Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 8s (2024)

Laplacian Kernel Ruzicka Indexive Deep Multilayer Perceptive Network For Palm Prints Detection Classification

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Article History:

***Received**: 20-04-2024*

***Revised**: 10-06-2024*

***Accepted**: 24-06-2024*

Abstract:

Palmprint is a biometric technology that involves identifying individuals based on the unique patterns and features present in their palmprints. Biometric technology is an important method to enhance security and access control through automated personal authentication. Biometric technologies includes various human traits, such as DNA, fingerprints, faces, iris patterns, palmprints, voice, signatures, and more, to perform personal authentication. Among these human traits, palmprint is an essential biometric technology, attracting significant attention in security systems. Several methods have been developed to achieve high accuracy in palmprint classification. However, challenges persist with images containing a large number of uncorrelated and redundant featuresto increase dimensionality, complicate time complexity, and reduce the accuracy.A novel method called the Laplacian Kernel Ruzicka Indexive Deep Multilayer Perceptive Network (LKRIDMPN) is introduced to enhance the accuracy of palmprint classification. The proposed palmprint identification system consists of four steps: image acquisition, preprocessing, feature extraction, and classification.During the image acquisition step, a collection of palm images is obtained from the image database. Subsequent to image acquisition, preprocessing is conducted to reduce noise and enhance image quality, thus ensuring consistency among the palm images. The Laplacian Kernel Gamma MAP filtering technique is employed to eliminate noise artifacts from the input palm image while enhancing image contrast.In the third step, the feature extraction process is carried out to minimize the time complexity of the classification process. Firstly, the Region of Interest (ROI) is extracted from the preprocessed images using the Ochiai-Barkman segmented regression method. This method helps in identifying the specific region within the image that is crucial for palmprint recognition, by assessing pixel similarity. Subsequently, a set of geometric features including principal lines, wrinkles, ridges, minutiae points, singular points, and texture features are extracted through the wavelet packet transform. These extracted features are then fed into the input layer of a deep multilayer perceptron neural network. The Ruzicka Indexive pattern matching technique is applied to analyze the extracted features with the stored templates. The Ruzicka Index score is utilized as a measure of similarity between the template and the extracted feature vector. A higher matching score indicates a stronger similarity. Classification is subsequently performed based on the matching results, leading to the palmprint recognition outcomes obtained. These results are employed to determine the individual's identity.Lastly, Powell's hybrid method is implemented to minimize the least square error, thereby enhancing the accuracy of palmprint classification at the output layer.Experimental evaluation is carried out on factors such as peak signal-to-noise ratio, palmprint detection accuracy, error rate and computational time with respect to number of images and image size.

Keywords: Palm print recognition,Laplacian kernel Gamma MAP filtering, Ochiai-Barkman segmented regression, wavelet packet transform,deep multilayer perceptive neural network,Ruzicka Indexive pattern matching, Powell's hybrid method

1. INTRODUCTION

Biometrics is a useful technology that uses physiological or behavioural characteristics of humans to authenticate users. Palmprint recognition is one of the main distinctive biometric technologies because of its abundance of features and relative stability. In security, especially in verification, a multitude of palmprint recognition techniques have been developed and implemented. Still, improving palmprint identification ability from small training sets of fingerprints is a difficult undertaking. In [1], a framework for Joint Constrained Least-Square Regression (JCLSR) was created.

In [1], a Joint Constrained Least-Square Regression (JCLSR) framework for palmprint detection using deep convolutional neural networks (DCNN) was created. The purpose of this framework was to improve palmprint recognition accuracy. Nevertheless, the time consumption performance was not substantially reduced by it. In order to recognise multispectral and contactless palmprint images, a streamlined version of the PalmNet-Gabor technique was presented in [2]. The Log-Gabor filtering approach was used in the preprocessing stage to improve the contrast of the features found on the palmprint. Nevertheless, it did not use the extensive databases for palmprint identification.

In [3], an algorithm for recognising palm prints and palm veins was created using a Principal Component Analysis (PCA) network. Yet, the peak signal-to-noise ratio was not improved by the intended approach. In order to achieve strong palmprint identification, a deep learning algorithm was implemented in [4]. Nevertheless, a higher degree of palmprint identification accuracy was not achieved by the designed method. For the purpose of automatically extracting features from palmprint photos for person recognition, the Convolutional Neural Network (CNN) was created in [5]. To improve the recognition process' accuracy, the model did not, however, take into account the filtering idea for picture denoising.

A robust feature fusion method was developed in [6] for supervised palmprint detection. The approach involved extracting robust morphological features using Principal Component Analysis (PCA). However, the designed model proved ineffective in significantly reducing the time required for palmprint detection. A generalizable deep learning-based framework was designed in [7] for recognizing the contactless palmprint based on deeply learned residual features.However, the context of large-scale contactless palmprint detection and identification was not evaluated.

A new Regularized Adversarial Domain Adaptative Hashing (R-ADAH) technique was designed in [8] for cross-domain palmprint recognition. However, it did not succeed in enhancing the verification performance. [9] created a learning complete and discriminative direction pattern (LCDDP).This technique involved the utilization of local direction features extracted from palmprint images. However, it failed to discover the more biometric recognition applications. A novel palmprint identification algorithm was developed in [10] aiming to achieve low computational complexity through the implementation of Convolutional Sparse Coding (CSC). However, it did not focus on improving the accuracy of palmprint identification.

1.1 paper contributions

The major contributions of this paper are summarized as given below,

- Pre-processing, feature extraction, and classification are just a few of the steps that have been incorporated into a LKRIDMPN approach to improve palmprint detection accuracy.
- The Laplacian kernel Gamma MAP filtering technique is integrated into the LKRIDMPN approach for palmprint picture noise reduction and contrast enhancement in order to improve the peak signal-to-noise ratio.
- The Region of Interest (ROI) in the image is extracted using the Ochiai-Barkman segmented regression approach, which reduces processing time. In order to break down the image and extract the feature vectors, the wavelet packet transform is then applied.
- To enhance accuracy, a deep multilayer perceptron neural network has been introduced, incorporating Ruzicka Index-based pattern matching and Powell's hybrid method. The Ruzicka Index is utilized for comparing the feature vectors, where a higher score indicates better matched results. Powell's hybrid method is employed to minimize the classification error associated with palmprint recognition.
- Finally, extensive simulations are conducted to estimate the performance of the LKRIDMPN technique and other related works.

