

Forensic Handwriting Identification Using Chicken Swarm Optimization-Enhanced Convolutional Neural Networks

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Forensic handwriting identification plays a pivotal role in criminal investigations and legal proceedings, requiring accurate and reliable techniques for analyzing handwriting samples. Convolutional Neural Networks (CNNs) are effective at feature extraction and classification for handwriting analysis, but their performance is highly sensitive to the choice of architectural hyperparameters, and manually tuned CNNs are prone to overfitting on forensic handwriting data. This study integrates the Chicken Swarm Optimization (CSO) algorithm with a CNN classifier (CSO-CNN) to automatically search the number of convolutional layers, the number and size of filters, and the batch size that minimize overfitting and maximize recognition accuracy. Handwritten samples were collected from staff and students of Ajayi Crowther University, Oyo, Nigeria, and organized into three variants (Original, Disguised, and Forged) with each variant split into training and test sets (72% and 28%, respectively) using a random-sampling hold-out procedure. CSO searched 30 candidate CNN configurations over the number of convolutional layers (1–3), the number of filters, the filter size, and the batch size, using recognition rate as the fitness function; the best-performing configuration used a single convolutional layer with 128 filters of size 3×3 and a batch size of 256. The resulting CSO-CNN model was compared against a standard, non-optimized CNN using accuracy, sensitivity, specificity, precision, false positive rate, and recognition time. CSO-CNN outperformed the standard CNN on every dataset variant: on the original dataset, accuracy improved from 82.14% to 86.43%; on the Disguised dataset, from 85.00% to 87.86%; and on the Forged dataset, from 83.57% to 89.29%, while recognition time was also reduced in all three cases. These results indicate that CSO-based hyperparameter search can meaningfully improve CNN-based forensic handwriting identification without requiring architectural redesign. As the evaluation reported here is based on a single hold-out split, repeated cross-validation and testing on independently collected datasets are recommended as a next step to confirm the statistical robustness and generalizability of these gains.

Povzetek: Raziskava predstavlja metodo, ki s samodejno optimizacijo nevronske mreže izboljšuje natančnost in hitrost forenzičnega prepoznavanja rokopisa.

1 Introduction

A person's personality is a conglomeration of their many traits and attributes. According to [1], it could be influenced by the development and evolution of a person's values, characteristics, connections with the community, and recollections of particular life events, routines, and abilities. An individual's personality greatly influences their actions and choices. An individual's handwritten features can be used to identify such a

personality trait [2]. Each person's handwriting may be different, and it can be used to infer information about their personality, behavior, and even some psychological traits. The study of personality based on handwriting is presented as the field of graphology, also known as grapho-analysis [3].

Since before computers, handwritten analysis has been widely used to describe a writer's identity. In banking systems, one of the most popular procedures is signature verification, in which a writer's signature is

used as identification [4]. This makes sense because every writer has their own style, even though most people learn to write by following the printed shapes in books. As a result, handwriting analysis has drawn the attention of neurologists, forensic specialists, and document examiners [5]. According to [6], handwriting is an intricate fine motor skill that involves cognitive, psychomotor, and biophysical processes.

Numerous neurological conditions, including autism, Parkinson's disease, and Alzheimer's disease, have been linked to handwriting [7]. Similarly, research has been done on the effects of aging [8] and psychotropic drugs [6] on handwriting. Among other characteristics, gender has been found to have a major impact on people's writing styles. Male and female differences in motor coordination and hormones are typically cited as the reason for the disparities in writing styles [8]; [9].

CNN has been widely used in recent years in advanced research in a number of fields, including natural language processing [11], speech recognition [12], computer vision [13], object detection [14], image classification [15], object detection [13], semantic segmentation [13], and image retrieval [16]. Nonetheless, it has been noted that CNNs possess the constraint of overfitting. Overfitting is a key difficulty in Deep Learning, particularly within supervised learning techniques. It limits the system's capacity to generalize models efficiently, resulting in a poor fit for both the training data and unseen data in the testing set. The accuracy of the system has frequently been damaged, resulting in a high False Positive Rate [17, 23].

