. https://doi.org/10.1109/ULTSYM.2017.8091946

[16] Deshpande, P. D., Tavildar, A. S., Dandwate, Y. H., & Shah, E. (2016). Fusion of dorsal palm vein and palm print modalities for higher security applications. *Conference on Advances in Signal Processing, CASP 2016*, 201–206. https://doi.org/10.1109/CASP.2016.7746165

[17] Dong, W., Ren, J., Su, Y., Wang, C., Sun, X., Zhu, Z., & Zeng, X. (2017). Research on multi-spectral adaptive method for palm vein capturing based on image quality. *Proceedings - 2017 32nd Youth Academic Annual Conference of Chinese Association of Automation, YAC 2017*, 1154–1157. https://doi.org/10.1109/YAC.2017.7967586

[18] Du, X., Zhong, D., & Shao, H. (2019). Building an active palmprint recognition system. *2019 IEEE International Conference on Image Processing (ICIP)*, 1685–1689.

[19] Elmas, Ç. (2003). *Yapay sinir ağları*.

[20] Fronitasari, D., & Gunawan, D. (2017). Palm vein recognition by using modified of local binary pattern (LBP) for extraction feature. *QiR 2017 - 2017 15th International Conference on Quality in Research (QiR): International Symposium on Electrical and Computer Engineering*, *2017-Decem*, 18–22. https://doi.org/10.1109/QIR.2017.8168444

[21] Fuksis, R., Kadikis, A., & Greitans, M. (2011). Biohashing and fusion of palmprint and palm vein biometric data. *2011 International Conference on Hand-Based Biometrics, ICHB 2011 - Proceedings*, 268–273. https://doi.org/10.1109/ICHB.2011.6094334

[22] Genovese, A., Piuri, V., Plataniotis, K. N., & Scotti, F. (2019). PalmNet: Gabor-PCA convolutional networks for touchless palmprint recognition. *IEEE Transactions on Information Forensics and Security*, *14*(12), 3160–3174.

[23] Goh, G. D., Sing, S. L., & Yeong, W. Y. (2021). A review on machine learning in 3D printing: applications, potential, and challenges. *Artificial Intelligence Review*, *54*(1), 63–94.

[24] Gonzalez, R. C., & Woods, R. E. (2018). Digital image processing, global edition. *Digital Image Processing, Global Edition*, *19*.

[25] Gupta, A., Walia, E., & Vaidya, M. (2014). Feature level fusion of palm print and fingerprint modalities using Discrete Cosine Transform. *2014 International Conference on Advances in Engineering and Technology Research, ICAETR 2014*, 1–5. https://doi.org/10.1109/ICAETR.2014.7012799

[26] Gusain, R., Jain, H., & Pratap, S. (2018). Enhancing bank security system using Face Recognition, Iris Scanner and Palm Vein Technology. *Proceedings - 2018 3rd International Conference On Internet of Things: Smart Innovation and Usages, IoT-SIU 2018*, 1–5. https://doi.org/10.1109/IoT-SIU.2018.8519850

[27] Han, W. Y., & Lee, J. C. (2012). Palm vein recognition using adaptive Gabor filter. *Expert Systems with Applications*, *39*(18), 13225–13234. https://doi.org/10.1016/j.eswa.2012.05.079

[28] Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction* (Vol. 2). Springer.

[29] Jain, A. K., Ross, A., & Prabhakar, S. (2004). An Introduction to Biometric Recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, *14*(1), 4–20. https://doi.org/10.1109/TCSVT.2003.818349

[30] Kang, W., Liu, Y., Wu, Q., & Yue, X. (2014). Contact-free palm-vein recognition based on local invariant features. *PLoS ONE*, *9*(5), e97548. https://doi.org/10.1371/journal.pone.0097548

[31] Kang, W., & Wu, Q. (2014). Contactless palm vein recognition using a mutual foreground-based local binary pattern. *IEEE Transactions on Information Forensics and Security*, *9*(11), 1974–1985. https://doi.org/10.1109/TIFS.2014.2361020

[32] Kumar, G., & Bhatia, P. K. (2014). A detailed review of feature extraction in image processing systems. *2014 Fourth International Conference on Advanced Computing & Communication Technologies*, 5–12.