1.1 outline of paper:

The arrangement of the paper is as follows: Section 2 offers a summary of relevant literature. An algorithm and a block diagram are used to accompany the detailed description of the suggested LKRIDMPN palmprint identification technique in Section 3. In addition to a thorough quantitative analysis and comparison, the experimental data are presented in Section 4. Finally, the paper is concluded in Section 5.

2. RELATED WORKS

AFixed Key point extraction (FIKEN) method was developed in [11] for palmprint characterization and recognition. But it failed to perform a pre-processing step that makes the higher recognition accuracy.

A meta-Siamese network (MSN) was developed in [12] for small-sample palmprint recognition.However, the recognition scenario was not improved by adding semantic palmprint information to the network. The goal of [13] was to improve heterogeneous palmprint recognition by developing a concurrent method for learning and recording heterogeneous palmprint information. However, this approach did not improve the accuracy of face recognition.In [14], a heuristic approach to palmprint recognition was presented with the objective of obtaining three different kinds of palmprint features. However, it did not investigate other kinds of manually created features to enhance palmprint recognition performance even further.

In [14], a heuristic method for palmprint detection was presented, emphasising the feature extraction of three different types. The other kinds of hand-crafted characteristics, on the other hand, that improve palmprint recognition performance were overlooked. In order to recognise palmprints, a brand-new technique called Joint Pixel and Feature Alignment (JPFA) using adaptive features was presented in [15]. But the technique didn't make palmprint identification any simpler or more effective.

In [16], a brand-new multimodal palmprint technique was created that combines the left and right palmprints via feature-level fusion. On the other hand, the palmprint recognition time complexity of this method is larger. In [17], a non-invertible palmprint template matching method was presented. However, this method did not investigate a number of computational geometry-based palmprint features that could improve recognition rates and lower mistake rates. In [18], BIT—a transform feature extractor with biological inspiration—was introduced for palmprint identification. This transformation, however, requires a lot of computing power.

A multimodal palmprint biometric system was developed in [19] by integrating both left and right palmprint images. This integration aimed to achieve an optimal recognition rate. However, this system utilized a relatively minimal dataset for its evaluation.A new deep-learning method was designed in [20] to extract principal lines and categorize palmprint phenotypes from palmprint images. However, the higher accuracy of the recognition was not achieved.

3. PROPOSAL METHODOLOGY

Biometrics is the use of computing techniques to human behavioural and physiological analysis in order to improve information security via personal authentication. The principal aim of biometrics is to reliably identify people through their unique characteristics. Diverse techniques have been devised to utilise distinct features of the human anatomy for accurate picture identification, such as hand-based biometrics and ear, face, gait, and posture biometrics. This work focusses on palmprint recognition utilising the LKRIDMPN approach for individual identification. To achieve accurate identification recognition, this technique involves several stages: feature extraction, image denoising, and final matching.

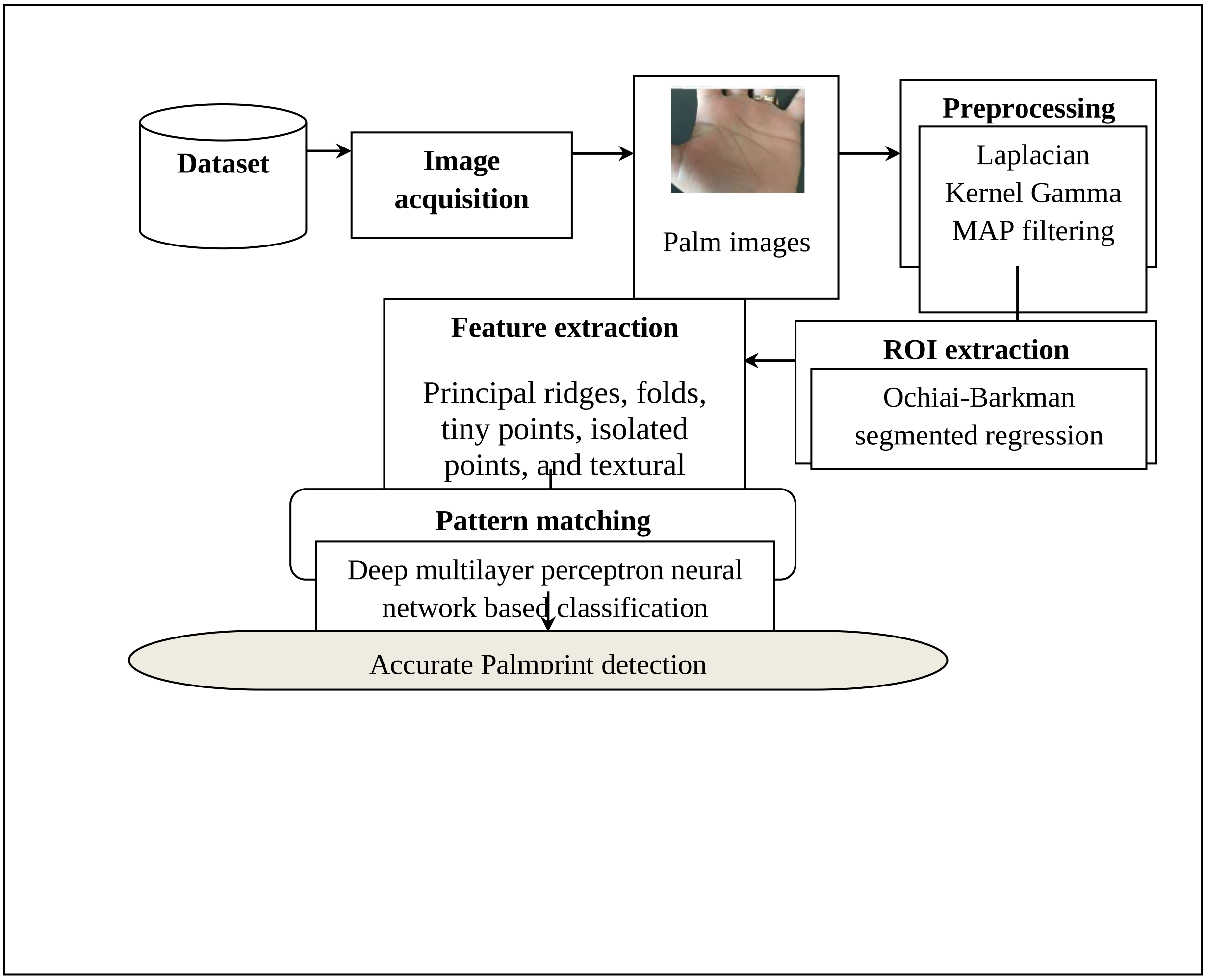

Figure 1 architecture of the LKRIDMPN method

The architecture diagram of the LKRIDMPN technique, which consists of four primary stages for palmprint detection and classification, is shown in Figure 1. A series of palm pictures, designated as $PI_1, PI_2, PI_3, \ldots., PI_n$, is taken from the dataset, as the figure illustrates. Laplacian Kernel Gamma MAP filtering is used for image preprocessing after image acquisition to improve image quality by removing noise. In the second step, Ochiai-Barkman segmented regression is used to extract the ROI (Region of Interest). Then, different features are retrieved, including primary lines, ridges, wrinkles, minutiae points, unique points, and textural features. Using the pre-stored templates and the extracted features, pattern matching is finally carried out. The LKRIDMPN method's unique procedures are explained in detail in the following subsections.