Numerous studies have suggested ways to modify the characteristics of neural networks using optimization techniques, such as bio-inspired algorithms like Particle Swarm Optimization (PSO) [18], Ant Colony Optimization (ACO) [19], and Firefly Algorithm (FA) [20]. These techniques include network pruning based on weight magnitude, which eliminates unnecessary connections between neurons, quantizing CNN weights and intermediate results, and vector quantization, which compresses weighting parameters with variable degrees of success.

Chicken Swarm Optimization (CSO) is widely employed in various fields such power systems, control system, communications, scheduling, feature selection, and community recognition of social networks. Experimental results as described in previous research works also confirm that CSO outperforms several nature-inspired algorithms including FA, PSO, and GA in solving a wide range of conventional benchmark and real-life issues [21, 24]. Some of the distinctive characteristics of CSO include the separation of search space into roosters, hens, and chicks; the distinct food-searching abilities of roosters, hens, and chicks; and the fact that chicks follow their mothers, which leads to efficient population use and a healthy balance between exploration and exploitation.

Thus, this work applies CSO to CNN to address the overfitting problem by introducing a regularization strategy which distinguishes or selects more optimal weight parameters from initial randomized weight

parameters and then apply it to forensic handwritten identification system.

Guided by this motivation, the study addresses the following research questions: (RQ1) Does optimizing CNN hyper-parameters with Chicken Swarm Optimization improve recognition accuracy over a manually configured, non-optimized CNN for forensic handwriting identification? (RQ2) Does this improvement hold consistently across handwriting samples of differing difficulty (Original, Disguised, and Forged) or is it limited to specific conditions? (RQ3) What effect does CSO-based hyper-parameter search have on recognition time, alongside accuracy, sensitivity, specificity, precision, and false positive rate?

The rest of this paper is organized as follows: Section two contains the literature review, while Section three contains the method of developing an improved CNN for forensic handwriting identification system. Section four presents the results and discussion, and Section five provides the conclusion, along with future scope.

2 Literature review

2.1 Forensic handwritten analysis

The investigation of forensic handwriting identification, which is a component of criminology, yields numerous elements pertaining to personnel writing. Since the sixteenth century, forging has been a recognized crime, and forensic document examiners (FDE) have had a challenging challenge [22]. Usually, the forensic handwriting identification is conducted by experts utilizing optical equipment and/or chemicals procedures. The manual features extraction technique can generate doubts about the writer identify [23, 25]. In addition, multiple examiners can extract the same features from a single document in a different way. Then, the usage of semi-automatic systems can be valuable and helpful to the experts when the difficulty is to identify the forger's identity [24].

A frequent goal of forensic handwritten inspection is the determination, by a forensic document examiner, of which individual is the actual writer of a given document. Recently, there has been an increasing interest in the development of forensic handwriting biometric systems that can assist with this decision process. Forensic handwriting biometric systems tend to focus on two key goals. The first step, known as writer verification, is the determination of whether or not two texts were produced by a single writer. The second task, generally referred to as handwriting biometric identification, is the selection from a collection of known writers of a short list of prospective writers for a particular document.

2.2 Related works

Ref [25] created a Handwriting identification system utilizing deep convolutional neural network approach. The IAM handwriting dataset, which had 100 writer classes, was used to train the model. When using

grayscale images instead of binary or inverted binary images, the pre-trained model Visual Geometry Group with 19 deep layers (VGG19) performs the best, according to training and testing results. The finding also indicates that handwriting picture in sentences form may be used directly without any segmentation or feature extraction method needed. The downside of this research is the long time it required to conclude training process. Training method takes about 10 hours to accomplish 100 epochs.

