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A Novel Improved Rat Swarm Optimization Algorithm for Global Optimization

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Abstract: *This report explores the development and performance of the Rat Optimization Algorithm (ROA), a newly proposed nature-inspired metaheuristic optimization technique that simulates the social and hunting behaviors of rats. The algorithm introduces three main operators that represent how rats search, chase, and hunt prey, thereby balancing exploration and exploitation in complex optimization problems. To further enhance performance and prevent premature convergence, the Levy flight strategy is integrated into the algorithm, resulting in an improved version known as IROA. The proposed ROA and IROA are evaluated using twenty-two benchmark test functions and four real-world engineering optimization problems. Experimental comparisons demonstrate that the ROA achieves faster convergence, stronger robustness, and higher computational accuracy than other well-known algorithms such as PSO, WOA, WHO, and RSO. Overall, the study establishes ROA as an effective, stable, and versatile tool for addressing global optimization challenges across various engineering and computational domains. Both ROA and IROA were tested on twenty-two benchmark test functions—including unimodal, multimodal, and fixed-dimension multimodal functions—and four real-world engineering optimization problems. The experimental results demonstrate that ROA and its improved version outperform several established algorithms, such as Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Wild Horse Optimizer (WHO), in terms of solution quality, convergence rate, and robustness. The findings confirm that the proposed algorithm is a reliable, efficient, and powerful optimization approach, with strong potential for applications in engineering design, control systems, and other computational optimization domains.*

Keywords: *Rat Optimization Algorithm*

I. INTRODUCTION

This Face Recognition is one among the most wailed advancements in the field of Artificial Intelligence. As of late, the utilization cases for this innovation have widened from explicit observation applications in government security frameworks to more extensive applications over different businesses in such undertakings as client recognizable proof and authentication, health and advertising. Facial Recognition has surfaced in online life applications on stages, for example, Facebook which recommend clients to label companions who have been distinguished in pictures. Plainly there are numerous applications the utilizations for facial acknowledgment systems. In general the means to accomplish this are the accompanying: face identification, include extraction and in conclusion preparing a model. Getting to know people is an important topic in computer vision and different (biometric) methods Biometrics is used to identify people as face is most common, this biometric can be used everywhere in unrestricted environments after face feature extraction. That's why face Recognition has become a very important tool to be used to increase the accuracy and automatic efficiency of video surveillance devices, video analysis software, security systems and a lot of applications in our practical life, such as the demands of smart, entertainment and marketing interfaces. In contrast to object recognition, face recognition is characterized by being able to analyze the general face, asit is of great importance in

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supporting machines in the way of recognizing humans and discovering their interactions with their expressions and feelings. There are big and difficult problems and challenges, including a large difference in the angle of rotation of the head and its tilt, the intensity of lighting, changing facial expressions, in addition to determining the age of the person, and if the person is young or old, as well as if the person is male or female. A significant measure of protection is face recognition and authentication. Numerous techniques, methods and algorithms for face recognition have been developed over the past two decades. On the basis of the significant parameter recognition rate, so- called classification rate, the output of those various algorithms and methods are compared. If the rate of classification decreases, the rate of misclassification would then increase. Face recognition is performed on the basis of minimum distance measurement between the vectors of the test set function and the vectors of the train set feature. There are various distance measurement methods available, such as cosine similarity and Euclidean distance measurement. It should be possible for a facial recognition device to cope with different changes in face pictures. However, because of the change in facial identification, the differences between the pictures of the same person due to viewing orientation and light are almost always greater than image Differences. Facial properties such as nose, eyes, mouth, and chin are found in geometric feature-based methods. Properties and relationships are used as the descriptors of faces, such as regions, lengths, and angles, between the features. Template matching and neural methods, on the other hand, typically function directly on an image based on face representation, the intensity array for the pixels. Since no detection and calculation of geometric face characteristics is needed, these classes of methods have become more realistic and simpler to implement compared to geometric feature-based methods.