[33] Ladoux, P. O., Rosenberger, C., & Dorizzi, B. (2009). Palm vein verification system based on SIFT matching. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5558 LNCS*, 1290–1298. https://doi.org/10.1007/978-3-642-01793-3_130

[34] Lahaw, Z. B., Essaidani, D., & Seddik, H. (2018). Robust face recognition approaches using PCA, ICA, LDA based on DWT, and SVM algorithms. *2018 41st International Conference on Telecommunications and Signal Processing (TSP)*, 1–5.

[35] Lee, J. C. (2012). A novel biometric system based on palm vein image. *Pattern Recognition Letters*, *33*(12), 1520–1528. https://doi.org/10.1016/j.patrec.2012.04.007

[36] Lee, Y. P. (2015). Palm vein recognition based on a modified (2D)2 LDA. *Signal, Image and Video Processing*, *9*(1), 229–242. https://doi.org/10.1007/s11760-013-0425-6

[37] Leng, L., Li, M., & Teoh, A. B. J. (2013). Conjugate 2DPalmHash code for secure palm-print-vein verification. *Proceedings of the 2013 6th International Congress on Image and Signal Processing, CISP 2013*, *3*, 1705–1710. https://doi.org/10.1109/CISP.2013.6743951

[38] Li, C.-N., Shao, Y.-H., Chen, W.-J., Wang, Z., & Deng, N.-Y. (2021). Generalized two-dimensional linear discriminant analysis with regularization. *Neural Networks*, *142*, 73–91.

[39] Li, M., Wang, H., Liu, H., & Meng, Q. (2022). Palmprint recognition based on the line feature local tri-directional patterns. *IET Biometrics*.

[40] Li, P., Miao, Z., & Wang, Z. (2014). Fusion of palmprint and palm vein images for person recognition. *International Conference on Signal Processing Proceedings, ICSP*, *2015-Janua*(October), 2407–2410. https://doi.org/10.1109/ICOSP.2014.7015426

[41] Lin, S., & Tai, Y. (2016). A combination recognition method of palmprint and palm vein based on gray surface matching. *Proceedings - 2015 8th International Congress on Image and Signal Processing, CISP 2015*, 567–571. https://doi.org/10.1109/CISP.2015.7407943

[42] Lou, J., & Wang, B. (2022). Palm Vein Recognition via Multi-task Loss Function and Attention Layer. *ArXiv Preprint ArXiv:2211.05970*.

[43] Lumini, A., & Nanni, L. (2017). Overview of the combination of biometric matchers. *Information Fusion*, *33*, 71–85. https://doi.org/10.1016/j.inffus.2016.05.003

[44] Ma, X., Jing, X., Huang, H., Cui, Y., & Mu, J. (2017). Palm vein recognition scheme based on an adaptive Gabor filter. *IET Biometrics*, *6*(5), 325–333. https://doi.org/10.1049/iet-bmt.2016.0085

[45] Michael, G. K. O., Connie, T., & Jin, A. T. B. (2010). Design and implementation of a contactless palm print and palm vein sensor. *11th International Conference on Control, Automation, Robotics and Vision, ICARCV 2010*, 1268–1273. https://doi.org/10.1109/ICARCV.2010.5707951

[46] Michael, G. K. O., Connie, T., & Teoh, A. B. J. (2012). A contactless biometric system using multiple hand features. *Journal of Visual Communication and Image Representation*, *23*(7), 1068–1084. https://doi.org/10.1016/j.jvcir.2012.07.004

[47] Mirmohamadsadeghi, L., & Drygajlo, A. (2014). Palm vein recognition with local texture patterns. *IET Biometrics*, *3*(4), 198–206. https://doi.org/10.1049/iet-bmt.2013.0041

[48] Nayar, G. R., Bhaskar, A., Satheesh, L., Kumar, P. S., & Aneesh, R. P. (2016). Personal authentication using partial palmprint and palmvein images with image quality measures. *2015 International Conference on Computing and Network Communications, CoCoNet 2015*, 191–198. https://doi.org/10.1109/CoCoNet.2015.7411186

[49] Negnevitsky, M., & Intelligence, A. (2005). A guide to intelligent systems. *Artificial Intelligence*.

