

Development of an Optimized Extreme Learning Machine Model for Face-Based Crime Control Recognition System Using Mantis Search Algorithm

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DOI: <https://doi.org/10.51244/IJRSI.2026.1308000206>

Received: 26 August 2026; Accepted: 31 August 2026; Published: 15 September 2026

ABSTRACT

Face recognition can be used for crime control and public security, due to its ability to identify individuals without physical contact. However, variations in illumination, pose, image quality and occlusion affect its accuracy, worsened in real-world settings where surveillance cameras rarely capture a clear shot of a face. A fast, simple classifier, Extreme Learning Machine (ELM), was introduced, but it suffers from random initialization of its hidden-layer weights and biases, producing inconsistent accuracy. This led to proposing an optimized model, Mantis Search Algorithm-Extreme Learning Machine (MSA-ELM), which searches for the ELM configuration giving the best accuracy rather than choosing randomly. Images were acquired from the Federal School of Surveying, Oyo, comprising 300 individuals with three images each (900 images), grouped into crime-suspect and non-crime-suspect classes. The dataset was split 70% training and 30% testing, pre-processed by resizing, cropping and grayscale conversion, then features extracted using Local Binary Pattern (LBP) prior to classification. The model was implemented in MATLAB R2016a with an interactive GUI for training, testing and identification. MSA-ELM achieved 95.93% accuracy, 3.42% FAR and 4.58% FRR against 92.22%, 7.69% and 7.84% for traditional ELM, reducing recognition time from 73.79 to 55.87 seconds, supporting its consideration for real-world surveillance and suspect-identification deployment.

Keywords: Face Recognition, Crime Control, Mantis Search Algorithm, Extreme Learning Machine, Local Binary Pattern, Biometric Recognition, Machine Learning.

INTRODUCTION

Modern security systems has adopted as Biometric technology one of the most reliable techniques of recognizing and authenticating individuals. Biometric systems recognize people by their unique physiological or behavioral characteristics that are difficult to lose, copy or impersonate unlike passwords, Personal Identification Numbers (PINs) and identity cards [4]. Among the available biometrics modalities, face recognition has become one of the most widely adopted modalities [2], because it can identify individuals without physical contact, using facial images captured remotely by surveillance cameras. For this reason, face recognition is always applied popular in border security, access control, forensic investigation and crime-control surveillance.

The increasing use of facial recognition technology in law enforcement and public security for criminal investigation, suspect identification, missing person search, and public safety monitoring have contributed to

the rise of intelligent surveillance systems. However, in real-world face recognition, the recognition accuracy is reduced and the possibility of false classification increases because the facial images captured by surveillance cameras are often under poor lighting, different viewing angles, low image quality [6], aging, and partial occlusion [8].

The Extreme Learning Machine (ELM) as one of the machine learning based face recognition techniques has received much attention due to its fast training speed, simple structure, and good generalization ability [3, 5]. However, the traditional ELM randomly initializes its hidden-layer weights and biases before training, which may lead to inconsistent recognition accuracy among different training runs [7]. To overcome this limitation, researchers have used metaheuristic optimization algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to optimize ELM parameters. Recently, Mantis Search Algorithm (MSA), a bio-inspired optimization technique, being able to balance between global exploration and local exploitation and has demonstrated competitive performance on general optimization benchmarks [1]. Nevertheless, application of MSA to optimize ELM for face-based crime-control recognition has not been explored yet. Thus, this study aims to investigate the integration of MSA with ELM to increase facial recognition accuracy, reduce the false acceptance and false rejection rates, and improve the computational efficiency of face-based crime-control recognition systems.

The objectives of this research are to (i) develop an optimized ELM model for face-based crime control recognition using MSA, (ii) implement the developed model in MATLAB R2016a, and (iii) evaluate the model performance using Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), and Recognition Time.

METHODOLOGY

The development of the MSA-ELM face recognition model involved five stages: face image acquisition, image pre-processing, feature extraction, MSA-based optimization of ELM parameters, and performance evaluation.

Face Image Acquisition and Pre-processing

A facial image dataset of 300 individuals, each with three samples (900 images in total), was captured from the Federal School of Surveying, Oyo State, and labelled into two categories: crime suspects class and non-crime suspects class. The dataset was partitioned using a random sub-sampling cross-validation method, whereby 70% of the images was used for training and the remaining 30% was used for testing. The facial images were pre-processed by converting them to grayscale, cropping, resizing, and adjusting brightness and contrast to improve image quality prior to feature extraction.

The crime-suspect label was assigned to individuals appearing on the security watch-list maintained by the institution's security unit at the time of data collection, while the non-crime-suspect label was assigned to students with no such record. This labelling reflects an administrative record rather than a judicial determination of guilt, and its implications are discussed further in Section IV.

