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Development Of Convolutional Neural Network-Based Pelican Optimization Algorithm for Handwriting Identification System

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ABSTRACT

Handwriting identification remains a significant challenge in the field of information processing and Optical Character Recognition (OCR) due to the diverse nature of human writing styles. Traditional Convolutional Neural Network (CNN) models, although widely used, often suffer from overfitting, hyperparameter sensitivity, and limited adaptability to different handwriting patterns. This research addressed these challenges by optimizing Convolutional Neural Network (CNN) with Pelican Optimization Algorithm (POA) for Handwriting identification System (HRS). A handwriting dataset comprising 3000 forged handwriting samples and 3000 original handwriting samples was obtained from Kaggle,com. The images were resized, normalized, and augmented to enhance model generalization. POA-CNN was developed by using Pelican Optimization Algorithm to fine-tune CNN hyperparameters of learning rate, layer size, activation functions, and batch sizes with Keras support packages. The POA-CNN model was implemented in MATLAB R(2023a).The system's performance was evaluated across varying decision thresholds with six key metrics employed: False Positive Rate (FPR), Specificity (SPEC), Sensitivity (SEN), Precision (PREC), Accuracy (ACC), and Computational Time (CT). The model was compared with traditional CNN. The optimum threshold was 0.51. The FPR, SPEC, SEN, PREC, ACC and CT for POA-CNN were 3.20%, 96.80%, 96.70%, 96.80%, 96.75%, and 81.95 s, respectively. The corresponding values for CNN were 4.77%, 95.23%, 95.13%, 95.23%, 95.18%, and 91.20 s, respectively. The developed POA-CNN for handwriting identification system demonstrated better performance than the traditional CNN, across all metrics. Overall, the results demonstrate that POA-based hyperparameter optimization significantly improves the accuracy and reliability of CNN-based handwriting identification for effective forgery detection.

INTRODUCTION

Handwriting is a style of writing produced using a writing instrument such as a pen or pencil, and it is inherently personal and unique to each individual. Despite the rapid advancement and widespread adoption of digital technologies, handwriting and its recognition remain relevant in modern society (Smith, 2022). Handwriting continues to play a critical role in several domains, including academic activities, business documentation, examinations, medical diagnoses, and prescription writing (Mangen, 2016; Ogundepo *et al.*, 2022). In educational environments, studies have demonstrated that handwriting enhances cognitive development, improves memory retention, and supports deeper learning outcomes when compared with typing (Mueller and Oppenheimer, 2014). This is particularly evident in examination settings, where handwritten responses are often required to assess comprehension, reasoning, and critical thinking skills (Scribe, 2020).

In professional and healthcare environments, handwriting remains indispensable. Handwritten notes are commonly used during meetings, brainstorming sessions, and planning activities, allowing for faster and more flexible idea capture compared to structured digital formats (Oppenheimer, 2014). In healthcare systems, handwriting is still prevalent in prescriptions and medical documentation, where individual writing styles serve as an additional layer of identification and accountability, helping to minimize clinical errors (Athreon, 2021). Moreover, in forensic science, handwriting analysis remains a vital tool for document authentication, signature verification, and legal investigations, as handwritten signatures often retain legal validity beyond that of digital alternatives (National Institute of Standards and Technology, 2021). These continued applications underscore the importance of developing accurate and reliable handwriting identification systems.

Handwriting identification has long posed significant challenges in computer science due to the variability, ambiguity, and complexity of human writing styles. Early handwriting identification systems relied on traditional approaches such as template matching and handcrafted feature extraction, which depended heavily on predefined rules and heuristics (Nagy, 2000). While these methods achieved limited success under constrained conditions, they struggled with generalization and robustness when exposed to diverse handwriting samples. This limitation prompted a paradigm shift toward machine learning–based approaches, which offered improved adaptability and learning capability by automatically extracting discriminative features from data.

In recent years, Convolutional Neural Networks (CNNs) have achieved remarkable success in handwriting identification tasks, owing to their hierarchical feature learning capability and strong performance on image-based data (Oguntoye *et al*., 2023; Olayiwola *et al*., 2023; Atanda *et al*., 2023). However, CNN performance is highly sensitive to hyperparameter selection, including learning rate, network depth, activation functions, and batch size. Conventional hyperparameter optimization techniques such as Grid Search and Random Search are computationally expensive and inefficient in high-dimensional search spaces, while Bayesian Optimization often struggles with scalability as model complexity increases. Evolutionary approaches such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been applied to deep learning optimization; however, they may suffer from premature convergence, high computational cost, and imbalance between exploration and exploitation (Ruder, 2016; Bottou, 2010; Goodfellow *et al*., 2016). These limitations highlight the need for more adaptive and efficient optimization strategies for handwriting identification systems.