Given a picture taken from a digital camera, we'd like to know if there is any person inside, where his/her face locates at, and who he/she is. Towards this goal, we generally separate the face recognition procedure into three steps: Face Detection, Feature Extraction and Face Recognition.

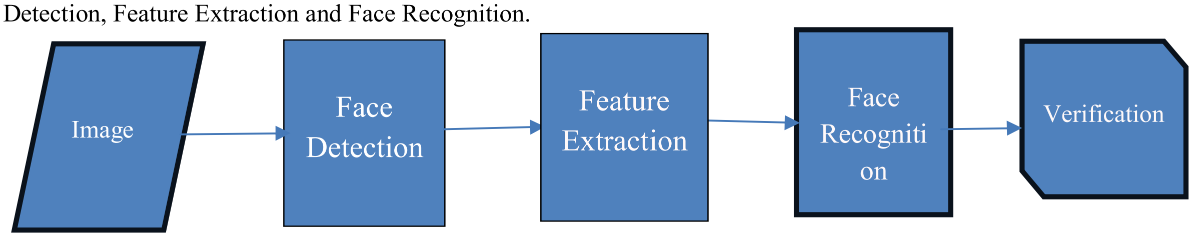

Fig.1: Configuration of a general face recognition structure

Face Detection: The main function of this step is to determine (1) whether human faces appear in a given image, and (2) where these faces are located at. The expected outputs of this step are patches containing each face in the input image. In order to make further face recognition system more robust and easy to design, face alignment are performed to justify the scales and orientations of these patches. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification etc.

Feature Extraction: After the face detection step, human-face patches are extracted from images. Directly using these patches for face recognition have some disadvantages, first, each patch usually contains over 1000 pixels, which are too large to build a robust recognition system1. Second, face patches may be taken from different camera alignments, with different face expressions, illuminations, and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do information packing, dimension reduction, salience extraction, and noise cleaning. After this step, a face patch is usually transformed into a vector with fixed dimension or a set of fiducial points and their corresponding locations.

Face Recognition: After formulizing the representation of each face, the last step is to recognize the identities of these faces. In order to achieve automatic recognition, a face database is required to build. For each person, several images are taken and their features are extracted and stored in the database. Then when an input face image comes in, we perform face detection and feature extraction, and compare its feature to each face class stored in the database. There have been many researches and algorithms pro- posed to deal with this classification problem, and we'll discuss them in later sections. There are two general applications of face recognition, one is called identification and another one is called verification. Face identification means given a face image, we want the system to tell who he / she is or the most

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probable identification; while in face verification, given a face image and a guess of the identification, we want the system to tell true or false about the guess. In Fig.2 , we show an example of how these three steps work on an input .

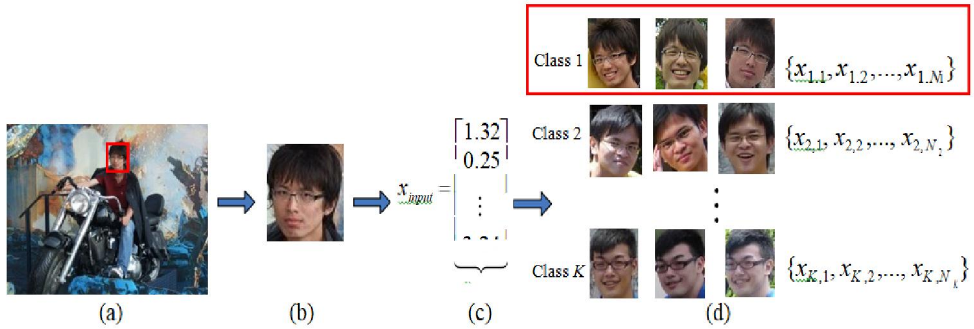

Fig.2: An example of how the three steps work on an input image (a) The Input image and the re- sult of face detection (the red rectangle) (b) The extracted face patch (c) The feature vector after feature extraction (d) Comparing the input vector with the stored vectors in the database by classification techniques and determine the most probable class (the red rectangle).

