Laplacian Kernel and Deep Learning for Palmprint Classification

Sirlus Andreanto Jasman Duli[1], Bradika Almandin Wisesa[2*], Evvin Faristasari[3], Vivin Mahat Putri[4], Peprizal[5], Resma Fadila[6]
[1,3,5,6] Department of Electrical and Agricultural Industry, Bangka Belitung State Manufacturing Polytechnic, Sungailiat, 33211, Indonesia
[2,4] Department of Informatics and Business, Bangka Belitung State Manufacturing Polytechnic, Sungailiat, 33211, Indonesia

Informasi Artikel

Diterima	:	20 Mei 2025
Revisi	:	16 June 2025
Publikasi	:	20 June 2025

Kata Kunci:

Palmprint
Deep Learning
Laplacian Kernel
DMPN

ABSTRACT

Palmprint classification is a robust biometric method for personal identification due to its uniqueness and stability. This study explores the use of deep learning combined with the Laplacian Kernel and Deep Morphological Processing Network (DMPN) for palmprint classification. We trained the proposed system on a dataset of palmprint images collected from 10 participants, each contributing 10 palm images. The results demonstrated that the model achieved an accuracy of 90%, with weighted precision, recall, and F1-score all at 0.9007, indicating a well-balanced classification performance. Additionally, the model achieved a weighted precision of 0.9045, emphasizing its ability to minimize false positives. The average Equal Error Rate (EER) of 0.0917 indicates an effective balance between the false acceptance rate (FAR) and false rejection rate (FRR). The system was tested under various conditions, including different orientations, lighting, and backgrounds, demonstrating its robustness in real-world scenarios. This study also compares the results with recent palmprint classification techniques, such as deep learning, GANs, and few-shot learning, and discusses potential improvements, including incorporating multi-spectral data fusion and few-shot learning to enhance performance in real-world applications.

ABSTRACT

Palmprint classification is a robust biometric method for personal identification due to its uniqueness and stability. This study explores the use of deep learning combined with the Laplacian Kernel and Deep Morphological Processing Network (DMPN) for palmprint classification. We trained the proposed system on a dataset of palmprint images collected from 10 participants, each contributing 10 palm images. The results demonstrated that the model achieved an accuracy of 90%, with weighted precision, recall, and F1-score all at 0.9007, indicating a well-balanced classification performance. Additionally, the model achieved a weighted precision of 0.9045, emphasizing its ability to minimize false positives. The average Equal Error Rate (EER) of 0.0917 indicates an effective balance between the false acceptance rate (FAR) and false rejection rate (FRR). The system was tested under various conditions, including different orientations, lighting, and backgrounds, demonstrating its robustness in real-world scenarios. This study also compares the results with recent palmprint classification techniques, such as deep learning, GANs, and few-shot learning, and discusses potential improvements, including incorporating multi-spectral data fusion and few-shot learning to enhance performance in real-world applications.

***Penulis Koresponden**

Email: bradika@polman-babel.ac.id

IEEE citation::

S. A. J. Duli, B. A. Wisesa, E. Faristasari, V. M. Putri, Peprizal, and R. Fadila, “Laplacian Kernel and Deep Learning for Palmprint Classification,” *Journal of Artificial Intelligence and Software Engineering (J-AISE)*, vol. 5, no. 2, p. 799-806, June 2025. doi:10.30811/jaise.v5i2.6978

1. INTRODUCTION

Biometric systems have become an essential part of modern identity verification, providing a more reliable and secure alternative to traditional methods such as passwords and PIN codes. As the demand for real-time personal identity recognition rises, particularly in sectors like security, healthcare, and consumer technology, the need for efficient and accurate systems has never been more critical. Among various biometric modalities, palmprint recognition stands out due to its unique and identifiable features, including principal lines, wrinkles, and ridges. Palmprints offer a non-invasive and highly stable method that is less susceptible to environmental factors such as lighting conditions and hand positioning [1, 2].

Despite its advantages, palmprint recognition faces several challenges, particularly in real-time processing environments where both speed and accuracy are crucial. Traditional recognition techniques often rely on computationally intensive algorithms for feature extraction and matching, making them inefficient for processing large datasets or operating on devices with limited processing power, such as smartphones [3, 6]. Therefore, there is a pressing need for faster, more efficient algorithms that can deliver real-time performance without sacrificing accuracy.