3.1 Laplacian Kernel Gamma MAP filtering based image preprocessing

Image preprocessing is a fundamental step in image analysis that involves applying filtering techniques to enhance the quality of an image before the processing. The mainobjective of image preprocessing is to improve the accuracy and efficiency of recognition and feature extraction. In the context of the LKRIDMPN method, the image preprocessing step involves the application of Laplacian Kernel Gamma MAP filtering to the collected palm images. This technique helps to enhance image quality by reducing noise.

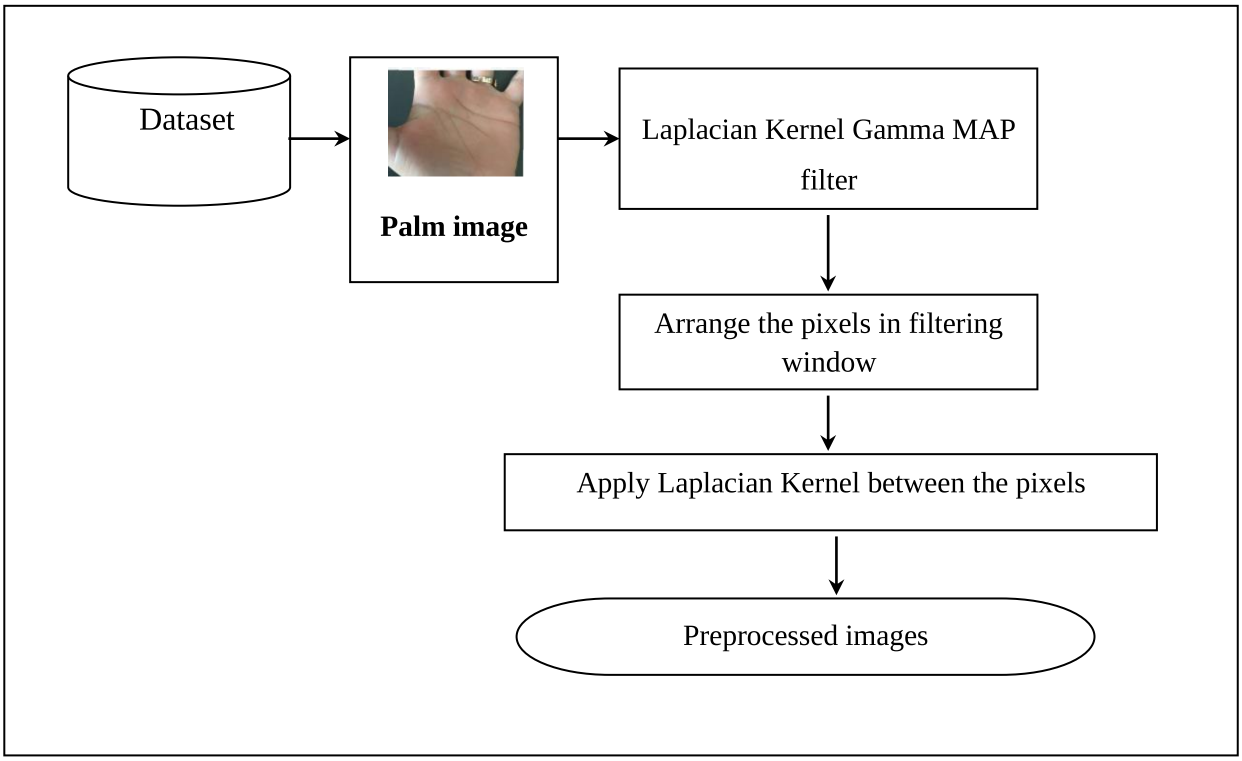

Figure 2 Structure of Laplacian Kernel Gamma MAP filtering -based preprocessing model

From the above figure 2, process of Laplacian Kernel Gamma MAP filtering is illustrated and obtain the quality enhanced image. Let us consider the sample palm image 'PI' with which pixels$Z_{1,}Z_2, Z_3, \dots Z_m$ are extracted from the image.

Z_{11}	Z_{12}	Z_{13}
Z_{21}	$Z_{i,j}$	Z_{23}
Z_{31}	Z_{32}	Z_{33}

Figure 3. 3×3 square neighborhood Window

The 3x3 filtering window with the picture pixels arranged according to rows (i) and columns (j) is shown in Figure 3. The values of the centre pixel are taken and the numbers of pixels are organised in ascending order. The centre pixel is determined by taking the average of these two pixels if there are any even neighbourhood pixels.

The Laplacian kernel function is used to represent the Gamma MAP Filter's output, which measures the probability between the pixels.

The Laplacian kernel function is formulated as follows,

$$L(Z_{ij}, m) = exp\left(\frac{|Z_{ij}-m|}{\vartheta}\right) \quad (1)$$

Where, $L(Z_c, Z_{nn})$indicates a Laplacian kernel function, Z_{ij} denotes a pixels in filtering window, m denotes a mean, ϑ denotes a standard deviation. From the analysis, the pixels that deviated from the local mean value is filtered. Finally, the quality improved images are obtained for increasing the brain tumor detection accuracy. The algorithm of Laplacian Kernel Gamma MAP filtering based image denoising is illustrated as follows,

Algorithm 1 : Laplacian Kernel Gamma MAP filtering based image preprocessing
Input: Dataset, Number of palm images $PI_1, PI_2, PI_3, \dots, PI_n$ **Output:** preprocessed image
Begin **Step 1:Collect number of** palm images $PI_1, PI_2, PI_3, \dots, PI_n$ **from dataset** **Step 2:For each** input palm image (PI_i) **Step 3:** Arrange the pixels in an filter window **Step 4:** Compute the maximum likelihood using (1) **Step 5:** **Find noisy pixels using** **Step 6:** Remove noisy pixels **Step 7:End for** **Step 8:** **Return (preprocessed image)** **End**

Algorithm 1 outlines the image denoising process aimed at enhancing the image quality. The initial step involves collecting the palm images from the dataset. Subsequently, the image pixels are organized within a filtering window.The likelihood between the pixels and the mean value is estimated using the Laplacian Kernel. Pixels that significantly deviate from this mean value are identified as noisy and consequently removed from the image. As a result, the algorithm produces enhanced image quality.

