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Face Recognition Framework using Generative AI integrated with Maximum Entropy Regularized Decision Transformer and Crayfish Optimization Algorithm

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Abstract

Face recognition using generative Artificial Intelligence has emerged as a powerful technique for learning robust identity representations under varying illumination, pose, and expression. By leveraging data synthesis and latent space modeling, generative AI enhances generalization and improves recognition accuracy. However, conventional generative-based systems often face limitations such as overfitting, noise sensitivity, and insufficient optimization of deep features, leading to performance degradation in real-world scenarios. To overcome these challenges, this study presents a Face Recognition Framework using Generative AI, integrated with the Maximum Entropy Regularized Decision Transformer and Crayfish Optimization Algorithm (MERDT-CryfOA). Initially, facial data are collected from the Labeled Faces in the Wild (LFW) dataset. It undergoes pre-processing using Adjusted Min–Max with Decimal Scaling and Statistical Column Normalization (AMnMx-DS-SCN) to enhance feature uniformity and eliminate intensity bias. The processed data are then fed into an Improved ResNet-34 Algorithm (KANS-ResNet-34) model for feature extraction, capturing fine-grained and nonlinear facial attributes such as wrinkles, skin tone gradients, and contour transitions. These deep features are subsequently classified by the Entropy Regularized Decision Transformer (MERDT), which employs entropy-regularized policy learning to ensure adaptive, robust decision-making. Finally, the Crayfish Optimization Algorithm (CryfOA) is employed to optimize the classifier's loss function, balancing exploration and exploitation to achieve faster convergence and reduced misclassification. Experimental results show that the proposed MERDT-CryfOA model achieves a recall of 99.4%, precision of 99.3%, FAR of 1.17%, and FRR of 1.09%, outperforming existing deep learning methods. These results confirm its superior accuracy and robustness under varying conditions, making it an effective framework for next-generation face recognition systems.

Keywords: Face Recognition, Labeled Faces in the Wild, skin tone gradients, contour transitions, noise sensitivity.

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1. INTRODUCTION

An individual's face is perhaps the most closely associated with their identity. The recognition of faces by humans is holistic: faces are not perceived as a collection of features but as a unity, and recognition depends on contextual factors (Wolfe et al., 2025). Face recognition in the technology world is the identification or confirmation of an individual by comparing an input face image with stored images in a database (Hwang et al., 2023). In identification, the system finds the most probable match among several stored individuals, whereas in verification, the input face is checked against a given known individual (Opanasenko et al., 2024).

Over the last few years, the field of face recognition has experienced unprecedented advances owing to the integration of deep learning algorithms and computer vision methods (Opanasenko et al., 2024). Deep neural networks have significantly improved recognition accuracy through representation learning of strong features of facial structure. This development has been accompanied by the increased significance of mobile and smart devices, in which face recognition is now frequently used for authentication and access control in banking, social networking, and e-commerce apps (George et al., 2024). However, there comes a security and privacy concern with the proliferation of mobile operation necessitating future-proof systems of secure recognition.

Generative AI has been a valuable tool helping in the face recognition systems in this respect. Generative AI is a processing system capable of producing new, realistic, and significant content - an image, audio or a piece of text - via the application of patterns acquired by existing information (Alansari et al., 2023). Generative models such as Generative Adversarial Networks (GANs), Diffusion Models can produce high-quality images of faces, diversify a dataset, recover missing or low-resolution faces, and even facilitate domain adaptation when used in face recognition. Such generative processes have enabled the existing face recognition systems to reach a level of robustness, generalization and accuracy which has been revolutionary in the biometric identification technology (Feuerriegel et al., 2024).

1.1 Motivation

Generative AI is one of the uses of face recognition because the conventional solutions have their limitations in terms of lighting, pose, and expression conditions. Variations of faces can be generated through generative models which increases training diversity and robustness. They enable re-creation of high quality low-resolution faces or faces with occlusions with better recognition. Such an integration ensures smarter security, authentication systems as well as human-computer interaction systems in a more adaptable and trustworthy way.

