Development of A Palm-Vein Recognition System for Identification and Verification Systems using Enhanced Convolutional Neural Network

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ORIGINAL RESEARCH

Abstract— Biometric authentication systems have gained significant attention in access control applications due to their ability to provide enhanced security and convenience. Among various biometric modalities, palm-vein recognition has emerged as a promising approach, offering high accuracy, reliability, and resistance to forgery. However, existing palm-vein recognition systems often face challenges in implementation costs, computational efficiency, and performance limitations. This research aimed to develop an enhanced palm-vein recognition system for access control applications by optimizing a Convolutional Neural Network (CNN) architecture. A palm-vein dataset comprising 1000 images from 200 LAUTECH students was acquired, with 5 images per individual. The dataset was split into 700 training images and 300 testing images. The acquired images were pre-processed for quality enhancement and region of interest extraction. A Gravitational Search Algorithm (GSA) optimized CNN (GSA-CNN) was then employed to extract deep features from the pre-processed images, which were classified using a SoftMax layer. Experimental results revealed that the CNN technique achieved a specificity, sensitivity, False Positive Rate (FPR), accuracy of 74.60%, 79.89%, 25.40%, 77.67% at 117.52 seconds, respectively. In contrast, the proposed GSA-CNN technique demonstrated superior performance, achieving a specificity, sensitivity, FPR, accuracy of 92.06%, 92.53%, 7.94%, 92.33% at 97.14 seconds, respectively. The GSA-CNN system outperformed the conventional CNN approach in terms of accuracy, specificity, sensitivity, FPR, and processing time, demonstrating its potential for reliable and efficient palm-vein recognition in access control applications. The findings have significant implications for developing robust and secure access control systems, contributing to enhanced privacy and security across various domains.

Keywords— Recognition System, Biometric Authentication, Convolutional Neural Network, Gravitational Search Algorithm, Hyperparameter Optimization, Palm-Vein Recognition

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1 INTRODUCTION

Biometric recognition systems have gained significant traction in recent years for access control and security applications due to their ability to provide reliable personal identification and verification (Jain *et al.*, 2016; Adetunji *et al.*, 2018). Among various biometric modalities, palm-vein recognition has emerged as a promising approach because it offers several advantages over traditional methods such as fingerprint and iris recognition (Shaheed *et al.*, 2021; Oguntoye *et al.*, 2019). Palm-vein recognition is a cutting-edge biometric technology that uses unique vein patterns in the palm identification (Stanuch *et al.*, 2020). Among various biometric modalities, palm-vein recognition has emerged as a promising approach, providing enhanced security, accuracy, privacy, versatility, and convenience (Amrouni *et al.*, 2023; Okediran and Oguntoye, 2023).

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Palm-vein patterns are unique to each individual, highly secure as they are internal features of the body, and resistant to forgery or tampering attempts (Oguntoye *et al.*, 2019). Deep learning, specifically Convolutional Neural Networks (CNNs), is utilized in palm-vein recognition to enhance accuracy and efficiency. CNNs streamline the authentication process by utilizing palm-vein features for user identification, reducing manual labour and simplifying the process (Fanjiang *et al.*, 2021). These specialized neural networks have demonstrated remarkable performance in various computer vision tasks, including image recognition, object detection, and biometric identification, due to their ability to learn hierarchical representations from raw data and capture complex patterns (Jaapar *et al.*, 2018; Khan *et al.*, 2020; Oguntoye *et al.*, 2023).

Hyperparameter optimization is crucial for maximizing the performance of CNNs in palm-vein recognition systems (Famuyiwa *et al.*, 2022; Ola *et al.*, 2020; Obayya *et al.*, 2020). Techniques like the Gravitational Search Algorithm (GSA), a nature-inspired metaheuristic optimization algorithm, can be employed to fine-tune hyperparameters, enhancing the network's ability to learn and make accurate predictions

(Akay *et al.,* 2022; Dayana and Emmanuel, 2023). GSA is based on the principles of Newtonian laws of gravity and mass interactions, where the solutions are represented as objects with masses (Rashedi *et al.,* 2009). GSA is known for its exploration and exploitation capabilities, making it effective in finding optimal or near-optimal solutions in complex search spaces (Ola *et al.,* 2019; Ogundepo *et al.,* 2022). This optimization process is essential for achieving low False Positive Rates (FPR) and False Negative Rates (FNR), ensuring robust security and reliability in access control systems (Adetunji *et al.,* 2015; Gifty *et al.,* 2019; Sasikala, 2024).

