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Dance Rehearsal Simulation and Optimization Algorithm Based on Virtual Reality Technology

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Abstract: - The use of virtual reality (VR) for industrial training helps minimize risks and costs by allowing more frequent and varied use of experiential learning activities, leading to active and improved learning. However, creating VR training experiences is costly and time consuming, requiring software development experts. In this manuscript, Attentive Evolutionary Generative Adversarial Network based Dance rehearsal based on virtual reality technology (DVR-AEGAN-COA)is proposed. The input data are collected from Real Time Data from various public dance dataset. Then the data are fed in to pre-processing using Geometric Interaction Augmented Graph Collaborative Filtering (GGCF) to remove noise and enhancing data. The pre-processed data are given into Adaptive Synchro Extracting Transform (ASET) for Feature extraction to align the dance movements, such features are tempo, beats, and rhythm. Then the extracted features are given into Attentive Evolutionary Generative Adversarial Network (AEGAN) for classification of attributes, styles and emotions. In general, the AEGAN does no express adapting optimization strategies to determine optimal parameters. To ensure accurate classification, the Coati Optimization Algorithm (COA) is introduced for optimizing AEGAN. The proposed DVR-AEGAN-COA is implemented in Python working platform and the analyzed performance metrics likes precision, accuracy, F-score, computational time, specificity and sensitivity. The proposed method attains higher accuracy25%, 29% and 25%, higher specificity 27.32%, 24.43%, 38.24% and higher recall 31.13%, 23.33% and 38.13% than the existing methods like enhanced Dance Rehearsal Virtual Reality through Artificial Neural Network (DVR-ANN), Dance Rehearsal Virtual Reality through Circle Search Algorithm (DVR-CSA) and Dance Rehearsal Virtual Reality through Skill Optimization Algorithm (DVR-SOA) respectively.

Keywords: Geometric Interaction Augmented Graph Collaborative Filtering, Attentive Evolutionary Generative Adversarial Network, Bio-Vision Hierarchy Dataset, Coati Optimization Algorithm, Adaptive Synchro Extracting Transform.

I. INTRODUCTION

Because of its immersion, interaction, and inventiveness, virtual reality technology has already demonstrated its distinct and wide excellence in the educational sector [1]. The use of cutting-edge teaching techniques, predicated on virtual reality technology, into professional courses converts the theoretical learning process into a practical one, assisting students in developing a thorough understanding of the research process [2].Virtual reality technology also has a lot of promise for teaching dance. Dancing is the natural fusion of music and movement. For the purpose of fostering Sensor motor Synchronization (SMS), dancers should coordinate their body motions with musical beat [3]. The latter describes how the rhythmic motions are synchronized with the outside beats. The beat is a perceptual phenomenon that depends on beat induction, which is a method of periodically extracting pulses from music, rather than a physical aspect of music itself [4].Additionally, beat induction involves more than just extracting periodic pulses from music; it also involves synchronizing the beat of the body with the pulses. In dance teaching activities, dance rhythm training refers to enhancing students' performance by strengthening their ability to sense rhythm and promoting sensor motor synchronization [5, 6]. Virtual teaching, which is based on virtual reality technology, emphasizes situational teaching of students and integrates environment, body, and cognition to enhance teaching efficiency [7]. VR technology creates an immersive and communicating learning atmosphere that empowers students to actively shape their own learning; moreover, the positive feedback that results has a wide range of applications in dance rhythm instruction. Few research have examined the use of VR technology in dance rhythm training, despite the fact that VR technology has been applied in many instructional activities [8, 9].Consequently, in order to provide fresh concepts for improving dance teaching modalities, this study explores the viability of utilizing VR technology in dance rhythm instruction. In order to improve users' dance rhythm, a novel system for training dance rhythms is created. It is based on the immersive Cave Automatic Virtual Environment (CAVE), where

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users must follow the beat of the music and move their bodies accordingly in real-time to accomplish the SMS job [10].

Traditional dance rehearsals are expensive, time-consuming, and limited by physical space. VR technology proposals a solution by creating a simulated environment for cost-effective rehearsals with greater flexibility, safety, and the potential for enhanced feedback through real-time analysis and optimization algorithms. This combination can revolutionize dance rehearsal by making it faster, cheaper, and safer, while significantly improving dancer performance.

A. Contribution Statement

The main contribution of this work is,

- The study utilizes data from the Real time data, which is a benchmark dataset commonly used for storing motion capture data.
- The manuscript employs preprocessing techniques such as Geometric Interaction Augmented Graph Collaborative Filtering (GGCF) to remove the noise data from the input images. Feature extraction is performed using the Adaptive Synchro Extracting Transform (ASET).
- The classification task is carried out using Attentive Evolutionary Generative Adversarial Network (AEGAN)
- The manuscript introduces the Coati Optimization Algorithm (COA) for optimizing the AEGAN model.