Segmentation-free writer identification (SEG-WI), based on convolutional neural networks, was proposed by [26]. This is a deep convolution neural network (DCNN) that does not require segmentation for identifying writers offline. A unique training technique without segmentation and pre-processing is the key contribution of this research. The region selection and training scheme are also introduced to increase the performance of the SEG-WI model. A comparative evaluation of the SEG-WI model is undertaken for several datasets of different languages. The comparative results illustrate the resilience of the SEG-WI model versus existing state-of-the-art approaches. The performance analysis of SEG-WI in several settings indicates a large boost in performance and also verifies its effectiveness. The recognition system did not, however, examine the problem of overfitting. Improved Handwritten Digit Recognition Using Convolutional Neural Networks (CNN) was created by [27] which analyzed convolutional neural network variations to circumvent the intricate ensemble (classifier combination) approach, expensive feature extraction, and complicated pre-processing required for a conventional recognition system. This research suggests the role of various hyper-parameters and that fine adjustment of CNN architecture is vital in increasing the performance of CNN architecture by utilizing Adam optimizer. In order to optimize CNN learning parameters namely; the number of layers, learning rate, and kernel sizes of convolutional filters. It was proposed that bio-inspired and evolutionary algorithms be investigated.

The overfitting issue was tackled by [28] in Deep Learning-Based Solutions for Next Generation Data-Driven Networks. The develops a maximum pooling dropout algorithm in the pooling layer and introduces weights in the backpropagation. The weight attenuation method is used to lower the complexity of the deep learning model, so as to avoid the overfitting of the deep learning model in training and improve the robustness of network data exchange. There are two key innovations in this essay. One is the design of the maximum pooling dropout, which uses the unit value sorting of the pooled region to create the unit (neuron) discarding mechanism. The second method is to construct the weight attenuation by adding a penalty term to the backpropagation. The implementation process: theoretical analysis and experimental comparison verify that the strategy in this research can avoid overfitting and improve the generalization performance of the network. However, the

approach presented in this paper still has complex difficulties. When the maximum pooling dropout is employed, the semi-linear activation function (ReLU) of the front convolutional layer may produce non-maximum output unit value 0, so that the neuron corresponding to the unit will not be updated in the future (the gradient is 0), that is, dead nerve.

From the examined literature, it is obvious that CNN models suffer from the problem of overfitting. Overfitting shows that the model is too complex for the problem that is solving, i.e. it contains too many features, filters and layers. This leads the model to know the example data well but perform poorly against any new data. However, this can be fixed by applying optimization techniques to adjust the CNN hyper-parameters. For this reason, this work introduced the Chicken Swarm Optimization methodology to adjust the CNN hyper-parameters and lessen the overfitting issue. The handwriting identification system was then implemented using CNN that had been optimized.

2.3 Summary of the state of the art and research gap

Table 1: Summary of reviewed CNN-Based handwriting/document identification studies (as reported in Section 2.2)

Ref.	Method / Architecture	Dataset	Reported Outcome	Noted Limitation
[25]	Pre-trained VGG19 CNN	IAM handwriting dataset (100 writer classes)	Best results with grayscale input; no segmentation/feature extraction required	~10 hours training time for 100 epochs
[26]	Segmentation-free DCNN (SEG-WI)	Multiple multilingual writer-identification datasets	Reported large performance gains over prior approaches (specific figures not stated in the reviewed text)	Overfitting not addressed

[27]	CNN variants with Adam optimizer	Handwritten digit recognition	Demonstrated importance of tuning layers, learning rate, and kernel size	Motivated the need for bio-inspired hyper-parameter search
[28]	CNN with max-pooling dropout + weight attenuation	General deep learning networks	Reduced overfitting and improved generalization in the authors' analysis	Max-pooling dropout can cause a “dead neuron” effect with ReLU

Note: reported outcomes above reflect only what is summarized from each study in Section 2.2 of this manuscript; where a specific accuracy or F1-score was not stated there, we have not invented one. Authors should verify and, where possible, add exact metrics by consulting the original cited papers directly before final submission.

Table 1 makes the recurring gaps in the reviewed literature explicit. First, several studies ([25], [27]) report long training times or rely on hyper-parameters chosen manually, without a systematic search procedure, which plausibly contributes to inconsistent generalization across datasets. Second, at least one study ([26]) does not address overfitting at all despite using a deep architecture. Third, where overfitting is addressed directly ([28]), the proposed fix introduces its own side effects (dead neurons under ReLU). These gaps motivate the present study: rather than manually tuning the CNN or applying a fixed regularization heuristic, we use Chicken Swarm Optimization to search the hyper-parameter space (number of convolutional layers, filter count and size, batch size) directly against recognition accuracy, addressing the manual-tuning and overfitting gaps identified above in a single, unified procedure.