3.2 ROI (Region of Interest) extraction is performed using Ochiai-Barkman segmented regression

The extraction of the Region of Interest (ROI) involves identifying and separating particular areas within a palm image for further analysis. ROI extraction plays a vital role in reducing computational time and improving the efficiency of palmprint detection. Ochiai-Barkman segmented regression is a machine learning technique to segment theROI from the input palm image by measuring the relationship between the pixels.

The ROI extraction is performed using pixel-level segmentation. Let us consider the number of pixels in an palm images$Z_{1,} Z_2, Z_3, \dots Z_m$. The similarity between the pixels is measured as given below. Ochiai-Barkman coefficient is applied for measuring the similarity between as given below,

$$Q\ (PI_i, PI_j)\ = \frac{|Z_i \cap Z_j|}{\sqrt{\sum Z_i{}^2}\sqrt{\sum Z_j{}^2}} \quad (2)$$

Where, Q denotes an Ochiai-Barkman similarity coefficient, $\cap$ denotes a mutual dependence between the two pixels, $\sum Z_i{}^2$ symbolizes a squared score of Z_i, $\sqrt{\sum Z_j{}^2}$ denotes a signifies a squared score of Z_j. Based on the similarity measure, similar pixels are identified and extract the region of interest. As a result, the central part of the palm images is extracted with bounding box.

Followed by different features such as Principal lines, wrinkles, ridges, minutiae points, singular points, and texture features are extracted from the ROI. First, ROI of the palm images are decomposed into multi-scale wavelet sub-images using Wavelet Packet Transform (WPT).

TheWPTis types of discrete wavelet transform by allowing more flexible decomposition of the image into different subbands. It provides a richer representation of the feature content.

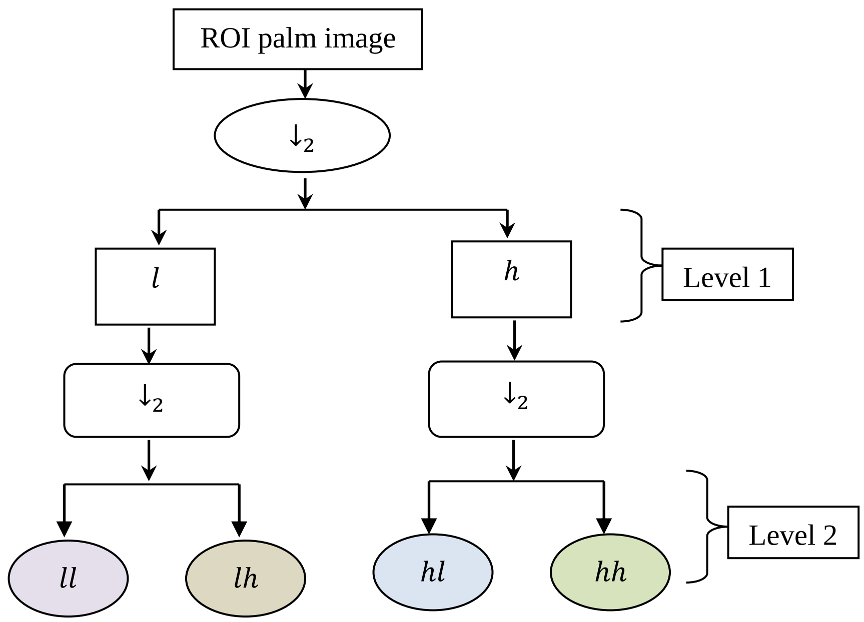

Figure 4 process of Wavelet Packet Transform

Figure 4 depicts the image decomposition using wavelet packet transform. The wavelet transformation process is expressed as follows,

$\omega\ (t) = \sqrt{2}\sum_{k=0}^{M} l_k\, \omega_n(2t-k)$(3)

$\omega\ (t) = \sqrt{2}\sum_{k=0}^{M} h_k\, \omega_n(2t-k)$(4)

Where, l_k and $h_k$are low-pass and high-pass filters coefficients of length M, $\omega\ (t)$indicates the wavelet transform.In the level 1 transformation, the input ROI image are decomposed into two levels namely low (l) and high(h). In the second level transformation, each block is applied to the downsampling by two (i.e.$\downarrow_2$) and creates the four sub-blocksll_1, lh_2, hl_1, hh_2. The same process is applied to each block and generates the next sub-blocks. After the wavelet sub-blocks are generated, the mean of each block is calculated as follows.

$$\mu_j = \frac{1}{uv} \sum_{x=1}^{u} \sum_{y=1}^{v} g\ (x, y) \quad (5)$$

Where, μ_j denotes a mean of block 'j' , $g\ (x, y)$ indicates a gray value of the pixel point (x, y) of the block,

Then the wavelet sub blocks are normalizedthat changes the range of pixel values into a consistent range. The normalization (N) is performed based on maxima of the image.

$$N = \frac{\mu_j - \mu_{j_{(mn)}}}{\mu_{j_{(mn)}} - \mu_{j_{(mx)}}} \quad (6)$$

Where, $\mu_{j_{(mx)}}$and$\mu_{j_{(mn)}}$denotes a maximal and minimal value of the mean of the block.

The featurevectors of each block 'F_j' is represented as follows,

$$F_j = [PL_j, L_j, MP_j, SP_j, T_j] \quad (7) \quad \text{Where, } j = 1,2, ..M$$

Where, $PL_j, L_j, MP_j, SP_j, T_j$ denotes a Principal lines, wrinkles, ridges, minutiae points, singular points, and texture features respectively. Finally, the feature vectors of each waveletsub-blocks are combined into a vector, called thepalmprint feature vector.

$$PFV = \sum_{i=1}^{M} [F_j] \quad (8)$$

Where, PFV denotes a palmprint feature vector. Extracting the featuresis used for distinguishing one person's palmprint from another's. Algorithm of Ochiai-Barkman Wavelet transformed regression based feature extraction is given below,

