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Hyperparameter Optimization of Lightweight CNN Architectures Using Chicken Swarm Optimization for Improved Palm-Vein Biometric Performance

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***Abstract*—Palm-vein biometrics recognition is suitable for secure human identification systems owing to its high discriminative capability against spoofing. This study presents an optimized palm-vein biometric recognition system using a lightweight Convolutional Neural Network enhanced with the Chicken Swarm Optimization algorithm (CSO-CNN). A total of 150 genuine and 250 impostor, palm vein samples, were employed for evaluation. The palm-vein images were subjected to standard preprocessing to enhance vein patterns prior to feature extraction. The CSO algorithm was integrated to optimize critical hyperparameters of the lightweight CNN architecture, thereby improving convergence behavior, recognition accuracy, and computational efficiency. Feature extraction was performed using the optimized CNN model, while classification was achieved using a SoftMax classifier. The system was implemented in MATLAB R2023a and optimal performance was achieved at a threshold of 0.8. Experimental results revealed that the proposed CSO-CNN significantly outperformed the conventional CNN, achieving a lower False Acceptance Rate (FAR) of 6.00%, False Rejection Rate (FRR) of 12.00%, Equal Error Rate (EER) of 10.67%, and a higher recognition accuracy of 91.75%, compared to the baseline CNN, which recorded FAR of 7.20%, FRR of 14.67%, EER of 13.33%, and accuracy of 90.00%. The optimized model reduced recognition time from 180.53 seconds to 130.52 seconds. Statistical analysis using a paired sample t-test confirmed that the observed improvement in accuracy was statistically significant ($p < 0.05$). These results demonstrate that CSO-based hyperparameter optimization enhances the performance of lightweight CNNs for palm-vein biometric recognition, making the proposed approach suitable for real-time and high-security authentication applications.**

***Index Terms*—Palm vein recognition, vascular biometrics, lightweight convolutional neural networks, hyperparameter optimization, Chicken Swarm Optimization, deep learning.**

I. INTRODUCTION

Vascular biometrics, and in particular palm-vein recognition, have emerged as a compelling modality for reliable person authentication due to intrinsic advantages such as high distinctiveness, resistance to spoofing, and the capability for non-contact acquisition of subcutaneous vein patterns using near-infrared (NIR) imaging (Zhou and Kumar, 2011; Mohamed, A., Salama, A., & Ismail, A. ,2025). Both early and contemporary systems have demonstrated that palm-vein imaging yields highly discriminative vascular structures suitable for automated recognition across diverse acquisition setups and device costs (Cao *et al.*, 2015; Tome and Marcel, 2015). Practical deployment scenarios ranging from low-cost mobile capture to kiosk and walkthrough authentication systems have motivated continued research into robust feature extraction, region-of-interest localization, and matching strategies tailored for vascular imagery (Zhang *et al.*, 2007; Matsuda *et al.*, 2017).

The rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly enhanced biometric recognition by enabling hierarchical and task-specific feature learning directly from image data, often surpassing handcrafted representations (Krizhevsky *et al.*, 2012; LeCun *et al*., 2012). In vascular biometrics, CNN-based approaches have demonstrated improved robustness to intra-subject variability, sensor noise, and acquisition inconsistencies in both identification and verification tasks (Huang *et al.,* 2017; Rastogi, S., Kumar, S., Ali, M., & Sait, A. R. W., 2026). Furthermore, lightweight CNN architectures have been proposed to facilitate on-device or resource-constrained deployment while maintaining competitive recognition performance (Zhao *et al*., 2020; Kuzu *et al.*, 2020). Such compact architectures are particularly attractive for real-world biometric systems, where latency, memory footprint, energy consumption, and privacy preservation are critical considerations (Van *et al.,* 2019; Jothibasu, M., Akshayaa, T., Nithya, G., Kowsalya, P., & Gokila, P., 2026, January).

Despite these advances, the performance of CNN-based palm-vein recognition systems is highly sensitive to hyperparameter configuration. Parameters such as learning rate, filter size, network depth, regularization strength, dropout rate, and batch size significantly influence convergence behavior, generalization capability, and computational efficiency (Srivastava *et al*., 2014). Selecting appropriate hyperparameters is a complex, high-dimensional, and non-convex optimization problem. Manual tuning and grid-based search methods are computationally expensive and often fail to identify near-optimal configurations in large search spaces (Bergstra and Bengio, 2012). Consequently, metaheuristic and population-based optimization techniques have been increasingly adopted to automate hyperparameter selection, demonstrating improved model accuracy and training efficiency across image-based tasks (Wang *et al.*, 2019; Kowdiki, M., Deshmukh, V., & Khaparde, A., 2026).

Among swarm-intelligence algorithms, Chicken Swarm Optimization (CSO) has gained attention due to its hierarchical structure and balanced exploration exploitation mechanism inspired by the social behavior of chicken flocks (Meng *et al.*, 2014). CSO categorizes individuals into roosters, hens, and chicks, enabling cooperative and competitive interactions that guide the search process. The algorithm has shown promising results in solving complex, constrained optimization problems and in parameter tuning tasks across multiple domains (Amador-Angulo *et al.*, 2021; Bharanidharan and Rajaguru, 2020). Hybrid approaches combining swarm optimizers with deep learning models have further demonstrated improvements in convergence stability and generalization performance (Gao *et al.,* 2020; Li *et al.*, 2019).

Nevertheless, standard CSO may experience premature convergence and reduced population diversity when applied to high-dimensional optimization problems such as CNN hyperparameter tuning (Wu *et al.*, 2016; He *et al.*, 2017; Ibrahim, M. Q., Hussein, N. K., Guinovart, D., & Qaraad, M., 2025). While prior studies have explored metaheuristic optimization of CNNs using algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) the application of enhanced CSO techniques to optimize lightweight CNN architectures specifically for palm-vein biometric recognition remains relatively underexplored. Moreover, few studies have systematically investigated the trade-off between recognition accuracy, computational efficiency, and deployment constraints in such optimization frameworks.