The remaining manuscript systematized as: Segment 2 presents literature survey, Segment 3 describes proposed methodology, Segment 4 proves results, Segment5 concludes manuscript.

II. LITERATURE SURVEY

Previously, a large number of research employing deep learning and virtual reality technologies to simulate dance rehearsals were submitted; a selection of these papers were examined here.

Rivas et al. [11] have presented a variety of self-learning techniques, including many types of Artificial Neural Networks (ANNs) and tree-based models, to a publicly available dataset. It has been discovered that, once these tactics have been applied to the dataset, a key factor influencing student performance is the frequency with which students browse the materials made available on VLE platforms. Low sensitivity and great precision are its features.

Qais et al. [12] have presented Inspired by the geometrical characteristics of circles, the Circle Search Algorithm (CSA) was a groundbreaking metaheuristic optimization method. The circle, with its tangent lines, diameter, center, and perimeter, is the most well-known geometric object. Radius to tangent line segment ratio was the orthogonal function of the angle opposite the orthogonal radius. This frame of view was essential to the CSA's plans for exploration and extraction. Low specificity and great accuracy are its features.

Givi et al. [13] have presented The Skill Optimization technique (SOA) is a novel metaheuristic approach that was proposed to handle optimization problems. The design of SOA was primarily inspired by the advancement and augmentation of human capacities. Two phases were used to quantitatively represent different stages of SOA: (i) exploration, which involves learning from experts, and (ii) exploitation, which involves improving skills via practice and personal effort. The efficacy of SOA in optimization applications was investigated by testing this method on a set of twenty-three common benchmark functions of different unimodal, high-dimensional multimodal, and fixed-dimensional multimodal types. Low F1-score and high RoC are provided.

Cassola et al. [14] have presented a brand-new interactive method that allows trainers to fully write VR-based experiential instruction from within the virtual world on their own, independently of development professionals. Identification of unmanageable components, such as 3-D models, machinery, tools, locations, and environments, was part of the design process. As a kind of virtual choreography, the trainer also demonstrates the movements that the trainees were expected to do. The actions that students do during the course were also recorded as virtual choreographies and compared to the trainer's specifications. Trainers and trainees were thereby placed culturally inside their local semantics and social discourse, instead of assimilating VR system notions for the learning materials. It provides high RoC and low F1-score.

Zhou et al. [15] have presented the deep learning method's autonomous formation mechanism for continuous choreography. Firstly, by using dynamic segmentation and process segmentation of the automatic generation architecture, it circumvents the technical limitation of classical choreography, which is its incapacity to achieve global optimization. Second, it was an architecture that generates automatically for continuous end-to-end dance notation, providing temporal classifier access. A dynamic time-stamping model was developed for frame clustering in light of this. In the end, experiments show that the model provides high-performance movement time-stamping. Additionally, it integrates global motion recognition technology with continuous motion recognition to achieve the sophisticated creation of continuous choreography, after which motion duration was marked. It provides high accuracy and low sensitivity.

Pang et al. [16] have presented an improved motion recognition design plan it was suggested to do computer vision and image processing-based research on dancing videos. To extract the character characteristics from the video picture, preprocessing techniques such as grayscale, background removal, and filter de-noising were applied to the gathered dance video. Next, to achieve the recognition of dancing movements, the computer vision technique known as self-organizing mapping neural network (SOM) was employed. It provides high F1-score and low accuracy.

Yuan et al. [17] have presented the drawbacks of conventional dance education and the creative application of virtual reality (VR) technology in dance education, including the development of an online resource library for dance, the creation of an immersive learning environment for dance instruction, the conduct of virtual choreography and rehearsals, and the provision of simulation training. Low accuracy and a high F1-score are its features.

III. PROPOSED METHODOLOGY

In this section the proposed methodology for DVR-AEGAN–COA is described. This study leverages the data from Real Time Data from various public dance dataset and employs pre-processing GGCF technique. By applying the GGCF technique, it removes noise and data enhancement in a dance rehearsal dataset captured using virtual reality technology. Then feature extraction is performed utilizing Adaptive Synchro extracting Transform (ASET),used to extract features, which can capture the temporal dynamics and frequency components of the movements performed by the dancers. Then the classification using AEGAN is performed. The classification task focuses on categorizing attributes, styles and emotions. The introduction of the Coati Optimization Algorithm (COA) for optimizing the AEGAN method in the context of dance action identification and aims to enhance the accuracy, efficiency, and performance of categorizing attributes, styles, and emotions in dance movements through a cooperative optimization approach. The block diagram of proposed DVR-AEGAN–COA method is shown in figure 1.