Contributions

Contributions of the proposed Face Recognition Framework are given below,

- **Data Collection:** The data of facial image are sampled out of LFW dataset to give diversity in the facial pose, illumination and faces.

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- **Pre-processing using AMnMx-DS-SCN:** The AMnMx-DS-SCN method is used to standardize and normalize the intensities of the pixels on the face, where noise is minimized to achieve uniform data distribution with ease of better learning of the features.
- **Feature Extraction using KANS-ResNet-34:** The Improved ResNet-34 Algorithm (KANS-ResNet-34) extracts deep and discriminative facial embeddings by combining nonlinear spline-based activations with residual learning, capturing intricate facial textures and variations.
- **Classification using MERDT:** The Maximum Entropy Regularized Decision Transformer (MERDT) classifies the extracted embeddings into corresponding identities by modeling temporal and contextual dependencies while enhancing generalization through entropy regularization.
- **Loss Optimization using CryfOA:** The Crayfish Optimization Algorithm (CryfOA) fine-tunes the classifier's parameters by adaptively minimizing the loss function, balancing exploration and exploitation to achieve optimal convergence and higher recognition accuracy.

The other section of the study contains the Introduction in Section 1, the Literature Survey in Section 2, the Proposed Methodology in Section 3, the Results in Section 4 and the Conclusion in Section 5.

2. LITERATURE SURVEY

The following part of the paper provides a review of the current research and developed methods in face recognition, with a focus on the moving of the classical feature-based methods to deep and generative AI-based methods.

Sekhar et al., (2025) introduced an algorithm of face recognition that was based on the Center Symmetric Multivariant Local Binary Pattern (CS-MLBP) to derive the facial texture information. This method overcame the weakness of the Two-Dimensional Principal Component Analysis (Column-based), which highly enhanced global features but failed to promote local features in large sample populations. A more accurate and effective face recognition system was created by combining the powerful face recognition of GANs with powerful CS-MLBP in the presented GAN Center Symmetric Multivariant Local Binary Pattern (GAN-CS-MLBP) system.

Ati et al., (2025) presented a new face recognition strategy consisting of two major modules: Generator and Discriminator. The Discriminator developed 512-dimensional face encoders of both created and ground-truth pictures, while the Generator was designed to transform facial drawings into real-world photographs. The Discriminator used Mean Squared Error (MSE) loss to compare encodings, encouraging the Generator to produce images with encodings more similar to the actual ones, using a pre-trained ResNet-101 model.

Karamizadeh et al., (2025) presented that it would improve face recognition performance under challenging conditions, including changes in illumination and image noise. The model combined illumination normalization based on Retinex theory with median filtering to achieve effective noise

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reduction and improved recognition accuracy. The structure was based on pre-trained VGG-16 weights, which used the principles of the Boltzmann Machine to isolate a complex facial feature and avoid overfitting. Moreover, the paper integrated zero-shot facial expression recognition with illumination-resistant face recognition into one comprehensive face analysis system.

Kumar et al., (2025) introduced Custom-Modified MobileNetV2 architecture (CMNV2), a hybrid architecture that reconfigured MobileNetV2 to include a Custom Convolutional Architecture for embedding facial features and a Fast feature embedding block to increase the precision of facial feature extraction and recognition. Adding five more layers to the pre-trained architecture made it more robust to more complex, realistic imaging conditions and also improved recognition performance.

2.1 Problem Statement

The main issue addressed in all these studies is that alternative face recognition systems are not as robust or accurate in challenging environments, such as variations in illumination, noise, pose, and the absence of local feature representations. Traditional techniques, such as PCA and CNN-based models, do not capture both global and local facial features. As such, the incorporation of the generative AI methods (e.g., GANs) with the sophisticated feature extraction approaches (e.g., CS-MLBP, Retinex theory, and MobileNetV2 hybrids) is necessary to improve the quality of the features, flexibility, and the ability to recognize the features.