3 Methodology

3.1 Research approach

In developing a Chicken Swarm Optimization based Convolutional Neural Network (CSO-CNN) for handwritten identification system, the following steps were involved;

- The first stage is to acquire data. This was obtained from handwritten samples of staff and students of Ajayi Crowther University, Oyo. The handwritten datasets consist of original datasets, disguised datasets and forged datasets.
- The next stage is to pre-process the acquired data images. Image normalization, thinning, image

augmentation and image segmentation were the pre-processing techniques used on both the training dataset and the test dataset.

- The CSO was applied to CNN to address the problem of overfitting in standard CNN. CSO-CNN was then used for the handwritten identification system.
- The performance of the developed technique on the handwritten identification system was evaluated using metrics such as sensitivity, specificity, precision, false positive rate, recognition accuracy and recognition time for all the variants.

3.2 Data acquisition

Handwritten images were obtained from handwritten samples provided by Ajayi Crowther University students and Staff as part of the Local Handwritten Database. Using the random sampling cross-validation approach, the data samples were split into two groups: 72% training datasets and 28% testing datasets. This means that 360 document data samples were used for training and 140 for testing, for a total of 500 document data samples for the Original, Disguised, and Forged datasets, respectively. This 72%/28% split is not an arbitrary deviation from the conventional 70/30 or 80/20 ratios; it follows directly from dividing each 500-sample dataset variant into 360 training and 140 testing samples ($360/500 = 72\%$, $140/500 = 28\%$), which was the fixed sample allocation used for data collection. We note this as a limitation: results reported in Section 4 reflect a single such hold-out split rather than an averaged result over repeated random splits or cross-validation folds, so the reported performance differences should be interpreted with appropriate caution until confirmed by repeated-trial evaluation.

3.3 Data pre-processing

Data pre-processing plays an important role in any recognition process. To shape the input images in a form suitable for segmentation, the pre-processing methods, such as conversion to grayscale scaling, image normalization, thinning, image augmentation and segmentation were used.

3.4 Formulation of CSO-CNN

The pre-trained CNN designs have various limitations. The highlighted restrictions are that most of the hyper-parameters of any such pre-trained CNN cannot be updated and has some of the hyper-parameters which require optimal selection specifically, the mini-batch size and also the unit numbers in every dense layer and the dropout layer. In this work, the CSO algorithm was utilized in the CNN architecture models classifier portion to optimize the mini-batch size and dropout layer rate. In the learning phase, the CNN architecture models were utilized to classify the handwritten images. There are 16-layers in the conventional CNN architecture; the completely linked levels consist of a dropout layer, flatten layer, batch normalization layer, and two dense

layers. Weight parameters of CNN at each of these layers were optimized by CSO. To avoid ambiguity: the 16-layer figure above describes the depth of the baseline, non-optimized CNN (its convolutional/pooling stack together with the dropout, flatten, batch-normalization, and two dense layers). CSO does not search over this fixed baseline depth directly; instead, as shown in Table 2, it searches candidate configurations that vary the number of convolutional layers (1 to 3), the number and size of filters, and the batch size, and selects the configuration that maximizes recognition rate. The best configuration found (Table 2, configuration 9) used a single convolutional layer with 128 filters of size 3×3 and a batch size of 256; this shallower, CSO-selected architecture, not the 16-layer baseline, is the one evaluated in Section 4. The key component of this system is to construct the method for the categorization of handwritten photographs using deep learning Convolutional neural networks. The handwritten images were rated as disguised, fabricated, duplicate or authentic. These handwritten images are given as the input to this system and the result might be the precise classified image. CNN is fine-tuned by employing the CSO algorithm. By applying this optimization strategy, CNN is retrained with handwritten images to reach the exact classification output. This strategy is an efficient way of boosting the CNN network's efficiency via pre-trained CNN networks. To attain the optimum performance of the technique, the hyper-parameters of the CNN is optimized using CSO algorithm.