[50] Nikisins, O., Eglitis, T., Pudzs, M., & Greitans, M. (2015). Algorithms for a novel touchless bimodal palm biometric system. *Proceedings of 2015 International Conference on Biometrics, ICB 2015*, 436–443. https://doi.org/10.1109/ICB.2015.7139107

[51] Oloyede, M. O., Hancke, G. P., & Myburgh, H. C. (2020). A review on face recognition systems: recent approaches and challenges. *Multimedia Tools and Applications*, *79*(37), 27891–27922.

[52] Perwira, D. Y., Agung, B. W. T., & Sulistiyo, M. D. (2014). Personal palm vein identification using principal component analysis and probabilistic neural network. *2014 International Conference on Information Technology Systems and Innovation, ICITSI 2014 - Proceedings*, 99–104. https://doi.org/10.1109/ICITSI.2014.7048245

[53] Piciucco, E., Maiorana, E., & Campisi, P. (2018). Palm vein recognition using a high dynamic range approach. *IET Biometrics*, *7*(5), 439–446. https://doi.org/10.1049/iet-bmt.2017.0192

[54] Rajalakshmi, M., & Annapurani Panaiyappan, K. (2022). A multimodal architecture using Adapt-HKFCT segmentation and feature-based chaos integrated deep neural networks (Chaos-DNN-SPOA) for contactless biometricpalm vein recognition system. *International Journal of Intelligent Systems*, *37*(3), 1846–1879.

[55] Ramalho, M., Singh, S., Correia, P. L., & Soares, L. D. (2011). Secure multi-spectral hand recognition system. *European Signal Processing Conference*, 2269–2273.

[56] Raut, S. D., & Humbe, V. T. (2016). Palm vein recognition system based on corner point detection. *2015 IEEE International WIE Conference on Electrical and Computer Engineering, WIECON-ECE 2015*, 499–502. https://doi.org/10.1109/WIECON-ECE.2015.7443978

[57] Rizki, F., Wirayuda, T. A. B., & Ramadhani, K. N. (2016). Identity recognition based on palm vein feature using two-dimensional linear discriminant analysis. *Proceedings - 2016 1st International Conference on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2016*, 21–25. https://doi.org/10.1109/ICITISEE.2016.7803041

[58] Rosenblatt, F. (1961). *Principles of neurodynamics. perceptrons and the theory of brain mechanisms*. Cornell Aeronautical Lab Inc Buffalo NY.

[59] Ruslau, M. F. V, Pratama, R. A., & Meirista, E. (2020). Edge detection of digital image with different edge types. *Journal of Physics: Conference Series, 1569*(4), 042069.

[60] Salau, A. O., & Jain, S. (2019). Feature extraction: a survey of the types, techniques, applications. *2019 International Conference on Signal Processing and Communication (ICSC)*, 158–164.

[61] Samoil, S., Lai, K., & Yanushkevich, S. N. (2014). Multispectral hand biometrics. *Proceedings - 2014 International Conference on Emerging Security Technologies, EST 2014*, 24–29. https://doi.org/10.1109/EST.2014.10

[62] Savitha, A. P., & Ramegowda. (2017). A Comparative Study of Palm Vein Feature Extraction and Classification. *Materials Today: Proceedings*, *4*(11), 11882–11887. https://doi.org/10.1016/j.matpr.2017.09.107

[63] Sen, P. C., Hajra, M., & Ghosh, M. (2020). Supervised classification algorithms in machine learning: A survey and review. In *Emerging technology in modelling and graphics* (pp. 99–111). Springer.