Despite the tremendous potential of palm-vein recognition technology, existing systems often face challenges in terms of implementation costs, accuracy, and efficiency (Zhong *et al.,* 2019; Dargan and Kumar, 2020). Enhancing the performance and feasibility of palm-vein recognition systems is crucial for their widespread adoption in biometric security and access control applications (Ahmad *et al.,* 2019; Zhou *et al.,* 2020; Adedeji *et al.,* 2021). This research aims to address these challenges by developing a robust palm-vein recognition system using an enhanced Convolutional Neural Network architecture optimized through the Gravitational Search Algorithm.

2 RELATED WORKS

Convolutional Neural Networks (CNNs) have emerged as a powerful tool for palm-vein recognition systems, as evidenced by several studies in this review. CNNs' ability to learn hierarchical representations and extract intricate patterns from raw data makes them well-suited for this task. However, the performance of CNN-based palm-vein recognition systems is heavily influenced by factors such as network architecture, optimization techniques, and data augmentation strategies. The development of accurate and efficient palm-vein recognition systems for verification and identification has been an active area of research. Several studies have explored the use of machine learning and deep learning techniques to improve the performance of these systems. Ganiyu *et al.* (2018) proposed a multimodal biometric system that fuses palm-vein and fingerprint features using Gabor filters, aiming to enhance security and accuracy. Their approach demonstrated the potential of combining biometric modalities for robust personal authentication. Oguntoye *et al.* (2019) proposed a particle swarm optimization (PSO) method to optimize support vector machine (SVM) parameters, achieving improved recognition accuracy compared to traditional SVM. Lefkovits *et al.* (2019) and Jhong *et al.* (2020) demonstrated the effectiveness of convolutional neural networks (CNNs) for palm-vein identification, with Lefkovits et al. comparing various CNN architectures and Jhong *et al.* achieving high

accuracy using adaptive background filtering and cloud computing.

Qin *et al.* (2021) introduced a single-sample-per-person (SSPP) approach using a multi-scale and multi-direction generative adversarial network (MSMDGAN) for data augmentation and a CNN for classification, achieving state-of-the-art results. Hernández-García *et al.* (2022) developed a CNN-based model for gender and age classification using palm-vein images, achieving state-of-the-art performance. Alshakree *et al.* (2023) proposed a method combining deep learning networks and the gray wolf optimization algorithm for palm print recognition, outperforming existing methods. Wulandari *et al.* (2024) combined discrete wavelet transform, histogram of oriented gradient, and CNNs, demonstrating promising results in terms of accuracy, area under receiver operating characteristic curve (AUC), and equal error rate (EER) on multiple datasets. Ezzat *et al.* (2021) developed an optimized deep learning architecture for the diagnosis of COVID-19 disease. The authors used a Convolution Neural Network architecture called DenseNet121 and an optimization algorithm called Gravitational search algorithm (GSA) to select optimal values for the hyper-parameters of the CNN architecture with accuracy of 98.38% achieved.

The reviewed studies demonstrate the potential of CNN-based approaches for palm-vein recognition systems, particularly when combined with optimization techniques, data augmentation strategies, and hybrid feature extraction methods. The proposed research aligns well with these findings and aims to contribute to the advancement of palm-vein recognition systems for verification and identification applications by optimizing CNN hyperparameters using the Gravitational Search Algorithm.

3 RESEARCH METHODOLOGY

The methodology for developing a Palm-vein Recognition System for Access Control involves acquiring palm-vein data, pre-processing the data, extracting deep features using a CNN, classifying with SoftMax, and evaluating system performance. The aim is to create an accurate and reliable system for secure identification based on unique palm-vein patterns.

