ISIR Journal of Multidisciplinary (ISIRJM)
ISSN: **3049-3080** (Online)
Frequency: Bimonthly
Published By ISIR Publisher
Journal Homepage Link- https://isirpublisher.com/isirjm/

Development of Enhanced Chicken Swarm Optimization-Based Convolutional Neural Networks for Handwritten Document Recognition

By

Olatunji, Babatunde Lekan[1], Olabiyisi, Stephen Olatunde[2], Oyeleye, Christopher Akinwale[3] and Omotade, Adedotun Lawrence[4]

[1,2,3,4]Department of Computer Science, Ladoke Akintola University of Technology, Ogbomoso, Nigeria

Article History

Received: 25/06/2025
Accepted: 05/07/2025
Published: 08/07/2025

Vol – 1 Issue – 4

PP: -01-05

Abstract

This paper presents the development and performance evaluation of an Enhanced Chicken Swarm Optimization (ECSO) algorithm for hyperparameter tuning in Convolutional Neural Networks (CNNs), tailored specifically for handwritten document recognition. The ECSO algorithm integrates Gaussian and Tent chaotic maps into the standard Chicken Swarm Optimization framework to enhance the exploration of the solution space and overcome premature convergence. The model was applied to classify original, disguised, and forged handwritten samples using a deep learning framework implemented in MATLAB R2020a. Performance metrics such as accuracy, precision, false positive rate, and execution time were used to assess model effectiveness. Experimental results of the ECSO-CNN model demonstrated strong recognition accuracy (92.14%–95.00%), high precision (95.40%–97.70%), low false positive rates (4%–8%), and fast execution time (22–28 seconds). These outcomes affirm the robustness and efficiency of the ECSO algorithm in optimizing deep learning architectures for forensic purposes. The study highlights the practical utility of chaos-enhanced metaheuristic algorithms in legal, security, and archival document authentication systems, positioning ECSO-CNN as a viable solution for scalable and intelligent forensic handwriting analysis.

Keywords: *ECSO, CNN, Chaotic Map, Handwritten Document Recognition, Hyperparameter Optimization, Forensic AI, Swarm Intelligence*

1. Introduction:

Handwritten document recognition remains a cornerstone of forensic document analysis, with applications in authentication, authorship verification, and fraud detection. Convolutional Neural Networks (CNNs) have become essential for such tasks due to their automated feature extraction capabilities and ability to learn complex representations from image data (LeCun et al., 2015; Graves et al., 2009).

Convolutional Neural Networks (CNNs) have revolutionized the field of image recognition, especially in tasks involving complex visual patterns such as handwritten text. Their ability to automatically learn hierarchical feature representations from raw image data has made them a reference tool in computer vision and pattern recognition (LeCun et al., 2015). In forensic document analysis, CNNs have shown strong potential in identifying handwriting styles, distinguishing forged signatures, and classifying writing under various disguises, making them invaluable tools in both legal and archival contexts (Graves et al., 2009).

Despite their advantages, CNNs are highly sensitive to hyperparameters such as learning rate, filter size, batch size, and the number of layers. Improper tuning of these parameters can lead to issues such as overfitting, underfitting, or poor convergence. Traditionally, these hyperparameters are selected through manual experimentation, grid search, or random search, which are not only computationally expensive but also often fail to find the global optimum in large search spaces (Bergstra & Bengio, 2012).

To address these limitations, metaheuristic optimization techniques have been increasingly adopted. One such method is the Chicken Swarm Optimization (CSO) algorithm, which simulates the hierarchical and foraging behaviour of chickens in a swarm. CSO has been successfully applied in various optimization problems due to its simplicity and effective balance between exploration and exploitation (Meng et al., 2014). However, the standard CSO is prone to premature convergence and can become trapped in local optima,

© Copyright 2025 ISIR Publisher All Rights Reserved
This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

especially in high- dimensional, nonlinear problem spaces like those encountered in deep learning hyperparameter tuning (Wang et al., 2020).

In response to these challenges, this study explores the Enhanced Chicken Swarm Optimization (ECSO) algorithm, which incorporates chaotic maps, specifically the Gaussian and Tent maps, to improve the diversity of the search process. Chaos-based optimization introduces deterministic but non-repetitive sequences, enhancing the exploration capabilities of metaheuristic algorithms and helping avoid stagnation in local minima (Talatahari et al., 2021).