Table 2: Parameter of the baseline reference CNN and CSO-selected best configuration

Parameter	Baseline Reference CNN (16 layers)	CSO-Selected Best Configuration (Config 9)
Number of convolutional layers	Part of fixed conv/pool stack (multiple layers)	1
Number of filters	Not searched (fixed)	128
Filter size	Not searched (fixed)	3×3
Batch size	Not searched (fixed)	256
Fully connected layers	Dropout, flatten, batch norm, 2 dense	Same FC structure retained
Total architecture depth	16 layers	Shallower (fewer conv layers)
Selected by	Manually fixed reference architecture	CSO search (30 candidates × 50 iterations)

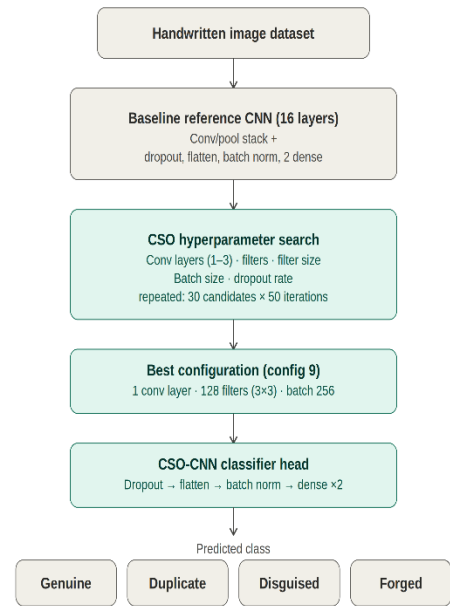


Figure 1: CSO-CNN architecture flowdiagram

3.5 Performance evaluation of the system

The performance of the developed technique CSO-CNN and standard CNN in forensic handwritten recognition system were evaluated based on accuracy, False Positive Rate, Sensitivity, Specificity, Precision and computation time as shown in Equation 1 - 6

$$\text{False Positive Rate} = \frac{FP}{TN+FP} \times 100 \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100 \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100 \quad (3)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100 \quad (4)$$

$$\text{Overall Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (5)$$

$$\text{Computation Time} = \frac{\text{No of Identified Handwritten Characters}}{\text{Total No of Handwritten Characters}} \times \text{Time}(s) \quad (6)$$

4 Results and discussion

The results of the evaluation of Forensic handwritten Identification system using Enhanced Convolutional Neural Network were presented in this chapter. The pre-processed and segmented images used for the study were grouped into original, forged and disguised and are presented in Figure 2. All performance metrics were analysed using a square dimension pixel resolution at different average threshold of 0.1, 0.28, 0.43 and 0.75 from a range of 0-0.20, 0.21-0.35, 0.36-0.50 and 0.51-1.00 respectively. Each threshold values range generated the same accuracy but changes at 0.21, 0.36 and 0.51

threshold values respectively. Seventy-two percent (72%) of the total images were used for training and Twenty-Eight (28%) were used for testing using random sampling cross-validation method.

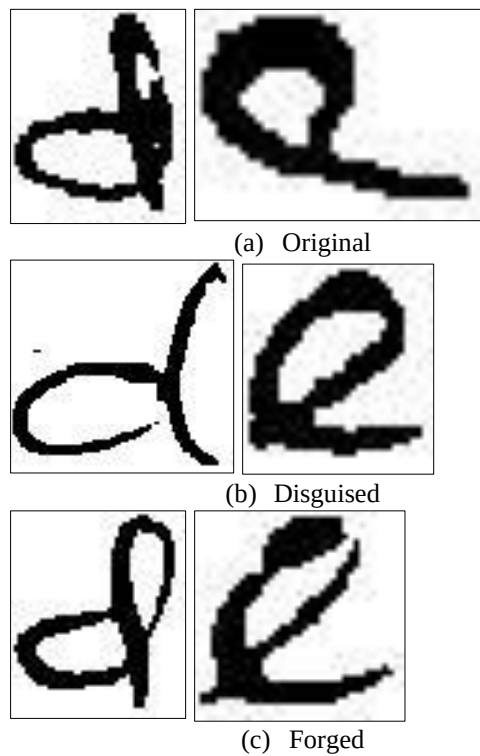


Figure 2: Pre-processed and Segmented Image

Table 3 shows the optimization results of CSO on CNN at 30 iterations with different number of convolutional layers, the number of filters, the filter size or filter dimension used in each convolutional and the batch size number: this value represents the number of images that are entered into CNN in each training block. Recognition rate was used as the objective function. The best recognition rate was achieved at a value of 99.17% as defined. Based on the results, the optimal CNN architecture attained by application of CSO is: 1 convolutional layer, 128 filters per layer with a filter size of 3×3 , and the batch size with a value of 256 for CSO.