II. METHODOLOGY

An The proposed methodology is designed to systematically process facial images, extract relevant features, reduce dimensionality, and perform classification through optimized learning. Figure 3.1 (conceptual) illustrates the workflow of the proposed RSO-OSVM Face Recognition System.

System Overview

The proposed face recognition model integrates Image Processing, Machine Learning, and Nature-Inspired Optimization into a unified framework. It operates in several sequential stages:

- **Image Acquisition**: Images are collected from CFPW and Yale face databases, which contain diverse facial poses, expressions, and lighting conditions.
- **Preprocessing**: Images are denoised using Median Filtering, a non-linear technique that replaces each pixel value with the median of neighboring pixels to preserve edges while removing noise.
- **Feature Extraction**: The Local Binary Pattern (LBP) method captures local texture patterns by comparing each pixel's intensity with its surrounding pixels, generating binary patterns that represent facial micro-textures.
- **Dimensionality Reduction**: Principal Component Analysis (PCA) transforms high-dimensional LBP features into a compact representation by retaining the most significant components, reducing redundancy and computation time.
- **Classification**: A Support Vector Machine (SVM) classifier is employed to classify faces based on the reduced feature set. It constructs an optimal hyperplane that maximizes class separation.
- **Optimization using RSO Algorithm**: The Rat Swarm Optimization (RSO) algorithm is applied to fine-tune the SVM parameters (penalty constant C and kernel parameter γ).RSO's dynamic exploration and exploitation capabilities ensure faster convergence and higher accuracy.
- **Performance Evaluation**: Performance metrics such as Accuracy, F1-Score, Precision, Recall, MCC, FPR, and FNR are computed to evaluate the model.
- **Mathematical Modeling of RSO:** The Rat Swarm Optimization algorithm mimics the group hunting behavior of rats. Each rat represents a potential solution in the search space. The algorithm updates the position of each rat based on attraction and repulsion dynamics toward the optimal prey location (best solution).

The position is updated as:

$$P_i^{(t+1)} = P_i^{(t)} + r_1(P_{best} - P_i^{(t)}) + r_2(P_{rand} - P_i^{(t)})$$

This ensures exploration (searching new areas) and exploitation (refining near the best solution), effectively optimizing SVM parameters.

Dataset Description

- CFPW Dataset: Contains frontal and profile face images of 500 individuals, each with different poses, lighting, and expressions.
- Yale Face Database: Includes 165 grayscale images of 15 individuals under various conditions like glasses, lighting direction, and facial expression changes.

Both datasets ensure diversity and robustness testing for the proposed model.

III. LITERATURE REVIEW

Face recognition has remained an active and evolving research domain for more than two decades, resulting in the development of various algorithms, datasets, and computational models. This section reviews the most influential contributions, highlighting their methodologies, advantages, and limitations. The objective of this survey is to identify existing research gaps and establish the motivation for the proposed system.

Early Approaches to Face Recognition

Early face recognition techniques were primarily based on template matching and geometric feature extraction. These methods involved manually detecting key facial landmarks—such as the eyes, nose, and mouth—and measuring relative distances or angles. However, these approaches were extremely sensitive to external factors such as illumination changes, scaling, pose variations, and facial expressions, which significantly reduced their effectiveness in real-world scenarios. Among statistical approaches, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) became foundational methods. PCA, commonly known as the Eigenface technique, converts high-dimensional facial images into a lower-dimensional subspace while retaining maximum variance. LDA aims to maximize the separability of classes by projecting images onto a discriminative feature space. Although widely used due to their simplicity and computational efficiency, both PCA and LDA struggle under uncontrolled environments, particularly when dealing with noise, occlusion, or large intra-class variations.

