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# Effective Face Recognition Using Rat Swarm Optimisation with SVM Algorithm

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**Abstract:** *Human facial characteristics are a key biometric trait for identifying and distinguishing individuals, making face recognition an essential technology in applications such as criminal identification, smartphone unlocking, and home security systems. Unlike traditional authentication methods that rely on keys or cards, face recognition systems require only facial images, offering enhanced security and convenience across multiple applications. Recent deep learning–enabled face recognition models have reduced dependency on complex encryption techniques; however, conventional approaches still fail to meet current demands due to low recognition accuracy. To overcome these limitations, an advanced deep learning–based face recognition framework is developed to accurately authenticate individuals using facial images collected from standard benchmark databases. The images are first pre-processed using median filtering to reduce noise and improve quality, followed by spatial feature extraction using Local Binary Patterns (LBP) and Local Vector Patterns (LVP) to capture discriminative facial features. Optimal feature selection is achieved using the Improved Rat Swarm Optimization (IRSO) algorithm, and the final recognition is performed using an Adaptive Multi-Scale Transformer-based ResNet (AMT-ResNet), with its network parameters further optimized by IRSO. The performance of the proposed model is validated through comparisons with various heuristic optimization algorithms and existing baseline face recognition methods, demonstrating its effectiveness and improved accuracy.*

**Keywords***:* Face Recognition; Facial Images; Optimal Pattern Extraction Rate; Local Binary Patterns; Local Vector Patterns; Improved Rat Swarm Optimization Algorithm

## I. INTRODUCTION

Face recognition has emerged as one of the most reliable and widely adopted biometric technologies for personal identification and authentication [1], [2]. Human facial characteristics are unique, non-intrusive, and convenient, making them highly suitable for identifying individuals in applications such as criminal investigation, surveillance systems, smartphone unlocking, access control, and home security [3]. Unlike traditional authentication mechanisms that rely on passwords, keys, or smart cards, face recognition systems use facial images directly, thereby improving usability while offering enhanced security [4]. Due to the increasing deployment of smart devices and automated security systems, there is a growing demand for face recognition techniques that are accurate, robust, and scalable in real-world environments.

Conventional face recognition approaches based on handcrafted features and classical machine learning algorithms often suffer from performance degradation under challenging conditions such as variations in illumination, facial expressions, pose, occlusion, and background clutter [5]. These limitations restrict their applicability in unconstrained scenarios and lead to reduced recognition accuracy. Although encryption-based security mechanisms have been employed to enhance protection, they introduce additional computational complexity and interdependencies. The emergence of deep learning has significantly transformed face recognition by enabling automatic feature learning, improved generalization, and end-to-end optimization, thereby reducing the dependency on complex encryption methods [6].

Recent deep learning–based face recognition frameworks integrate effective preprocessing, discriminative feature extraction, optimization strategies, and powerful classification models to overcome the shortcomings of traditional techniques [3], [4]. Texture-based descriptors such as Local Binary Patterns (LBP) have proven effective in capturing local facial structures [5], while deep residual networks and transformer-based architectures further enhance recognition performance by learning multi-scale and contextual representations [6]. These advanced approaches demonstrate superior accuracy, robustness, and adaptability, making them well suited to meet the increasing security and authentication requirements of modern biometric systems.

## II. LITERATURE SURVEY

Face recognition has gained significant attention in recent years due to its wide applicability in security, surveillance, and human–computer interaction systems. With the advancement of deep learning techniques, several researchers have proposed robust models to address the challenges associated with facial variations such as pose, illumination, expression, and occlusion. Al-Waisy et al. [6] introduced a multimodal deep learning framework using local feature representations for face recognition under unconstrained environments. Their approach effectively combined handcrafted features with a deep belief network to enhance recognition accuracy; however, the model suffered from increased computational complexity when applied to large-scale datasets.

Durga and Rajesh [7] developed a ResNet-based deep learning model for facial recognition in multimedia applications. The proposed architecture effectively reduced artifacts and improved gradient flow, resulting in enhanced recognition accuracy. Nevertheless, the model required optimized parameter tuning and high computational resources, limiting its adaptability to real-time systems. Gao et al. [8] proposed a supervised autoencoder-based face recognition method that learned robust facial representations from limited training samples. Although the approach demonstrated strong generalization under occlusion and illumination variations, its scalability was constrained due to the need for extensive training data for complex scenarios.