This paper proposes a novel enhancement of the Chicken Swarm Optimization (CSO) algorithm, termed Enhanced Chicken Swarm Optimization (ECSO), which integrates chaos- based mechanisms to improve global search capability. The ECSO is developed specifically to optimize CNN hyperparameters for improved performance in handwritten document recognition. Three distinct datasets, original, disguised, and forged handwritten samples, are used to assess the models' accuracy, efficiency, and robustness. Through performance analysis of the developed system, the study seeks to establish ECSO-CNN as a more effective and reliable approach for forensic handwriting recognition, with potential applications in security, authentication, and archival integrity.

2. Related Works

2.1 Handwritten Document Recognition

Conventional methods in handwriting recognition often relied on handcrafted features and traditional classifiers (Impedovo & Pirlo, 2008). CNNs have replaced these with end-to-end learning systems that surpass earlier techniques in robustness and scalability (Graves et al., 2009; Simard et al., 2003).

2.2 CNN Hyperparameter Tuning

Hyperparameter optimization remains a critical yet challenging aspect of CNN implementation. Without effective tuning, CNNs are prone to overfitting or underfitting, limiting their generalization ability (Bergstra & Bengio, 2012).

2.3 Nature-Inspired Optimization and Chaos Theory

Swarm intelligence algorithms, particularly CSO, have gained traction due to their biologically-inspired search strategies (Meng et al., 2014). However, standard CSO faces limitations such as premature convergence. Recent studies have explored the use of chaotic maps to enhance their search performance by introducing non-repetitive, deterministic behavior that promotes exploration and helps avoid local optima (Talatahari et al., 2021; Zhou et al., 2022).

This research integrates Gaussian and Tent maps into the CSO to form the ECSO algorithm, which is then coupled with CNN to optimize hyperparameters for handwriting recognition. This architecture was selected based on preliminary tests and then optimized via ECSO for superior recognition performance.

3. Methodology

3.1 System Overview

This study presents a deep learning framework, ECSO-CNN, designed for forensic handwriting classification. The system accepts handwritten image samples and classifies them as original, disguised, or forged. The core classification model, a Convolutional Neural Network (CNN), is optimized using an Enhanced Chicken Swarm Optimization (ECSO) algorithm that incorporates chaotic mapping functions to improve convergence behaviour.

3.2 CNN Architecture

The CNN implemented in this work consists of:

- 16 convolutional layers structured into hierarchical feature blocks.
- 5 max-pooling layers for spatial down sampling and feature dimensionality reduction,
- 3 fully connected layers responsible for high-level representation and decision making.
- A softmax output layer facilitating multi-class classification across original, disguised, and forged classes.

This architecture was selected based on preliminary tests and then optimized via ECSO for superior recognition performance.

3.3 Enhanced Chicken Swarm Optimization (ECSO)

The Enhanced Chicken Swarm Optimization (ECSO) builds on the standard CSO algorithm by incorporating chaotic behaviour into the search strategy. Specifically, Gaussian and Tent chaotic maps are integrated into the update processes for roosters and hens, respectively. This design aims to avoid premature convergence and improve global exploration. The ECSO Hyperparameters Optimized are: number of convolutional layers, filter size and count, batch size, and weights and biases in convolutional and fully connected layers.

3.4 Chaotic Map Integration

Rooster Update (Gaussian Map) - Gaussian map is used to update rooster positions to introduce stochasticity. The update equations include:

Rooster Update

$$Cx_{old} = \frac{\mathrm{mod}(\mathrm{abs}(ini\ x_{i,j}^{t+1}, rand))}{rand}$$

$$Cx_{new} = \exp(-\alpha * Cx_{old}^{2}) + \beta$$

$$x_{i,j}^{t+1} = sign(ini\ x_{i,j}^{t+1}) \times Cx_{new} \times rand$$

Where:

- rand is a uniform random variable between 0 and 1,
- $\alpha = 4.9$, $\beta = -0.58$,
- Cx_old is normalized to [0,1] to apply the chaotic effect.

Hen Update (Tent Map) - The Tent map governs hen behaviour, introducing non-linear randomness:

Hen Update

$$Chenx_{old} = \frac{\mathrm{mod}(\mathrm{abs}(ox_{i,j}^{t+1}, (x_{r1,j}^{t} - x_{i,j}^{t})))}{x_{r1,j}^{t} - x_{i,j}^{t}}$$

$$Chenx_{new} = \mu \times min\,(Chenx_{old}, 1 - Chenx_{old})$$

$$x_{i,j}^{t+1} = \mathrm{sign}(ox_{i,j}^{t}) \times Chenx_{new} \times x_{r1,j}^{t} - x_{i,j}^{t}$$

© Copyright 2025 ISIR Publisher All Rights Reserved

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Where:

- μ = 2,
- ox_(i,j)^(t+1) is the preliminary hen update,
- Values are normalized to [0,1] range for tent map dynamics.