The Pelican Optimization Algorithm (POA) has recently emerged as a promising nature-inspired optimization technique designed to maintain a dynamic balance between exploration and exploitation within the search space. POA incorporates adaptive hunting and cooperative behaviors that enable efficient navigation of complex, high-dimensional optimization landscapes, leading to faster convergence and improved solution quality. Unlike traditional optimization methods, POA demonstrates enhanced stability and reduced susceptibility to local optima, making it particularly suitable for hyperparameter tuning in deep learning models. When applied to handwriting identification, POA offers the potential to optimize CNN hyperparameters more effectively, thereby improving classification accuracy, reducing overfitting, and enhancing computational efficiency (Alrowais *et al*., 2023). This study is therefore justified in exploring POA as a robust alternative for CNN optimization in handwriting identification systems.

METHODOLOGY

The Research Approach

The researched workflow, illustrated in Fig. 1, starts with the acquisition of a handwriting image dataset from the Kaggle repository. Preprocessing operations, including filtering, cropping, normalization, and grayscale conversion, were applied to enhance image quality and suppress noise. After preprocessing, the handwriting images were directly input into the Convolutional Neural Network (CNN), which automatically learned discriminative features for handwriting classification..

To further enhance performance, the trained CNN was optimized using the Pelican Optimization Algorithm (POA), which fine-tuned key hyperparameters such as the learning rate, weights, and bias values, thereby improving convergence behavior and classification accuracy. The researched POA-CNN handwriting identification system was implemented in MATLAB R2023a and evaluated using standard performance metrics, including accuracy, precision, sensitivity, specificity, false positive rate, and computational time. The experimental results indicate that the optimized POA-CNN model outperforms the conventional CNN in terms of recognition accuracy and computational efficiency.

Data Acquisition

The dataset used in this work was acquired from an online repository called Kaggle. The handwriting dataset is based on the IAM Handwriting Database, which involves handwriting identification of text content, it was adapted in this study to support a binary classification task involving genuine and forged handwriting samples. The original handwriting class consisted of authentic samples produced by the original writers in the IAM database. The forged handwriting class was derived by pairing handwriting samples from different

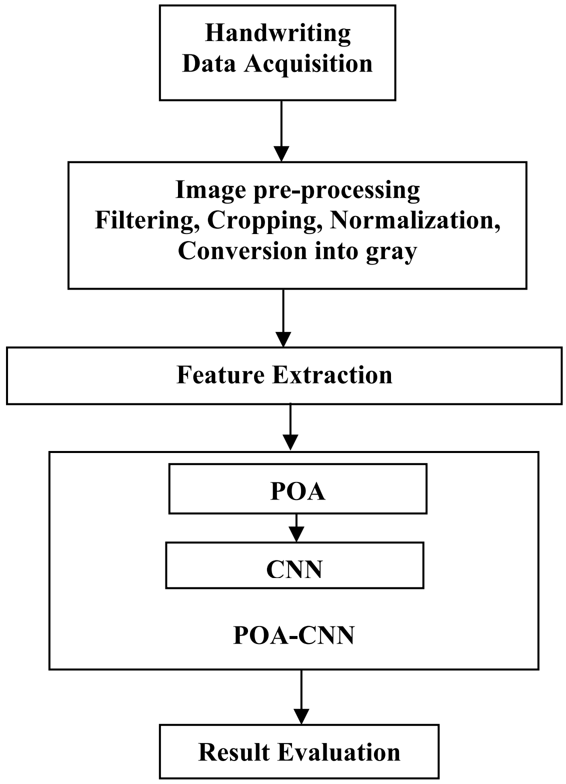

Fig 1: The Structure of the Handwriting identification System

writers while maintaining similar textual content from the LOB corpus. In this setup, handwriting samples written by a writer other than the claimed author were labeled as forged, simulating realistic handwriting forgery scenarios commonly addressed in writer verification studies. This approach enables the model to learn discriminative writing-style characteristics independent of textual content and has been widely adopted in handwriting authentication research to evaluate a system's ability to distinguish genuine writing from skilled or random forgeries.