Feature Extraction Using Local Binary Pattern

This involved extracting discriminative facial features from the pre-processed images using the Local Binary Pattern (LBP) technique, to encode local texture information by comparing each pixel with its neighbours. The resulting feature vectors were used as inputs to the Extreme Learning Machine classifier.

Optimization of ELM Using the Mantis Search Algorithm

The Extreme Learning Machine classifies inputs using a single hidden-layer feedforward network. The input weights and hidden-layer biases are randomly assigned before the output weights are computed using the Moore-Penrose pseudo-inverse [3]. In this study, instead of choosing these settings randomly, the Mantis Search Algorithm (MSA) searches for the ELM configuration that provides better recognition performance. The best ELM parameter configuration obtained from MSA is then used to construct the final recognition

model. MSA is a bio-inspired optimization method modelled on the hunting behaviour and sexual cannibalism of the praying mantis [1]. It works in three main stages: searching for prey (exploration), attacking prey (exploitation), and sexual cannibalism. These stages help the algorithm explore many possible solutions and then focus on improving the best ones. During training, MSA repeatedly tested different combinations of input weights and biases and selected the combinations that produced the lowest classification error. These optimized settings were then used to train the final MSA-ELM model. In short, MSA helps the ELM replace its random settings with better-optimized ones, that can improve its classification performance.

Performance Evaluation Metrics

The developed MSA-ELM model was compared with the conventional ELM under same preprocessing and dataset conditions. Performance was evaluated using Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), and Recognition Time, computed across a range of threshold values using True Positive, False Positive, True Negative, and False Negative classification outcomes.

Precision, recall, F1-score and ROC-AUC were not computed in this study, and the reported figures reflect a single 70/30 train-test split rather than repeated cross-validated trials; the scope and limitations of this evaluation protocol are discussed in Section IV.

MODELING AND ANALYSIS

The MSA-ELM recognition framework was implemented in two phases, illustrated in Figure 1. In the training phase, facial images were loaded, pre-processed, and passed through LBP for feature extraction before the classifier was trained and the trained model saved. In the testing phase, new facial images underwent the same pre-processing and feature-extraction steps before being matched against the trained model to predict whether the subject was a crime suspect or a non-crime suspect.