Lu et al. [9] presented a joint feature learning framework for face recognition that simultaneously learned discriminative facial features and similarity metrics. Their method improved recognition accuracy by capturing both global and local information; however, it showed sensitivity to variations in pose and aging. Roy et al. [10] introduced an interpretable local frequency binary pattern–based continual learning network for heterogeneous face recognition. While the method improved interpretability and cross-domain learning, it faced challenges in handling high-dimensional feature spaces efficiently.

Galea and Farrugia [11] explored deep convolutional neural networks combined with transfer learning for matching software-generated facial sketches with photographs. The proposed approach achieved improved recognition performance using morphed face data, but its effectiveness was limited when dealing with extreme facial variations. Faizabadi et al. [12] proposed a region-of-interest–based metric learning technique for effective face recognition, which improved discriminative power by focusing on salient facial regions. However, the model required careful region selection and was sensitive to inaccurate landmark detection.

From the existing literature, it is evident that although deep learning–based face recognition models have significantly improved performance, challenges such as optimal feature selection, parameter tuning, scalability, and robustness under real-world conditions still persist. These limitations motivate the development of the proposed framework, which integrates optimal pattern extraction using an Improved Rat Swarm Optimization (IRSO) algorithm and an Adaptive Multi-scale Transformer-based ResNet (AMT-ResNet) to achieve enhanced accuracy and robustness in face recognition.

## III. PROPOSED FACE RECOGNITION MODEL

The overall architecture of the proposed face recognition model is designed as a sequential and optimized pipeline that integrates preprocessing, feature extraction, feature optimization, and deep learning–based classification to achieve high recognition accuracy. The architecture ensures robustness against variations in illumination, pose, expression, and noise, which are commonly encountered in real-world face recognition scenarios.

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The process begins with **facial image acquisition**, where input images are collected from standard benchmark face databases. These images are first passed through a **preprocessing module**, where median filtering is applied to suppress impulsive noise while preserving essential facial edges and texture information. This step improves image clarity and ensures consistent input quality for the subsequent stages.

In the next stage, **spatial feature extraction** is performed using two complementary texture descriptors: **Local Binary Patterns (LBP)** and **Local Vector Patterns (LVP)**. LBP encodes local texture variations by comparing each pixel with its neighboring pixels, generating robust binary patterns that effectively represent micro-level facial structures. LVP, on the other hand, captures directional and structural information by analyzing vector relationships among neighboring pixels, enabling the extraction of more discriminative and orientation-sensitive features. The combination of LBP and LVP provides a comprehensive representation of both local textures and spatial relationships in facial images.

To enhance feature quality and reduce redundancy, an **Improved Rat Swarm Optimization (IRSO)** algorithm is employed for **optimal pattern selection**. IRSO mimics the social and foraging behavior of rats to explore and exploit the feature space efficiently. In the proposed architecture, IRSO selects the most relevant and discriminative features from the combined LBP–LVP feature set, thereby reducing dimensionality and improving classification efficiency. Additionally, IRSO helps avoid local optima and accelerates convergence during the optimization process.

The optimally selected features are then input to the **Adaptive Multi-scale Transformer-based ResNet (AMT-ResNet)** for face recognition. The ResNet backbone facilitates deep feature learning through residual connections, which mitigate the vanishing gradient problem and enable the training of deeper networks. The multi-scale transformer module incorporates attention mechanisms that capture both local and global contextual dependencies across facial regions at different scales. This adaptive learning strategy allows the model to focus on salient facial regions while maintaining global consistency.