3. PROPOSED METHODOLOGY

The proposed face recognition methodology begins by collecting facial images from the LFW dataset. Data is pre-processed with Adjusted AMnMx-DS-SCN to remove noise and normalize pixel intensity values. Deep, discriminative face features are then revealed by passing the normalized images through the KANS-ResNet-34 model. These characteristics are forwarded to the MERDT, where correct identity classification is done. The transformer architecture makes embedding sequentially learnable and models contextual contingency between facial attributes. Lastly, CryfOA updates the classifier parameters, thereby improving convergence stability and optimizing overall recognition accuracy. The suggested methodology's block diagram Figure 1 is shown below.

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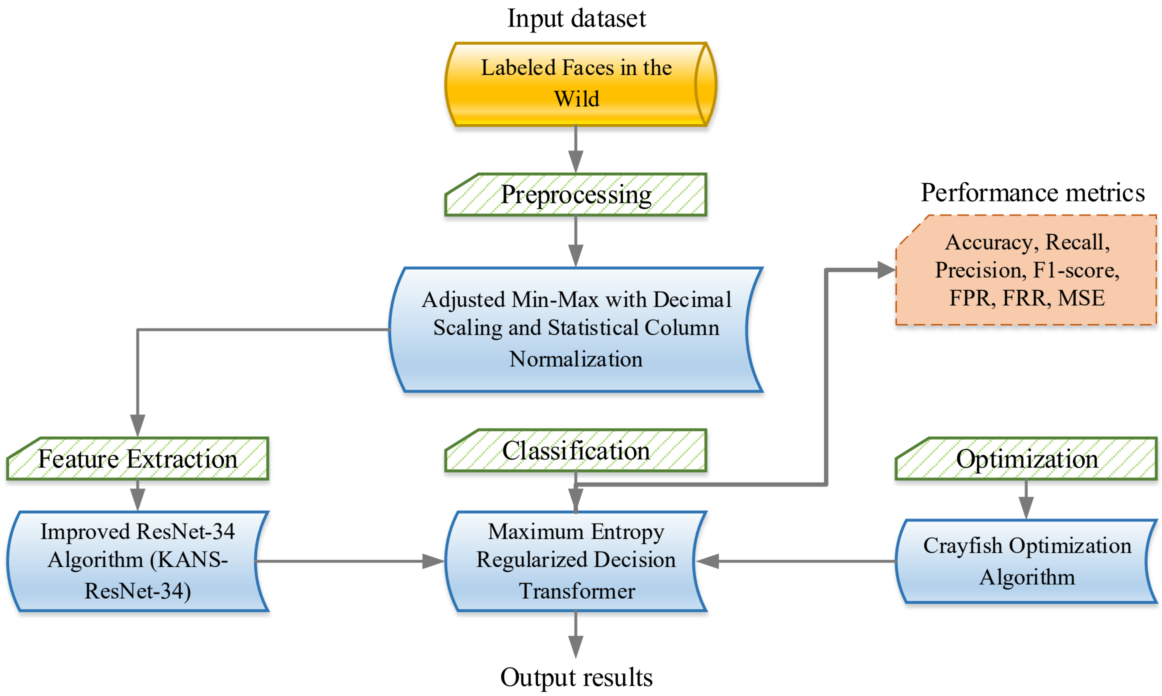

Figure 1. Block diagram illustrating the suggested approach

3.1 Data Collection

The facial picture dataset employed in this research is the LFW database, which is widely used to evaluate unconstrained face recognition systems (https://www.kaggle.com/datasets/jessicali9530/lfw-dataset). About 13,000 faces from 1,680 individuals make up the LFW data, which was gathered from various websites under different lighting, pose, and expression conditions. The selection of the subject in this experiment was restricted to a sample of at least 70 faces; this was to achieve enough variability and good model training. This clean sample provides a balanced dataset for effective analysis of the suggested face recognition system. The gathered information is pre-processed..