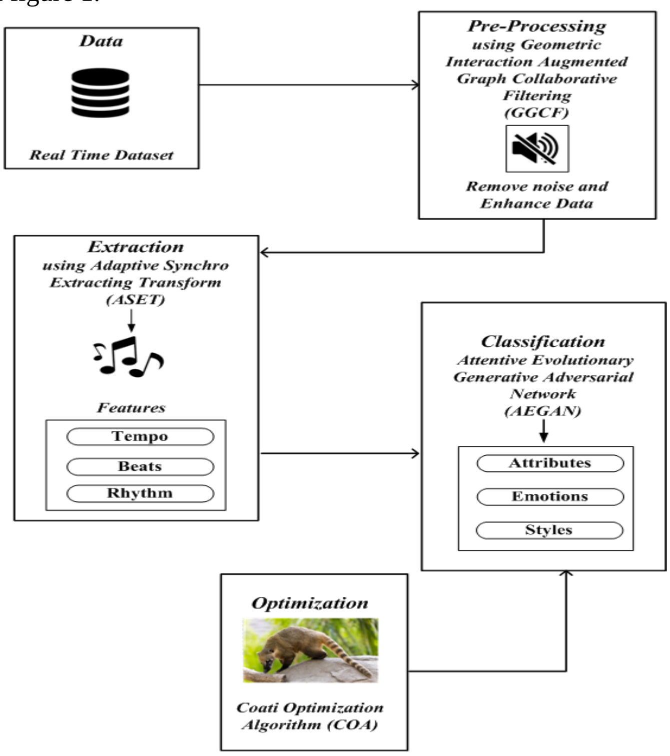

Fig 1: Block diagram of proposed DVR-AEGAN–COA method

A. Data Collection

First, real-time data from many public dance data sets are used to acquire the data. The initial stage in the process of recognizing and categorizing creative dance moves is the collecting and arranging of data [18].These data ought to contain dancing moves of various genres, levels of difficulty, and viewpoints. Professional dancers are expected to annotate each dance video clip with information such as the sort of dance activity, start and stop times, etc. Combine the gathered and annotated data to create a training, verification, and test set that is appropriate for deep learning training.

B. Pre-processing using Geometric Interaction Augmented Graph Collaborative Filtering (GGCF)

To remove the noise and enhancing data, the pre-processing can be done using GGCF [19]. This approach is particularly useful for extract the noise data from the surroundings. The GGCF is designed to meticulously extract modality-wise meaningful and well-aligned data from extensive, noisy image-text pair datasets. It is used to apply data normalization, data improvement, and noise removal (such as fuzzy, weak light or video clips with bad shooting angles) to visual data. In the content of blind filtering, it can be used to evaluate cross-modal entailment relationships between images and text.

1) Steps for pre-processing

Graph convolution networks have shown their powerful ability in recommender systems. Inspired by Light GCF which observes feature transformation and nonlinear activation in GCFs could be burdensome for collaborative filtering, by adopting the simple neighbour aggregator in our method. Given the input embeddings $e_u^{k,(k)}$ and $e_i^{k,(k)}$ for user c and item i in either hyperbolic H spaces $(k \in \{R, H\})$or Euclidean R, for the kth graph convolution layer,

$$h_u^{k,(k)} = Agg_{i\in N_u}^{k}(w_{ui}, e_i^{k,(k)}), h_u^{k,(k)} = Agg_{u\in N_i}^{k}\left(w_{ui}, e_u^{k,(k)}\right) \quad (1)$$

Where N_u, N_i are the set of neighbours of u and i respectively and $w_{ui} = 1\Big/\left(\sqrt{|N_u|}\sqrt{|N_i|}\right)$ denoted as euclidean weighted mean is the definition of the aggregator Agg^k in Euclidean space, which is the weight between u and i:

$$Agg_{i\in N_u}^{R}\left(w_{ui}, e_u^{R,(k)}\right) = \sum_{i\in N_u} w_{ui} e_i^{R,(k)} = h_u^{R,(k)} \quad (2)$$

The Frechet mean, which minimizes an expectation of (squared) distances given a set of points, is the definition of the weighted mean in non-Euclidean space. Nevertheless, there is no closed form solution for the Frechet mean, and stochastic gradient descent is not a practical method for calculating it. The leverage of an elegant neighborhood aggregation approach based on the centroid.

$$Agg_{i\in N_u}^{H}\left(w_{ui}, e_i^{H,(k)}\right) = \frac{\sum_{i\in N_u} w_{ui} e_i^{H,(k)}}{\left|\left|\left|\sum_{i\in N_u} w_{ui} e_i^{H,(k)}\right|\right|L\right|} = h_i^{H,(k)} \quad (3)$$

Thus, the features $h_i^{R,(k)}$ and $h_i^{H,(k)}$ can be easily obtained by aggregating their neighbours.