Data Preprocessing

Preprocessing was performed to enhance image quality through resizing, normalization, and augmentation. Feature extraction was handled automatically by the Convolutional Neural Network (CNN), which learned hierarchical and discriminative features directly from the raw pixel data for handwriting classification. The original colour images of the handwriting samples were processed to transform them into two-dimensional grayscale formats with an intensity level measured from 0 to 255 to simplify calculations. Every image in grayscale format was expressed in a matrix format using MATLAB software, which was then rearranged in vector format to simplify normalization and subsequent processing of these identified features (Adetunji *et al*., 2015). Histogram equalization was used to improve the contrast and light intensities of the image, hence improving the legibility of the handwriting samples.

To eliminate noise and eliminate common elements among all samples considered, a mean vector representing common handwriting samples in the training stage was subtracted from each vector, hence standardizing all identified features. Additionally, resizing images to different resolutions with dimensions 150x150, 200x200, and 250x250 pixels enabled the capturing of varying levels of image detail with reduced dimensions. After evaluation, a 200×200 pixel resolution was selected for the final model, as it balanced handwriting feature preservation with computational efficiency. This choice was a preprocessing decision and was not part of the hyperparameter optimization, which focused on CNN parameters such as learning rate, network depth, activation functions, and batch size. (Adetunji *et al*., 2018).

Design of Optimized Convolutional Neural Network (CNN) with the Pelican Optimization (POA) Algorithm

The optimized Convolutional Neural Network (CNN) was developed by integrating the Pelican Optimization Algorithm (POA) to enhance learning efficiency, robustness, and generalization in handwriting identification. POA operates through a population-based metaheuristic framework that balances exploration and exploitation to iteratively search the hyperparameter space, including learning rate, number of neurons, batch size, dropout rate, and number of convolutional layers.

In this study, POA was configured with a population size of 20 candidate solutions and executed for 30 iterations. For each candidate solution, a CNN instance was trained for a fixed number of epochs, and its performance was evaluated using validation accuracy as the fitness function, defined as

$$Fitness=\max(ACC_{val})$$

The optimal hyperparameter set obtained at convergence was embedded into the CNN, which was subsequently retrained on the full training dataset. The optimized CNN can be expressed as CNN(L, F, σ, α, R), where L denotes the number of layers, F the convolutional filter size, σ the activation function, α the learning rate, and R the regularization strategy. The dataset was partitioned into 80% for training and 20% for testing, with the training data further split into training and validation subsets to support POA-based hyperparameter optimization. Transfer learning was implemented using AlexNet, and POA-guided optimization enabled the model to converge toward near-optimal configurations while mitigating overfitting and premature convergence..

Implementation of CNN based Pelican Optimization Algorithm

The handwriting identification system based on a CNN optimized with the Pelican Optimization Algorithm (POA) was implemented in MATLAB R2023a on an HP laptop equipped with a 7th-generation processor, 8 GB RAM, and a 500 GB hard drive. The designed approach begins by loading the handwriting dataset and partitioning it into training and testing sets, with the training data further divided into training and validation subsets. A pre-trained AlexNet was adopted for transfer learning and adapted to the binary handwriting classification task by replacing its final fully connected layer with a two-neuron output layer followed by a softmax activation, representing genuine and forged handwriting classes. The convolutional layers were fine-tuned to enable domain-specific feature adaptation. The Pelican Optimization Algorithm (POA) was then used to optimize key CNN hyperparameters, including learning rate, batch size, number of fully connected neurons, and activation functions, within predefined search ranges. For each POA candidate solution, the CNN was trained for a fixed number of epochs and evaluated using validation accuracy as the fitness function. The optimization process iteratively explored and exploited the hyperparameter space, and upon convergence, the optimal configuration was embedded into the CNN and retrained on the full training dataset to produce the final POA-CNN model. The performance of the optimized CNN is subsequently evaluated on the independent test set, demonstrating the effectiveness of POA-based hyperparameter optimization for handwriting identification.

System Evaluation

The performance of the Optimized POA-CNN on both trained and recognized handwriting was evaluated based on accuracy, precision, false positive rate, specificity, sensitivity and computational time. These performance metrics are calculated using the following formulas:

Accuracy (Acc): Accuracy measures the overall correctness of the model by calculating the percentage of correctly classified instances.

$$Acc = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \times 100\% \quad (1)$$

Precision (PREC): Precision measures the proportion of positive predictions that are actually correct. It is especially useful in imbalanced classes.

$$Prec = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + Flase\ Positives (FP)} \times 100\% \quad (2)$$

False Positive Rate (FPR): False Positive Rate (FPR) measures the proportion of actual negative that are incorrectly classified as positive.