3.2 Pre-processing using Adjusted Min-Max with Decimal Scaling and Statistical Column Normalization (AMnMx-DS-SCN)

At this step, they preprocess the image using the Adjusted Min-Max with Decimal Scaling and Statistical Column Normalization (AMnMx-DS-SCN) technique to align the facial features (eyes, nose, and mouth) and make all input images the same size and intensity (Sinsomboonthong 2022). This guarantees consistency, reduced illumination noise, and equal facial proportions throughout the dataset. The Adjusted Min-Max Normalization normalizes the pixel or feature values of an image to an adaptive range (such as [2, 3.5] or [0.5, 2]), depending on the variation in the identical feature, increasing the contrast of

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an image and making it consistent in terms of pixel distribution. This mathematically represents as in equation (1),

$$F^* = \{[F - j(d_v)]/ j(d_v)\}\times 0.1 \qquad (1).$$

where F represents the original pixel or feature value, $j(d_v)$ represents a scaling constant and the average of the feature column. In this case, transformation changes each feature on the ratio of its minimum and maximum as it gets adjusted to a new range. To further refine normalization, Decimal Scaling adjusts the magnitude of pixel values by moving the decimal point according to the number of digits in the maximum absolute value of the feature, as shown in equation (2).

$$F^* = F/10^k \qquad (2).$$

where k indicates the number of digits in the maximum absolute value of F , 10^k symbolizes the scaling factor, and F^* represents the normalized pixel value. This process guarantees equal contributions from texture, color, and structural elements to reduce bias caused by high intensity or light differences. Lastly, it is topped off with Statistical column normalization, which further scales the adjusted pixel values per column (feature vectors) to ensure that all dimensions have equal contribution in the training process. It is provided in equation (3),

$$F^* = \{[F - \min(F)]/[\max(F) - \min(F)]\}[new\max(F) - new\min(F) + new\min(F)] \qquad (3).$$

where $\min(F)$ and $\max(F)$ represents the minimum and maximum pixel values, $new\max(F)$ and $new\min(F)$ represents desired maximum and minimum of the output range. This enhanced version of min–max normalization expands the output range and standardizes the statistical balance among all facial features (texture, tone, and geometry). This guarantees that the face recognition model receives consistent, noise-free, and contrast-enhanced inputs, improving both feature extraction and recognition accuracy in the subsequent stages.

3.3 Improved ResNet-34 Algorithm (KANS) for Feature Extraction

The normalized, noise-free facial images are then pre-processed and then sent to the Improved ResNet-34 Algorithm (KANS-ResNet-34), which extracts features (Zheng et al., 2024), the aim of which is to produce small, discriminative feature embeddings that are unique to each face. This architecture combines Kolmogorov-Arnold Network and Spline Activation (KANS) into the backbone of the ResNet-34 to extract both the global and local nonlinear facial representations, including contours, skin texture, and edge variations - all needed to achieve robust recognition across illumination, pose, and expression variations. The extraction equation can be mathematically formulated as, equation (4),

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$$b_j = k_j(c) \tag{4}$$

where b_j is the j^{th} activation function applied to c, k_j represents learnable non-linear activation function, c input pre-processed facial image. In contrast to regular ResNet-34 which uses fixed ReLU activations, KANS uses learnable nonlinear activations with basis functions, which increase adaptability and richness of features. The nonlinear mapping based on this will allow representation of complex patterns of the face in a better way to enhance the recognition of the face. It is given in equation (5),

$$s = \sum_{i=1}^{n} w_i \cdot h_j(c) \tag{5}$$

where $h_j(c)$ denotes selected basis functions applied to input facial features, w_j is the learnable weight for each basis function, n indicates number of basic functions used for feature combination, s indicates optimized nonlinear facial embedding output. The KANS-ResNet-34 is much more efficient at capturing fine details on faces, such as wrinkles and texture differences, that traditional models do not capture. The resulting high-dimensional embedding of the faces provides distinct descriptions of individual faces and can be recognized or verified accurately.