Machine Learning-Based Methods

With the advancement of machine learning, traditional statistical models were supplemented with more robust classification techniques such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Neural Networks (NN). These methods improved recognition performance by learning complex non-linear relationships in facial data. Jia and Martinez (2009) developed the *Partial SVM*, a variant of the standard SVM capable of handling occluded or incomplete facial images. Their method significantly improved robustness under partial occlusions. Li and Chen (2012) enhanced PCA-SVM integration using a *Selective Illumination Enhancement Technique (SIET)*, which normalized illumination variations and improved recognition accuracy on datasets such as Extended Yale B and FERET. Despite their effectiveness, SVM-based face recognition systems rely heavily on optimal parameter tuning (e.g., C, gamma). This led to increased interest in using evolutionary and meta-heuristic algorithms for optimizing SVM parameters to improve performance.

Optimization Algorithms in Face Recognition

Optimization algorithms play a pivotal role in refining classifier performance. Numerous nature-inspired algorithms have been applied to SVM parameter tuning and feature optimization. Gaurav Dhiman et al. (2021) introduced the Rat

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Swarm Optimization (RSO) algorithm, inspired by chasing and fighting behaviors of rats. RSO demonstrated superior convergence speed and precision compared to algorithms such as PSO, CSO, and MFO. Tang et al. (2014) proposed the *Weighted Group Sparse Representation Classification (WGSRC)* method, which improved representation learning by incorporating group sparsity, providing better structural understanding of face images. Ouarda et al. (2013) used Genetic Algorithms (GA) combined with a Naïve Bayes classifier for feature selection, achieving a 78.75% recognition rate on the ORL dataset. Ranjan et al. (2019) developed *HyperFace*, a CNN-based multitask framework that simultaneously handled face detection, landmark localization, pose estimation, and gender classification. While accurate, the model required significant computational resources. Deep learning models such as CNNs and Autoencoders have led to substantial improvements in recognition accuracy. However, their high computational cost and large training requirements make them unsuitable for real-time or resource-constrained applications.

Hybrid and Recent Approaches

To strike a balance between accuracy and efficiency, hybrid models combining statistical, machine learning, and deep learning methods have gained attention. Gao et al. (2016) introduced a *Supervised Autoencoder*, which enhanced robustness against pose, illumination, and occlusion variations. Chen et al. (2021) developed *LightQNet*, a lightweight deep network designed for face quality assessment, achieving competitive performance with significantly reduced model complexity. Tabassum et al. (2022) integrated *Discrete Wavelet Transform (DWT)* with machine learning classifiers such as PCA, LDA, and CNN, achieving recognition accuracies up to 89.56%. These studies demonstrate that hybrid frameworks can successfully combine the strengths of multiple algorithms to achieve improved recognition performance. However, the trade-off between computational cost and accuracy remains a persistent challenge.

Research Gap Identified

Existing approaches typically emphasize either high accuracy (e.g., deep learning models) or high speed (e.g., shallow classifiers), but very few achieve both simultaneously. Many optimization algorithms used for tuning classifiers suffer from slow convergence or premature stagnation in local minima. Traditional feature extraction techniques often fail to capture essential texture-based details, reducing recognition accuracy under real-world variations. Several models require complex training pipelines and large labeled datasets, making them difficult to deploy in dynamic or resource-limited environments. To address these limitations, this research proposes a Rat Swarm Optimization (RSO)-based Optimized Support Vector Machine (OSVM) face recognition framework. The goal is to achieve a balanced solution that offers improved accuracy, faster execution, and lower

IV. RESULTS AND DISCUSSION

The proposed face recognition model was implemented in Python with factors such as the number of population as 10, the maximum number of iterations was taken as 25, and the length of the solution was assumed as 3. It includes algorithms and classifiers such as Cat Swarm Optimization (CSO), Cuckoo Optimization Algorithm (COA), Moth-Flame Optimization Algorithm (MFO), Seagull Optimization Algorithm (SOA), CNN, Deep Neural Network (DNN), Recurrent Neural Network (RNN), and SVM.