In particular, using the distance between the hyperbolic feature ($h_i^{H,(k)}$) and the euclidean feature ($h_i^{R,(k)}$) of item i, one may assess how comparable the features are and combine them as follows:

$$\begin{aligned} f_i^{R,(k)} &= h_i^{R,(k)} + \left(\gamma\, d_R\left(h_i^{R,(k)}, \log_0(h_i^{H,(k)}\right)\right) \times \log_0\left(h_i^{H,(k)}\right), \\ f_i^{H,(k)} &= h_i^{H,(k)} \oplus \left(\gamma' d_H\left(h_i^{H,(k)}, \exp_0\left(h_i^{R,(k)}\right)\right) \otimes \exp_0\left(h_i^{R,(k)}\right)\right) \end{aligned} \quad (4)$$

In this case, the features are transformed between euclidean and hyperbolic spaces using, $\exp_0(\cdot)$ and $\log_0(\cdot)$ .Trainable scalar β, β' scales the euclidean distance d_R hyperbolic distance d_H , which measures similarity between various spatial characteristics. $\oplus$ Additionally, $\oplus$ are defined in hyperbolic spaces as scalar multiplication and addiction. These multiplications, given feature vectors $x, y \in H, v \in T_x H$ and a scalar (r) , are defined as These multiplications are defined as follows given feature vectors and a scalar:

$$x \oplus y = \exp_x \left(P_{o \to x}\left(\log_0(y)\right)\right), P_{0 \to x}(v) = v + (0 + x) \cdot \langle x, v \rangle L \big/ \left(1 - \langle 0,\ x \rangle L\right) \tag{5}$$

$$r \otimes x = \exp_0\left(r.\log_0(x)\right) \tag{6}$$

After preprocessing the images are transferred in to feature extraction phase.

C. Feature Extraction by Adaptive Synchro extracting Transform

The ASET [20]is Adaptive Synchro Extraction Transform variation. The following features, which may be retrieved using computer vision technology, are derived from the morphological characteristics, such as the dancer's body posture, movement range, limb angle, etc., in order to identify and classify dance art movements.

For a given signal $s(u) \in L^2(R)$, The signal's ASET after accounting for an extra phase shift

$e^{-\omega t}$ is [20]:

$$\mathrm{ASET}(t, \omega) = \int_{-\infty}^{+\infty} g(u - t) s(u) e^{-i\omega(u-t)} du \tag{7}$$

Here ω is the angular frequency and $g(u - t)$ is a moving time frame.

Based on Parseval's theorem, let $g_\omega(u) = g(u - t)e^{i\omega(u-t)}$ Eq. (7) is rephrased as follows in the frequency domain:

$$\mathrm{ASET}(t, \omega) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} G_\omega^*(\xi) \cdot S(\xi) d\xi \tag{8}$$

Here $G_\omega(\xi)$ and $S(\xi)$ are the Fourier transforms of $g_\omega(u)$ and $s(u)$, respectively, and * stands for a complex conjugation. The equation then becomes:

$$G_\omega(\xi) = \int_{-\infty}^{+\infty} g(u - t) e^{i\omega(u-t)} e^{-i\xi t} du \tag{9}$$

Let $u - t = \tau$, Eq. (9) can be rewritten as:

$$G_\omega(\xi) = e^{-i\xi t} \int_{-\infty}^{+\infty} G(\tau) e^{-i(\xi - \omega)\tau} d\tau = e^{-i\xi t} G(\xi - \omega) \tag{10}$$

Here $G(\xi - \omega)$ represents the moving time window $g(u - t)$ Fourier transform. The ASET of $s(u)$ may be rewritten as follows by substituting Eq. (10) into Eq. (8):

(10)

$$ASET(t, \omega) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} G(\xi - \omega) \cdot S(\xi) \cdot e^{i\xi t} d\xi \tag{11}$$

Observing that $s(t) = A \cdot e^{i\omega_0 t}$ is a completely harmonic signal, and its Fourier transform

$$S(\xi) = 2\pi A \cdot \delta(\xi - \omega_0) \tag{12}$$

Substituting Eq. (12) into Eq. (11):

$$\mathrm{ASET}\ (t, \omega) = A \cdot G(\omega - \omega_0) \cdot e^{i\omega_0 t} \tag{13}$$

By separating out (13) in terms of the amount of time to have:

$$\omega_0(t, \omega) = \frac{\partial_t \mathrm{ASET}(t, \omega)}{i\mathrm{ASET}(t, \omega)} \tag{14}$$

Where ω_0 represents the instantaneous frequency (IF) in two dimensions that are estimated.