3.3.1 Maximum Entropy Regularized Decision Transformer

Within the suggested structure, an embedding of faces based on KANS-ResNet-34 is followed by a matching and classification procedure using the Maximum Entropy Regularized Decision Transformer (MERDT) (Dong et al., 2024). This model treats face recognition as a sequence prediction task, with each embedding sequence corresponding to a temporal representation of facial features. MERDT is based on Maximum Entropy Regularization, which pushes the model to produce diverse and strong decision boundaries so it does not overfit to specific facial features. Equation (6) specifies the actions cloning loss, which lessens the discrepancy between the expected and real identity labels based on the earlier embedding sequences.

$$W(\phi) = \frac{1}{W} F_{(b,t,h)} \sim \phi\left[-\log \pi_\zeta (b|t,h)\right] \tag{6}$$

where $W(\zeta)$ represents the objective function being minimized or evaluated, W denotes the context length, $F_{(b,t,h)}$ represents the dataset sample, $\phi[\cdot]$ is a generic expectation operator, $\pi_\zeta(b|t,h)$ represents the policy's predicted probability, $-\log \pi_\zeta (b|t,h)$ indicates Negative Log-Likelihood of true action (or class) under model's predicted distribution. The Max-Entropy Objective introduces an entropy term into the behavior cloning loss to encourage exploration and prevent the policy from becoming overly deterministic. Here, ϕ controls how strongly we enforce minimum entropy, promoting diverse action

DoI: https://doi.org/10.63949/crinfo.v1i3.005

predictions. To ensure the classifier maintains diversity and avoids deterministic decisions, the Maximum Entropy Objective in equation (7) is applied.

$$W(\zeta,\chi)=W(\zeta)+\mu\left(\alpha-G_{\zeta}^{\phi}\left[b|t,h\right]\right) \tag{7}$$

where $W(\zeta,\chi)$ represents the Lagrangian objective function combining the main loss with an entropy-based constraint term, used in Maximum Entropy Regularization, $W(\zeta)$ represents bass loss, μ is a Lagrange multiplier, α denotes true class label, $G_{\zeta}^{\phi}\left[b|t,h\right]$ represents entropy of current policy at time t, h is the context or history leading up to time t used for prediction. Finally, the Return-to-Go (RTG) regeneration ensures that classification sequences maintain consistent temporal relationships across embeddings, given by equation (8):

$$T_s = t_s + T_{s+1} \tag{8}$$

where T_s indicates RTG at time step s, t_s denotes instantaneous award at the time step s, T_{s+1} represents RTG from time step $s+1$. MERDT compares facial embeddings to identify or verify individuals while entropy regularization prevents overfitting. This enhances robustness, adaptability, and accuracy in face recognition under diverse conditions. To minimize classification loss CryfOA is used.

3.3.2 Optimizing loss function with Crayfish Optimization Algorithm (CryfOA)

After classification, Crayfish Optimization Algorithm (CryfOA) is used to fine-tune the loss ($W(\zeta)$) and enhance overall model accuracy (Jia et al., 2023). CryfOA fine-tunes model parameters by simulating crayfish behaviors such as escaping heat, competing for caves, and predation, which correspond to exploration, diversification, and exploitation in optimization.