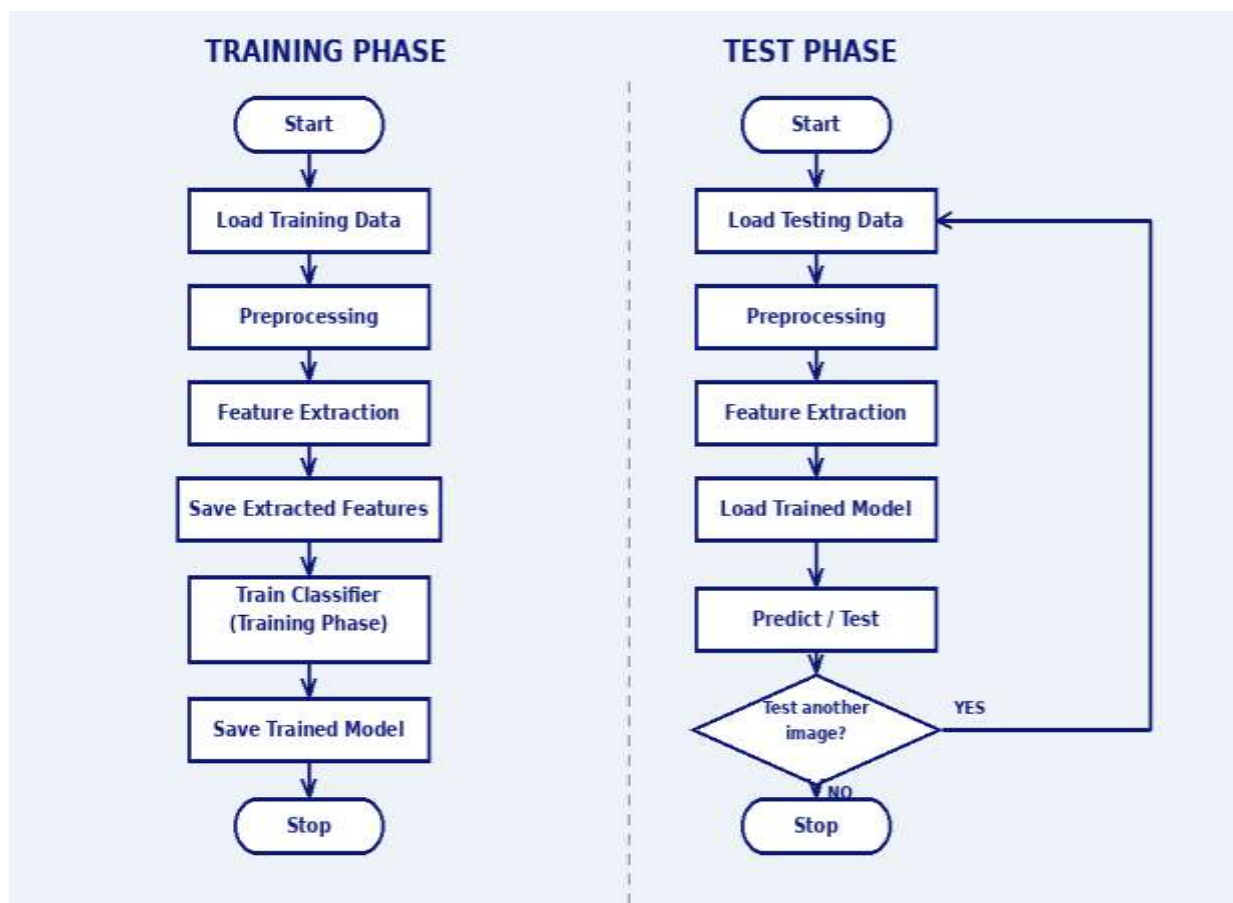


Figure 1: Training and testing phase flowchart of the MSA-ELM model.

An interactive Graphical User Interface (GUI) was developed in MATLAB R2016a using the image processing, computer vision, and optimization toolboxes to support model training, testing, and identification. The GUI allowed threshold values to be adjusted, cropped face images to be visualized, classification outcomes to be displayed in tabular form, and the ELM and MSA-ELM techniques to be toggled and compared directly

RESULTS AND DISCUSSION

The developed GUI (Figure 2) demonstrated the model's training and testing workflow, displaying the detected face alongside its recognition result. Across four test trials, the MSA-ELM model recorded True Positive values ranging from 146 to 149 with relatively low false-positive and false-negative counts, indicating robust generalization on unseen facial images

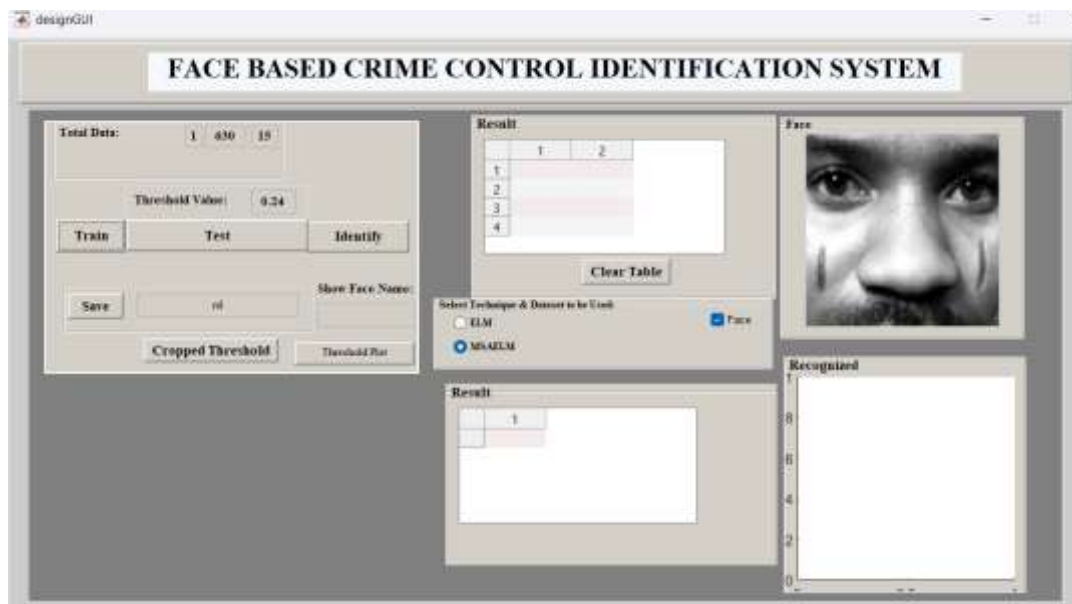


Figure 2: Graphical User Interface of the MSA-ELM face-based crime control recognition system.

Table 1 compares the performance of the traditional ELM and the proposed MSA-ELM model at their respective optimal threshold settings. ELM achieved its best performance at higher thresholds (0.51–0.98), with 92.22% accuracy, 7.69% FAR, 7.84% FRR, and an average recognition time of 73.79 seconds. In comparison, the MSA-ELM model achieved 95.93% accuracy, 3.42% FAR, and 4.58% FRR at the same threshold range, while reducing recognition time to approximately 55.87 seconds.