Table 3: CSO-CNN parameters

S/N	No. Layers	No. Filters	Filter Size	Batch Size	Recognition Rate (%)
1	3	74	5x5	209	95.60
2	3	32	3 x3	112	96.24
3	3	35	3 x3	213	96.01
4	2	34	7 x7	132	97.73
5	1	32	5 x5	226	98.65

6	1	128	3 x3	194	97.28
7	3	128	3 x3	201	97.14
8	1	128	6x6	133	96.52
9	1	128	3x3	256	99.17
10	1	128	7 x7	256	97.05
11	1	128	7 x7	256	95.79
12	1	128	7 x7	256	96.09
13	3	128	4 x4	256	96.84
14	3	128	4 x4	256	96.01
15	3	128	5 x5	256	96.55
16	3	128	5 x5	256	97.09
17	1	128	4 x4	256	95.52
18	1	128	4 x4	256	96.41
19	2	128	4 x4	256	95.94
20	2	128	7x7	256	97.26
21	1	128	7x7	256	97.89
22	3	128	4 x4	256	98.49
23	2	128	5 x5	256	99.03
24	1	128	7x7	256	97.38
25	2	128	3x3	256	96.03
26	2	128	5 x5	256	96.80
27	1	128	7x7	256	97.47
28	1	128	7x7	256	96.54
29	1	128	4 x4	256	98.63
30	1	128	4 x4	256	95.51

Results for CSO-CNN

The result as shown in Tables 4, 5 and 6 depict the result of the CSO-CNN technique based on 500 handwritten image datasets each for original, disguised and forged at optimum threshold of 0.75. The Tables expressed a combined result of CNN, and CSO-CNN, at identifying handwritten datasets with respect to the metrics used for this research. The result obtained at optimum threshold of 0.75 showed that CSO-CNN technique has a lower recognition time compared with the corresponding CNN technique.

Similarly, FPR, sensitivity, specificity, accuracy and recognition time of CSO-CNN technique and CNN technique were compared; the study discovered that CSO-CNN technique has better performance in accuracy,

sensitivity, specificity, precision, and false positive rate than CNN technique as enumerated in Tables 4, 5 and 6. For Original dataset, 86.43% accuracy, 87.78% sensitivity, 84% specificity and 90.80% precision with CSO-CNN technique while 82.14% accuracy, 84.44% sensitivity, 78% specificity, 87.36% precision with CNN technique. For disguised dataset, 87.86% accuracy, 88.89% sensitivity, 86% specificity and 91.95% precision with CSO-CNN technique while 85.00% accuracy, 86.67% sensitivity, 82% specificity, 89.66% precision with CNN technique. For Forged dataset, 89.29% accuracy, 90.00% sensitivity, 88% specificity and 93.10% precision with CSO-CNN technique while 83.57% accuracy, 85.56% sensitivity, 80% specificity, 88.51% precision with CNN technique. Figure 3 show accuracy chart for Original, Disguised and Forged Datasets. In view of the results, CSO-CNN is more accurate due to low number of false positive at reduced recognition time and which was achieved by standard CSO which selects the best combination of weights at the input convolution layer, hidden convolution layer and output classification layer of the CNNs. The optimal weights selected improved the computational time and accuracy of CNNs network during training and classification process and as well overcome the problem of overfitting.