3.1 IMAGE ACQUISITION

The palm-vein pattern, due to its visibility in the near infrared spectrum and inability to be captured by ordinary cameras under visible light, necessitated the use of near infrared CCD sensitive cameras. In this study, 200 individuals' palm-vein images were captured using such cameras. The images were acquired in the 256RGB colour format, with each channel having 8 bits per pixel. The

resolution of the images was set at 640×480 pixels. For each individual, five palm-vein images were captured, resulting in a total of 1000 images (200 individuals × 5 images). Out of these, 700 palm-vein images were utilized for training the system, while the remaining 300 images were employed for testing the system's performance.

3.2 IMAGE PRE-PROCESSING

In this study, the pre-processing steps encompassed the localization of Region of Interests (ROIs) and normalization using the Histogram Equalization technique. The emphasis was on identifying and isolating the ROIs to specifically target the relevant palm-vein patterns, thereby optimizing recognition performance. The following steps were employed to extract the ROIs for palm-vein:

i.   Image binarization;
ii. Determination of gap boundaries;
iii. Calculation of tangents for the two gaps;
iv. Using the tangent as the Y-axis of the palm coordinate, establish a line connecting points (x1, y1) and (x2, y2);
v.   Utilizing a line passing through the midpoint of points (x1, y1) and (x2, y2), perpendicular to the Y-axis, establish the X-axis line perpendicular to the tangent determined in step iii;
vi. Locate the ROI as a fixed-size square centered at a fixed distance from the origin of the palm coordinate;
vii. Extract the sub-image within the ROI.

Deep learning approaches, such as CNN, were employed for certain pre-processing tasks, including the segmentation of data from a noisy background. The Histogram Equalization technique was utilized for enhancement of palm-vein images. Histogram equalization typically enhances the global contrast of an image. These pre-processing techniques significantly contribute to enhancing the overall quality and robustness of the biometric recognition system. Figure 1 shows some of the pre-processed and original images.
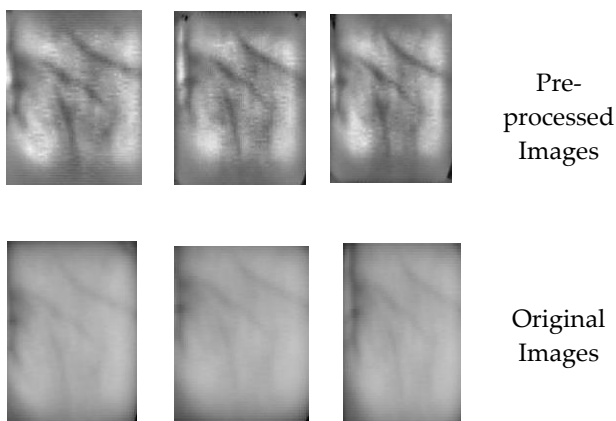

Pre-processed Images

Original Images

Fig. 1: Some of the pre-processed and original images

3.3 THE STANDARD CNN

In this study, a CNN architecture with four layers is utilized to process the palm-vein images. The Convolutional Neural Network employed in this study comprises four basic layers: the convolution layer, the rectified linear unit (ReLU) layer, the max pooling layer, and the fully connected layer.

3.3.1 CONVOLUTION LAYER

The first layer of CNN is convolution layer in which the original image ($i(x, y)$) is convolved with the filter kernel (F_k) as given in Equation 1. This layer is also called as hidden feature extractor which describes the internal connectivity of the image region. The dimensions of the filter kernel used for convolution are 5×5×6. To maintain the size of convolutional map the original image is zero padded on the border. The filter weights are adjusted using mini-batch gradient descent learning method.

$$I_{CONV} = i(x, y) \otimes F_{K(5 \times 5 \times 6)} \qquad (1)$$

3.3.2 Rectified Linear Unit (ReLU) Layer

ReLU is applied after convolutional layer which uses nonlinear activation function as shown in Equation 2 to minimize the linearity introduced in the convolutional layer and. In this layer the all the neurons with negative weights are forced to zero.

$$I_{RELU}(x, y) = max(I_{CONV}(x, y), 0) \qquad (2)$$

3.3.3 MAX POOLING LAYER

Max pooling layer acts as non-linear down sampling method to reduce the number of neurons in the ReLU layer output. It divides the image into the non-overlapping region of N×N pixel and consider the maximum value of the local region. This layer minimizes the computation time and also control the overfitting.