Table 1: Comparison of ELM and MSA-ELM performance at optimal threshold.

Metric	ELM	MSA-ELM	Improvement
Accuracy (%)	92.22	95.93	+3.71
False Acceptance Rate (%)	7.69	3.42	-4.27
False Rejection Rate (%)	7.84	4.58	-3.26
Recognition Time (sec)	73.79	55.87	-17.92

The results show that the optimized MSA-ELM's input weights and hidden-layer biases consistently outperformed the randomly initialized traditional ELM across all evaluated metrics. The reduction in FAR indicates improved separation between crime suspect class and non-crime suspect class, while the reduction in FRR indicates that crime suspects were less frequently misclassified as non-suspects. The improvement in accuracy and the reduction in recognition time together indicate that MSA's exploration–exploitation search strategy enabled the ELM to converge on parameter configurations that produced a more discriminative and computationally efficient classifier than random initialization. These findings are consistent with the view that the accuracy of ELM is sensitive to its initial parameters [7], and that intelligent optimization can help the model escape poor local configurations to achieve a more globally optimal solution.

Limitations of the Study

Several limitations constrain the strength and generalizability of these findings. First, the dataset comprises only 300 individuals drawn from a single institution (the Federal School of Surveying, Oyo), which limits the extent to which the reported accuracy, FAR and FRR figures can be expected to generalize to more diverse populations, other demographic groups, or independent real-world surveillance settings. Second, the labelling of individuals as “crime suspects” or “non-crime suspects”, based on an institutional watch-list, is a simplification that raises genuine concerns about labelling criteria and potential bias, as such a label reflects an administrative record rather than a judicial finding and only for the purpose of this research. Third, the performance figures reported in Table 1 are drawn from a single random 70/30 train-test split; no cross-validation, repeated trials, confidence intervals, or statistical significance testing were performed, so the consistency of MSA-ELM's advantage over ELM across different data partitions has not been established. Fourth, MSA-ELM was compared only against conventional ELM and was not benchmarked against contemporary deep-learning-based face recognition approaches (e.g., CNN-based methods), which limits the strength of any claim of state-of-the-art performance. Finally, the evaluation is limited to Accuracy, FAR, FRR and recognition time; precision, recall, F1-score, ROC-AUC, and the computational resources used were not reported, which limits comparability with other studies. These limitations do not undermine the study's core methodological contribution – the use of MSA to replace ELM's random parameter initialization – but they do mean the reported performance figures should be read as evidence from a single controlled experiment rather than as generalizable, deployment-ready benchmarks.

CONCLUSION

This study developed and evaluated an optimized Extreme Learning Machine model, MSA-ELM, for face-based crime control recognition, in which the Mantis Search Algorithm was used to select the ELM's input weights and hidden-layer biases in place of random initialization. Using a dataset of 900 facial images from 300 individuals and Local Binary Pattern feature extraction, the MSA-ELM model achieved higher recognition accuracy, lower false acceptance and false rejection rates, and shorter recognition time than the conventional ELM. These results demonstrate that MSA is an effective optimizer for improving the stability and reliability of ELM-based facial recognition and support its consideration for deployment in surveillance and suspect-identification systems. Future work may explore parallel or distributed processing to further improve real-time performance, as well as extending the MSA-ELM approach to multimodal biometric systems that combine facial data with other modalities such as fingerprint or iris. However, in light of the limitations discussed in Section IV – particularly the modest and single-institution dataset, the absence of cross-validation and statistical significance testing, the lack of comparison with deep-learning methods, and the unresolved bias, privacy and fairness questions raised by watch-list-based labelling – the model should be regarded as a proof-of-concept rather than a deployment-ready system, and its consideration for real-world surveillance or suspect-identification applications should follow further work that addresses these concerns. Future work should also expand the dataset to include a larger and more demographically diverse population drawn from multiple institutions and realistic surveillance conditions; test the model under systematically controlled variations in illumination, pose, occlusion, facial expression, and image resolution; adopt cross-validation, repeated experiments, confidence intervals, and appropriate statistical significance tests; benchmark MSA-ELM against contemporary deep-learning-based (e.g., CNN-based) and other state-of-the-art face recognition methods;

report a fuller set of metrics, including precision, recall, F1-score, ROC-AUC, and computational resource requirements; and explicitly document and justify labelling protocols while addressing privacy, fairness, security, and responsible-deployment considerations before any recommendation of real-world deployment.

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