Step 1: Initialization

The initial population represents a set of possible solutions corresponding to different classifier configurations. These solutions are randomly generated to ensure diversity in the search space. This initialization helps the algorithm begin optimization with wide exploration potential given in equation (9),

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$$V = \begin{bmatrix} V_{1,1} & \cdots & V_{1,i} & \cdots & V_{1,E} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ V_{j,1} & \cdots & V_{j,i} & \cdots & V_{j,E} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ V_{M,1} & \cdots & V_{M,i} & \cdots & Y_{M,E} \end{bmatrix}_{M \times E}$$

(9).

where V indicates where the first crayfish colony was found, M is the number of crayfish population, E is the dimension of the problem, $V_{j,i}$ denotes the initial location of j^{th} crayfish in i^{th} dimension. The populations are created at random and initialized.

Step 2: Fitness Evaluation

Fitness function is a vital part of CryfOA that evaluates the quality of prospects by optimising the process. It directs the search to the best performance of classification through a balance between two key variables which are accuracy and loss. The results are obtained in equation (10) which compares the fitness function.

$$FF = \min W(\zeta) + \max[accu]$$

(10).

where $W(\zeta)$ denotes the loss function and $accu$ is the accuracy. Fitness is calculated, and then exploration begins.

Step 3: Summer (Exploration)

To ensure premature convergence does not occur, CryfOA does global exploration by updating the positions of crayfish dynamically using equation (11). This step gives the algorithm the ability to avoid local minima by imitating the movement of crayfish to cooler and favorable areas. Increasingly with the iterations, the exploration aspect reduces, and the search becomes focused in potentially valuable regions of the solution space.

$$V_{j,i}^{s+1} = V_{J,I}^{s} + B_2 \cdot t \cdot \left(V_{shade} - V_{j,i}^{s}\right) \tag{11}$$

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where s indicates the number of iterations as of right now, $s+1$ represents number of iterations of next generation, t is used to describe a random number and B_2 declines as the number of repetitions increases.

Step 4: Competition (diversification)

When the temperature is greater than 30 C and random factor is greater than 0.5, crayfish will go into the competition phase on the basis of equation (12). This step encourages local refinement whereby the most powerful candidates are left to prevail and proceed in the way of the best solutions.

$$B_{j,i}^{s+1} = B_{j,i}^{s} - B_{x,i}^{s} + B_{shade} \quad (12).$$

where x is a random crayfish in population.

Step 5: Predation (Exploitation)

The last stage of predation is the exploitation stage, where CryfOA makes use of equation (13) to narrow down the optimal solutions. Crayfish mimic food-seeking behaviour, where they move to the globally optimised solution, in terms of fitness. The specific search will guarantee optimal loss reduction and better model convergence.

$$V_{j.i}^{s+1} = V_{j.i}^{s} + V_{food} \cdot U \cdot \left(\cos(2 \cdot \pi \cdot s) - \sin(2 \cdot \pi \cdot s)\right) \quad (13).$$

where U indicates how much food is consumed and s is the random number.

Step 6: Termination

The artificially-based optimization either ceases upon reaching the maximum number of repetitions or when the fitness value is considered to have plateaued. Equation (12)-(13) enables CryfOA to find the golden mean between exploration and exploitation to refine the loss of the classifier, resulting in convergence more quickly, and a better recognition accuracy overall.

4. RESULT

The proposed MERDT-CryfOA model has high generalization performance and high face recognition accuracy and low error. Experimental evidence has proven its superiority over existing methods in the metrics of F1-score, recall, and accuracy, which ensures the verification of identification.