// Algorithm 2 : Ochiai-Barkman Wavelet transformed regression based feature extraction
Input: Dataset, Number of palm images $\boldsymbol{PI_1, PI_2, PI_3, \dots, PI_n}$ **Output:** Extracted palm features
Begin **Step 1: For each**preprocessedpalm image ($\boldsymbol{PI_i}$) **Step 2:** Measure the similarity between pixels using (2) **Step 3:**Segment the ROI **Step 4: end for** **Step 5: For each ROI** **Step 6:**Apply transformation using (3) (4) **Step 7:**Decompose ROI into sub-blocks **Step 8:For each** sub-blocks

Step 9:	Compute mean value '$\boldsymbol{\mu_j}$'
Step 10:	Perform normalization using **(6)**
Step 11:	Form feature vector for each block using **(7)**
Step 12:	Combine block feature vector into palmprint feature vector using (8)
Step 13:	**End for**
End	

Algorithm 2 outlines the process of minimizing time complexity in palmprint recognition through efficient ROI extraction and feature extraction. The algorithm begins with preprocessed images as input. Next, it quantifies pixel similarities to perform ROI segmentation using Ochiai-Barkman segmented regression. This provides distinct regions of interest within the images.Once the ROIs are extracted, the algorithm applies wavelet packet transform to decompose each ROI into multiple sub-blocks. For each sub-block, the mean value is computed as a representative feature. Subsequently, normalization is executed to standardize the feature values. At this point, individual feature vectors are generated for each sub-block.Finally, these feature vectors are combined to create a complete palmprint feature vector. This vector summarizes the distinctive information from all the sub-blocks within the ROI. This approach to feature extraction ensures efficient palmprint recognition by minimizing computational time.

3.3 Ruzicka Indexive Deep multilayer perceptron neural network based palmprint detection

Upon extracting the palmprint features, classification is performed using deep multilayer perceptron neural network.A deep multilayer perceptron is a type of artificial neural network architecture that consists of multiple hidden layers between the input and output layers. The term deep refers to the presence of multiple hidden layers, allowing the network to learn features. Each layer consists of multiple neurons (also known as units or nodes) that perform computations on the input data. The main advantage is to solve complex nonlinear problems and handles large amounts of input sampleswith lesser time.

This network comprises multiple layers, including an input layer, hidden layers, and an output layer.The extracted palmprint feature vectors are fed into the input layer of the neural network. The layers consist of neurons like nodes are connected from one layer to successive layer. The input features vector from one layer is transformed into the next layer with different weights.

Each of these features vector is associated with a weight '$Q_1, Q_2, \dots, Q_n$' and added with bias 'B'.

$$Z(t) = [\sum_{i=1}^{n} PFV_i(t) * Q_i] + B \quad (9)$$

Where, the activity of neuron at input layer '$Z(t)$' denotes that the weighted 'Q_i' sum of the input features '$PFV_i(t)$' and add to the bias function 'B' that stored the value is '1'. Then the input is transferred into the hidden layer of the network. Two hidden layers are positioned between the input and output layers.

In the hidden layer,Ruzicka Indexis applied for perform pattern matching with the extracted feature vector and the stored templates features.

Ruzicka index is statistical technique used to measure the similarity between two features sets.

$$S_c = \frac{[PFV \cap SFV]}{\sum PFV + \sum SFV - [PFV \cap SFV]} \quad (10)$$

Where, 'S_c' denotes asimilaritycoefficient,PFV denotes a set of 'extracted feature vectortor and SFV indicates stored templates features, $PFV \cap SFV$ denotes a mutual dependence between the features vector. The coefficient (S_c) provides the output ranges between 0 and 1.

The binary step activation function is applied for validating the similaritycoefficient results.

$$A = \begin{cases} 1 \ ; & S_c > 0.5 \\ 0 \ ; & otherwise \end{cases} \quad (11)$$

The binary step activation function ' A ' provides output ' 1 ' when the similaritycoefficientresult is greater than 0.5. The activation function 'A' provides output '0'when the similaritycoefficientresult is lesser than 0.5. As a result, the output '1' indicates the two features correctly matched and output ' 0 ' indicates the two features not matched. Classification is subsequently performed based on the matching results.

In order to reduce the pattern matching error, the weight gets updated by,

$$Q_{i+1} = Q_i * \delta\left(\frac{\partial ER}{\partial Q_i}\right) \quad (12)$$

Where, Q_{i+1} denotes an updated weight, $Q_i$indicates a current weight, δindicates a learning rate ($\delta < 1$), '$\left(\frac{\partial ER}{\partial Q_i}\right)$' denotes a partial derivative of the error 'ER' with respect to current weight 'Q_i '.This procedure is carried out repeatedly until Powell's approach determines the minimum error. Its purpose is to determine the local minimum of a function or error.

$$F = arg\, min\, ER \quad (13)$$

Where, F denotes an output of Powell's method, arg min indicates an argument of minimum function, ER denotes an error rate. Consequently, the palmprint detection outcomes are obtained at the output layer. The algorithmic process of Ruzicka Indexive Deep multilayer perceptron neural network is given below,

// Algorithm 3: Ruzicka Indexive Deep multilayer perceptron neural network
Input: Extracted relevant features **Output:** Increase the classification accuracy
Begin **Step 1: Number of** extracted features vector'PFV'taken **at the input layer** **Step 2:For each** features vector'PFV

Step 3: Assign weight **'**Q_i**'** and add bias 'B'

Step 4: Obtain the neuron activity at input layer '$Z(t)$'

Step 5:end for

Step 6:For eachextracted features vectorwithstoredfeature vector–**[hidden layer]**

Step 7: Measure the similarity using (10)

Step 8: Apply binary step activation function

Step 9:If ($F = +1$) **then**

Step 10: features correctly matched

Step 11:else

Step 12:features not matched

Step 13:End if

Step 14: For each classification results

Step 15: Measure the error rate 'ER'

Step 16: Update the weight 'Q_{i+1}'

Step 17: Find minimum error using (13)

Step 18: Obtain palprint detection results with minimum error **at the output layer**

End

Algorithm 1 outlines the process of palmprint classification and detection using the Ruzicka Indexive Deep Multilayer Perceptron neural network. The extracted feature vectors are fed into the input layer of the network. For each input, the network's weights and biases are assigned. The inputs are then transmitted to the neurons in the hidden layer.The Ruzicka index is employed to quantify the similarity between the extracted feature vectors and the pre-stored feature vector.An activation function with a binary step is applied to the computed similarity coefficient value. After assessing the similarity value, the activation function returns a value of either "1" or "0." A match of '0' indicates a mismatch in the features, whereas an output of '1' indicates an accurate match.. Following the classification, the error rate is calculated. For each output, the network's weights are updated to minimize the error. Finally, the results of palmprint detection are presented at the output layer, leading to improved accuracy.