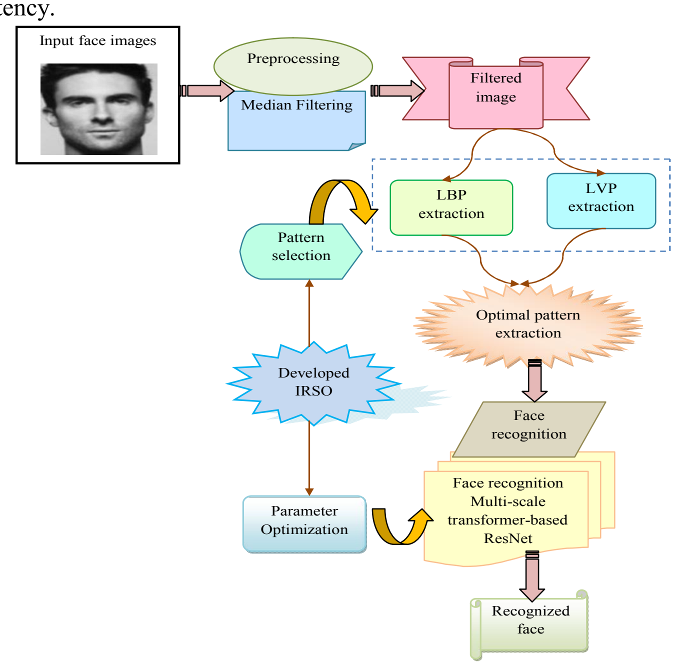


Fig 1. Architectural Illustration of developed Face Recognition Model

Furthermore, IRSO is also utilized to **optimize the parameters of the AMT-ResNet**, such as learning rates, weight parameters, and hidden neuron configurations. This dual-level optimization—feature selection and network parameter tuning—significantly enhances recognition accuracy and generalization capability. Finally, the output layer of the AMT-ResNet performs identity classification, producing the recognized class label for each input facial image.

Overall, the proposed architecture effectively combines robust preprocessing, discriminative feature extraction, intelligent optimization, and advanced deep learning classification. The integrated framework ensures improved

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accuracy, reduced computational complexity, and strong adaptability to real-world face recognition applications such as surveillance, access control, and biometric authentication systems. Fig 1 Depicts the overall architecture of the propose model

## IV. RESULTS AND DISCUSSIONS

### A. EXPERIMENTAL SETUP

The newly implemented IRSO-AMT-ResNet-based face recognition approach was designed in Python tool. Moreover, the implementation results of the implemented approach have been analyzed among various heuristic algorithms and conventional face recognition methodologies for validating the efficacy of the developed model. The population count and the maximum number of iterations that should be taken for performing the comparative analysis were 10 and 25, respectively. The heuristic algorithms to be taken for performing the comparative analysis on the developed IRSO-AMT-ResNet-based face recognition approach were Cat Swarm Optimization (CSO), Cuckoo Optimization Algorithm (COA), Moth Flame Optimization (MFO) and Rat Swarm Optimization (RSO)and the conventional face recognition approaches to be considered for analyzing the performance on the developed model was CNN , LSTM, VGG16 and ResNet. Various positive, as well as negative measures were used for analyzing the efficiency of the implemented face recognition model.

### B. VALIDATION MEASURES

The performance metrics used to validate the effectiveness of the developed face recognition model are several positive measures such as sensitivity, accuracy, specificity, precision, NPV, MCC, and F1-score, and also negative measures like FDR, FNR, and FPR. The formula used to calculate the positive and negative measures is summarized as below.

$$\Pr ecision = \frac{R_P}{R_P + L_P}$$

$$F1-score = \frac{2R_P}{2R_P + L_P + L_N}$$

$$Sensitivity = \frac{R_P}{R_P + L_N}$$

$$Specificity = \frac{R_N}{R_N + L_P}$$

$$FPR = \frac{L_P}{R_N + L_P}$$

$$FNR = \frac{L_N}{R_P + L_N}$$

$$FDR = \frac{R_P}{R_N + L_N}$$

$$MCC = \frac{R_P + R_N - L_P + L_N}{\sqrt{(R_P + L_P)(R_N + L_P)(R_P + L_N)(R_N + L_N)}}$$

### C. CONVERGENCE VALIDATION FOR THE SUGGESTED MODEL

Fig. 2 has depicted the convergence validation over the newly suggested face recognition techniques for datasets in which the developed RSO-OSVM model has acquired lower values that improve the performance of the model.