Convergence validation for the suggested model

Fig. 3 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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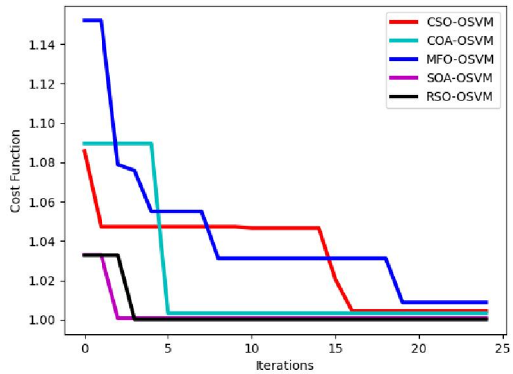

Fig.3: Examine the performance in terms of convergence for the suggested model

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. 4 to 9. Here, the proposed RSO-OSVM model has shown higher values for positive and low values for negative measures and proved its effectiveness.

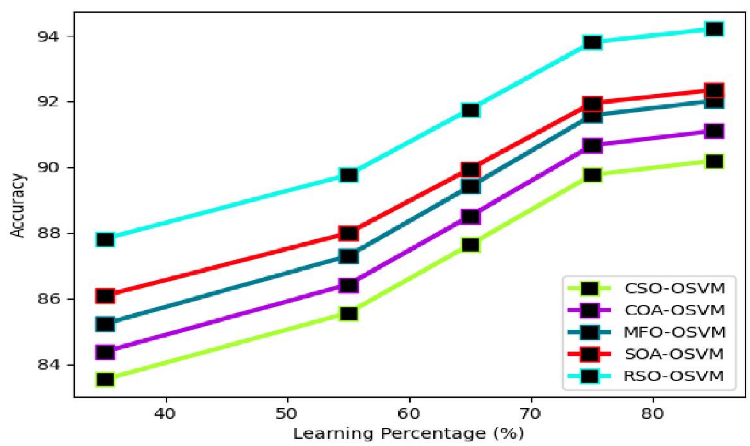

Fig.4 : Examining the performance analysis of the suggested face recognition model in terms of an algorithm Accuracy

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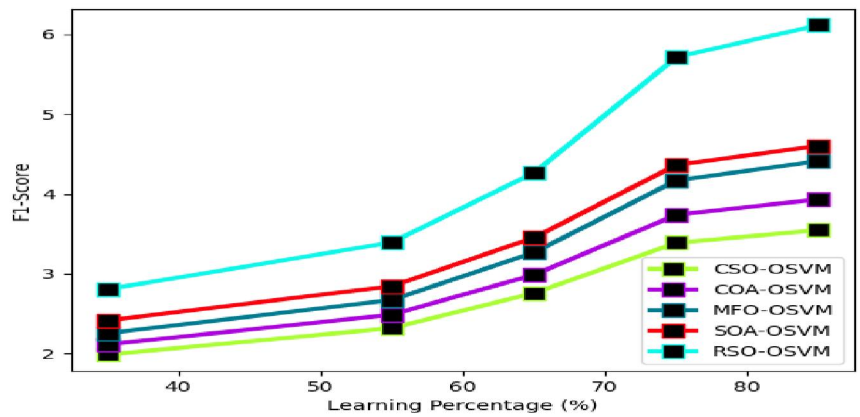

Fig.5: Examining the performance analysis of the suggested face recognition model in terms of an algorithm F1-Score