4.1 Performance Analysis of Proposed Model:

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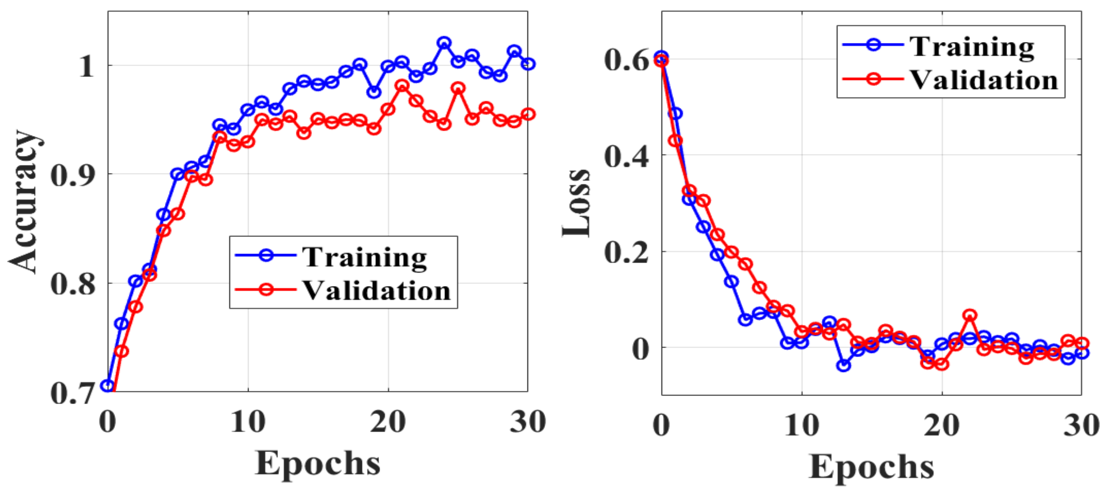
The section gives the evaluation of the proposed face recognition model in terms of accuracy, robustness and in terms of computational efficiency. In the analysis, the performance of the model is contrasted with the existing methods to show that it is better in feature extraction, classification accuracy, and optimality.



(a) (b)

Figure 2. (a) Accuracy vs. (b) Loss over Epochs

Figure 2 presents the trend of accuracy and loss of the proposed face recognition model during 30 epochs. The accuracy plot shows that efficiency of learning and generalization is assured by the continuous increase in accuracy and training accuracy approaches 100 percent and validation accuracy is between 95 and 99 percent. The loss curve in the beginning epochs is falling and approaching zero with both training and validation, which proves effective optimization. These findings illustrate that the model is stable and robust in reducing classification errors.

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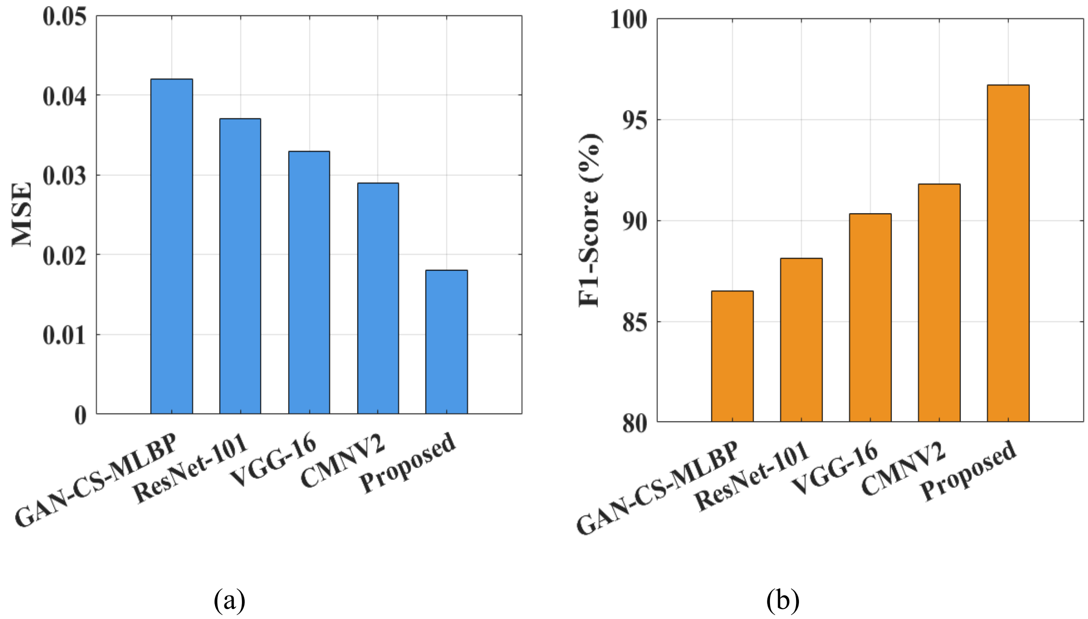