This study therefore investigates hyperparameter optimization of lightweight CNN architectures using a Chicken Swarm Optimization framework to enhance palm-vein biometric performance. Building on the demonstrated capability of CNNs for vascular feature learning and the global search strengths of CSO, the proposed approach integrates a mutation-enhanced CSO mechanism to improve search diversity and convergence behavior. The objective is to jointly optimize recognition accuracy, error rates, and computational efficiency while preserving model compactness suitable for resource-constrained deployment. By coupling lightweight CNN modeling with an effective swarm-based hyperparameter search strategy, this work aims to advance the trade-off frontier between biometric recognition performance and practical deployability.

The main contributions of this study are summarized as follows:

1. The development and application of an enhanced Chicken Swarm Optimization framework tailored for hyperparameter optimization of lightweight CNN architectures in palm-vein biometric recognition.
2. The integration of mutation-based improvements within the CSO algorithm to mitigate premature convergence and enhance search diversity in high-dimensional hyperparameter spaces.
3. A comprehensive experimental evaluation comparing the proposed CSO-optimized CNN with baseline CNN and standard CSO configurations for palm-vein authentication.
4. Performance validation using rigorous biometric metrics, including accuracy, precision, False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and computational time, demonstrating improved recognition efficiency and robustness.

II. LITERATURE REVIEW

Recent advances in vascular biometrics and deep learning have together driven significant improvements in palm-vein recognition systems. Palm-vein imaging, typically captured using near-infrared sensors, offers subcutaneous vascular patterns that are inherently difficult to spoof and display strong inter-subject discriminability, motivating their use as a robust biometric modality (Zhang and Hu, 2010; Uhl, 2020).

Concurrently, the rise of convolutional neural networks (CNNs) has transformed image-based biometric recognition by enabling hierarchical feature learning that frequently outperforms hand-crafted representations (Ahmad *et al.,* 2019). In the domain of vascular biometrics, CNNs and other deep architectures have been successfully applied to both finger-vein and palm-vein recognition, demonstrating improved robustness to intra-subject variability and noise (Das *et al*., 2018). Practical deployment considerations have encouraged research into lightweight CNN designs that trade minimal accuracy loss for reduced memory, latency and energy consumption an important direction for on-device authentication on resource-constrained platforms (Jhong *et al.,* 2020).

Despite these modelling advances, model performance is strongly influenced by hyperparameter choices (e.g., learning rates, architecture depth, kernel sizes, regularization), which determine convergence behavior and generalization (Srivastava *et al*., 2021). Manual or exhaustive grid search is prohibitively expensive for deep models and may fail to find good configurations in high-dimensional search spaces (Wang *et al.*, 2019b). This has motivated the application of metaheuristic optimization methods particularly population-based and swarm intelligence algorithms to automate hyperparameter tuning and improve model performance and training efficiency across image-based tasks (Qolomany *et al*., 2017).

Chicken Swarm Optimization (CSO) is one such swarm intelligence algorithm inspired by the hierarchical social interactions of chicken flocks. CSO divides the population into roles (roosters, hens and chicks) and uses role-dependent update rules to balance exploration and exploitation, showing fast convergence and robustness on a variety of benchmark problems (Amador-Angulo *et al.,* 2021). Several studies have explored CSO and its variants for parameter tuning and classification tasks, reporting competitive performance with other metaheuristics and suitability for complex, multimodal search spaces (Lin *et al*., 2018). CSO's simplicity and effectiveness make it an attractive candidate for hyperparameter optimization in constrained settings such as lightweight CNN design for biometric systems (Qu *et al.*, 2021).

Metaheuristic approaches beyond CSO have also been applied to optimize machine learning and deep learning models relevant to biometrics. Particle Swarm Optimization (PSO), Genetic Algorithms (GA) and hybrid algorithms have been used to tune classifier parameters and network hyperparameters to boost recognition rates while controlling model complexity (Oguntoye *et al.*, 2019). Hybrid approaches that combine deep learning with swarm-based optimization show promise for biometrics. CSO's favorable exploration-exploitation trade-offs and adaptability have led to successful applications in image classification and parameter tuning in related domains (Meng *et al.,* 2014; Amador-Angulo *et al.*, 2021). This gap suggests both the novelty and potential value of a CSO-driven hyperparameter optimization framework targeted at lightweight CNNs for palm-vein authentication (Kuzu *et al.,* 2020; Sayeed, F., Ahmed, K. R., & Swamy, S. M., 2025). These observations support investigating a CSO-based hyperparameter tuning pipeline for lightweight CNNs to improve palm-vein recognition performance under practical constraints.

III. METHODOLOGY

A structured machine-learning framework was adopted for the development of the proposed palm-vein biometric recognition system. The overall workflow of the study, from image acquisition to final decision-making, is presented in Figure 1 illustrating the overall scheme of the proposed palm vein recognition system, providing a high-level representation of the major processing stages. Palm-vein images were acquired using a near-infrared CCD camera and subjected to preprocessing operations including grayscale conversion, region-of-interest extraction, normalization, and contrast enhancement to enhance vascular visibility and suppress background artefacts. The detailed unimodal palm-vein recognition architecture, comprising distinct training and testing phases with optimized deep feature learning and template storage, is illustrated in Figure 2. The effectiveness of the proposed system was evaluated using standard biometric performance metrics, including recognition accuracy, false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER).

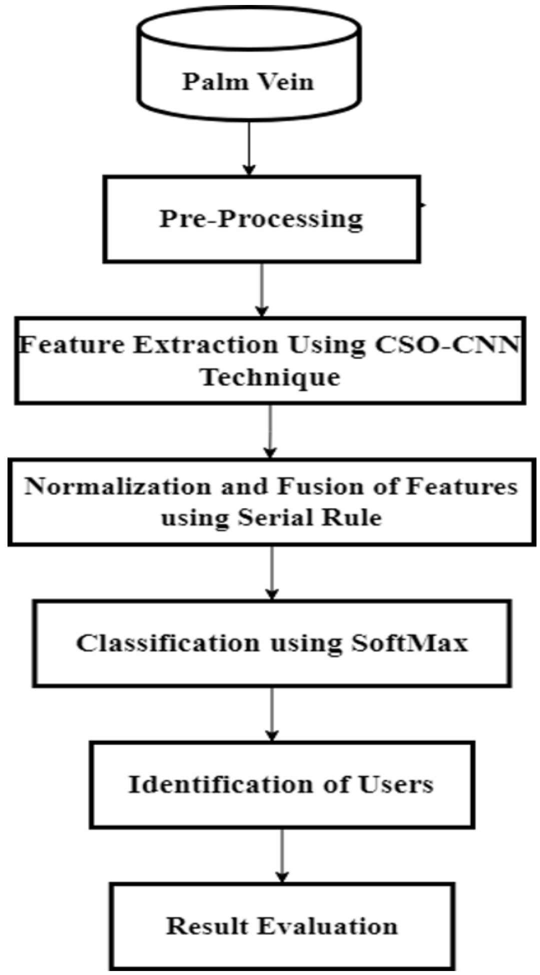

Figure 1: Block diagram of proposed palm vein biometric recognition system.