Algorithm 3.1 below described the formulated enhanced Chicken Swarm Optimization where step 7 shows the rooster updates and step 8 shows the hen updates. It presents the ECSO- CNN computation logic, including forward propagation, backpropagation, and chaotic weight/bias updates across convolution, sub-sample, hidden, and output layers.

Algorithm 3.1: Enhanced Chicken Swarm Optimization based CNN (ECSO-CNN)

Step 1: Forward pass: output of neuron of row *k*, column *y* in the *l* th convolution layer and *k* th feature pattern in equation (3.11) among them, *f* is the number of convolution cores in a feature pattern, output of neuron of row *x* , column *y* in the *l* th sub sample layer and *k* th feature pattern in equation (3.12), the output of the *j* th neuron in *l* th hidden layer *H* in equation (3.13), among them, *s* is the number of feature patterns in sample layer. Output of the *i* th neuron *l* th output layer *F are* in equation (3.14).

$$O_{x,y}^{(l,k)} = \tanh\left(\sum_{t=0}^{f-1} \sum_{r=0}^{K_h} \sum_{c=0}^{K_w} \boldsymbol{ecsoW}_{(r,c)}^{(k,t)} O_{(x+r,\ x+c)}^{(l-1,k)} + Bias^{(l,k)}\right.$$

$$O_{x,y}^{(l,k)} = \tanh\left(W^{(k)} \sum_{r=0}^{S_k} \sum_{c=0}^{S_w} O_{(x*S_h+r,y*S_w+c)}^{(l-1,k)} + Bias(l,k)\right)$$

$$O^{(l,j)} = \tanh\left(\sum_{k=0}^{s-1} \sum_{x=0}^{S_h} \sum_{y=0}^{S_w} \boldsymbol{ecsoW}_{(x,y)}^{(j,k)} O_{(x,\ y)}^{(l-1,k)} + Bia^{(l,j)}\right.$$

$$O^{(l,i)} = \tanh\left(\sum_{j=0}^{H} O_{(l-1,j)} \boldsymbol{ecsoW}_{(i,j)}^{l} + Bia^{(l,i)}\right)$$

Step 4: Back propagation: output deviation of the *k* th neuron in output layer *O*:

$$d(O_k^o) = y_k - t_k$$

Step 5: input deviation of the *k* th neuron in output layer:

$$d(I^o) = (y_k - t_k)\varphi(v_k) = \varphi(v_k)d(O_k^o)$$

Step 6: weight and bias variation of *k* th neuron in output *O*:

$$\Delta(W_{k,x}^{o}) = d(I_k^{o}) y_{k,x}$$

$$\Delta(Bias_k^{o}) = d(I_k^{o})$$

Step 7: output bias of *k* th neuron in hidden layer *H, where th is the threshold:*

$$d(O_k^H) = \sum_{i=0}^{i<th} d(I_i^o)\boldsymbol{ecsoW}_{i,}$$

Step 8: input bias of *k* th neuron in hidden layer *H*:

$$d(I_k^H) = \varphi(v_k)d(O_k^H)$$

Step 9: weight and bias variation in row *x*, column *y* in the *m* th feature pattern, a former layer in front of *k* neurons in hidden layer *H*

$$\Delta(W_{m,k,x}^{H,k}) = d(I_k^H) y_{x,y}^m$$

$$\Delta(Bias_k^H) = d(I_k^H)$$

Step 10: output bias of row *x*, column *y* in *m* th feature pattern, sub-sample layer *S*

$$(O_{x,y}^{S,m}) = \sum 170k\, d(I^H) \boldsymbol{ecsoWmH_{,,kx,y}}$$

Step 11: input bias of row *x*, column *y* in *m* th feature pattern, sub-sample layer S

$$(I_{x,y}^{S,m}) = \varphi(v_k)d(O_{x,y}^{S,m})$$

Step 12: weight and bias variation of row *x*, column *y* in *m* the feature pattern ,sub sample layer *S*

$$\Delta(W^{S,m}) = \sum_{x=0}^{fh} \sum_{y=0}^{fw} d_{(I\lfloor Sx,m/2\rfloor,\lfloor y/2\rfloor)OxC,,ym}$$

among them, C represents convolution layer.