By combining ASET with a synchro-extracting operator $SEO(t, \omega) = \delta(\omega - \omega_0(t, \omega))$, ASET extracts the coefficients of (t, ω) exclusively at the IF trajectory $\omega = \omega_0$ as follows:

$$IF(\omega_o) = ASET(t, \omega) * SEO(t, \omega) \tag{15}$$

Then the selected features are transferred in to classification phase.

D. Classification by Attentive Evolutionary Generative Adversarial Network

In this Part, classification and detection of attributes, emotions and styles using AEGAN is discussed[21]. The AEGAN is a deep learning method used for classification task, especially in its corresponding dance style and content in virtual reality. The data (likely videos) needs to be processed into a format suitable for the deep learning model. Frames from the videos may need to be extracted, or they may need to be represented numerically. High dynamic dancing motions are a difficult challenge to recognize in the realm of human motion recognition. AEGAN is the term given to the proposed method due to its self attention module.

The deep features are denoted by$x \in R^{C\times N}$, while C and$N$represents the station quantity and feature placements, correspondingly. First, x is converted into $f(x)$and$g(x)$, Here $f$and $g$are specified by,

$$f(x) = W_f x, g(x) = W_g x \tag{16}$$

The AEGAN acquires knowledge of the weight matrices $W_g \in R^{\bar{C}\times C}$,$W_f \in R^{\bar{C}\times C}$. To enhance storage efficiency, the channel amount C is decreased to toc/mtostorage, with m set to 2.

The normalize the feature vector in the direction of the channel as, The feature vector is normalized in the channel's direction as,

$$norm(x) = \frac{x}{||x||} \tag{17}$$

When producing the j[th] area, the self-attention $map\beta_{ji}$signifies the amount of the model of the i[th]location. The self-attention $map\beta_{ji}$ is defined as follows:

$$\beta_{ji} = {exp\left(norm\left(f^T(x)\right).norm\left(g^T(x)\right)\right)} \Big/ {\sum_{i=1}^{N} exp\left(norm\left(f^T(x)\right).norm\left(g^T(x)\right)\right)} \tag{18}$$

The result of the regularizedGAN layer $o = \left(o_1, o_2, \ldots, o_j, \ldots, o_N\right) \in R^{C\times N}$is computed by,

$$o_j = v\left(\sum_{i=1}^{N} \beta_{ij} m(x_i)\right) \tag{19}$$

$$m(x_i) = W_m X_i . \tag{20}$$

The final result y_i is calculated by,

$y_i = \mu 0_i + x(21)$

where $0i$ is the attention layer's output, μ is a scale parameter, and x is the input. Here the AEGAN is applied with COA for turning the weight parameters.

E. Optimizing using Coati Optimization Algorithm

The Coati Optimization Algorithm (COA) [22] is used to determine the optimal parameters for the AEGAN classifier. The COA is a recent nature-inspired approach to solving optimization problems. It mimics the behaviour of coatis; interesting mammal's native to South America, to achieve optimal solutions. The inspiration for the Coati Optimization Algorithm (COA) comes from the social and reactive behaviours of coatis, fascinating mammals from South America. COA mimics two key aspects of coati life: Hunting Iguanas: Coatis exhibit teamwork when hunting iguanas. Part of the group climbs trees to frighten the prey down, while others wait strategically on the ground to catch them. Escaping Predators: When facing danger from predators, coatis prioritize survival and quickly flee, abandoning their hunt.

Step 1: Initialization

Initially in AGEAN, a solution candidate (F) matrix representing the starting positional vectors of the search is identified. This matrix is originally established as random values inside a search space. Additionally, each position vector has a value for the initial fitness function. The steps of the suggested COA initialization are mathematically expression is given in equation (22)

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_2 \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,j} \cdots x_{1,m} \\ \vdots \ \ddots \ \vdots \ \iddots \ \vdots \\ x_{i,1} \cdots x_{i,j} \cdots \ x_{i,m} \\ \vdots \ \iddots \ \vdots \ \ddots \ \vdots \\ x_{N,1} \cdots x_{N,j} \cdots x_{N,m} \end{bmatrix}_{N\times m} \tag{22}$$

The random beginning population placements are represented by the matrix X, where N denotes the number of coatis and m is the number of problem dimensions. N

Step 2: Random generation

Parameters for the input are created at random after startup. Therefore, optimization process of COA and it transfer from exploration to exploitation steps utilizing various behaviours depend on this condition.