3.3.4 FULLY CONNECTED LAYER

In fully connected layer, neurons from different layers are connected in one layer. Most of the classifiers needed the data in one dimensional therefore multidimensional feature map is converted in to 1-dimensional vector.

For the learning of CNN mini batch gradient descent optimization algorithm is used. In the mini-batch gradient descent algorithm, the sum or average of the gradients is chosen. Taking the average helps reduce the variation of the gradient. This approach combines the robustness of stochastic gradient descent and the effectiveness of batch gradient descent. The mini-batch gradient descent method is frequently used in deep learning algorithms due to its computational efficiency. For each training epoch, the total

number of iterations is determined by T, where T is calculated as T = n/b, with "n" representing the total number of training dataset samples and "b" representing the batch size. The weights (w) of the CNN are optimized using an error function defined in Equation 3, specific to this study. This optimization process aims to improve the performance and accuracy of the CNN model.

$$E_t[f(w)] = \frac{1}{b} \sum_{i=(t-1)b+1}^{tb} f(w, x_i) \qquad (3)$$

Where x_i is ith sample of training data. At each iteration the weights are updated by rule mini batch gradient descent update rule with learning rate μ given in Equation 4.

$$w^{t+1} = w^t - \mu \nabla_w E_t[f(w^t)] \qquad (4)$$

3.4 THE GSA-CNN

The proposed method employs the GSA to optimize the hyperparameters of a CNN for palm-vein recognition. The GSA is a population-based metaheuristic inspired by Newton's law of gravitation, where agents (solutions) are attracted by the force of gravity toward more massive agents (better solutions). The steps of the GSA-CNN technique are as follows:

1. Initialize a population of N agents $X_i(1, 2, \ldots, N)$ with random positions within the hyperparameter ranges.
2. Initialize the gravitational constant G_0 and set the current iteration t = 0.
3. Evaluate the fitness $fit_i(t)$ for each agent $X_i(t)$ by training and evaluating the CNN with the corresponding hyperparameter values.
4. Update the best fitness value $best_{fit}$ and the best solution $best_X$ found so FPR.
5. Calculate the mass $M_i(t)$ for each agent $X_i(t)$ based on its fitness:

$$M_i(t) = \frac{fit_i(t) - Worst_{fit}(t)}{best_{fit}(t) - Worst_{fit}(t)} \qquad (5)$$

Where $Worst_{fit}(t)$ is the fitness of the worst agent in the current population.

6. Update the gravitational constant G(t) for the current iteration:

$$G(t) = G_0 * \exp\left(-\alpha * \left(\frac{t}{max_{iter}}\right)\right) \qquad (6)$$

Where α is a constant, and max_{iter} is the maximum number of iterations.

7. Calculate the total force $F_i(t)$ acting on each agent $X_i(t)$:
   For each agent $X_j(t)$ ($j \neq 1$):
   Calculate the Euclidean distance $R_{ij}(t)$ between $X_i(t)$ and $X_j(t)$
   Calculate the force $F_{ij}(t)$ acting on $X_i(t)$ due to $X_j(t)$:

$$F_{ij}(t) = G(t) * \frac{M_i(t) * M_j(t)}{R_{ij}(t)^2} * \left(X_j(t) - X_i(t)\right) \qquad (7)$$

Update the total force $F_i(t)$ acting on $X_i(t)$:

$$F_i(t) = F_i(t) + F_{ij}(t) \qquad (8)$$

8. Calculate the acceleration $a_i(t)$ for each agent $X_i(t)$:

$$a_i(t) = \frac{F_i(t)}{M_i(t)} \qquad (9)$$

9. Update the velocity $v_i(t + 1)$ and position $X_i(t + 1)$ for each agent:

$$v_i(t + 1) = rand_i * v_i(t) + a_i(t) \qquad (10)$$
$$X_i(t + 1) = X_i(t) + v_i(t + 1) \qquad (11)$$

Where $rand_i$ is a random number in [0, 1].