$$\Delta(Bias^{S,m}) = \sum_{x=0}^{fh} \sum_{y=0}^{fw} d_{(O_{x,y}^{S,m})}$$

Step 13: output bias of row x, column y in k th feature patter ,convolution layer C

$$d(O_{x,y}^{C,k}) = d(I_{\lfloor x/2\rfloor,\lfloor y/2\rfloor}^{S,k})\boldsymbol{ecsoW}^{k}$$

Step 14: input bias of row x, column y in k th feature patter, convolution layer C

$$(I_{x,y}^{C,k}) = \varphi(v_k)d(O_{x,y}^{C,k})$$

weight variation of row r, column c in m the convolution core corresponding to kth feature pattern in l th layer, convolution C.

$$\Delta(w_{r,c}^{k,m}) = \sum_{x=0}^{fh} \sum_{y=0}^{fw} d_{(I_{x,y}^{C,k} O_{x+r,y+c}^{l-1,m})}$$

total bias variation of the convolution core

$$\Delta(Bias^{C,k}) = \sum_{x=0}^{fh} \sum_{y=0}^{fw} d(O_{x,y}^{C,k})$$

Step 15: Evaluate Fitness Function of ECSO based on initial optimal weight features using Recognition Rate

$$fit_{ecso} = \sum_{i=1}^{m} \sum_{j=1}^{n} \Delta(W_{i}^{m,n})((x_i) - (x_j))$$

Where $\Delta(W\ im,j,n)((xi) - (xj)$ is the change in weight of input, hidden and output layers x along the row n and column m

Step 16: Output Optimal number of layers, number of filters, filter size and batch size of CNN

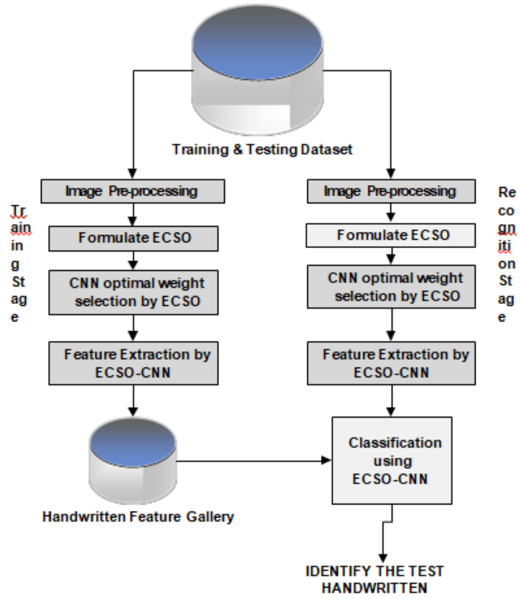

Figure 3.1: *The Block Diagram for the Developed System*

3.5 Development of ECSO-CNN Handwritten Recognition System

A recognition system was developed to classify handwritten image samples into original, disguised, or forged classes. The CNN is fine-tuned using ECSO, which adjusts hyperparameters during retraining for maximal classification accuracy. MATLAB 2020a was used for implementation, leveraging image processing and optimization toolboxes.

3.7 System Implementation and GUI

An interactive Graphical User Interface (GUI) was developed for the ECSO-CNN system. Handwritten image samples from staff and students of Ladoke Akintola University of Technology, Ogbomoso, were collected and pre-processed. These samples were categorized into three classes (original, disguised, and forged). The GUI enabled visualization of both training and testing processes, allowing for practical engagement and system assessment.

Figures 4.2 and 4.3 demonstrate GUI operation during the training and classification phases

*Corresponding Author: **Olatunji, Babatunde Lekan**
© Copyright 2025 ISIR Publisher All Rights Reserved