4. EXPERIMENTAL SETTINGS

MATLAB was used to perform experimental evaluations of the proposed LKRIDMPN, the current JCLSR[1], and the condensed PalmNet-Gabor [2].Using data from https://www.kaggle.com/datasets/mahdieizadpanah/birjand-university-mobile-palmprint databasebmpd, the Birjand University Mobile Palmprint Database (BMPD) was used for these assessments. The Palmprint Database includes 1640 photos taken from 41 Iranian women's left and right hands over two sessions separated by two weeks. Participants were told to place their hands on a black background during the first session. Then, six pictures of each palm were taken in an open setting at a distance of 20 cm from the user's hand. 100–1000 pictures are taken from the database to carry out the experiments.Utilising various performance criteria, including peak signal to noise ratio, palmprint detection accuracy, error rate, and computing time, the effectiveness of suggested and current methods is examined.

4.1 Evaluates the performance of the peak signal to noise ratio

A statistic used in image processing to measure the quality difference between an original and a denoised image is the peak signal-to-noise ratio. It quantifies the potency of the noise that degrades the image quality in relation to the highest pixel value that may be achieved. The subsequent mathematical calculation is used to measure it,

, $$PSNR = 10 * log_{10}\left(\frac{(Mx\ (Z_i))^2}{mse}\right) \quad (14)$$

$$mse = [PI_o - PI_D]^2 \quad (15)$$

From the above equations (14) and (15), $PSNR$ indicates a peak signal to noise ratio, ' $Mx\ (Z_i)$' represents a maximum possible pixel value (i.e.255), mse indicates a mean square error, PI_o indicates the original sizes of input palm image, PI_D indicates de-noised palm image. The PSNR is measured in terms of decibels (dB).

Table I Results of the Peak signal to noise ratio experiment

Palmprintsize of images (MB)	**Peak signal to noise ratio (dB)**		
	LKRIDMPN	**JCLSR**	**Simplified PalmNet-Gabor**
1.15	64.60	60.17	56.08
1.44	63.02	60.52	55.26
1.42	62.55	59.50	55.66
1.26	63.02	59.83	56.53
1.53	58.02	55.46	53.64
1.68	56.53	53.01	51.48
1.55	57.76	55.87	52.56
1.86	55.87	54.87	50.51
1.84	54.87	52	49.44
1.82	53.01	51.60	48.85

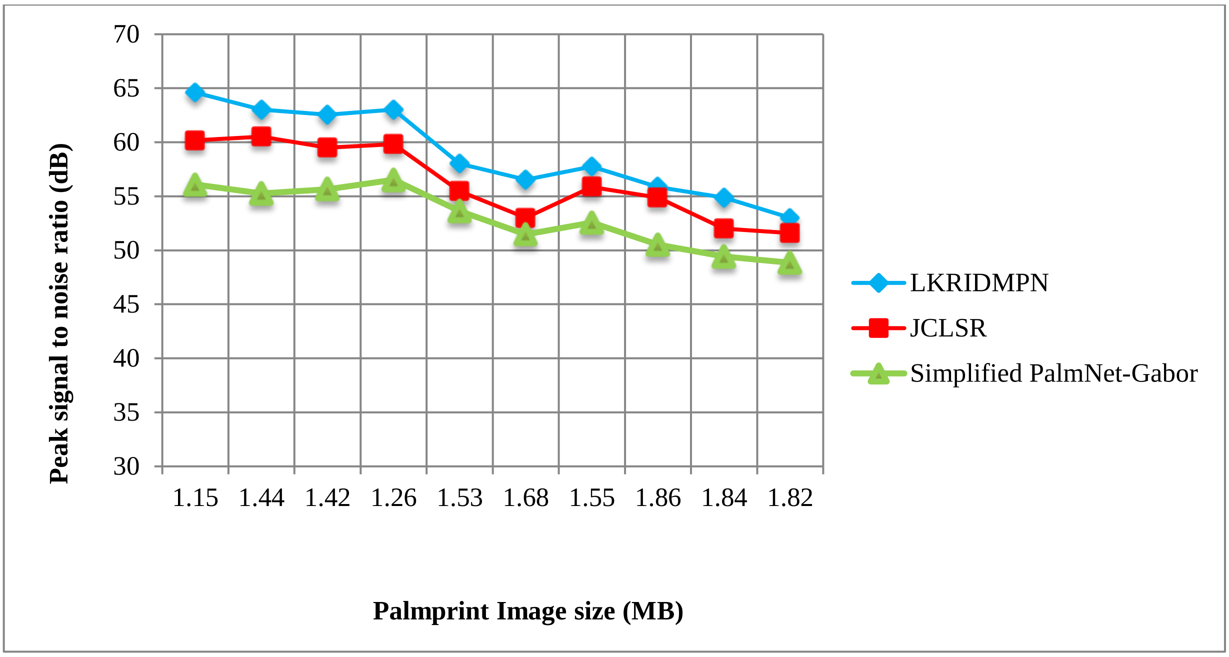

Figure.5. Peak signal to noise ratio graphically represented

The peak signal to noise ratio performance results are shown in Figure 5 as a function of input palmprint image size, expressed in kilobytes (KB). Three techniques are used to calculate PSNR: the simplified PalmNet-Gabor [2], the JCLSR [1], and LKRIDMPN. The approach with the highest PSNR performance among these three is the LKRIDMPN methodology. Laplacian Kernel Gamma MAP filtering is the means by which the LKRIDMPN approach is improved. The pixels of the image are first placed inside a filtering window. To calculate the probability between the pixels and the mean value, the Laplacian Kernel function is employed. Noise-producing pixels are those that exhibit a large deviation from the mean. As a result, the algorithm enhances image quality by filtering out the noisy pixels. The overall results indicate a 5% increase in PSNR compared to the existing JCLSR [1], and an 11% increase when compared to the simplified PalmNet-Gabor [2]

4.2 Performance analysis of Palmprint detection accuracy

The ratio of successfully identified fingerprint images to all fingerprint images is known as the accuracy of palmprint detection. Usually, this formula is used to calculate accuracy,

$$PDA = \sum_{i=1}^{n} \left(\frac{Correctly\ detected\ palmprint\ images}{PI_i} \right) * 100 \qquad (16)$$

Where, PDA indicates a palmprint detection accuracy, PI denotes a palmprint images. In terms of percentages (%), the accuracy is measured.