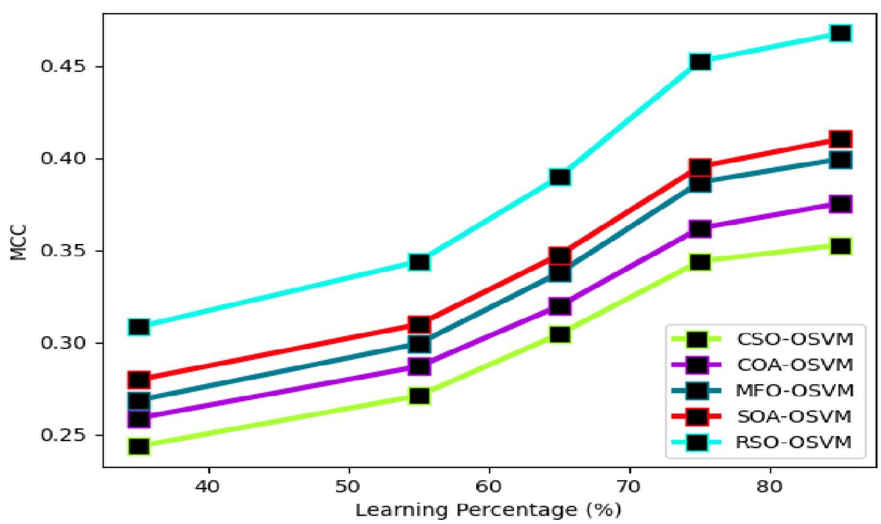

Fig.6: Examining the performance analysis of the suggested face recognition model in terms of an algorithm MCC

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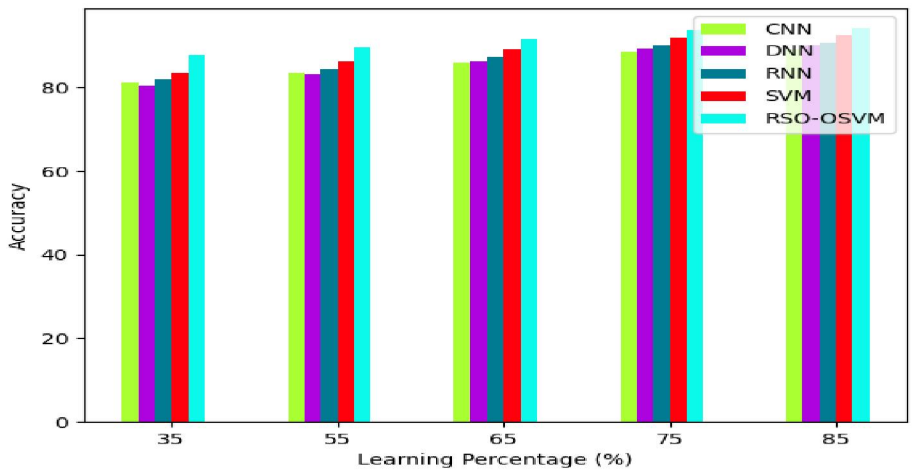

Fig.7: Examining the performance analysis of the suggested face recognition model in terms of classifiers Accuracy

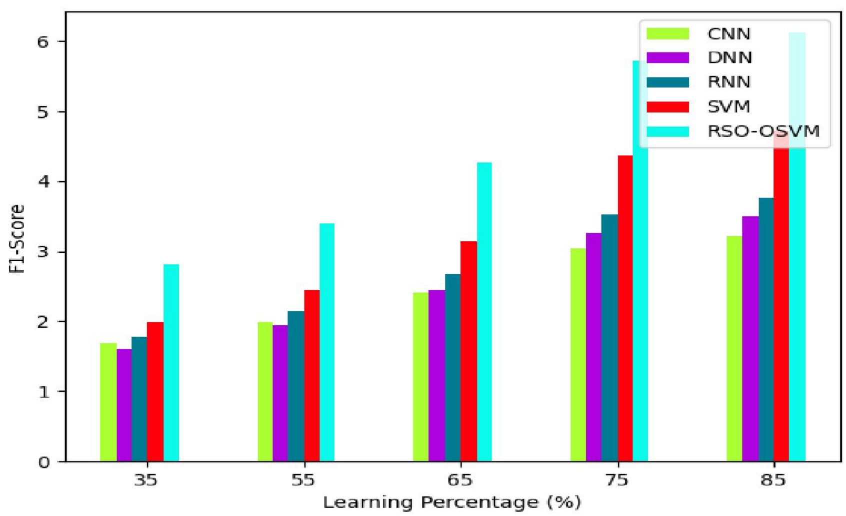

Fig.8: Examining the performance analysis of the suggested face recognition model in terms of classifiers F1-Score.