10. Check the stopping criteria. If the criteria are not met, increment t and go to step 3.
11. Return the best solution $best_X$, which represents the optimal hyperparameter values for the CNN.

In this algorithm, the positions of the agents symbolize various hyperparameter configurations, while the fitness function assesses the CNN's performance using these configurations for palm-vein recognition. The algorithm updates the agents' positions iteratively by considering the gravitational forces exerted on them, which are determined by their fitness values. Agents with higher fitness attract other agents towards their positions, directing the search towards optimal hyperparameter values. The process flow used in the study is illustrated in Figure 2.
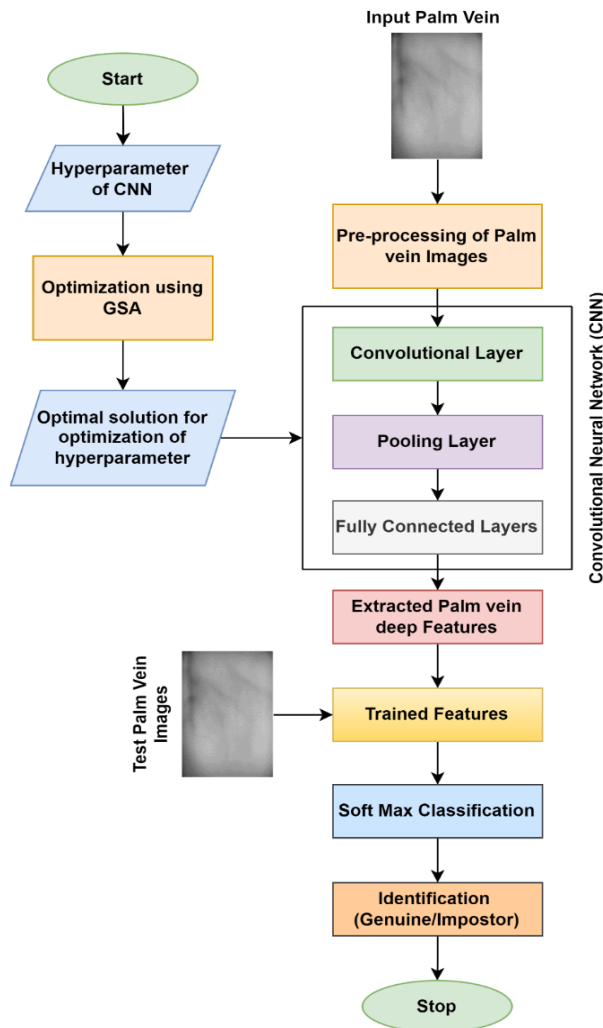
Fig. 2: The process flow

3.5 CLASSIFICATION MODULE

After applying the GSA-CNN technique to optimize the hyperparameters of the Convolutional Neural Network (CNN) for deep palm-vein feature extraction, the classification module employs a SoftMax layer to classify the extracted features. The SoftMax layer is a generalization of the logistic function that computes the probability distribution over multiple classes. The SoftMax function computes the probability of the input **x** belonging to each class j as follows:

$$P(y = j|x) = \frac{e^{w_j^T X + b_j}}{\sum_{k=1}^{K} e^{w_j^T X + b_j}} \quad (12)$$

where K is the number of classes, and w and b_j are the weight vector and bias corresponding to class j respectively. The SoftMax layer outputs a vector of K probabilities, one for each class, summing to 1. The class with the highest probability is then selected as the predicted class for the input palm-vein feature vector x.