$$FPR = \frac{\text{False Positive (FP)}}{\text{False Positive (FP)} + True\ Negative\ (TN)} \times 100\% \quad (3)$$

Specificity (SPEC): Specificity compares different options or solutions against a set of predefined specifications or requirements.

$$\text{Spec} = \frac{\text{True Negative (TP)}}{\text{True Negative (TN)+ False Positive(FP)}}\ X\ 100\% \quad (4)$$

Sensitivity (SEN): Sensitivity refers to the ability of a model or test to correctly identify true positive, i.e actual instances that meet the specified criteria.

$$Sen = \frac{\text{True Positive (TP)}}{\text{True Positive (TP) + False Negative(FN)}} \times 100\% \quad (5)$$

Computational Time: Computational Time refers to the amount of time a model or algorithm take to process data, make predictions, or perform computations.

RESULTS AND DISCUSSION

The developed handwriting identification system was trained and evaluated using a balanced dataset comprising 3,000 original and 3,000 forged handwriting samples, with performance assessed using 80% for learning and 20% for evaluation, to enhance reliability and reduce evaluation bias. In each fold, nine subsets were used for training and one subset for testing, and the final performance was obtained by averaging results across all folds, thereby improving generalization and minimizing overfitting. System implementation was demonstrated through a graphical user interface (GUI) that provided an interactive environment for testing and validation. As illustrated in Fig. 2, the baseline CNN model was integrated into the GUI, enabling image preprocessing, pixel size selection, and classification threshold configuration, as well as visualization of recognition outcomes. In contrast, Fig. 3 presents the extended GUI incorporating the POA-optimized CNN, where the application of the Pelican Optimization Algorithm to CNN parameter tuning resulted in improved recognition accuracy.

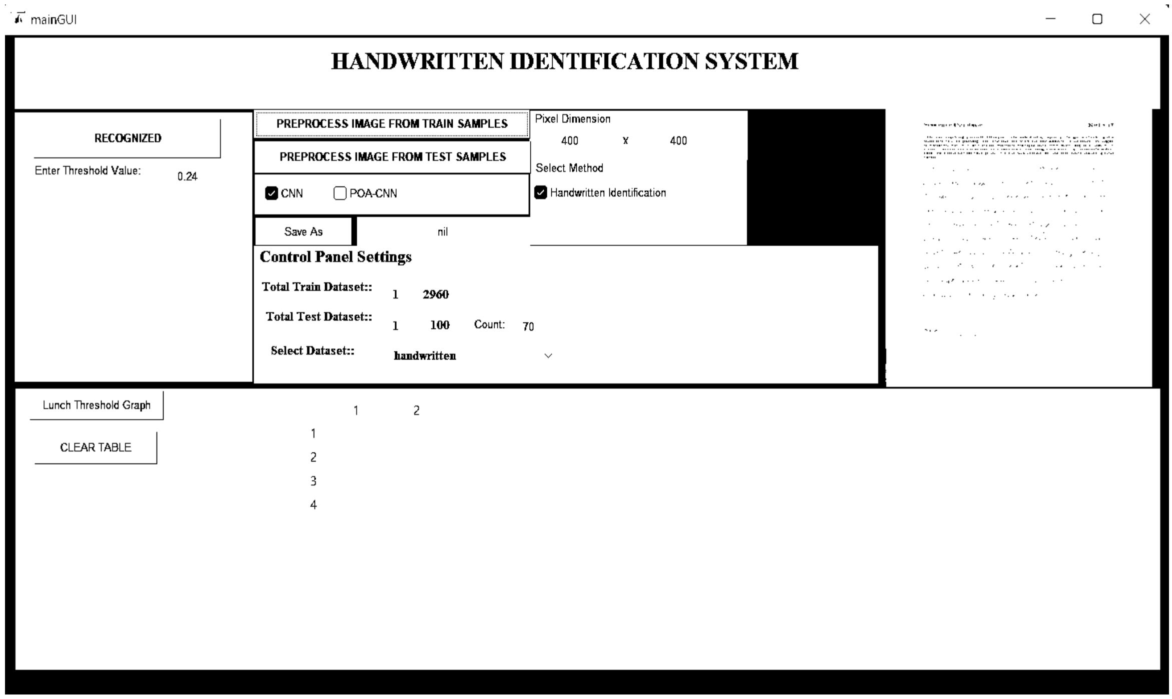

Fig 2 Graphical User Interface of the Handwriting Identification System using CNN