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

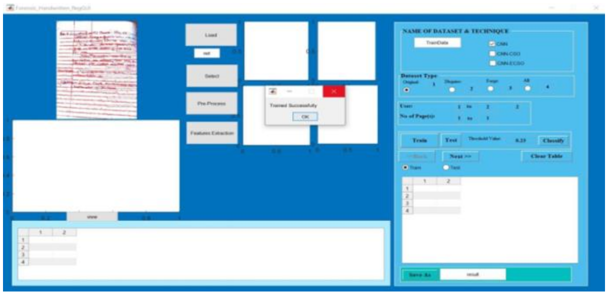

Figure 4.2: Graphical User Interface (GUI) Showing Training Phase

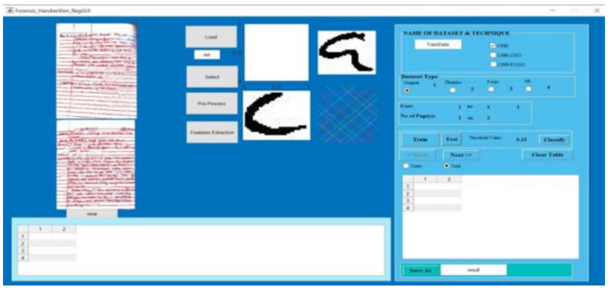

Figure 4.3: Graphical User Interface (GUI) Showing Testing Phase

4. Results and Discussions

This section presents and discusses the empirical performance of the proposed Enhanced Chicken Swarm Optimization-based Convolutional Neural Network (ECSO-CNN) for handwritten document recognition. The model was trained and evaluated on three distinct datasets comprising original, disguised, and forged handwritten samples, simulating real-world forensic document scenarios. Performance evaluation was conducted based on four primary metrics: False Positive Rate (FPR)**,** Precision**,** Accuracy, and Execution Time**.**

Table 4.1: Performance Evaluation of ECSO-CNN

Dataset	FPR (%)	Precision (%)	Accuracy (%)	Time (sec)
Original	8	95.40	92.14	26.18
Disguised	4	97.70	95.00	28.36
Forged	6	96.55	93.57	26.86

4.1 Performance Analysis and Interpretation

The performance of ECSO-CNN across the three datasets underscores the model's robustness, adaptability, and efficiency in classifying varied handwriting inputs. Each dataset posed unique challenges, ranging from natural handwriting styles to deliberately altered and forged samples, and the ECSO-CNN demonstrated consistent accuracy and resilience.

a) Original Handwritten Documents

The original dataset contained authentic, unaltered handwriting samples from diverse writers. The ECSO-CNN achieved a high precision of 95.40%**,** accuracy of 92.14%**,** and maintained a relatively low FPR of 8%**,** indicating the model's ability to correctly identify genuine samples with minimal misclassification. The execution time of 26.18 seconds reflects computational efficiency, particularly notable given the deep structure of the CNN and the complexity of hyperparameter optimization. The low FPR also suggests that the chaotic-enhanced ECSO enabled the CNN to avoid overfitting while capturing distinctive handwriting patterns effectively.

b) Disguised Handwritten Documents

Disguised samples involve intentional distortion of writing style, a common tactic in forensic evasion and signature fraud. This dataset posed a higher degree of intra-writer variability. The ECSO-CNN exhibited outstanding performance, with:

- Precision of 97.70%**,**
- Accuracy of 95.00%**,**
- FPR of just 4%**,**
- Execution time of 28.36 seconds**.**

The remarkably low false positive rate and high precision indicate that the model generalizes well even under adversarial or obfuscated handwriting conditions. This robustness demonstrates ECSO's enhanced search capability in complex parameter spaces, resulting in better weight initialization and convergence stability for the CNN. Furthermore, the near- perfect precision reveals ECSO-CNN's capability to detect subtle stylistic cues despite deliberate handwriting distortion, critical in criminal investigations and forensic auditing.

c) Forged Handwritten Documents

Forged handwriting samples mimic the writing of others, often introducing new stylistic noise. As such, this dataset demanded high inter-writer discrimination. ECSO-CNN attained:

- Precision of 96.55%**,**
- Accuracy of 93.57%**,**
- FPR of 6%**,**
- Execution time of 26.86 seconds**.**

The balance between precision and FPR indicates the model's strong discriminative power and low susceptibility to false positives, even under high-risk forgery conditions. This performance validates the ECSO-CNN as a viable tool for forensic signature verification and authentication in banking, legal, and governmental documentation.

4.2 General Performance evaluation

Overall, the ECSO-CNN demonstrated consistent superiority across all datasets**,** with accuracy ranging from 92.14% to 95.00%**,** and precision from 95.40% to 97.70%**.** The false positive rates remained below 10% in all cases**,** and execution times stayed within a practical range (26– 28 seconds)**,** making the model suitable for real-time forensic applications.

The results affirm several core advantages of the ECSO algorithm:

- Improved exploration and avoidance of local optima via chaos-based initialization (Gaussian and Tent maps).