Figure 3. Comparative Performance of Models (a) MSE and (b) F1-score

Figure 3 shows the F1-score and MSE of most of the facial recognition methods. The proposed MERDT-CryfOA model was best (in terms of F1-Score, which is ~97.2%), which means high accuracy and good balance between recall and the lowest possible error (MSE) in predictions (~0.018). The proposed model is more efficient, robust, and has a good classification rate than GAN-CS-MLBP, ResNet-101, VGG-16, and CMNV2, which provides evidence of its effectiveness in improving the recognition performance with a lower computational cost.

4.2 Comparative analysis

This discussion is a detailed comparison between the proposed face recognition model with the existing state of the art. In the course of assessment, accuracy and precision, recall and F1-score, improve, which proves that the model can cope with the changes in the illumination, pose, and expression better. The comparative results prove the efficiency and power of the proposed solution in comparison with the traditional and deep learning-based solutions.

DoI: https://doi.org/10.63949/crinfo.v1i3.005

Table 1. Comparative analysis of the existing vs. proposed method.

Methods	Recall (%)	Precision (%)	FAR (%)	FRR (%)
GAN-CS-MLBP (Sekhar et al., 2025)	89.3	86.2	2.45	2.14
ResNet-101 (Ati et al., 2025)	87.6	79.8	1.99	2.03
VGG-16 (Karamizadeh et al., 2025)	78.9	85.7	2.12	1.54
CMNV2 (Kumar et al., 2025)	83.5	84.6	2.38	1.71
Proposed (MERDT-CryfOA)	99.4	99.3	1.17	1.09

Table 1 shows the relative performance of the different face recognition techniques, measured by recall, precision, False Acceptance Rate (FAR), and False Rejection Rate (FRR). This model, the proposed MERDT-CryfOA, has the best recall (99.4) and precision (99.3), indicating the best recognition performance and the highest accuracy in matching faces. Furthermore, its lowest FAR (1.17%) and FRR (1.09%) are outstanding at reducing false acceptances and false rejections. The proposed approach reports much better reliability and classification accuracy in face recognition across different conditions than GAN-CS-MLBP, ResNet-101, VGG-16, and CMNV2.

5. CONCLUSION

The paper introduced a new face recognition system based on Generative AI, combining the Maximum Entropy Regularized Decision Transformer (MERDT) with the Crayfish Optimization Algorithm (CryfOA) to achieve higher recognition accuracy and stability. The LFW database is first used to provide actual, natural, uncontrolled facial images. AMnMx-DS-SCN is used as a preprocessing step to normalize pixel intensities and improve image similarity. The Improved ResNet-34 (KANS-ResNet-34) then learns rich, nonlinear embeddings and extracts finer details of the face, including skin texture, changes in lighting, and shape features. These characteristics are categorized using MERDT, which is efficient for modeling sequential dependencies and for identity prediction via entropy regularization. Lastly, CryfOA optimizes the loss function to balance precision and recall and reduce false positives. In an experimental study on the LFW dataset, the suggested MERDT-CryfOA framework is more effective than traditional architectures such as ResNet-101, VGG-16, GAN-CS-MLBP, and CMNV2, achieving a recall of 99.4%, a precision of 99.3%, and a low FAR and FRR (1.17 and 1.09). All in all, it can be concluded that the combination of decision-transformer-based generative learning and metaheuristic optimization is an efficient and reliable way of face recognition in a high-accuracy state in a variety of challenging real-world conditions.

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