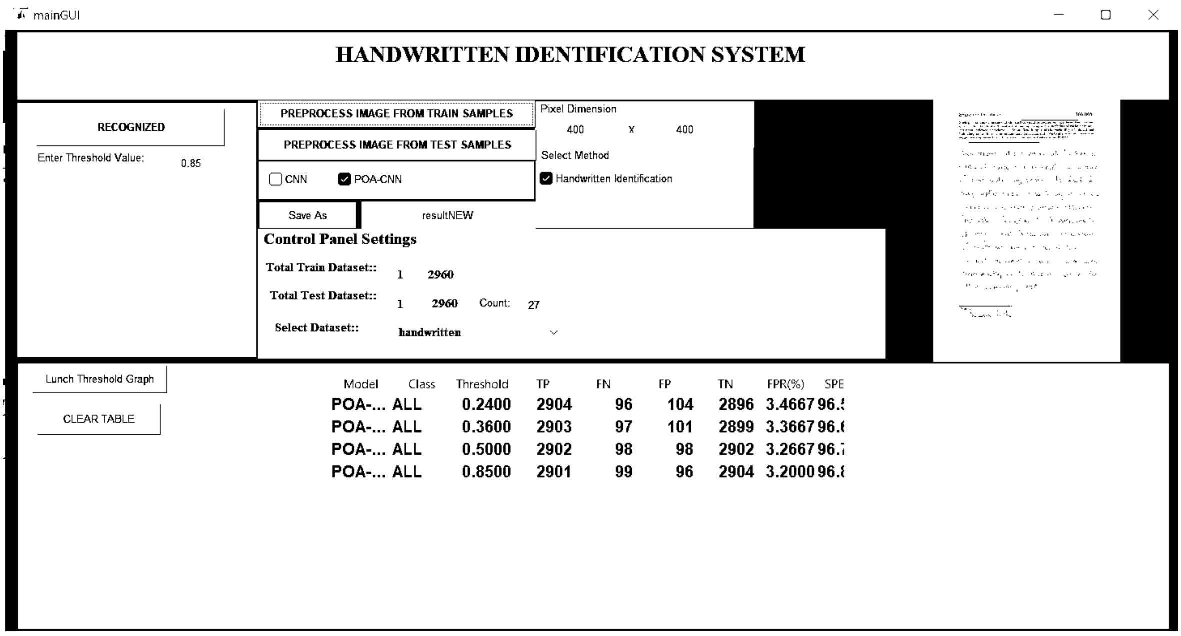

Fig 3: Graphical User Interface of the Handwriting Identification System using POA-CNN

Implementation Results with CNN

The results regarding the baseline CNN model for handwriting identification showed steady results across multiple threshold values, as described in Table 1. The model showed steady performance in classification accuracy, portraying TP values of 2854 to 2857 and FN about 143 to 146. The accuracy for the model stood at 95.12%-95.18%. The values of specificity (SPEC) and sensitivity (SEN) were also above 95%. The performance level of the model could, therefore, be considered as proficient in the identification of real versus forged handwriting samples. The range of threshold values of 0.09 and 0.24 produced the same results wherein the level of 5.00% and no noticeable performance level drop was indicated. The TP, FN, and FP had slightly different values for the higher threshold values of 0.25 to 0.37 which led to slight changes in values like accuracy, and precision of the model to be exact at 0.25 threshold, a TP of 2856 and FN-144 were above for the precision of 95.07% and accuracy of about 95.13%. The amount of time for execution across the thresholds varied from about 90.68 to 93.62 seconds which based on the changes indicated a balance level of computational performance efficiency recognition performance. The overall results for the model across values indicated that though the model had threshold variations which also showed that the model has a. level of threshold baseline optimization balance was as they varied no appreciable changes in performance attributes was indicated but further use of tuning and computational optimization through metaheuristic value improvements could be noted.