In this paper, we propose a novel approach that integrates the Laplacian Kernel with Deep Multilayer Perceptive Networks (DMPN) for palmprint classification. The Laplacian Kernel is used to reduce dimensionality and extract the most relevant features from palmprint images, such as wrinkles and ridges. These features are then processed by deep learning models, which are well-suited to learn complex patterns and manage large datasets efficiently [4]. Recent studies have shown that Laplacian Kernel techniques, when combined with deep learning, significantly enhance recognition accuracy and processing speed, making them ideal for real-time applications [9, 13].

The novelty of this approach lies in the fusion of Laplacian Kernel techniques with deep learning models, leading to improved recognition accuracy, sensitivity, and processing speed. This combination makes the system highly suitable for real-time applications, such as mobile authentication and access control systems, where both speed and precision are essential. Our method aligns with recent advancements in palmprint recognition, which emphasize the importance of deep learning and feature extraction for improving the performance of biometric systems [14, 15, 16]. The proposed approach meets the growing demand for scalable, rapid, and accurate biometric systems, particularly for real-time scenarios such as security systems and personal identification [17].

Many studies have been conducted on palmprint recognition using deep learning, but the majority of them use traditional feature extraction methods that are computationally intensive or rely on single types of data that do not handle real-world changes well. Furthermore, few studies have combined dimensionality reduction techniques, such as the Laplacian Kernel, with optimized deep learning architectures, such as Deep Morphological Processing Networks (DMPN), for real-time analysis. This study seeks to close this gap by proposing a novel approach that combines the Laplacian Kernel and DMPN to improve the accuracy and efficiency of palmprint recognition, particularly for resource-constrained devices.

2. RESEARCH METHOD

This section outlines the methodology employed in the development of a palmprint classification system using Laplacian kernel techniques combined with deep learning methods. The methods presented are designed to allow future researchers to replicate and verify the process. This section provides detailed information on the research flow, the tools and materials used, the characteristics of the dataset, and the evaluation metrics employed to assess the performance and accuracy of the palmprint classification system. The evaluation metrics include precision, recall, F1 score, and accuracy, which collectively provide a comprehensive understanding of the system's effectiveness. By systematically documenting each step and outcome, we aim to contribute to the ongoing research in biometric identification and enhance the reliability of palmprint classification systems.

2.1 Respondent Characteristic

The palmprint dataset used in this study includes images from a total of 10 participants, each contributing 10 palm images. These participants, aged between 28 and 35 years, were selected to ensure diversity in terms of gender and ethnicity. The palmprint images were captured under various conditions, such as different hand orientations, lighting conditions, and backgrounds, to simulate real-world variations. This diversity in data is crucial for training a model that can generalize effectively across different individuals and scenarios.

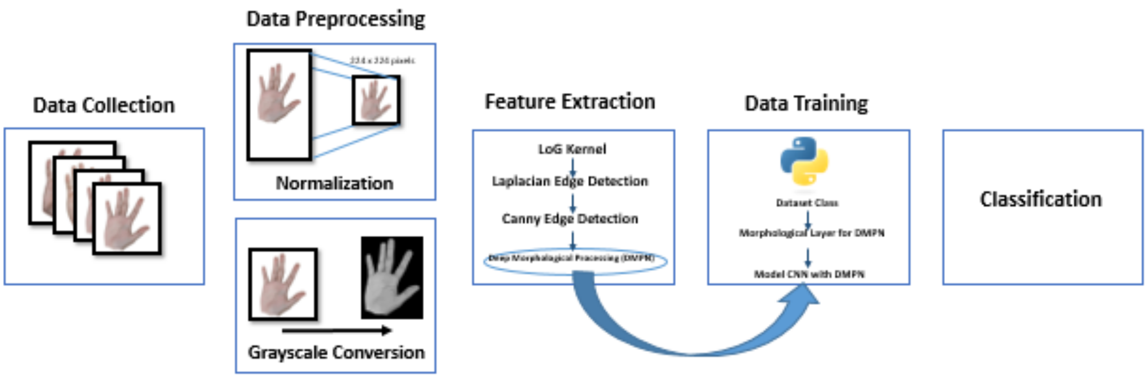

Figure 1. Flowchart Palmprint Classification

2.2 Data Collection

We collected the palmprint in this study using a smartphone camera with a 64 MP resolution. The palmprints were captured under varying conditions to simulate real-world scenarios, including different hand orientations, lighting conditions, and backgrounds. We carefully captured the palmprint images with the smartphone camera, yielding high-quality results like the one below. This procedure ensures that the model is trained with a wide variety of palmprint characteristics, improving its ability to generalize across different conditions and individuals. To further enhance the dataset, data augmentation techniques, including rotation, scaling, and cropping, were applied to introduce additional variability in the palmprint images.