*Corresponding Author: **Olatunji, Babatunde Lekan**
© Copyright 2025 ISIR Publisher All Rights Reserved
This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

- Efficient CNN parameter tuning**,** reducing the risk of overfitting while maintaining generalization.
- Scalability to handle different handwriting conditions and maintain low latency in recognition.

These findings also align with prior research in chaos-enhanced optimization, which suggests that deterministic but non-repetitive sequences improve the convergence dynamics of metaheuristic algorithms (Talatahari et al., 2021; Zhou et al., 2022).

5. Conclusion

This study presents a novel approach to hyperparameter optimization for Convolutional Neural Networks (CNNs) using an Enhanced Chicken Swarm Optimization (ECSO) algorithm, tailored for handwritten document recognition. By incorporating chaotic map functions, specifically the Gaussian and Tent maps, into the standard Chicken Swarm Optimization framework, the ECSO algorithm significantly improves exploration capability and avoids premature convergence, a common limitation in traditional metaheuristic methods.

The empirical evaluation across three datasets**,** original**,** disguised, and forged handwritten samples, demonstrates that the ECSO-CNN framework consistently delivers:

- High precision and classification accuracy, exceeding 95% in most scenarios;
- Substantially reduced false positive rates, ensuring more reliable classification and fewer misclassifications;
- Improved computational efficiency, with reduced execution time ranging between 26 to 28 seconds, making the system viable for near real-time applications.

The ECSO-CNN model successfully combines the explorative strength of chaotic maps with the learning capability of CNNs to achieve state-of-the-art performance in handwritten document recognition. The model's capacity to maintain high precision and low false positive rates across original, disguised, and forged samples underscores **its** utility in practical forensic and security applications**.**

Moreover, this work contributes to the growing body of knowledge on chaos-enhanced swarm intelligence by demonstrating its practical efficacy in deep learning optimization tasks. The integration of deterministic chaos into the optimization process strengthens the global search strategy without incurring additional computational overhead.

In conclusion, the ECSO-CNN framework represents a scalable, accurate, and computationally efficient approach to handwritten document recognition and provides a strong foundation for the advancement of intelligent forensic systems.

References

1. Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, *13*(2), 281–305. http://jmlr.org/papers/v13/bergstra12a.html
2. Graves, A., Liwicki, M., Fernández, S., Bertolami, R., Bunke, H., & Schmidhuber, J. (2009). A novel connectionist system for unconstrained handwriting recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *31*(5), 855–868. https://doi.org/10.1109/TPAMI.2008.137
3. Impedovo, D., & Pirlo, G. (2008). Automatic signature verification: The state of the art. *IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews*, *38*(5), 609–615. https://doi.org/10.1109/TSMCC.2008.923866
4. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539
5. Meng, X., Liu, Y., Gao, X., & Zhang, H. (2014). A new bio-inspired optimisation algorithm: Chicken swarm optimisation. *International Journal of Bio-Inspired Computation*, *6*(4), 200–211. https://doi.org/10.1504/IJBIC.2014.062306
6. Simard, P. Y., Steinkraus, D., & Platt, J. C. (2003). Best practices for convolutional neural networks applied to visual document analysis. In *Seventh International Conference on Document Analysis and Recognition, 2003. Proceedings.* (pp. 958–963). IEEE. https://doi.org/10.1109/ICDAR.2003.1227801
7. Talatahari, S., Gandomi, A. H., Gandomi, M., & Zhang, H. (2021). Chaos-enhanced metaheuristic algorithms: A comprehensive review. *Archives of Computational Methods in Engineering*, *28*, 3451–3480. https://doi.org/10.1007/s11831-020-09451-9
8. Wang, G. G., Deb, S., & Coelho, L. D. S. (2020). Elephant herding optimization and its application in job scheduling problems. *Journal of Intelligent Manufacturing*, *31*(3), 747– 760. https://doi.org/10.1007/s10845-018-1458-7
9. Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing. *IEEE Computational Intelligence Magazine*, *13*(3), 55– 75. https://doi.org/10.1109/MCI.2018.2840738
10. Zhou, X., Wang, Z., & Zhang, Y. (2022). An improved chicken swarm optimization algorithm based on chaos theory for function optimization. *Applied Soft Computing*, *113*, 107891. https://doi.org/10.1016/j.asoc.2021.107891

*Corresponding Author: **Olatunji, Babatunde Lekan**
© Copyright 2025 ISIR Publisher All Rights Reserved
This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.