[64] Setiawan, H., & Yuniarno, E. M. (2018). Biometric Recognition Based on Palm Vein Image Using Learning Vector Quantization. *Proceedings of 2017 5th International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering, ICICI-BME 2017*, 95–99. https://doi.org/10.1109/ICICI-BME.2017.8537770

[65] Shah, K., Patel, H., Sanghvi, D., & Shah, M. (2020). A comparative analysis of logistic regression, random forest and KNN models for the text classification. *Augmented Human Research*, *5*(1), 1–16.

[66] Shao, H., Zhong, D., Du, X., Du, S., & Veldhuis, R. N. J. (2021). Few-shot learning for palmprint recognition via meta-Siamese network. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1–12.

[67] Sierro, A., Ferrez, P., & Roduit, P. (2015). Contact-less palm/finger vein biometrics. *Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft Fur Informatik (GI)*, *P-245*, 1–12. https://doi.org/10.1109/BIOSIG.2015.7314596

[68] Simon Haykin. (n.d.). Neural Networks– a Comprehensive Foundation. *Prentice Hall, New Jersey, 2nd Edition, 1999. ISBN 0-13-273350-1.*

[69] Singh, A., Singh, S. K., & Tiwari, S. (2012). Comparison of face recognition algorithms on dummy faces. *The International Journal of Multimedia & Its Applications*, *4*(4), 121.

[70] Solimanv, H., Mohamed, A., & Atwan, A. (2012). Feature Level Fusion of Palm Veins and Signature Biometrics. *International Journal of Video & Image …*, *12*(February), 28–39.

[71] Somvanshi, M., Chavan, P., Tambade, S., & Shinde, S. V. (2016). A review of machine learning techniques using decision tree and support vector machine. *2016 International Conference on Computing Communication Control and Automation (ICCUBEA)*, 1–7.

[72] Tasneem, T., Kabir, M. M. J., & Xu, S. (2021). Diagnosis of cardiovascular diseases using artificial intelligence techniques: A review. *International Journal of Computer Applications*, *183*(3), 1–25.

[73] Tekade, P., & Shende, P. (2018). Enhancement of Security through Fused Multimodal Biometric System. *2017 International Conference on Computing, Communication, Control and Automation, ICCUBEA 2017*, 1–5. https://doi.org/10.1109/ICCUBEA.2017.8463928

[74] Toh, K. A., Eng, H. L., Choo, Y. S., Cha, Y. L., Yau, W. Y., & Low, K. S. (2006). Identity verification through palm vein and crease texture. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *3832 LNCS*, 546–553. https://doi.org/10.1007/11608288_73

[75] Tome, P., & Marcel, S. (2015). Palm vein database and experimental framework for reproducible research. *Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft Fur Informatik (GI)*, *P-245*, 1–7. https://doi.org/10.1109/BIOSIG.2015.7314614

[76] Trabelsi, R. B., Masmoudi, A. D., & Masmoudi, D. S. (2015). A bi-modal palmvein palmprint biometric human identification based on fusing new CDSDP features. *2015 International Conference on Advances in Biomedical Engineering, ICABME 2015*, 1–4. https://doi.org/10.1109/ICABME.2015.7323236

[77] Trabelsi, S., Samai, D., Dornaika, F., Benlamoudi, A., Bensid, K., & Taleb-Ahmed, A. (2022). Efficient palmprint biometric identification systems using deep learning and feature selection methods. *Neural Computing and Applications*, 1–23.

[78] Veigas, J. P., & Kumari M, S. (2022). Deep learning approach for Touchless Palmprint Recognition based on Alexnet and Fuzzy Support Vector Machine. *International Journal of Electrical and Computer Engineering Systems*, *13*(7), 551–559.