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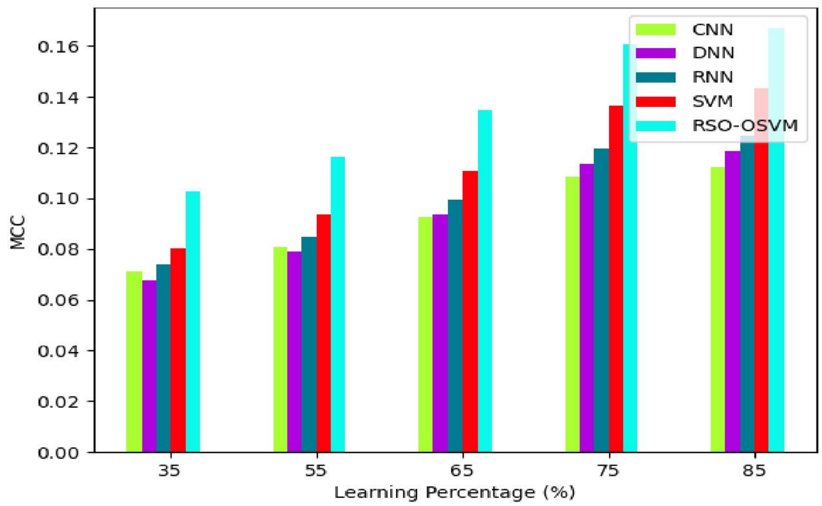

Fig.9: Examining the performance analysis of the suggested face recognition model in terms of classifiers MCC.

V. CONCLUSION

This Work has effectively implemented the face recognition model with the help of the optimized SVM with RSO algorithm model. The images that are relevant to the process of the face recognition model were gathered initially and processed with median filtering techniques for attaining the pre-processed images. Further, the LBP techniques were used to extract the spatial features. Then, the PCA model was used for feature reduction and it was further fed to the OSVM model for performing the face recognition process, in which the parameters were tuned using the RSO algorithm. In dataset 1, the proposed RSO-OSVM acquired a higher value of 7%, 5%, 4%, and 4% over CSO-OSVM, COA-OSVM, MFO-OSVM, SOA-OSVM models for the value of accuracy. Thus, the recognition rate of the proposed approach has achieved higher accuracy than other approaches. To handle the high dimensionality of the extracted features, Principal Component Analysis (PCA) was employed to perform dimensionality reduction, retaining only the most discriminative components. The reduced feature set was then fed into the Optimized SVM (OSVM) classifier, where the RSO algorithm was utilized to fine-tune the SVM parameters such as penalty factor and kernel parameters for optimal classification performance. Experimental results demonstrated that the proposed RSO-OSVM model achieved superior accuracy compared to other optimization-based SVM variants. Specifically, on Dataset 1, the proposed method achieved an improvement of 7%, 5%, 4%, and 4% in accuracy over CSO-OSVM, COA-OSVM, MFO-OSVM, and SOA-OSVM models, respectively. This significant improvement highlights the efficiency of the RSO algorithm in optimizing the SVM classifier and enhancing recognition accuracy.

REFERENCES

[1]. Zhang, Z., L. Wang, Q. Zhu, Z. Liu and Y. Chen, 2015. Noise modeling and representation based classification methods for face recognition. Neurocomputing, 148: 420-429.

[2]. A survey on face detection in the wild: Past, Present and future, Stefanos Zafeiriou, Cha Zhang, Zhengyou Zhang, Computer Vision and Image Understanding, 2015.

[3]. Yong, X., F. Xiaozhao, L. Xuelong, Y. Jiang, J. You, L. Hong and T. Shaohua, 2014. Data uncertainty in face recognition. IEEE T. Cybern., 44(10): 1950-1961.