Step 3: Fitness Function

The outcome is determined by initialized judgments and random responses. The fitness is then computed using the equation (23),

$$Fitness\ Function = optimizing\ (\mu) \tag{23}$$

Where, μ denotes the weight parameter

Step 4: Exploration Phase

There are two groups of coatis during the exploratory period. While the second group waits underneath the tree for the terrified prey to fall, the first group scales the tree to frighten the prey. Coati may do a thorough search of the issue area by moving in this fashion. The coatis calls its prey iguana.

$$X_i^{P1} : x_{i,j}^{P1} = x_{i,j} + r \cdot \left(Iguana_{\ j} - I \cdot x_{i,j}\right), \quad for \quad i = 1,2,\ldots,\left[\frac{N}{2}\right] and\ j = 1,2,\ldots,m \tag{24}$$

$$Iguana^G : Iguana_i^G = lb_j + r \cdot \left(ub_j - lb_j\right), j = 1,2,\ldots, m \tag{25}$$

The i coati's new position X_i^{P1} is retained if it has a higher fitness value than its previous position X_i. Where $Iguana$ is the prey's position, $x_{i,j}^{P1}$ is its j dimension, F_i^{P1} is the new position's fitness value, and r is a real random integer between zero and one, $Iguana^G$ represent the location of the victim on the ground. Fig 2 shows Flow chart of COA.

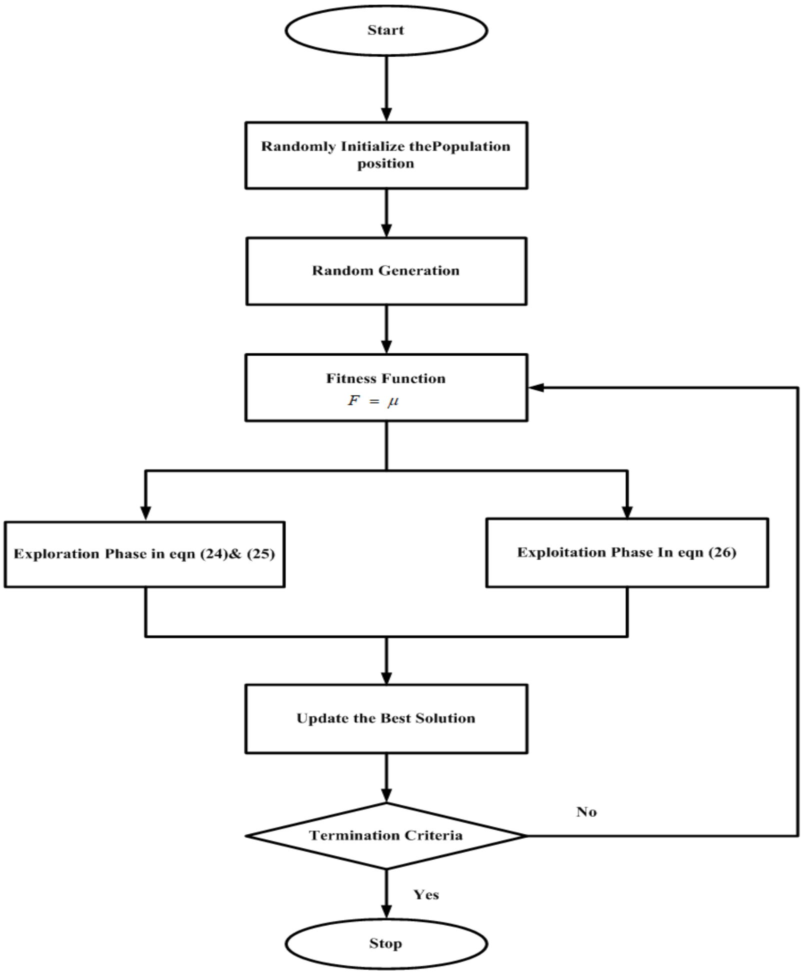

Fig 2: Flow chart of COA

Step 5: Exploitation phase for optimizing

A coati will migrate to a random location close to its spot when it is attacked by a predator. If the new location increases the fitness value, it is acceptable; the coati's position and fitness in the second phase are indicated by the suffix $P2$, lb_j^{local} & lb_j^{lcal} are the j decision variable's local lower and upper limits.

$$X_i^{P2} : x_{i,j}^{P2} = x_{i,j} + (1-2r)\cdot\left(lb_j^{local} + r\cdot\left(ub_j^{local} - lb_j^{local}\right)\right), \quad i = 1,2,\ldots N,\ j = 1,2,\ldots,m \qquad (26)$$

Step 6: Termination Condition

Verify the termination criteria; if it met, the best solution has been found; if not, go to step 3. Then AEGAN has accurately predicted and classified with Bio-Vision Hierarchy Dataset with higher tracking accuracy.

IV. RESULT & DISCUSSION

The result of proposed dance rehearsal simulation on virtual reality technology using Attentive Evolutionary Generative Adversarial Network optimized with the Coati Optimization Algorithm (DVR- AEGAN –COA) is discussed. The proposed technique performance is assessed using the MATLAB platform and associated with other approaches currently in use. The obtained results of the proposed with DVR- AEGAN –COA technique are evaluated with existing techniques like DVR-ANN, DVR-CNN and DVR-SOA methods.