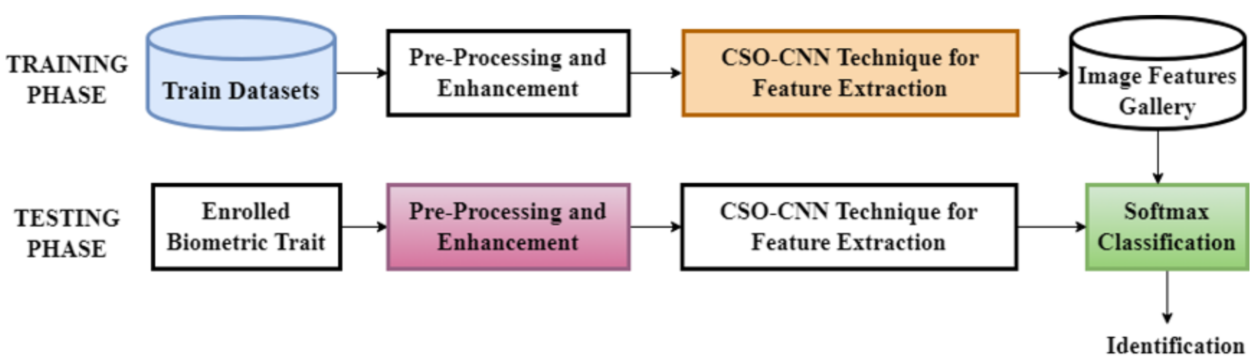

Figure 2: The scheme for the unimodal palm-vein biometric system.

3.1 Acquisition of Palm Vein Biometric Trait

This phase focuses on the acquisition of the palm vein biometric dataset, which forms the foundation for the proposed recognition system. A total of 1,000 palm vein images were collected from 200 subjects at Ladoke Akintola University of Technology (LAUTECH), Ogbomoso. The images were captured using an M2SYSTH Charge Coupled Device (CCD) camera sensitive to near-infrared (NIR) light. For each subject, images of both the left and right palms were taken five times, resulting in a comprehensive bi-instance dataset. The images were captured in various orientations to simulate realistic usage scenarios and to ensure robustness of the system under different hand positions. From the total dataset, 600 images were allocated for training the model, while the remaining 400 images were reserved for testing and validation, ensuring a balanced and representative sample distribution. Sample palm vein images are shown in Figure 3.

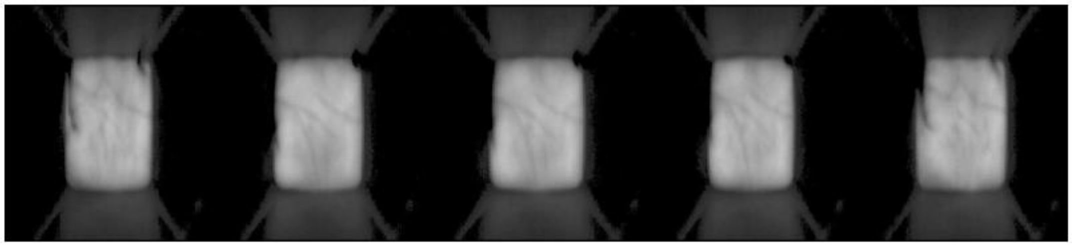

Figure 3: Some acquired palm vein images.

3.2 Pre-processing of Palm Vein Images

Preprocessing of palm vein images is a crucial step to enhance image quality and prepare the data for effective feature extraction and recognition. This phase involves several operations such as image cropping, resizing, contrast adjustment, normalization, and data augmentation to improve the discriminative quality of vascular patterns. The primary operation in preprocessing is the localization of the Region of Interest (ROI), which focuses on a specific area of the palm vein image containing the most relevant vein structures. Extracting features from this ROI significantly reduces computational complexity and improves recognition accuracy by minimizing variations caused by hand shifts or rotations during image capture.

To enhance the image quality before feature extraction, histogram equalization is applied. This technique improves the global contrast by stretching and reshaping the gray-level distribution of the image, making vein patterns more distinguishable. Mathematically, the transformation is given by Eq. (1).

$$f(x,y) = \frac{I_{min}-I_{max}}{h_{max}-h_{min}} (h(x,y) - h_{min}) + I_{max} \quad (1)$$

where $h(x, y)$ is the original histogram value at pixel (x, y), $f(x, y)$ is the enhanced histogram value, h_{min} and h_{max} are the minimum and maximum gray levels in the original image, while

I_{min} and I_{max} are the desired output intensity bounds.

To ensure compatibility with the lightweight CNN model, the ROI images are resized to

128 × 256 pixels. Additionally, various data augmentation techniques such as rotation, shearing, zooming, and shifting along width and height axes are employed to artificially expand the training dataset and reduce the risk of overfitting. This comprehensive preprocessing pipeline ensures that the palm vein images are optimized for robust feature extraction and subsequent classification. Some preprocessed images are shown in Figure 4.

Figure 4: Some preprocessed Images.