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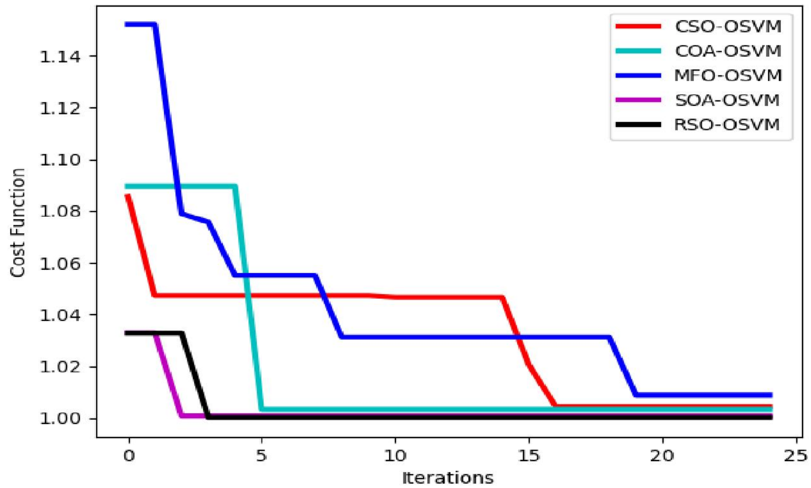


Fig 2 Examine the performance in terms of convergence for the suggested model

### D. PERFORMANCE ANALYSIS FOR THE SUGGESTED MODEL

The performance of the suggested face recognition framework over various algorithms and classifier models is examined by varying the learning percentage. The performance validation for datasets over numerous conventional algorithms and classifiers are depicted in Fig. 3 to Fig 6. Here, the proposed RSO-OSVM model has shown higher values for positive and low values for negative measures and proved its effectiveness.

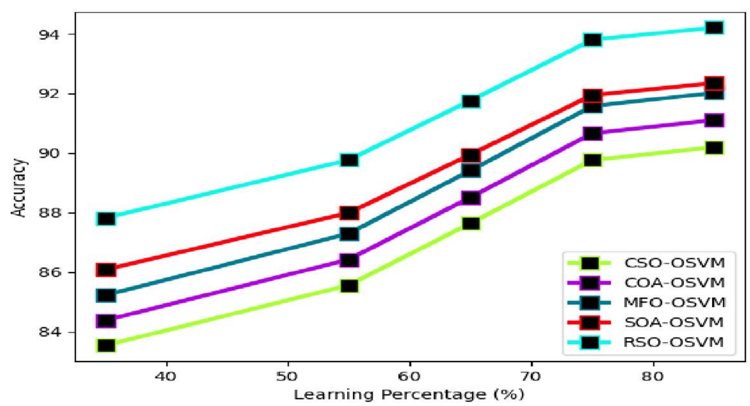


Fig 3: Examining the performance analysis of the suggested face recognition model in terms of an algorithm Accuracy


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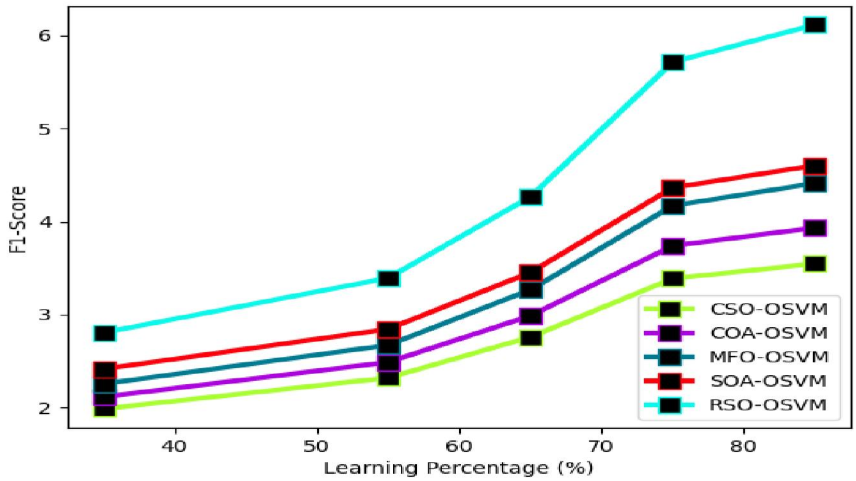


Fig 4: Examining the performance analysis of the suggested face recognition model in terms of an algorithm F1-Score