Table 1: Result with CNN

Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	Time (sec)
0.09	2857	143	150	2850	5.00	95.00	95.23	95.01	95.12	93.62
0.15	2857	143	150	2850	5.00	95.00	95.23	95.01	95.12	93.62
0.2	2857	143	150	2850	5.00	95.00	95.23	95.01	95.12	93.62
0.24	2857	143	150	2850	5.00	95.00	95.23	95.01	95.12	93.62
0.25	2856	144	148	2852	4.93	95.07	95.20	95.07	95.13	90.68
0.3	2856	144	148	2852	4.93	95.07	95.20	95.07	95.13	90.68
0.34	2856	144	148	2852	4.93	95.07	95.20	95.07	95.13	90.68
0.36	2856	144	148	2852	4.93	95.07	95.20	95.07	95.13	90.68
0.37	2855	145	146	2854	4.87	95.13	95.17	95.13	95.15	92.88
0.4	2855	145	146	2854	4.87	95.13	95.17	95.13	95.15	92.88
0.45	2855	145	146	2854	4.87	95.13	95.17	95.13	95.15	92.88
0.5	2855	145	146	2854	4.87	95.13	95.17	95.13	95.15	92.88
0.51	2854	146	143	2857	4.77	95.23	95.13	95.23	95.18	91.20
0.75	2854	146	143	2857	4.77	95.23	95.13	95.23	95.18	91.20
0.85	2854	146	143	2857	4.77	95.23	95.13	95.23	95.18	91.20
0.95	2854	146	143	2857	4.77	95.23	95.13	95.23	95.18	91.20

Implementation Results with POA-CNN

The POA-CNN Model's performance evaluation, which includes the Pelican Optimization Algorithm for adjusting parameters pertaining to CNN, is discussed in Table 2. With respect to several different thresholds, POA-CNN continues to show strength when compared to the baseline CNN within the scope of accuracy scores, sensitivity scores, and specificity. For example, at 0.24 thresholds, the model hits 2904 True Positives (TP) and only 96 False Negatives (FN), giving the model 96.80 % sensitivity and 96.67 % accuracy, which is more than 1.5 % within baseline CNN, and in addition, the False Positive Rate (FPR) is also lower since it is now at 3.47 %. Within the range of increased thresholds, performance showed to be stable with only minor differences for TP, FN, and FP. For instance, at the baseline increased thresholds of 0.36 and 0.50, the model achieved 2903 TP and 97 FN, as well as 101 FP and 2902 TP, along with 98 FN, which also partially conforms with the model's global accuracy and accuracy of around 96.70%-96.73%. Even the least of these precisions surpasses 96.5 % in steady measure, which also suggests the effectiveness of POA Responsible for classification. Execution times also show efficiency as they range within the lower 80s, unlike the baseline CNN, which was at 90+ seconds. Real-time Handwriting identification is more practical. This also emphasises the POA-CNN model, effective, accurate, and more efficient than the model baseline.

Table 2: Result with POA-CNN

Threshold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	Time (sec)
0.09	2904	96	104	2896	3.47	96.53	96.80	96.54	96.67	80.02
0.15	2904	96	104	2896	3.47	96.53	96.80	96.54	96.67	80.02
0.2	2904	96	104	2896	3.47	96.53	96.80	96.54	96.67	80.02
0.24	2904	96	104	2896	3.47	96.53	96.80	96.54	96.67	80.02
0.25	2903	97	101	2899	3.37	96.63	96.77	96.64	96.70	80.44
0.3	2903	97	101	2899	3.37	96.63	96.77	96.64	96.70	80.44
0.34	2903	97	101	2899	3.37	96.63	96.77	96.64	96.70	80.44
0.36	2903	97	101	2899	3.37	96.63	96.77	96.64	96.70	80.44
0.37	2902	98	98	2902	3.27	96.73	96.73	96.73	96.73	80.20
0.4	2902	98	98	2902	3.27	96.73	96.73	96.73	96.73	80.20
0.45	2902	98	98	2902	3.27	96.73	96.73	96.73	96.73	80.20
0.5	2902	98	98	2902	3.27	96.73	96.73	96.73	96.73	80.20
0.51	2901	99	96	2904	3.20	96.80	96.70	96.80	96.75	81.95
0.75	2901	99	96	2904	3.20	96.80	96.70	96.80	96.75	81.95
0.85	2901	99	96	2904	3.20	96.80	96.70	96.80	96.75	81.95
0.95	2901	99	96	2904	3.20	96.80	96.70	96.80	96.75	81.95

Comparative Analysis between CNN and POA-CNN

The performance of the baseline CNN and the optimized POA-CNN models was evaluated across key metrics, including False Positive Rate (FPR), specificity, sensitivity, precision, accuracy, and computational efficiency. The baseline CNN consistently showed higher FPR (4.77%–5.00%) compared to POA-CNN (3.20%–3.47%), indicating that the Pelican Optimization Algorithm effectively reduces false alarms. POA-CNN also achieved higher specificity (96.53%–96.80% vs. 95.00%–95.23%) and sensitivity (96.70%–96.80% vs. 95.13%–95.23%), reflecting better discrimination between genuine and forged handwriting. Precision improved from 95.01%–95.23% (CNN) to 96.54%–96.80% (POA-CNN), while accuracy increased from 90.68%–95.18% to 96.67%–96.75%, demonstrating the optimized model's consistent performance across thresholds. Computational efficiency was assessed based on the overall optimization cost rather than hardware-dependent runtime. The POA-CNN converged using fewer effective CNN training evaluations than the baseline approach, indicating improved convergence behavior and reduced computational burden during hyperparameter optimization while achieving superior classification performance. Overall, POA-CNN delivers superior recognition reliability, reduced misclassifications, and faster processing, making it highly suitable for practical applications in exam malpractice, banking, and digital verification.