2.3 Data Preprocessing

Once the images are collected, they undergo data preprocessing to standardize and prepare them for feature extraction. This procedure involves several sub-processes, including grayscale conversion, where the images are converted from their original color format to grayscale, reducing complexity while retaining key structural details. Next, the images are normalized so that the pixel values are scaled between 0 and 255, ensuring consistency across the dataset. The images are also resized to a fixed dimension (e.g., 224x224 px) to match the input size expected by the model, ensuring that all images have the same resolution and aspect ratio[6].

2.4 Feature Extraction

The next step is feature extraction, which aims to identify important patterns in the palmprint that are relevant for classification. We apply the Laplacian of Gaussian (LoG) kernel to the images to identify edges and textures, effectively highlighting significant features of the palmprint. Additionally, the Laplacian edge detection method is utilized to pinpoint areas with significant intensity changes, which typically correspond to ridges and other key structures in the palm. The Canny edge detection technique then refines the edges further, making it easier to identify sharp transitions in the palmprint. Finally, a Morphological Processing Layer (DMPN) enhances the extracted features by concentrating on specific regions of interest within the palmprint.[7]

The process involves:

1. **Laplacian of Gaussian (LoG) Kernel**: A discrete LoG kernel (7x7, σ=1.4) is applied to highlight edges and textures, emphasizing features like wrinkles and ridges. The LoG kernel is computed as:

$$LoG(x,y) = \frac{1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right)e^{-\frac{x^2+y^2}{2a^2}}$$

The resulting kernel is scaled to have a central value of -24 for edge enhancement.

2. **Canny Edge Detection**: Applied with thresholds (10, 50) to detect sharp intensity changes, further refining edge features.
3. **Combined Edge Features**: The LoG and Canny outputs are combined with equal weights (0.5 each) to produce a robust edge map.
4. **Deep Morphological Processing Network (DMPN)**: A morphological layer applies dilation and erosion operations using 3x3 kernels to enhance regions of interest, such as ridges and lines. The DMPN layer is defined as:

$$\text{Output} = \text{ReLU}\big(\text{Dilation}(x)\big) + \text{Erosion}(x))$$

where dilation and erosion are implemented via max-pooling and convolution operations.

The processed features are saved as edge-detected images for subsequent model training.

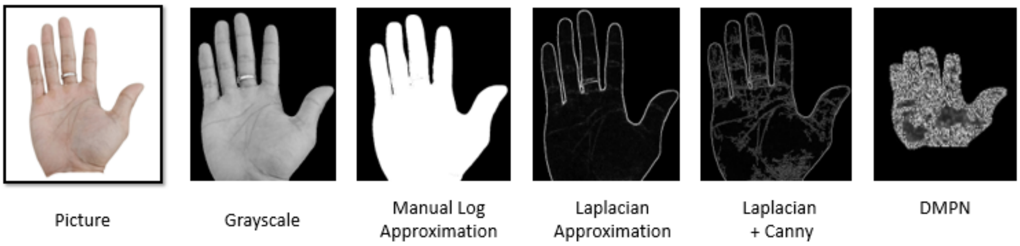

Figure 2. Palmprint Feature Extraction

2.5 Data Training

After extracting the features, the model undergoes data training to learn how to classify palmprints using the extracted features. The dataset is divided into training and testing sets, with the training set being used to train the model. The morphological layer for DMPN is incorporated into the model, helping to refine the extracted features. The morphological operations, such as erosion and dilation, enhance the features of the palmprint, emphasizing important details like ridges and lines. The model is trained using a Convolutional Neural Network (CNN), which learns to recognize complex patterns in the palmprint data, assisted by the morphological layer to improve the overall feature quality and enhance classification accuracy.[8]