3.3 The Lightweight CNN architecture

The Light Convolutional Neural Network is designed to have fewer convolution layer and fully connected layer to obtain the main features of palm vein automatically in a short time. The gained low dimensional features can represent the original palm vein images to the greatest extent, which makes it easier and faster for classification. In this study, the hidden layer of CNN includes convolution layer, pooling layer and fully connected layer. The second layer pays more attention to edges and corner. Layer 3 contains more information about complex invariance and similar textures. Layer 4 shows significant variations and is more class specific. Layer 5 describes that the palm vein has significant pose variations. The detailed description of the CNN network is given in Table 1. In this CNN architecture, the size of the input palm-vein image is 128×256.

Table 1: The Lightweight CNN architecture.

Type	Filter Size/Stride	Output Size
Conv1	3×3/1	32×60×128
Pool1	2×2/2	32×30×64
Conv2	3×3/1	64×30×64
Pool2	2×2/2	64×15×32
Conv3	3×3/1	128×15×32
Pool3	2×2/2	128×7×16
FC1	-	256
FC2	-	200

3.4 Chicken Swarm Optimization Based on Mutation Operator

The standard Chicken Swarm Optimization (CSO) often falls into local optima in high-dimensional problems due to reduced population diversity. To address this, a mutation strategy was integrated into the CSO position update so that chicks perform mutations immediately after their positions are updated, increasing diversity and enabling escapes from local extrema. The mutation produces a perturbed solution x_s^* as described in Eq. (2) using bounds and a mutation factor δ_s as shown in Eq. (3). Instead of purely random parameters, the mutation uses chaotic sequences The chaotic map used in this study is gauss map, and in the ith iteration $u_s = u_i$, then in the $(i + 1)th$ iteration is given as Eq. (4). This map generates chaotic sequences in (0, 1).

$$x_s^* = x_s + (x_s^u - x_s^l) \times \delta_s \tag{2}$$

where x_s^u and x_s^l are the upper and lower bounds of x_s.

$$\delta_s = \begin{cases} (2u_s)^{1/(\eta_m+1)} - 1 & if\ u_s \le 0.5, \\ 1 - (2 \times (1 - u_s))^{1/(\eta_m+1)}, & others \end{cases} \tag{3}$$

where u_s is a random number ranging from 0 to 1. η_m is the distribution index for the mutation operator. The phase for mutation is that u_s is calculated by chaotic maps in iterations.

$$u_s = u_{i+1} = \begin{cases} 0, & u_i = 0, \\ \frac{1}{u_i}\ mod(1), & otherwise \end{cases} \tag{4}$$

The mutation operator in the CSO algorithm helps chickens escape local optima by updating their positions, increasing the likelihood that new offspring have better fitness than existing roosters. Through the hierarchical order mechanism, roosters trapped in local optima are replaced by fitter hens, enhancing both search efficiency and speed.

3.5 Chicken Swarm Optimization CSO for Hyperparameter Optimization

The Chicken Swarm Optimization (CSO) technique with mutation operator, was employed to optimize the hyperparameters of the lightweight CNN for palm-vein recognition. The process begins with the initialization of the chicken swarm, including roosters, hens, and chicks, along with algorithm parameters such as the maximum number of iterations and frequency of hierarchical updates. Each chicken's fitness value is evaluated, and personal and global best positions are initialized. During each iteration, the hierarchical order of the swarm is updated, and the swarm is divided into subgroups to define relationships between hens and chicks. The positions of roosters, hens, and chicks are updated iteratively according to the following equations: for the rooster,

$$x_{i,j}^{t+1} = x_{i,j}^t \cdot \left(1 + N(0,1) \cdot \frac{f_i - f_k}{f_i + f_k}\right) \tag{5}$$

where $x_{i,j}^{t+1}$ and $x_{i,j}^t$ are the new and old positions of the $i-th$ rooster in the $j-th$ dimension, f_i and f_k are fitness values, and $N(0,1)$ is a standard normal distribution; for the hen,

$$x_{i,j}^{t+1} = x_{i,j}^t + r_1(x_{r1,j}^t - x_{i,j}^t) + r_2(x_{r2,j}^t - x_{i,j}^t) \tag{6}$$

where $r_1, r_2 \in [0,1]$ and $x_{r1,j}^t$, $x_{r2,j}^t$ represent the positions of the rooster of the same group and a randomly selected chicken, respectively; and for the chick,

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL.(x_{mother,j}^{t} - x_{i,j}^{t}) \quad (7)$$

where $FL \in [0,2]$ is a random factor, and $x_{mother,j}^{t}$ is the mother's position. After position updates, each chicken's personal best and the global best solution are recalculated, and the variance of the current iteration is computed as:

$$Var_t = Var_{mins} + \frac{(Var_{max} - Var_{min}).t}{T_{max}} \quad (8)$$

where Var_{max} and Var_{min} are the minimum and maximum variation rates, t is the current iteration, and T_{max} is the maximum number of iterations. Mutation is applied to the swarm positions according to Equation 2 to maintain diversity and prevent premature convergence. The process iterates until the maximum number of iterations is reached, at which point the global best position is selected as the optimal set of hyperparameters for the CNN. The overall workflow of the CSO for hyperparameter optimization is illustrated in Figure 5, demonstrating how the swarm hierarchy, mutation, and iterative updates converge toward optimal CNN parameters for palm-vein feature extraction.