- TP: True positive occurs when classification method correctly forecasts positive class as positive.
- TN: When a classification algorithm accurately predicts a negative class as negative, this is known as a true negative.
- FP: False positives happen when a classification algorithm mis predicts a negative class as positive.
- FN :When a classification algorithm predicts a positive class as negative, it is known as a false negative.

A. Performance Measures

To study the performance, the performance metrics as, precision, Error rate, accuracy, recall, ROC, specificity,F1-score, and sensitivity are determined.

1) Accuracy

The ratio of a precise prediction to the overall count of proceedings in the dataset is called accuracy. Accuracy is measured by the following equation (27)

$$Accuracy = \frac{(T_P + T_N)}{(T_P + F_P + T_N + F_N)} \qquad (27)$$

2) Error Rate

The proportion of misclassification is assessed using error. Error rate is calculated using equation (28)

$$Error = 100 - accuracy \qquad (28)$$

3) F1-Score

It evaluates the precision of the model on the dataset. It is determined by equation (29)

$$F1Score = \frac{T_P}{\left(T_P + \frac{1}{2}\left[F_P + F_N\right]\right)} \qquad (29)$$

4) Precision

Precision is the positive predict value. Precision is compute by following equation (30)

$$\Pr ecison = \frac{T_P}{T_P + F_P} \qquad (30)$$

5) Recall

The ratio of actual positive samples (including those that were correctly and wrongly forecasted as positive) to true positive predictions is known as recall. The formula of recall is shown in equation (31)

$$\text{Re}call = \frac{T_P}{T_P + F_N} \qquad (31)$$

6) ROC

ROC provides an overall performance indicator for the whole probable Classification. ROC is expressed in equation (32)

$$ROC = 0.5 \times \left(\frac{T_p}{T_P + F_N} + \frac{T_N}{T_N + F_P} \right) \tag{32}$$

7) Sensitivity

Sensitivity is calculated using the following equation (33)

$$Sensitivity = \frac{T_P}{T_P + F_N} \tag{33}$$

8) Specificity

A metric called specificity is used to assess the percentage of real negatives that are accurately detected. Specificity is calculated using the Following equation (34)

$$Specificity = \frac{T_N}{T_N + F_P} \tag{34}$$

B. Performance Analysis

The simulation result of the proposed DVR- AEGAN –COA method shows in fig 3-10. Then the proposed DVR- AEGAN–COA method is linked with existing system like DVR-ANN, DVR-CNN and DVR-SOA correspondingly. An evaluation experiment was conducted, and the findings demonstrated the efficacy of the proposed AEGAN classifier with optimization COA method.

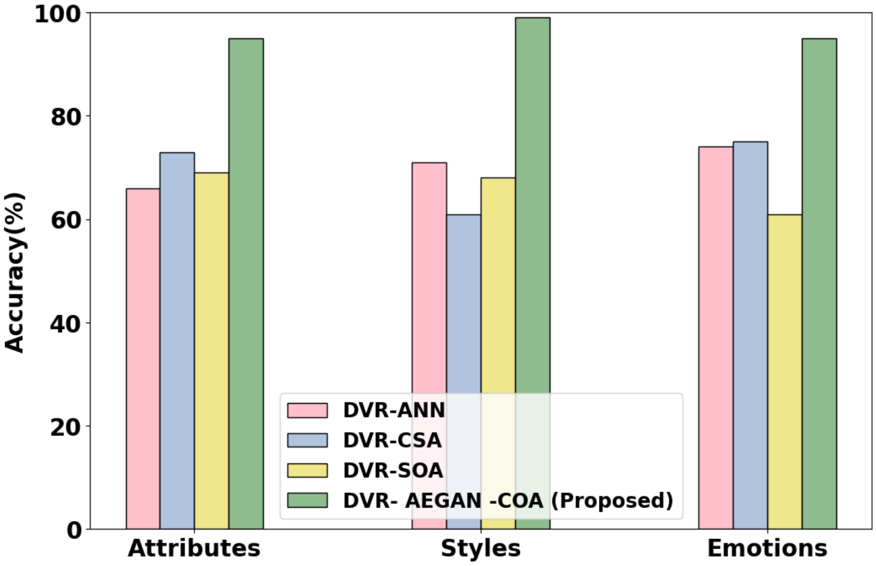

Fig 3: Accuracy Performance Analysis

The Accuracy Performance Analysis is displayed in fig 3. The performance accuracy of different models or approaches used to analyze the dance action. The proposed DVR-AEGAN-COA techniques of accuracy are 25% for attributes, 29% for style and 25% for emotions. The existing methods DVR-ANN, DVR-CSA and DVR-SOA methods of accuracy attains 35%, 40% and 38% for attributes, 40%, 30% and 35% for style and 40%, 41% and 30% for emotions. The proposed DVR-AEGAN-COA method shows the higher accuracy compared with other existing methods.