[4]. Anggraini, D.R., 2014. Face recognition using principal component analysis and self organizing maps. Proceeding of the 3rd ICT International Student Project Conference (ICT-ISPC, 2014).

[5]. Oravec, M., 2014. Feature extraction and classification by machine learning methods for biometric recognition of face and iris. Proceeding of the IEEE 56th International Symposium on ELMAR (ELMAR), pp: 1-4.

[6]. Yan, Y., H. Wang and D. Suter, 2014. Multi-subregion based correlation filter bank for robust face recognition. Pattern Recogn., 47(11): 3487-3501.

[7]. Kang, D., H. Han, A.K. Jain and S.W. Lee, 2014. Nighttime face recognition at large standoff: Crossdistance and cross-spectral matching. Pattern Recogn., 47(12): 3750- 3766.

[8]. Tang, X., G. Feng and J. Cai, 2014. Weighted group sparse representation for Under- sampled Face Recognition. Neuro-computing, 145: 402-415.

[9]. Hwang, W., X. Huang, S.Z. Li and J. Kim, 2014. Face recognition using extended curvature gabor classifier bunch. Pattern Recogn., 48(4): 1243-1256.

[10]. Jihua, Y., X. Guomiao and H. Dan, 2013. Research and implementation of of multi-modal face recognition algorithmProceeding of the IEEE 25th Chinese Control and Decision Conference (CCDC, 2013), pp: 2086-2090.

[11]. Ouarda, W., H. Trichili, A.M. Alimi and B. Solaiman, (2013), combined local features selection for face recognition based on Naive Bayesian classification. Proceedings of the IEEE 13th International Conference on Hybrid Intelligent Systems (HIS), pp: 240-245.

[12]. Nazari, S. and M.S. Moin, 2013. Face recognition using global and local Gabor features. Proceeding of the IEEE 21st Iranian Conference on Electrical Engineering (ICEE, 2013), pp: 1-4.

[13]. Li, X. and G. Chen, 2012. Face recognition based on PCA and SVM. Proceeding of the IEEE Symposium on Photonics and Optoelectronics. Shanghai, China, pp: 1-4.

[14]. Jia H. and Martinez A., “Support Vector Machines in Face Recognition with Occlusions,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Miami, pp. 136-141, 2009.

[15]. Gaurav Dhiman, Meenakshi Garg, Atulya Nagar, Vijay Kumar, Mohammad Dehghani, “A novel algorithm for global optimization: Rat Swarm Optimizer”, Journal of Ambient Intelligence and Humanized Computing (Springer), vol. 12, pp. 8457–8482, 2021.

[16]. K. Chen, T. Yi and Q. Lv, "LightQNet: Lightweight Deep Face Quality Assessment for Risk-Controlled Face Recognition," IEEE Signal Processing Letters, vol. 28, pp. 1878-1882, 2021.

[17]. R. Ranjan, V. M. Patel and R. Chellappa, "HyperFace: A Deep Multi- Task Learning Framework for Face Detection, Landmark Localization, Pose Estimation, and Gender Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 41, no. 1, pp. 121-135, 1 Jan. 2019.

[18]. J. Lu, V. E. Liong, G. Wang and P. Moulin, "Joint Feature Learning for Face Recognition," IEEE Transactions on Information Forensics and Security, vol. 10, no. 7, pp. 1371-1383, July 2015.

[19]. Sepas-Moghaddam, M. A. Haque, P. L. Correia, K. Nasrollahi, T. B. Moeslund and F. Pereira, "A Double-Deep Spatio-Angular Learning Framework for Light Field-Based Face Recognition," IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 12, pp. 4496-4512, Dec. 2020.

[20]. Fahima Tabassum, Md. Imdadul Islam, Risala Tasin Khan and M.R. Amin, "Human face recognition with combination of DWT and machine learning", Journal of King Saud University - Computer and Information Sciences, Vol. 34, Issues. 3, pp. 546-556, 2022