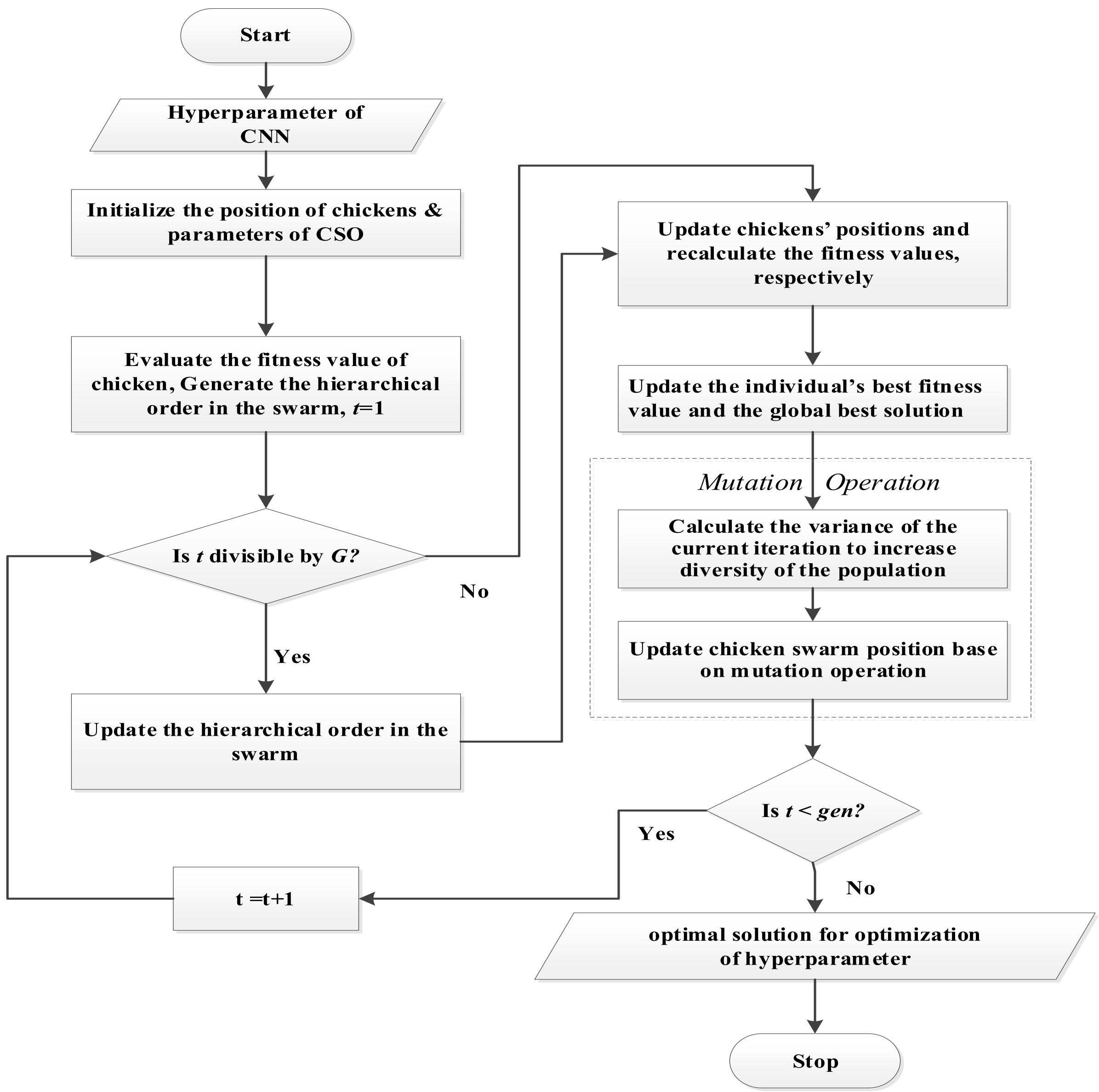

Figure 5: The flowchart of the CSO.

3.6 Hyperparameter Optimization

Hyperparameter tuning is a critical step in training convolutional neural networks, as these parameters govern the learning process and overall model performance. Key hyperparameters include learning rate, number of epochs, dropout rates, L1 and L2 regularization, batch normalization, and batch size. In this study, the Chicken Swarm Optimization (CSO) algorithm was employed to automatically determine the optimal hyperparameter values for the lightweight CNN architecture. By leveraging the mutation-enhanced CSO, the algorithm efficiently searches the hyperparameter space, balancing exploration and exploitation to achieve maximum recognition accuracy while minimizing training time and computational complexity. This approach ensures that the CNN model is configured with hyperparameters that are best suited for extracting discriminative features from palm-vein images, ultimately improving classification performance and robustness of the biometric system.

3.7 SoftMax Classifier

SoftMax classifier is a multi-class classification function. It takes a vector of n real numbers where n is equal to the number of classes, and then it normalizes the input into a vector of values that follows a probability distribution whose total sums up to 1. The output values are between 0 and 1, which accommodate as many classes in the neural network model. SoftMax classifier calculates the probabilities of each class over all possible classes, and the class that has the highest probability is the target class. Given the output vector, $F_{palm-vein}^{\varphi'}(t)$ from the final fully connected layer of the palm vein CNN, the SoftMax score for class *j* is computed
as shown in Eq. (9).

$$S_{palm-vein}\left(F_{palm-vein}^{\varphi'}(t)\right)_j = \frac{e^{F_{palm-vein}^{\varphi'}(t)_j}}{\sum_{n=1}^{K} e^{F_{palm-vein}^{\varphi'}(t)\times n}} \qquad (9)$$

where: K is the number of classes, $F_{palm-vein}^{\varphi'}(t)_j$ is the output for class j, and $S_{(palm-vein)_j}$ is the probability that the input belongs to class *j*. The class with the highest probability is selected as the predicted identity.

3.8 Feature-Level Representation

Feature-level representation in this study focuses exclusively on extracting and utilizing discriminative deep features from palm-vein images. The lightweight CNN model learns hierarchical palm-vein features during training, and the output of the second fully connected layer serves as the final feature vector representing each palm-vein sample. This feature vector is defined as in Equation 9

$$F_{palm} = \{f_1, f_2, \ldots\ldots, f_n\} \qquad (10)$$

where F_{palm} denotes the deep feature vector extracted from the palm-vein image. These features capture the unique vascular patterns of the palm and provide a compact and discriminative representation suitable for classification. The extracted palm-vein feature vector is subsequently passed to a SoftMax classifier, which computes similarity scores between the test and enrolled feature representations and performs identity recognition based on maximum posterior probability.