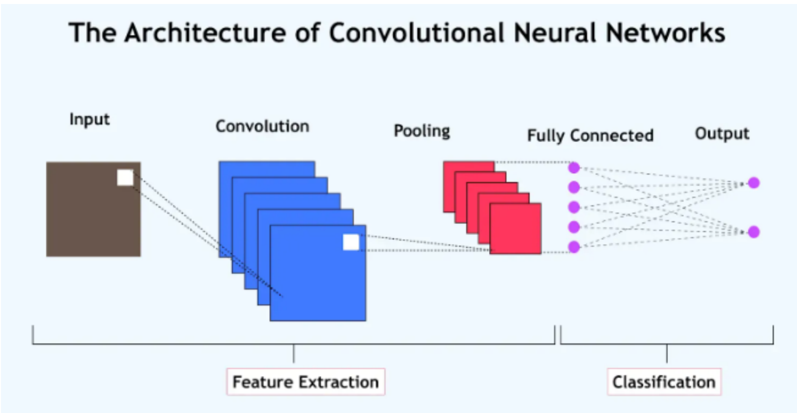

Figure 3. CNN Architecture

The dataset is split into training (80%) and validation (20%) sets. The training process uses a custom CNN integrated with the DMPN layer, implemented in PyTorch. The CNN architecture is described below, followed by training parameters.

CNN Architecture
The CNN model consists of the following layers, as illustrated in Figure [X] (to be included in the article):

1. **Morphological Layer (DMPN)**: Input (1x224x224), applies dilation and erosion with a 3x3 kernel, output (1x224x224).
2. **Convolutional Layer 1**: Input (1x224x224), 32 filters (3x3), stride 1, padding 1, ReLU activation, output (32x224x224).
3. **Convolutional Layer 2**: Input (32x224x224), 64 filters (3x3), stride 1, padding 1, ReLU activation, output (64x224x224).
4. **Adaptive Average Pooling**: Reduces spatial dimensions to 54x54, output (64x54x54).
5. **Fully Connected Layer 1**: Input (64x54x54=186,624), output 128, ReLU activation.
6. **Fully Connected Layer 2**: Input 128, output 10 (number of classes: 'evvin', 'sesa', 'sirlus', 'vivin', 'adi', 'dewi', deni', gilbert', 'rizal', 'eni').

Figure [X]: CNN Architecture Diagram (Description for article: The diagram illustrates the flow from input grayscale palmprint image (224x224) through the DMPN layer, two convolutional layers with ReLU activations, adaptive pooling, and fully connected layers to produce class probabilities. Include a schematic with labeled layers and dimensions.)

Training Parameters

- **Epochs**: 30 epochs, as specified in the training loop.
- **Learning Rate**: 0.001, used with the Adam optimizer.
- **Optimizer**: Adam, which adapts learning rates for each parameter to accelerate gradient descent.
- **Loss Function**: Cross-Entropy Loss, suitable for multi-class classification.
- **Batch Size**: 16, balancing computational efficiency and gradient stability.
- **Validation Strategy**: The model is evaluated on the validation set after training using accuracy as the metric. The validation accuracy is computed as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}}$$

The training process monitors loss per epoch, and the model is saved after training for subsequent evaluation and inference.

2.6 Classification

After the model has been trained, it moves on to the classification stage, where palmprints are categorized into predefined classes. The trained model is then applied to the testing set, predicting the class (e.g., an individual's identity) for each palmprint. The classification output represents the model's final prediction, indicating which class each palmprint belongs to based on the features it has learned. The model's success relies on its ability to generalize the features learned during training and accurately classify new, unseen palmprint images.

3. RESULTS AND DISCUSSION

3. 1 Result

In this section, we present the results of our palmprint classification model, which we evaluated using a confusion matrix alongside several performance metrics. The metrics include accuracy, weighted precision, weighted recall, weighted F1-score, and average Equal Error Rate (EER), all of which provide a comprehensive understanding of the model's performance. Additionally, we analyze the confusion matrix to highlight where the model makes correct predictions and where it encounters misclassifications.

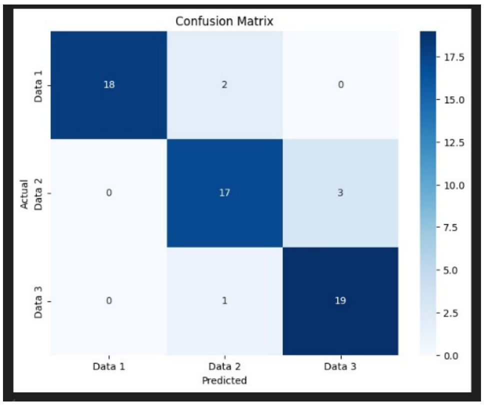

Figure 4. Confusion Matrix

The aggregated confusion matrix, based on 20 trials, offers helpful details about the performance of the palmprint classification model. The matrix shows that the model successfully identified 18 instances of Data 1, with only 2 misclassifications into Data 2, demonstrating high accuracy in recognizing Data 1. For Data 2, the model correctly classified 17 instances, but 3 instances were misclassified as Data 3, indicating some difficulty in distinguishing between Data 2 and Data 3. Despite this, Data 3 was accurately classified, with 19 instances correctly identified and only 1 misclassification in Data 2. This analysis reveals that the model performs well in classifying Data 1 and Data 3, with some confusion between Data 2 and Data 3, likely due to shared feature characteristics between these two classes. Overall, the model demonstrated strong performance, particularly for Data 1 and Data 3, which were classified correctly without significant misclassifications.