Table II Accurate palmprint detection outcomes of experiments

Number of palmprint images	Palmprint detection accuracy (%)		
	LKRIDMPN	JCLSR	Simplified PalmNet-Gabor
100	93	90	87
200	94.5	87.5	84
300	92.66	85	81.66
400	93.75	88.75	85
500	92.8	86	84
600	94.16	90.33	87.33
700	92.85	87.85	84.28
800	93.12	89.37	87.75
900	93.55	89.44	86.66
1000	91.1	86.5	84.1

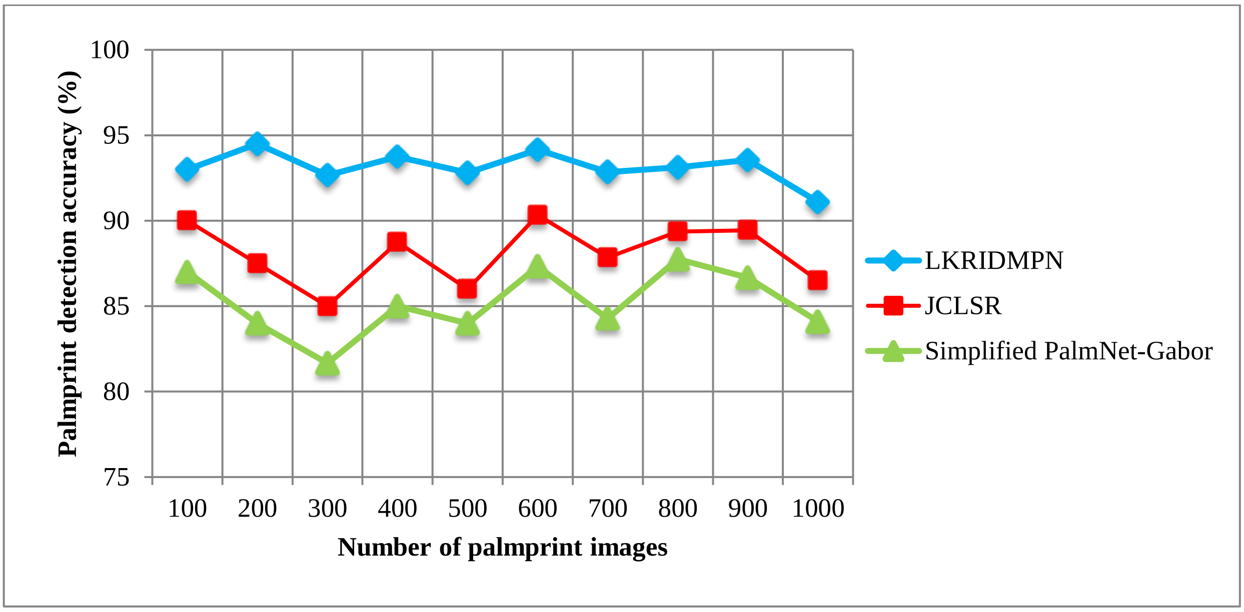

Figure 6 Graphical illustration of Palmprint detection accuracy

In Fig 6 The graphical results of palmprint detection accuracy utilising three distinct methods—LKRIDMPN, the current JCLSR [1], and the streamlined PalmNet-Gabor [2]—are shown in Figure 6. In comparison to the other approaches now in use, the graphical findings demonstrate an improvement in palmprint detection accuracy with the use of the LKRIDMPN technique. The integration of the Ruzicka Indexive Deep Multilayer Perceptron neural network for palmprint classification is what makes this improvement possible. The input layer of the network receives the extracted palmprint feature vectors. To improve the accuracy of palmprint detection, the Ruzicka index is employed to measure the degree of similarity between the extracted feature vectors and the reference feature vector that has been previously stored. The palmprint detection accuracy for the first iteration of the LKRIDMPN approach, which used 100 photos, was 93%. The application of [1] and [2] resulted in 90% and 87% palmprint detection accuracy, respectively. Every procedure underwent multiple rounds, with the final results being compared with the pre-existing findings. The palmprint detection accuracy increased by 6% and 9%, respectively, as compared to [1] and [2], according to the average of ten comparison findings for the LKRIDMPN approach.

4.3 Performance analysis of error rate

As the percentage of improperly identified palmprint photos relative to all photographs, the error rate is calculated. We use the following formula to calculate the error rate:

$$ER\_RT = \sum_{i=1}^{n} \left(\frac{Incorrectly\ detectd\ palmprint\ images}{PI_i} \right) * 100 \quad (17)$$

Where, ER_RT indicates anerror rate. The error rateis measured in terms of percentage (%).

Table III Experimental results of Error rate

Number of palmprint images	Error rate (%)		
	LKRIDMPN	JCLSR	Simplified PalmNet-Gabor
100	7	10	13
200	5.5	12.5	16
300	7.33	15	18.33
400	6.25	11.25	15
500	7.2	14	16
600	5.83	9.66	12.66
700	7.14	12.14	15.71
800	6.87	10.62	12.25
900	6.44	10.55	13.33
1000	8.9	13.5	15.9