Table 4: Result of the performance evaluation of CNN, CSO-CNN on original handwritten image dataset

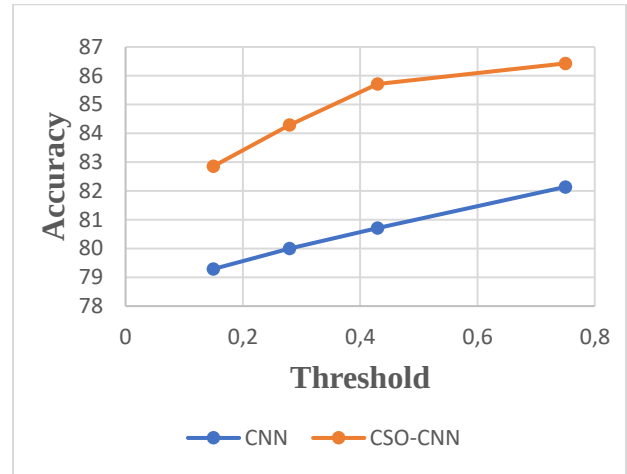
Algorithm	FPR (%)	Sen (%)	Spec (%)	Prec (%)	Acc (%)	Time (sec)
CNN	22	84.44	78	87.36	82.14	77.47
CSO-CNN	16	87.78	84	90.80	86.43	52.21

Table 5: Result of the performance evaluation of CNN, CSO-CNN on disguised handwritten image dataset

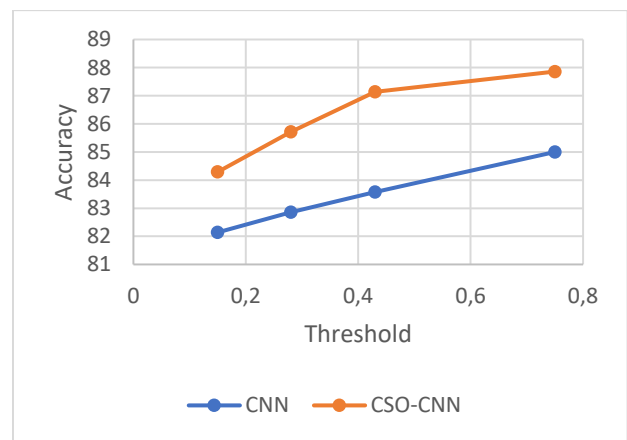
Algorithm	FPR (%)	Sen (%)	Spec (%)	Prec (%)	Acc (%)	Time (sec)
CNN	18	86.67	82	89.66	85.00	74.71
CSO-CNN	14	88.89	86	91.95	87.86	49.15

Table 6: Result of the performance evaluation of CNN, CSO-CNN on forged handwritten image dataset

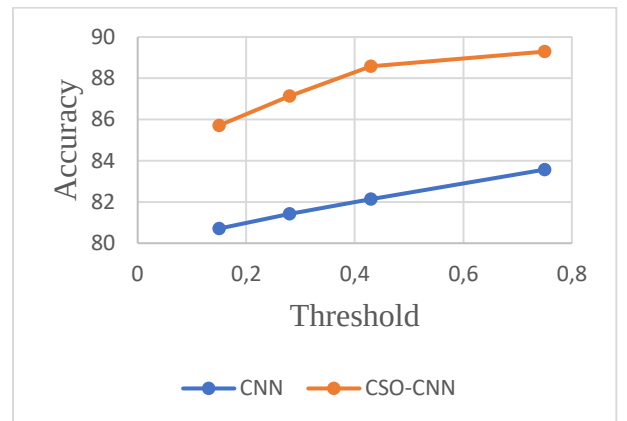
Algorithm	FPR (%)	Sen (%)	Spec (%)	Prec (%)	Acc (%)	Time (sec)
CNN	20	85.56	80	88.51	83.57	72.24
CSO-CNN	12	90.00	88	93.10	89.29	47.27