The palmprint classification model achieved an accuracy of 90.00% on the test dataset, meaning that it correctly classified 90% of the palmprint images. The result indicates that the model is highly effective in differentiating between the different palmprint classes. It also achieved a weighted precision of 0.9045, meaning that when the model predicted a class, it was correct 90.45% of the time, emphasizing its ability to reduce false positives. With a weighted recall of 0.9000, the model correctly identified 90% of the true positives, further reinforcing its effectiveness in recognizing instances belonging to each class. Additionally, the model achieved a weighted F1-score of 0.9007, providing a balanced performance across both precision and recall. The average Equal Error Rate (EER) was 0.0917, demonstrating that the model effectively balanced the false acceptance rate (FAR) and false rejection rate (FRR), a crucial factor in biometric systems. These metrics highlight the model's strong classification performance and its ability to generalize across various classes.

3.2 Discussion

The results from our palmprint classification model match several trends observed in recent research while also highlighting some areas for improvement. We compare our method's performance with those of recent studies on deep learning-based palmprint recognition and analyze how different approaches have contributed to the field.

Table 1. Comparison Research Study

Study	Methode	Key Focus	Comparison with Our Methode
Gao et al. (2025)[9]	Deep Learning in Palmprint Recognition	Survey of deep learning for palmprint recognition	This study also uses deep learning, similar to our approach. However, they do not utilize morphological processing, which is a key aspect of our model. Our use of DMPN enhances feature refinement, potentially improving accuracy in recognition.
Sinha & Verma (2024)[10]	Deep Learning and GAN Technologies	Improving recognition with GANs alongside deep learning	While both approaches rely on deep learning, they incorporate GANs,

			which we did not utilize. GANs could potentially improve the diversity of features generated for recognition, while our method uses morphological layers for feature enhancement.
Fan & Han (2024)[10]	Self-Supervised Learning and Uncertainty Loss	Self-supervised learning and loss-based improvements for palmprint recognition	This method uses self-supervised learning, while our model is based on supervised learning. The addition of uncertainty loss could improve robustness, but our approach still achieves high performance with feature refinement.
Shao et al. (2024)[11]	Few-Shot Learning via Meta-Siamese Network	Few-shot learning methods for palmprint recognition	This approach focuses on few-shot learning, which is useful when there is limited training data. Our model could benefit from integrating few-shot learning, particularly to handle misclassifications.
Xu et al. (2025)[12]	Multi-Spectral Palmprint Recognition with Deep Multi-view Representation Learning	Using multi-spectral data to improve palmprint recognition	This approach involves multi-spectral data fusion, which provides additional feature diversity. In contrast, our method relies solely on single-modal palmprint images, but could potentially benefit from multi-spectral fusion for improved accuracy.

4. CONCLUSION

In this study, we developed a palmprint classification system utilizing deep learning, combined with the Laplacian Kernel and Deep Morphological Processing Network (DMPN), to enhance feature extraction. The model achieved an accuracy of 90%, demonstrating its ability to effectively classify palmprint images under varied conditions. The model also performed strongly across other metrics, including precision, recall, and F1-score, achieving a weighted precision of 0.9045, weighted recall of 0.9000, and a weighted F1-score of 0.9007. This result highlights the efficacy of combining deep learning with morphological processing to improve classification accuracy, particularly in challenging conditions such as varying hand orientations and lighting. Our results compare favorably with recent methods in palmprint classification, showing that deep learning-based techniques outperform traditional methods in terms of accuracy and robustness. However, the study also identified areas for improvement, particularly in distinguishing between similar palmprint classes, such as Data 2 and Data 3. The confusion between these classes suggests that further refinement is needed, particularly in differentiating between them, which likely share some similar features. To improve the system's performance, future work could explore the use of few-shot learning and multi-spectral data fusion. These techniques could further refine the model and enhance its ability to classify palmprints with higher precision, even in challenging real-world conditions. Additionally, expanding the dataset and integrating more advanced feature extraction techniques, including the exploration of multi-modal data, could improve the model's generalization and performance across diverse palmprint images and scenarios.