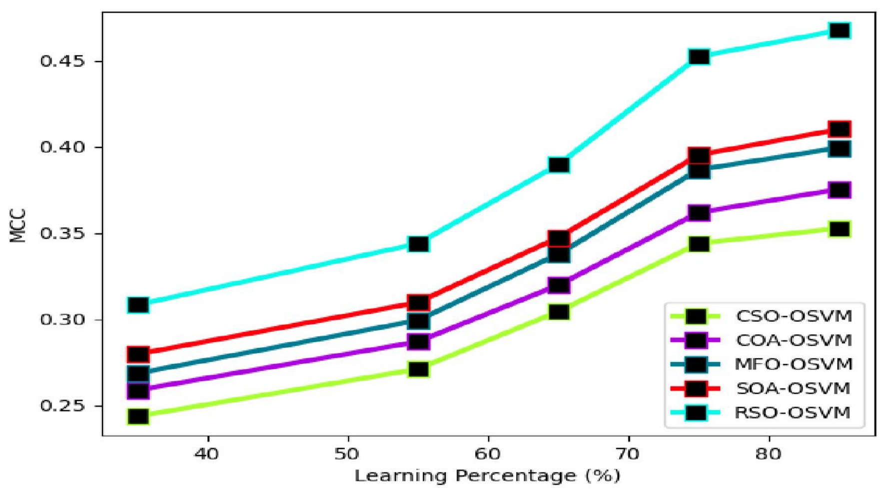


Fig 5: Examining the performance analysis of the suggested face recognition model in terms of an algorithm MCC

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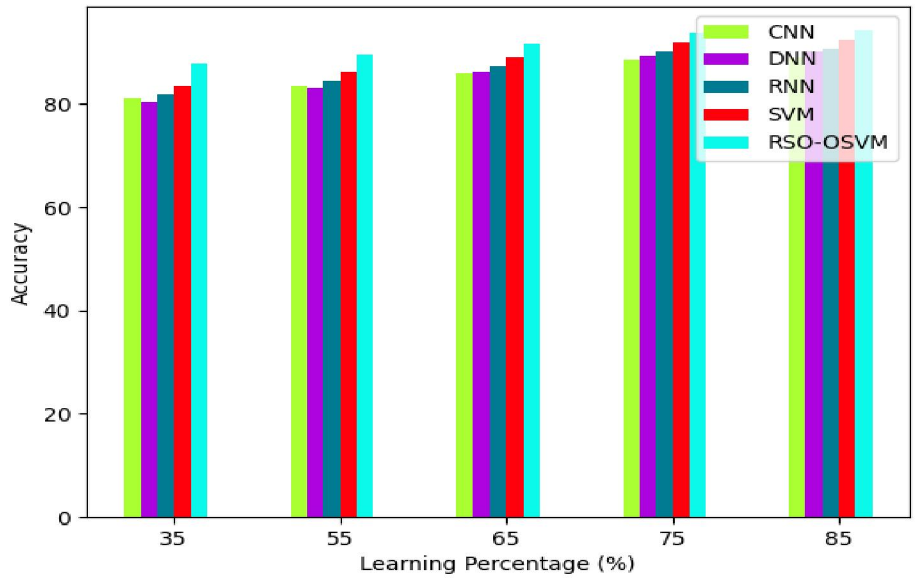


Fig 6: Examining the performance analysis of the suggested face recognition model in terms of classifiers Accuracy

## V. CONCLUSION

This paper presented an efficient deep learning–based face recognition framework that integrates optimal pattern extraction and adaptive classification to achieve high recognition accuracy under unconstrained conditions. The proposed model utilizes median filtering for effective noise removal, followed by the extraction of discriminative spatial features using Local Binary Patterns (LBP) and Local Vector Patterns (LVP). To enhance the quality of feature representation, an Improved Rat Swarm Optimization (IRSO) algorithm was employed to select optimal patterns and to fine-tune the network parameters. Furthermore, an Adaptive Multi-scale Transformer-based ResNet (AMT-ResNet) architecture was introduced to effectively learn both local and global facial representations, thereby improving robustness against variations in illumination, pose, expression, and background. Extensive experimental evaluations conducted on standard face databases demonstrated that the proposed IRSO–AMT-ResNet model outperforms several conventional deep learning models and heuristic optimization techniques. The developed framework achieved superior performance in terms of accuracy, sensitivity, specificity, F1-score, and convergence behavior. The comparative and ablation studies further validated the effectiveness of optimal pattern selection and parameter optimization in enhancing recognition performance. Overall, the proposed face recognition approach provides a reliable, accurate, and scalable solution for real-world biometric applications such as surveillance, access control, and security systems. Future work can focus on extending the model to handle large-scale datasets, real-time video-based face recognition, and cross-domain adaptation to further improve its applicability.

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