3.6 DECISION MODULE

The decision module determines the final classification of the input palm-vein image based on the output of the SoftMax layer. The decision module mathematically can be expressed as:

$Predicted\ Class$
$$= \begin{cases} Accept\ (Genuine), & if\ max_j\ P(y = j|x) \geq \theta \\ Reject(Impostor), & otherwise \end{cases} \quad (13)$$

The decision module compares the similarity score (output of the SoftMax layer) against the predetermined threshold θ.

The performances of the investigated biometric system were evaluated by calculating its specificity, sensitivity, false positive rate, accuracy. Confusion matrix was used to determine the value of the performance metrics. It contained True Positive (TP), False Positive (FP),

Fig. 3a: Confusion Matrix of CNN

Fig. 3b: Confusion Matrix of GSA-CNN

False Negative (FN) and True Negative (TN). These metrics are defined as follows:

$$Sensitivity = \frac{TP}{TP + FN} \quad (14)$$

$$Specificity = \frac{TN}{FP + TN} \quad (15)$$

$$FPR = \frac{FP}{FP + TN} \quad (16)$$

$$Accuracy = \frac{TP + TN}{FP + FN + TP + TN} \quad (17)$$

4   RESULTS AND DISCUSSION

The experimental setup for this study was conducted using MATLAB R2021a on a Hewlett-Packard G56 laptop with an Intel® Core™ i5 Duo processor, Windows 10 Professional 64-bit OS, 2.7GHz CPU, 16GB RAM, and a 1TB hard drive. The evaluation of the palm-vein recognition system's performance was conducted by analysing the results obtained from the Convolutional Neural Network (CNN) and the Gravitational Search Algorithm-CNN (GSA-CNN) techniques. Through empirical investigation, it was observed that the performance metrics of these techniques were significantly influenced by the threshold value employed. Notably, both methods exhibited optimal performance when the threshold value was set at 0.75. Consequently, the in-depth discussion and presentation of the results were primarily focused on the analysis and comparison of the two techniques at the threshold value of 0.75, as this value yielded the most favourable outcomes.

The dataset used in the evaluation consisted of 300 palm-vein datasets, with 174 being genuine and 126 being impostor samples. With the CNN technique, as shown in Figure 3a, it correctly identified 139 genuine palm-vein datasets while incorrectly classifying 35 genuine samples as impostors. This indicates a true positive rate of 79.9% (139/174) and a false positive rate of 20.1% (35/174). On the impostor side, the CNN technique misclassified 32 impostor samples as genuine, resulting in a false negative rate of 25.4% (32/126), and correctly identified 94 impostor samples, corresponding to a true negative rate of 74.6% (94/126).

These results highlight the trade-off between security and convenience in access control systems. The CNN technique demonstrates a relatively high false positive rate, implying a certain vulnerability to impostor attacks. While it achieves a satisfactory true positive rate, the misclassification of genuine palm-vein datasets as impostors can lead to access denial for legitimate users (Zayed et al., 2023). This may result in inconvenience and frustration for individuals attempting to gain authorized access. In contrast, the GSA-CNN technique, as depicted in Figure 3b, exhibits improved performance. It correctly classifies 161 genuine palm-vein datasets, achieving a true positive rate of 92.5% (161/174). However, it misclassifies 13 genuine samples as impostors, resulting in a false positive rate of 7.5% (13/174). On the impostor side, the GSA-CNN technique correctly identifies 116 impostor samples (true negative rate of 92.1%, 116/126) and misclassifies 10 impostor samples as genuine (false negative rate of 7.9%, 10/126).

The findings indicate that the GSA-CNN technique provides a higher level of accuracy and security compared

to the CNN technique. The reduced false positive rate suggests a lower risk of impostor attacks, minimizing the chances of unauthorized access. Also, the higher true positive rate implies improved identification of genuine users, leading to a decreased false rejection rate and enhanced user experience (Song et al., 2017).

Previous research studies on palm-vein biometrics have consistently reported observations pertaining to the inherent trade-off between security considerations and user convenience. Notably, these studies have underscored the critical importance of striking an optimal balance between the False Positive Rate (FPR) and the False Negative Rate (FNR) to achieve superior performance in access control systems (Jain et al., 2016). The results obtained from the Gravitational Search Algorithm-Convolutional Neural Network (GSA-CNN) technique exhibit a more favourable trade-off between FPR and FNR when compared to the conventional Convolutional Neural Network (CNN) technique.