REFERENCE

[1] Sinha, S., & Verma, S. B. (2024). Harnessing Deep Learning and GAN Technologies for Palmprint Recognition. In 2024 International Conference on Cybernation and Computation (CYBERCOM) (pp. 68-76). IEEE.

[2] Ma, S., Hu, Q., Zhao, S., Chen, S., & Jiang, L. (2024). SYEnet: Simple yet effective network for palmprint recognition. Information Sciences, 669, 120518.

[3] Fan, D., Liang, X., Jia, W., Chen, J., & Zhang, D. (2024). A Novel Hybrid Fusion Combining Palmprint and Palm Vein for Large-Scale Palm-Based Recognition. IEEE Transactions on Systems, Man, and Cybernetics: Systems.

[4] Chen, R., Tang, Y., Zhong, Y., Shi, Y., Huang, S., & Shen, L. (2024). Research On Palmprint Recognition Based On Mechanism And Data. In Proceedings of the International Conference on Computer Vision and Deep Learning (pp. 1-9).

[5] Shao, H., Liu, C., Li, X., & Zhong, D. (2023). Privacy preserving palmprint recognition via federated metric learning. IEEE Transactions on Information Forensics and Security, 19, 878-891.

[6] Jia, W., Hu, R. X., Gui, J., Zhao, Y., & Ren, X. M. (2012). Palmprint recognition across different devices. Sensors, 12(6), 7938-7964.

[7] Yang, Z., Chen, Y., Gao, C., Teoh, A. B. J., Zhang, B., & Zhang, Y. (2025). FedPalm: A General Federated Learning Framework for Closed-and Open-Set Palmprint Verification. arXiv preprint arXiv:2503.04837.

[8] S. Ganorkar, T. Mane, R. Patil, D. Sonawane, and V. Rothe. (2024). Optimizing CNNs for contactless palmprint recognition. *Int. J. Multidiscipl. Res.*, vol. 6, no. 2, Mar. 2024, doi: 10.36948/ijfmr.2024.v06i02.17585.

[9] Gao, C., Yang, Z., Jia, W., Leng, L., Zhang, B., & Teoh, A. B. J. (2025). Deep Learning in Palmprint Recognition-A Comprehensive Survey. arXiv preprint arXiv:2501.01166.

[10] Fan, R., & Han, X. (2024). Deep palmprint recognition algorithm based on self-supervised learning and uncertainty loss. Signal, Image and Video Processing, 18(5), 4661-4673.

[11] Shao, H., Zhong, D., Du, X., Du, S., & Veldhuis, R. N. (2021). Few-shot learning for palmprint recognition via meta-siamese network. IEEE transactions on instrumentation and measurement, 70, 1-12.

[12] Xu, X., Xu, N., Li, H., & Zhu, Q. (2019). Multi-spectral palmprint recognition with deep multi-view representation learning. In Machine Learning and Intelligent Communications: 4th International Conference, MLICOM 2019, Nanjing, China, August 24–25, 2019, Proceedings 4 (pp. 748-758). Springer International Publishing.

[13] N. Kohila and T. Ramprabha. (2024). Laplacian kernel Ruzicka indexive deep multilayer perceptive network for palm prints detection classification. *Commun. Appl. Nonlinear Anal.*, vol. 31, no. 3, pp. 124–136, Mar. 2024, doi: 10.52783/cana.v31.1459.

[14] Abirami B, & Krishnaveni K. (2024). A Deep Learning Multifractal Texture Analysis Using Principal Line Extraction Approach for Palmprint Recognition System. International Journal of Communication Networks and Information Security (IJCNIS), 16(1 (Special Issue), 237–250. Retrieved from https://www.ijcnis.org/index.php/ijcnis/article/view/6815

[15] Roşca, V., & Ignat, A. (2020). Quality of pre-trained deep-learning models for palmprint recognition. In 2020 22nd International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC) (pp. 202-209). IEEE.

[16] Wang, G., Kang, W., Wu, Q., Wang, Z., & Gao, J. (2018). Generative adversarial network (GAN) based data augmentation for palmprint recognition. In 2018 digital image computing: techniques and applications (DICTA) (pp. 1-7). IEEE.

[17] Sun, Q., Zhang, J., Yang, A., & Zhang, Q. (2017). Palmprint recognition with deep convolutional features. In Chinese Conference on Image and Graphics Technologies (pp. 12-19). Singapore: Springer Singapore.