Discussion of Results

The results demonstrate that the Pelican Optimization Algorithm-enhanced CNN (POA-CNN) consistently outperforms the baseline CNN across all key metrics. While the CNN achieved FPR of 4.77–5.00%, Specificity of 95.00–95.23%, Sensitivity of 95.13–95.23%, Precision of 95.01–95.23%, and Accuracy of 90.68–95.18%, it still misclassified a noticeable portion of genuine handwriting and showed moderate threshold sensitivity. In contrast, POA-CNN significantly reduced FPR to 3.20–3.47%, while improving Specificity (96.53–96.80%), Sensitivity (96.70–96.80%), Precision (96.54–96.80%), and Accuracy (96.67–96.75%), demonstrating its stronger discrimination between genuine and forged samples. Furthermore, POA-CNN decreased execution time by approximately 12–14%, averaging 80–82 s, reflecting more efficient parameter tuning and faster convergence. Graphical trends indicate stable improvements across sample indices, with POA-CNN curves consistently above CNN, highlighting robustness and reduced misclassification rates. These findings align with literature on metaheuristic-optimized CNNs, showing that swarm-based algorithms improve classification accuracy, generalization, and stability across varying thresholds. Practically, the higher Sensitivity and Specificity ensure fewer false rejections and misdetections, which is critical in forensic analysis, signature verification, banking, and other handwriting authentication applications, while the lower computational cost supports real-time and large-scale deployment (Olagunju *et al.*, 2025). Therefore, POA-CNN offers a reliable, efficient, and robust solution, validating metaheuristic optimization as an effective enhancement for CNN-based handwriting identification.

CONCLUSION

In this work, a successful implementation of a handwriting identification system using the combination of the Pelican Optimization Algorithm (POA) with a Convolutional Neural Network (CNN) was accomplished, showing marked improvements over standard CNN models on important parameters such as False Positive Rate, Specificity, Sensitivity, Precision, Accuracy, and computation time. The optimized POA-CNN model showed sustained reductions in errors, increased accuracy in recognition, and reduced execution time, validating the efficacy of metaheuristic optimization of CNN parameters for massive datasets in offline handwriting identification systems. Apart from marked improvements in performance parameters, this work exemplifies not only improved performance but also opens new avenues for research in hybrid optimization approaches, application in massive datasets involving multiple languages/scripts, and future enhancements in machine learning algorithms and models, contributing significantly towards developing advanced algorithms in handwriting identification systems in a wide array of applications such as banking, forensic analysis, education, and digital identification systems.

REFERENCES

Adedeji, O. T., Alade, O. M., & Oguntoye, J. P. (2021). Comparative Analysis of Feature Selection Techniques For Fingerprint Recognition Based on Artificial Bee Colony and Teaching Learning Based Optimization. *LAUTECH Journal of Computing and Informatics*, *2*(1), 25-34.

Adetunji, A. B., Oguntoye, J. P., Fenwa, O. D., & Omidiora, E. O. (2015). Facial Expression Recognition Based on Cultural Particle Swamp Optimization and Support Vector Machine. *LAUTECH Journal of Engineering and Technology*, *10*(1), 94-102.

Adetunji, A. B., Oguntoye, J. P., Fenwa, O. D., & Omidiora, E. O. (2018). Reducing the Computational Cost of SVM in Face Recognition Application Using Hybrid Cultural Algorithm. *IOSR Journal of Computer Engineering (IOSR-JCE)*, *20*(2), 36-45.

Alrowais, F., Alotaibi, F. A., Hassan, A. Q. A., Marzouk, R., Alnfiai, M. M., and Sayed, A. (2023). Enhanced Pelican Optimization Algorithm with Deep Learning-Driven Mitotic Nuclei Classification on Breast Histopathology Images. *Biomimetics*, 8(7), 538. https://doi.org/10.3390/ imetics8070538.