3.9 Decision Module

The decision module uses the SoftMax classification score to verify user identity. The predicted class probability $S_{palm-vein}$ is compared against a predefined threshold *th*. If the probability exceeds the threshold, the user is accepted as genuine; otherwise, the user is rejected as an impostor. Formally:

$$Decision(S_{palm-vein}) = \begin{cases} Accept\ (Genuine), & if \quad S_{palm-vein} > th \\ Reject(Impostor), & otherwise \end{cases} \qquad (11)$$

3.10 Implementation of the Biometric Recognition System

The unimodal biometric recognition systems will be considered for testing the effectiveness of the developed CSO-CNN technique for feature level fusion. The research was implemented using MATLAB 9.4 (R2018a) and was run on Hewlett-Packard G56 with Intel® Core ™ i5 Duo, Windows 10 Professional 64-bit operating system, Central Processing Unit (CPU) with a speed of 2.7GHz, 6GB Random Access Memory (RAM) and 1 TB hard disk drive. An interactive Graphic User Interface (GUI) application was developed with a real-time database consisting of finger-vein and palm-vein datasets. The GUI was designed using the GUI toolbox in MATLAB. The Graphics User interfaces (GUIs) of the developed system were displayed in Figure 6.

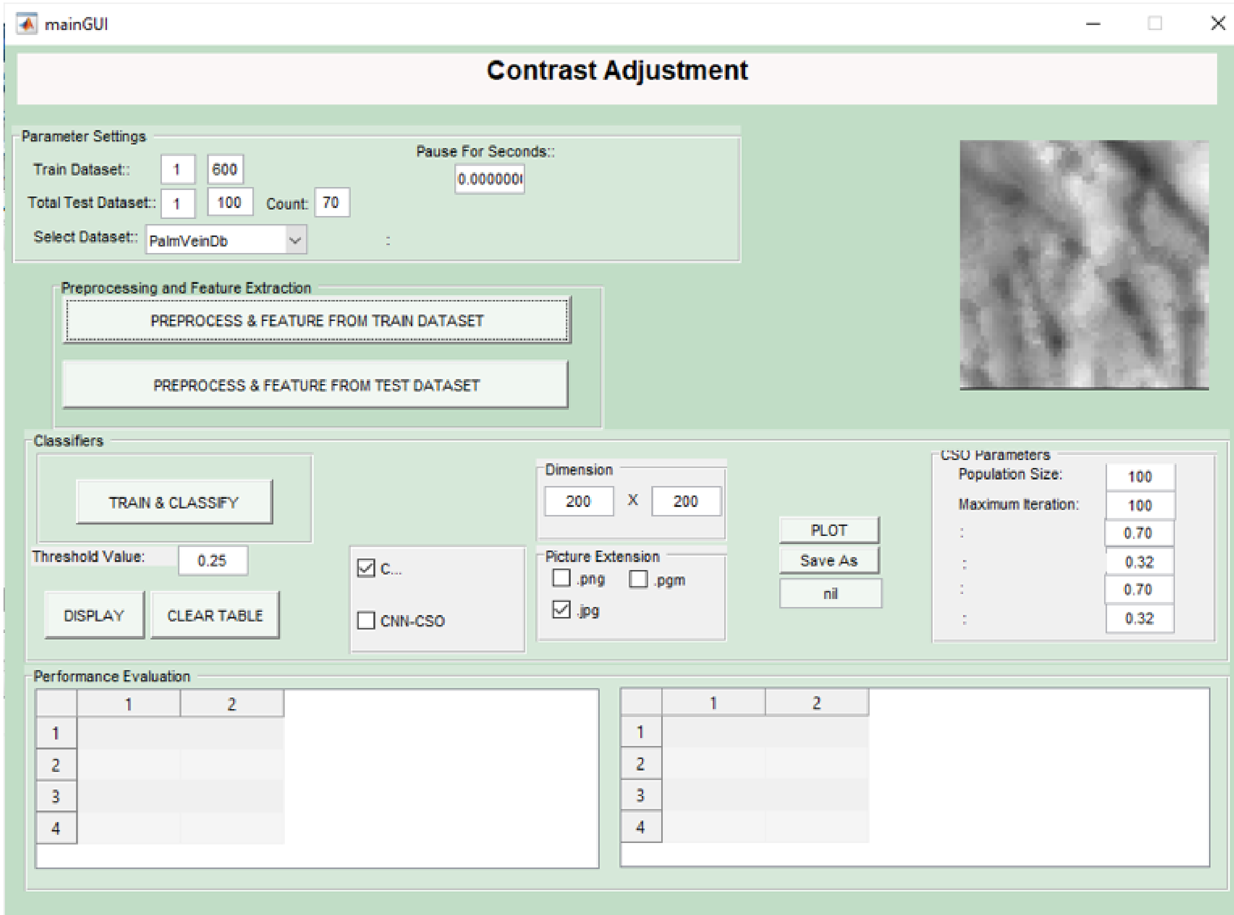

Figure 6: GUI Application for The Palm-vein Biometric.

3.11 Evaluation Measures

The performances of the investigated biometric systems were evaluated by calculating its False Acceptance Rate (FAR), Equal Error Rate (EER), False Rejection Rate (FRR) and Recognition Accuracy. The FAR, FRR, EER and accuracy are computed by generating all possible genuine and impostor matching scores and then set a threshold for deciding whether to accept or reject a match. Confusion matrix was used to determine the value of the performance metrics. It contained True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). The performance of the system was measured as follows:

$$FAR = \frac{FP}{FP + TN}\% \qquad (12)$$

$$FRR = \frac{FN}{FN + TP}\% \qquad (13)$$

$$Accuracy = \frac{TP + TN}{FP + FN + TP + TN}\% \qquad (14)$$

$$ERR = \frac{FAR(\eta) + FRR(\eta)}{2}\% \qquad (15)$$

IV. RESULT AND DISCUSSION

In this study, the performance evaluation of the proposed palm-vein biometric recognition system was conducted using a lightweight Convolutional Neural Network (CNN) and its optimized variant based on the Chicken Swarm Optimization algorithm (CSO-CNN). The experimental evaluation focused on assessing the effectiveness of hyperparameter optimization in improving recognition accuracy, reducing error rates, and minimizing computational cost. Since the decision threshold significantly influences biometric system performance, the lightweight CNN and CSO-CNN models were evaluated at threshold values of 0.2, 0.4, 0.6, and 0.8. Experimental observations revealed that optimal performance was consistently achieved at a threshold value of 0.8. Consequently, all detailed analyses and comparisons in these results are based on analysis obtained at this optimal threshold.