(a) Accuracy for Original Dataset



(b) Accuracy for Disguised Dataset



(c) Accuracy for Forged Dataset

Figure 3: Graph showing accuracy for original, disguised and forged dataset

5 Discussion

5.1 Comparison with the reviewed state of the art

The CSO-CNN results in Section 4 (86.43% accuracy on Original, 87.86% on Disguised, and 89.29% on Forged handwriting, each exceeding the corresponding standard-CNN baseline) are consistent

with the broader pattern identified in Section 2.3: studies that apply a systematic search or regularization strategy to CNN hyper-parameters tend to outperform those that do not. Unlike [26], which did not address overfitting at all, CSO-CNN targets it directly by searching the hyper-parameter space rather than fixing an architecture in advance. Unlike [28], whose max-pooling dropout regularization can cause dead ReLU units, CSO-CNN instead avoids overfitting-prone configurations before training rather than correcting for them during training, side-stepping that particular failure mode. It is also comparatively lightweight next to [25], whose VGG19-based approach required roughly 10 hours of training for 100 epochs: the CSO-selected architecture used here has a single convolutional layer, which is plausibly one reason recognition time was consistently lower for CSO-CNN than for the standard CNN baseline across all three dataset variants in Tables 4, 5 and 6.

5.2 Mechanistic interpretation and trade-offs

The accuracy gains are plausibly explained by CSO avoiding hyper-parameter configurations that overfit the training data: Table 3 shows recognition rate varying from 95.51% to 99.17% across the 30 candidate configurations evaluated, indicating that architecture choice alone accounts for a non-trivial performance range even before considering the CNN's learned weights. This gain is not free: running CSO over 30 candidate configurations adds a fixed up-front search cost that a manually configured CNN does not incur, and as a population-based metaheuristic, CSO offers no guarantee of finding the global optimum. We consider this an acceptable trade-off for a system that, once the search is complete, is deployed with a single fixed, and in this case shallower and faster, architecture.

5.3 Limitations

Several limitations should be considered when interpreting these results. First, the dataset was collected at a single institution (Ajayi Crowther University), and the manuscript does not report the demographic composition (age, gender distribution) of the contributing writers; the generalizability of the reported accuracies to other populations and handwriting traditions has not been established. Second, as noted in Section 3.2, the reported metrics reflect a single 72%/28% hold-out split rather than an average over repeated random splits or cross-validation folds, so the precision of the reported accuracy differences (e.g., 86.43% vs. 82.14%) has not been confirmed by repeated-trial statistical testing. Third, the model has not been evaluated on an independently collected, external dataset, so its performance under distribution shift (different scanners, writing surfaces, or languages) is untested. We recommend repeated cross-validation, external validation, and reporting of writer demographics as priorities for future work.

6 Conclusion

This study applied Chicken Swarm Optimization to search the number of convolutional layers, filter count and size, and batch size of a CNN for forensic handwriting identification. As detailed in Section 4 and discussed in Section 5, the resulting CSO-CNN outperformed a manually configured baseline CNN on all three dataset variants (Original, Disguised, and Forged) while also reducing recognition time, supporting RQ1 and RQ2; the trade-offs and boundary conditions of this improvement are discussed in Section 5.2, and its limitations in Section 5.3 rather than repeated here. Building on those limitations, priority directions for future work are: (i) validating these findings with repeated cross-validation and on an independently collected, external dataset to confirm statistical robustness and generalizability; (ii) expanding the dataset to a wider range of handwriting styles, languages, and writer demographics; (iii) benchmarking CSO against alternative population-based optimizers (e.g., particle swarm optimization, genetic algorithms) under the same protocol; and (iv) extending toward real-time handwriting verification and evaluating the approach in practical forensic deployment scenarios.

Declaration section

Ethical approval Not applicable in the sense of a clinical/medical ethics board review; however, the handwriting samples are primary data voluntarily provided by staff and students of Ajayi Crowther University, Oyo, Nigeria, with informed consent, and personally identifying information was removed (anonymized) prior to analysis.

Competing of interest

The authors declare that they have no competing interests concerning the publication of this paper.

Data availability statement

Data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset is not deposited in a public repository because it contains handwriting samples collected from identifiable volunteers.

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Consent to Publish declarations

All authors consented to publish this paper in Computers and Electrical Engineering

Author contributions: Conceptualizations, methodology writing—original draft, and data curation OSO, MOO, SAA, JOJ; methodology data curation visualization, validation, and software, MTO, JOJ, OOA, AKA; project administration, resources, editing and

review, supervision MOO, AKA. All authors have read and agreed to the published version of the manuscript.

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