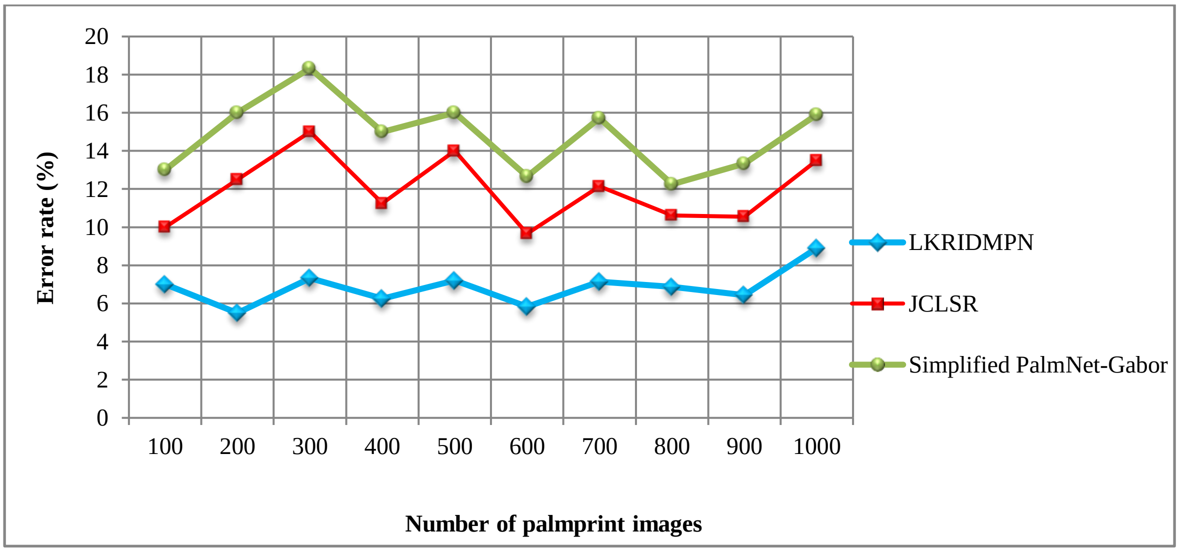

Figure 7 Graphical illustration of error rate

Figure 7 illustrates a visual comparison of the error rate performance achieved using three different techniques. The graph presents the number of input images on the 'x' axis and the corresponding error rate performance on the 'y' axis. The error rate was evaluated through three distinct techniques. The graph shows that using a Ruzicka Indexive Deep Multilayer Perceptron neural network for palmprint categorisation was the method that reduced error rate the most out of the three approaches. By using a Deep Multilayer Perceptron neural network and Powell's technique, this is accomplished. By lowering the squared disparities between the actual and anticipated classification results, this application seeks to minimise false detections. The analysis of 10 averaged results shows that the error rate performance was lower than that of the approach presented in [1] and higher than that of the method in [2], by 42% and 53%, respectively.

4.4Computational time performance analysis

Computational timeis measured as the amount of time consumed by the algorithm for palmprint detection. The overall time consumption of the algorithm is estimated as follows,

$$Comp\_T = \sum_{i=1}^{n} PI_i * T \ \ [DPI] \quad (18)$$

Where, $Comp\_T$ indicates the computational time, T indicates a time, DPI indicates detecting the single palmprint image (DPI). Milliseconds (ms) are used to measure the palmprint detection process' total computational time.

Table IV Experimental Evaluation of computational time

Number of palmprint images	Computational time (ms)		
	LKRIDMPN	JCLSR	Simplified PalmNet-Gabor
100	41	45	51
200	46	52	56
300	54	60	66
400	60	68	72
500	65	70	75
600	72	78	84
700	77	80.5	87.5
800	80	84	92
900	84.6	88.2	95.4
1000	88	92	98

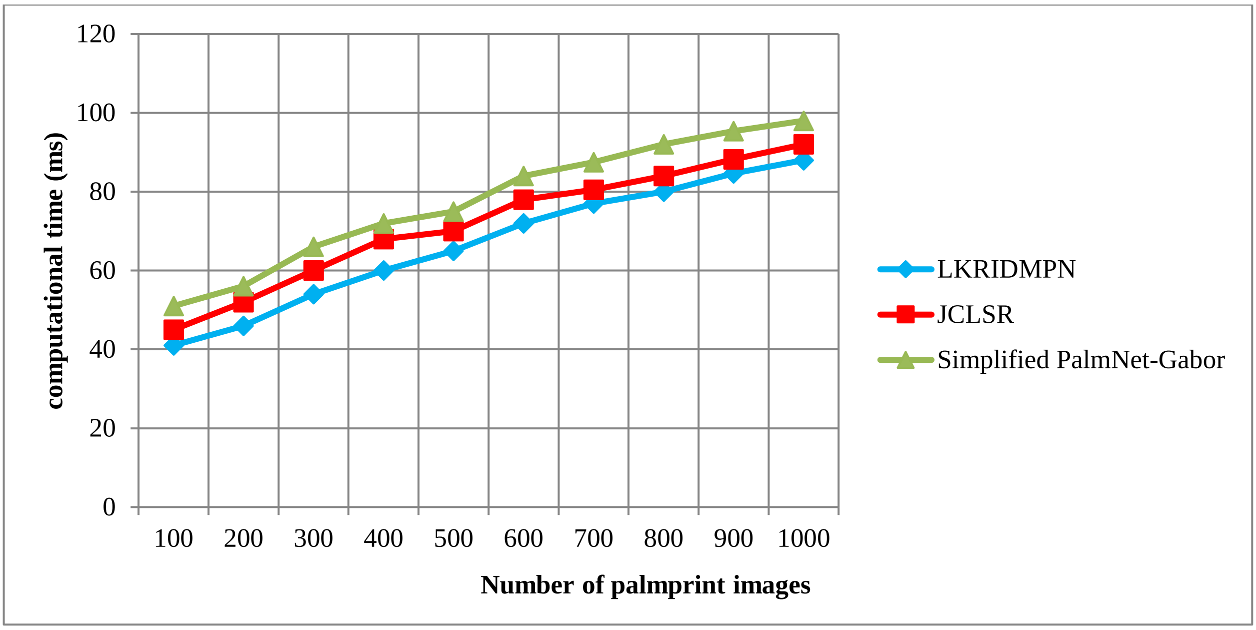

Figure 8 Graphical illustration of computational time

Figure 8 represent the performance ofexecution time and the number of palmprint images. The quantitative comparative analysis demonstrates a significant reduction in the computational time for palmprint detection compared to existing techniques. Let us consider the statistical evaluation using 100 input images. Specifically, the palmprint detection time of the LKRIDMPN method was found to be at $41ms$, whereas the other two methods [1] and [2] exhibited detection times of $45ms$and $51ms$, respectively.Similarly, various performance metrics were employed and compared. A comprehensive comparison of ten results reveals that the LKRIDMPN technique reduces computational time by 7% and 15% in comparison to [1] and [2], respectively. The merging of ROI selection and feature extraction techniques is what makes this improvement possible.The LKRIDMPN technique utilizes the Ochiai-Barkman Wavelet transformed regression to segment the ROI from the preprocessed input image. Subsequently, the wavelet packet transform is applied to decompose the image into distinct sub-blocks. Palm characteristics are retrieved from each block. Ultimately, a comprehensive set of palmprint traits for classification is formed by combining the data from each block.

5. CONCLUSION

In this work, an efficient and effective LKRIDMPN method for quick palmprint recognition is created in this work. To improve the quality of the images, the pre-processing stage of the suggested LKRIDMPN method applies denoising filtering techniques. After the Region of Interest (ROI) has been identified, the images are broken down and features are retrieved using wavelet packet transform, which reduces the amount of time needed to detect palmprints. Using the Ruzicka Indexive pattern matching method, the Ruzicka Multilayer Perceptron neural network is used for palmprint detection. Various palmprint photos of varying sizes are used to train and assess the effectiveness of the proposed LKRIDMPN methodology in comparison to existing techniques. Thorough assessments reveal that the LKRIDMPN method outperforms the current approaches in terms of accurate palmprint detection, high peak signal-to-noise ratio, shortened processing times, and lower error rates.

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