The performance evaluation was conducted using a palm-vein dataset consisting of 400 samples, comprising 150 genuine and 250 impostor instances. The confusion matrices for the CNN and CSO-CNN techniques, presented in Table 2(a) and Table 2(b) below respectively, summarize the genuine impostor classification performance of both models. Using the standard CNN technique, 128 genuine palm-vein TP samples were correctly classified, while 22 genuine FN samples were incorrectly rejected. In addition, 232 impostor TN samples were correctly identified, whereas 18 impostor FP samples were falsely accepted. These results indicate a relatively higher false rejection tendency and moderate false acceptance behavior for the baseline CNN model.

In contrast, the CSO-CNN technique demonstrated classification capability. As shown in Table 2(b) below, 132 genuine palm-vein TP samples were correctly accepted, with only 18 misclassified FN as impostors. Furthermore, 235 impostor TN samples were correctly rejected, while 15 FP were incorrectly accepted. The reduction in both false rejection and false acceptance errors reflect the enhanced discriminative power of the optimized CNN model. This improvement can be attributed to the ability of the CSO algorithm to effectively tune the CNN hyperparameters, thereby improving feature representation and decision boundaries.

Table 2: Performance of the Techniques based on Palm-vein biometric.

		Predicted Class	
		Genuine	Imposter
Actual Class	Genuine (150)	132 (TP)	18 (FN)
	Imposter (250)	15 (FP)	235 (TN)

(a) Contingency table for Genuine/Imposter classification stage using CSO-CNN Technique.

		Predicted Class	
		Genuine	Imposter
Actual Class	Genuine (150)	128 (TP)	22 (FN)
	Imposter (250)	18 (FP)	232 (TN)

(b) Contingency table for Genuine/Imposter classification stage using CSO-CNN Technique.

The quantitative performance metrics derived from the confusion matrices are presented in Table 2(c) below. At the optimal threshold of 0.8, the CNN technique achieved a False Acceptance Rate (FAR) of 7.20%, a False Rejection Rate (FRR) of 14.67%, and an overall recognition accuracy of 90.00%, with a recognition time of 180.53 seconds. By comparison, the CSO-CNN technique attained a lower FAR of 6.00%, a reduced FRR of 12.00%, and a higher accuracy of 91.75%, while also significantly decreasing the recognition time to 130.53 seconds. These results demonstrate that the CSO-CNN technique not only improves recognition accuracy but also enhances computational efficiency. Figure 7 below depicts the performance of the techniques based on recognition time with respect to palm-vein biometric. From the graph, it was discovered that optimization of the parameter of lightweight CNN technique resulted into reduced recognition time.

Threshold value	Technique	FAR (%)	FRR (%)	Accuracy (%)	Recognition Time (seconds)
0.80	CNN	7.20	14.67	90.00	180.53
	CSO-CNN	6.00	12.00	91.75	130.53

(c) Results based on evaluation Measures.

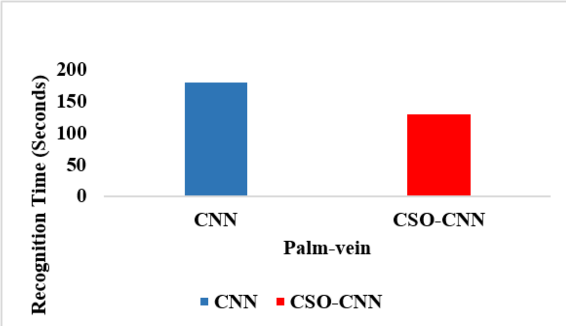

Figure 7: Recognition Time of and palm-vein Biometric.

An important observation from the results is the inverse relationship between FAR and FRR as the decision threshold increases. As the threshold becomes more stringent, the system becomes less accessible to impostors, resulting in a decrease in FAR, while simultaneously increasing the likelihood of rejecting genuine users, thereby increasing FRR. This trade-off highlights the importance of selecting an optimal threshold that balances system security and user convenience. The results obtained at a threshold of 0.8 indicate that the CSO-CNN technique achieves a more favorable balance between these competing objectives when compared to the standard CNN.

The Equal Error Rate (EER) above provides an additional and widely accepted measure of biometric system reliability. Figure 8 below illustrates the intersection of the FAR and FRR curves for both CNN and CSO-CNN techniques based on palm-vein biometric data. From the graphical analysis, the CNN technique produced an EER of 13.33%, whereas the CSO-CNN technique achieved a lower EER of 10.67%. The reduction in EER indicates that the optimized model offers a better equilibrium between false acceptance and false rejection errors, thereby enhancing the overall robustness of the palm-vein biometric system.

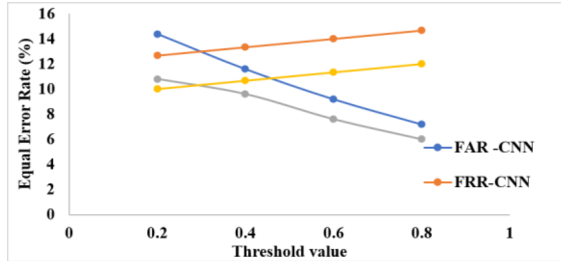

Figure 8: Equal Error Rate for palm-vein biometric.

The reduction in EER, together with the accuracy and reduced recognition time, confirms that the CSO-CNN technique outperforms the baseline CNN model for palm-vein biometric recognition. A lower EER is indicative of a more reliable biometric system, as it signifies discrimination between genuine and impostor users. This finding aligns with established assertions that a biometric system with a lower EER exhibits superior performance and operational reliability.

Statistical Analysis of Palm-Vein Recognition Accuracy

In addition to conventional biometric performance metrics, inferential statistical analysis was conducted to validate the significance of the accuracy improvement achieved by the CSO-CNN technique over the baseline CNN for palm-vein biometric recognition. A paired sampled t-test was employed to statistically compare the recognition accuracies of the two techniques. The test was performed at a 5% level of significance using SPSS, and the detailed outputs are provided bellow:

```
T-TEST PAIRS=P_V CSOCNN CSOCNN_P WITH
F_V CNN CNN_P (PAIRED)
/CRITERIA=CI(.9500)
/MISSING=ANALYSIS.
```

T-Test

Paired Samples Statistics					
		Mean	N	Std. Deviation	Std. Error Mean
Accuracy	Palm-vein	89.4063	8	1.75732	.62131
Palm-vein	CSO-CNN	90.5625	4	1.00778	.50389
	CNN	88.2500	4	1.62019	.81009

The statistical analysis was conducted to test the null hypothesis (H_0) that there is no significant difference between the recognition accuracy of the CNN and CSO-CNN techniques for palm-vein biometric recognition, against the alternative hypothesis (H_1) that a significant difference exists between the two techniques. The hypotheses are defined as follows:

H_0: There is no significant difference between the CNN and CSO-CNN techniques in terms of palm-vein recognition accuracy.