[79] Wang, J. G., Yau, W. Y., Suwandy, A., & Sung, E. (2008). Person recognition by fusing palmprint and palm vein images based on "Laplacianpalm" representation. *Pattern Recognition*, *41*(5), 1514–1527. https://doi.org/10.1016/j.patcog.2007.10.021

[80] Wang, R., Wang, G., Chen, Z., Zeng, Z., & Wang, Y. (2014). A palm vein identification system based on Gabor wavelet features. *Neural Computing and Applications*, *24*(1), 161–168. https://doi.org/10.1007/s00521-013-1514-8

[81] Wang, Y., Li, Z., Vu, T., Nyayapathi, N., Oh, K. W., Xu, W., & Xia, J. (2018). A robust and secure palm vessel biometric sensing system based on photoacoustics. *IEEE Sensors Journal*, *18*(14), 5993–6000. https://doi.org/10.1109/JSEN.2018.2843119

[82] Wirayuda, T. A. B. (2015). Palm vein recognition based-on minutiae feature and feature matching. *Proceedings - 5th International Conference on Electrical Engineering and Informatics: Bridging the Knowledge between Academic, Industry, and Community, ICEEI 2015*, 350–355. https://doi.org/10.1109/ICEEI.2015.7352525

[83] Wu, K. S., Lee, J. C., Lo, T. M., Chang, K. C., & Chang, C. P. (2013). A secure palm vein recognition system. *Journal of Systems and Software*, *86*(11), 2870–2876. https://doi.org/10.1016/j.jss.2013.06.065

[84] Wu, X., & Zhang, D. (2006). Palm line extraction and matching for personal authentication. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, *36*(5), 978–987. https://doi.org/10.1109/TSMCA.2006.871797

[85] Y. Zhou, & A. Kumar. (2011a). Human identification using palm-vein images. *IEEE Transactions on Information Forensics and Security*, *6*(4), 1259–1274.

[86] Y. Zhou, & A. Kumar. (2011b). Human identification using palm-vein images. *IEEE Transactions on Information Forensics and Security*, *6*(4), 1259–1274.

[87] Yan, X., Deng, F., & Kang, W. (2015). Palm vein recognition based on multi-algorithm and score-level fusion. *Proceedings - 2014 7th International Symposium on Computational Intelligence and Design, ISCID 2014*, *1*, 441–444. https://doi.org/10.1109/ISCID.2014.93

[88] Yang, C., Ku, G. W., Lee, J. G., & Lee, S. H. (2020). Interval-based LDA algorithm for electrocardiograms for individual verification. *Applied Sciences (Switzerland)*, *10*(17), 6025. https://doi.org/10.3390/app10176025

[89] Yang, X., & Sun, D. (2016). Feature-level fusion of palmprint and palm vein base on canonical correlation analysis. *International Conference on Signal Processing Proceedings, ICSP*, *0*, 1353–1356. https://doi.org/10.1109/ICSP.2016.7878047

[90] Yazdani, F., & Andani, M. E. (2017). Verification based on palm vein by estimating wavelet coefficient with autoregressive model. *2nd Conference on Swarm Intelligence and Evolutionary Computation, CSIEC 2017 - Proceedings*, 118–122. https://doi.org/10.1109/CSIEC.2017.7940166

[91] Yunanto, P. E., Nugroho, H., & Budi, W. T. A. (2017). Automatic features reduction procedures in palm vein recognition. *2016 International Conference on Advanced Computer Science and Information Systems, ICACSIS 2016*, 421–426. https://doi.org/10.1109/ICACSIS.2016.7872738

[92] Zhang, L., Li, L., Yang, A., Shen, Y., & Yang, M. (2017). Towards contactless palmprint recognition: A novel device, a new benchmark, and a collaborative representation based identification approach. *Pattern Recognition*, *69*, 199–212.

[93] Zhong, D., & Zhu, J. (2019). Centralized large margin cosine loss for open-set deep palmprint recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, *30*(6), 1559–1568.

[94] Zhou, Y., & Kumar, A. (2010). Contactless palm vein identification using multiple representations. *IEEE 4th International Conference on Biometrics: Theory, Applications and Systems, BTAS 2010*, 1–6. https://doi.org/10.1109/BTAS.2010.5634470

[95] 宮本健司. (1988). David E. Rumelhart, James L. McClelland and the PDP Research Group 著," Parallel Distributed Processing Explorations in the Microstructure of Cognition", Vol. 1, Vol. 2, MIT Press, 約\7,480, 1986. 情報処理, *29*(9), 1035–1036.