Theoretical standards, such as the ISO/IEC 19795-1:2011 biometric performance testing and reporting standard, provide guidelines for evaluating biometric systems. These standards emphasize the need for low FPR and FNR rates to ensure accurate and reliable identification (ISO/IEC, 2011). The GSA-CNN technique's performance, with its lower false positive and false negative rates, aligns more closely with these theoretical standards compared to the CNN technique. The results indicate that the GSA-CNN technique outperforms the CNN technique in several aspects. GSA-CNN demonstrates higher specificity (92.06%) compared to CNN (74.60%), indicating a lower false positive rate as described in Table 1. This implies reduced vulnerability to impostor attacks, improving the security of access control systems. GSA-CNN also exhibits higher sensitivity (92.53%) compared to CNN (79.89%), indicating a higher true positive rate and improved identification of genuine palm-vein samples as described in Table 1.

Table 1: Performance of the Techniques

Techniques	Specificity (%)	Sensitivity (%)	FPR (%)	Accuracy (%)	Time (seconds)
CNN	74.60	79.89	25.40	77.67	117.52
GSA-CNN	92.06	92.53	7.94	92.33	97.14

The lower FPR of GSA-CNN (7.94%) compared to CNN (25.40%) further supports its superiority. A lower FPR ensures fewer instances of genuine samples being misclassified as impostors, minimizing inconvenience and

access denial for authorized users. Moreover, GSA-CNN achieves a higher accuracy rate (92.33%) compared to CNN (77.67%), indicating better overall performance in palm-vein recognition. The processing time of GSA-CNN (97.14 seconds) is also significantly lower than that of CNN (117.52 seconds). This implies that GSA-CNN offers faster palm-vein recognition, potentially leading to improved system efficiency and user experience.

The superior performance of the GSA-CNN technique can be attributed to the effective optimization of the hyperparameters of the CNN by the Gravitational Search Algorithm. This optimization process enables the CNN to learn more discriminative features from the palm-vein data,

5 CONCLUSIONS

The proposed palm-vein recognition system employing a Convolutional Neural Network optimized by the Gravitational Search Algorithm (GSA-CNN) has demonstrated superior performance compared to the conventional CNN approach. The GSA-CNN technique achieved higher specificity, sensitivity, and accuracy rates, along with lower false positive and false negative rates. These improvements can be attributed to the effective hyperparameter optimization by the GSA, enabling the CNN to learn more discriminative features from the palm-vein data. Additionally, the GSA-CNN exhibited a significantly lower processing time, making it suitable for real-time access control applications. Based on the promising results of the GSA-CNN technique, it is

leading to improved classification accuracy, sensitivity, specificity, and reduced false positive and false negative rates. These findings are consistent with the observations of Bergstra and Bengio (2012), who demonstrated the significant impact of hyperparameter optimization on the performance of deep learning models. It also aligns with the findings of Wang *et al.* (2021), who emphasized the importance of minimizing false negatives in biometric recognition systems to ensure reliable user authentication and prevent unauthorized access denial. Therefore, the implementation of GSA-CNN can enhance the security and accuracy of palm-vein biometric recognition, reducing the risk of impostor attacks and access denial for genuine users.

recommended to consider its deployment in practical access control systems, where robust security, accurate user identification, and efficient processing are critical requirements. Furthermore, the integration of the GSA-CNN system with other biometric modalities, such as fingerprint or facial recognition, could be explored to develop a multi-modal biometric system, potentially enhancing the overall security and reliability of the access control system. Future work includes exploring advanced optimization algorithms, data augmentation, and transfer learning to further enhance performance and generalization. Evaluating robustness under varying conditions, integrating with additional security measures, and developing scalable and adaptive learning mechanisms to handle larger databases and pattern changes over time are also recommended to improve real-world applicability

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