H_1: There is a significant difference between the CNN and CSO-CNN techniques in terms of palm-vein recognition accuracy.

The outcome of the paired sampled t-test results for palm-vein biometric accuracy is presented in Table 3 below. The analysis produced a t-value of 7.034 with 3 degrees of freedom and a corresponding p-value of 0.006. Since the p-value is less than the significance level of 0.05, the null hypothesis was rejected. This indicates that the difference in recognition accuracy between the CNN and CSO-CNN techniques for palm-vein biometric recognition is statistically significant.

Table 3: Summary of Result of T-test of accuracy for CSO-CNN and CNN technique.

Parameter	T	Degree of Freedom (df)	p-value	Comment
Palm-vein	7.034	3	0.006	Significant

The statistical result further revealed a mean accuracy improvement of approximately 2.323% achieved by the CSO-CNN technique over the baseline CNN. This confirms that the observed performance improvement is not due to random variation but is a direct consequence of hyperparameter optimization using the Chicken Swarm Optimization algorithm. The statistical evidence therefore validates the superiority of the CSO-CNN technique in enhancing palm-vein biometric recognition accuracy.

V. DISCUSSION OF RESULTS

The experimental results obtained in this study demonstrate the effectiveness of optimizing a lightweight CNN architecture using the Chicken Swarm Optimization (CSO) algorithm for palm-vein biometric recognition. Performance evaluation was conducted in terms of recognition accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and recognition time. The results revealed that the optimal performance of both CNN and CSO-CNN techniques was achieved at a threshold value of 0.8. This observation is consistent with the findings of Deb *et al.* (2019), who reported that biometric systems generally exhibit discriminative performance as the threshold value approaches unity.

The recognition time analysis indicated that the CSO-optimized lightweight CNN achieved a reduced processing time compared with the baseline CNN. This improvement can be attributed to effective hyperparameter tuning, which enhances convergence behaviour and reduces redundant computations. This finding supports the assertion of Qolomany *et al.* (2017), who demonstrated that optimizing CNN hyperparameters significantly reduces computational cost while maintaining or improving classification accuracy. The reduced recognition time observed for the palm-vein biometric can also be linked to its structured vascular patterns and consistent feature distribution, which facilitate efficient feature extraction and classification.

In terms of accuracy, FAR, FRR, and EER, the CSO-CNN technique consistently outperformed the baseline CNN. The optimized model achieved higher recognition accuracy alongside lower FAR and FRR values, indicating system security and user convenience. The inverse relationship observed between FAR and FRR aligns with established biometric principles, as reported by Jain *et al.* (2006) and Sabhanayagam *et al.* (2018), which state that decreasing FAR often results in an increase in FRR and vice versa. This trade-off underscores the importance of EER as a comprehensive performance indicator.

The Equal Error Rate analysis further confirmed the superiority of the CSO-CNN technique for palm-vein biometric recognition. The lower EER achieved by the optimized model indicates a more favourable balance between false acceptance and false rejection errors. This observation corroborates the findings of Zhang *et al.* (2009) and Buschek *et al.* (2015), who established that a biometric system with a lower EER is inherently more reliable and robust. The reduced EER achieved in this study demonstrates the enhanced discriminative capability of the CSO-CNN model.

The statistical analysis conducted using a paired sampled t-test further validated the observed performance improvement. The significant p-value obtained for palm-vein recognition accuracy confirms that the accuracy gain achieved by the CSO-CNN technique is statistically significant and not due to random variation. This outcome reinforces the effectiveness of metaheuristic-based optimization strategies for improving deep learning performance, as also reported by Nikbakht *et al.* (2021), Assim and Alkababji (2021), and Benaouda *et al.* (2021).

Furthermore, the high recognition accuracy achieved for the palm-vein biometric modality can be attributed to its rich and highly discriminative vascular features. The palm provides a larger surface area than other hand-based biometric traits, allowing the capture of a greater number of stable and distinctive features. This observation is consistent with the findings of Ahmad *et al.* (2019) and Qin *et al.* (2021), who reported that palm-vein biometrics offer enhanced recognition performance due to their complex internal structures. Similarly, Bhilare *et al.* (2018) demonstrated that palm-vein biometrics generally achieve higher accuracy compared with other vein-based modalities because of the increased density of vascular information.

The results obtained in this study confirm that hyperparameter optimization using Chicken Swarm Optimization significantly enhances the performance of lightweight CNN models for palm-vein biometric recognition. The accuracy, reduced error rates, lower EER, and faster recognition time collectively demonstrate the robustness and efficiency of the CSO-CNN technique. These findings align with existing literature and further validate the suitability of optimized deep learning models for secure and reliable palm-vein biometric authentication systems.

VI. CONCLUSION AND RECOMMENDATIONS

This study developed an optimized palm-vein biometric recognition system using a Chicken Swarm Optimization enhanced lightweight Convolutional Neural Network (CSO-CNN) and demonstrated clear performance improvements over the conventional CNN model. Experimental results showed that the CSO-CNN achieved higher recognition accuracy, lower Equal Error Rate, and reduced recognition time, while statistical analysis confirmed that these improvements were significant. The findings validate the effectiveness of metaheuristic-based hyperparameter optimization in enhancing the discriminative capability and computational efficiency of lightweight deep learning models for palm-vein biometrics. Based on these results, future work should investigate improved or hybrid CSO variants, expand the palm-vein dataset to improve generalizability, and explore deployment on real-time or edge-computing platforms to support practical biometric security applications.

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