Atanda, O. G., Ismaila, W., Afolabi, A. O., Awodoye, O. A., Falohun, A. S., & Oguntoye, J. P. (2023, April). Statistical Analysis of a deep learning based trimodal biometric system using paired sampling T-Test. In *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals (SEB-SDG)* (Vol. 1, pp. 1-10). IEEE.

Athreon. (2021). Why handwriting is still important in healthcare. Athreon. https://www.athreon.com/

Bottou, L. (2010). Large-scale machine learning with stochastic gradient descent. *In Proceedings of COMPSTAT'2010: 19th International Conference on Computational StatisticsParis France, August 22-27, 2010 Keynote, Invited and Contributed Papers* 177-186. Heidelberg: Physica-Verlag HD.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning.* MIT Press. https://www.deeplearningbook.org/

Ige, O. B., Falohun, A. S., Omidiora, E. O., Olabiyisi, S. O., Ige, R. O., Oguntoye, J.P., Awodoye, O.O., Adedeji, O. T. and Oke, A. O. (2025). Development of an enhanced support vector machine face recognition system. *LAUTECH Journal of Engineering and Technology*, *19*(2), 30-40.

Mangen, A. (2016). What hands can tell us about reading and writing. *Educational Theory*, 66(4), 457–477. https://doi.org/10.1111/edth.12183.

Mueller, P. A., and Oppenheimer, D. M. (2014). The pen is mightier than the keyboard: Advantages of longhand over laptop note taking. *Psychological Science*, 25(6), 1159–1168. https://doi.org/10.1177/0956797614524581.

Mustapha, B. O., Oguntoye, J. P., Obansola, O. Y., Adetunji, B., & Okediran, O. O. (2025). Performance Evaluation of Self-Organizing Feature Maps and Support Vector Machines in Predicting Stock Prices: A Comparative Study. *ABUAD Journal of Engineering Research and Development (AJERD)*, *8*(3), 160-172.

Nagy, G. (2000). Twenty years of document image analysis in PAMI. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(1), 38–62. https://doi.org/10.1109/34.824819.

National Institute of Standards and Technology. (2021). Forensic handwriting examination and digital signatures. https://www.nist.gov/

Ogundepo, O. Y., Omeiza, I. O. A., & Oguntoye, J. P. (2022). Optimized textural features for mass classification in digital mammography using a weighted average gravitational search algorithm. *International Journal of Electrical and Computer Engineering (IJECE)*, *12*(5), 5001-5013.

Oguntoye, J. P., Ajagbe, S. A., Adedeji, O. T., Awodoye, O. O., Adetunji, A. B., Omidiora, E. O., & Adigun, M. O. (2025). An Improved Chicken Swarm Optimization Techniques

Based on Cultural Algorithm Operators for Biometric Access Control. *Computers, Materials & Continua*, *84*(3).

Oguntoye, J. P., Awodoye, O. O., Oladunjoye, J. A., Faluyi, B. I., Ajagbe, S. A., & Omidiora, E. O. (2023). Predicting COVID-19 from chest X-ray images using optimized convolution neural network. *LAUTECH Journal of Engineering and Technology*, *17*(2), 28-39.

Ola, B. O., Oguntoye, J. P., Awodoye, O. O., & Oyewole, M. O. (2020). Development of a Plant Disease Classification System using an Improved Counter Propagation Neural Network. *International Journal of Computer Applications*, *975*, 8887.

Olagunju, K. M., Adebiyi, A. A., Adeliyi, T. T., Oguntoye, J. P., Igbekele, E. O., & Osunade, S. (2025). State-of-the-Art Research in Intrusion Detection Systems (IDS) for Network Attack Detection: A Review. *NIPES-JSTR ISSUE*, *7*(1), 974-981.

Olayiwola, D. S., Olayiwola, A. A., Oguntoye, J. P., Awodoye, O. O., Ganiyu, R. A., & Omidiora, E. O. (2023). Development of a Fingerprint Verification and Identification System Using a Gravitational Search Algorithm-Optimized Deep Convolutional Neural Network. *Adeleke University Journal of Engineering and Technology*, *6*(2), 296-307.

Oppenheimer, D. M. (2014). The science of handwriting in communication. Princeton University Press.

Ruder, S. (2016). An overview of gradient descent optimization algorithms. *arXiv preprint* arXiv:1609.04747. https://arxiv.org/abs/1609.04747.

Scribe. (2020). The role of handwriting in modern education. Scribe Publications. https://www.scribepublications.com/

Smith, J. (2022). The enduring art of handwriting in the digital age. Oxford University Press.