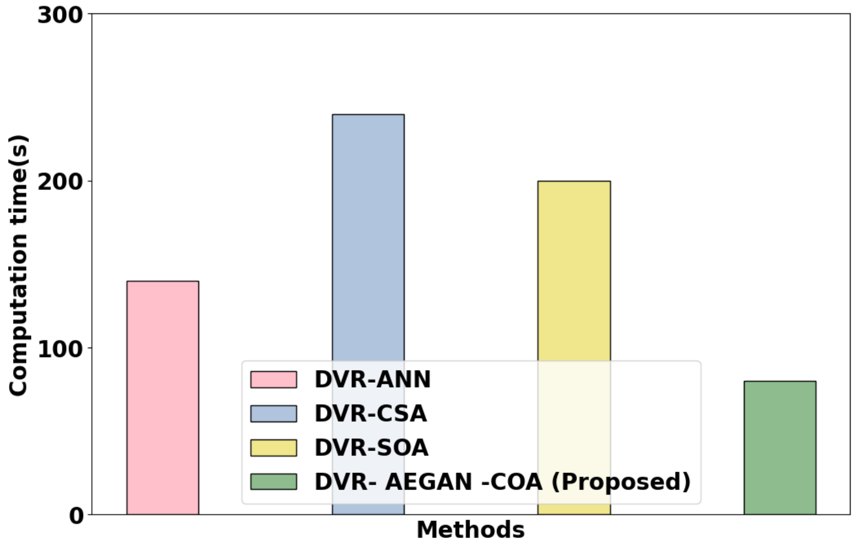

Fig 4: Comparative analysis of computation time

The comparative analyses of computation time is displays in fig 4.In the DVR-ANN method computation time is 10sec, DVR-CSA method computation time is 20sec, DVR-SOA method computation time is 25sec and then the proposed DVR-AEGAN-COA method computation time is 8sec.The proposed AGFS-SAGAN-PDO method shows less computation time compared with other existing methods.

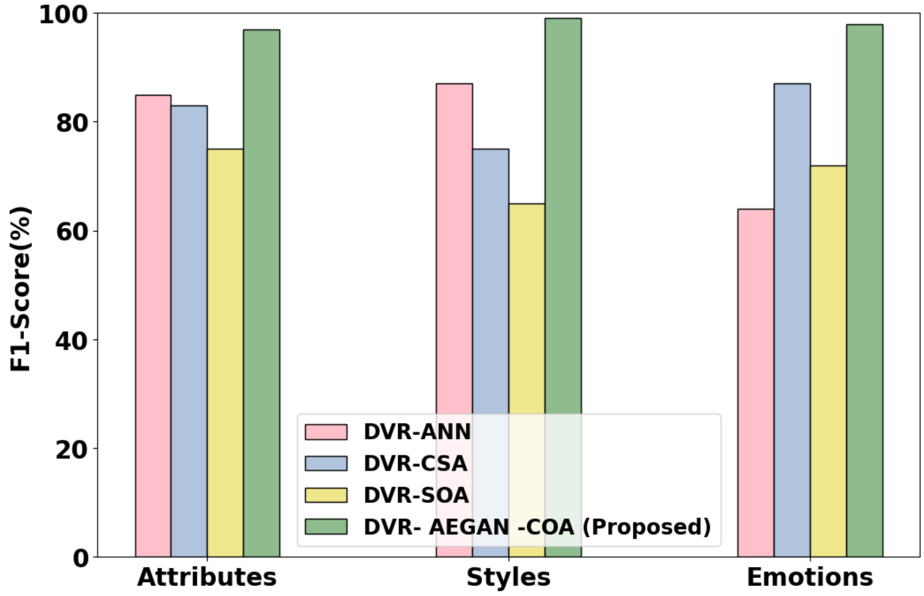

Fig 5: Analysis of the F1-score using current and suggested techniques

The Analysis of the F1-score using current and suggested techniques is displays in fig 5. Compare the performance of different approaches for analyzing the dance action based on their F1-score values. The proposed DVR-AEGAN-COA method F1-score are 28% for attributes29% for styles and 28% for emotions. The existing methods DVR-ANN, DVR-CSA, DVR-SOA method of F1-score are 35%, 37%, 30% for attributes, 32%, 29%, 30% for styles and36%, 32%, 35% for emotions. When associated to other current approach, the proposed DVR-AEGAN-COA method exhibits a higher F1-score value. Analysis of the F1-score using current and suggested techniques

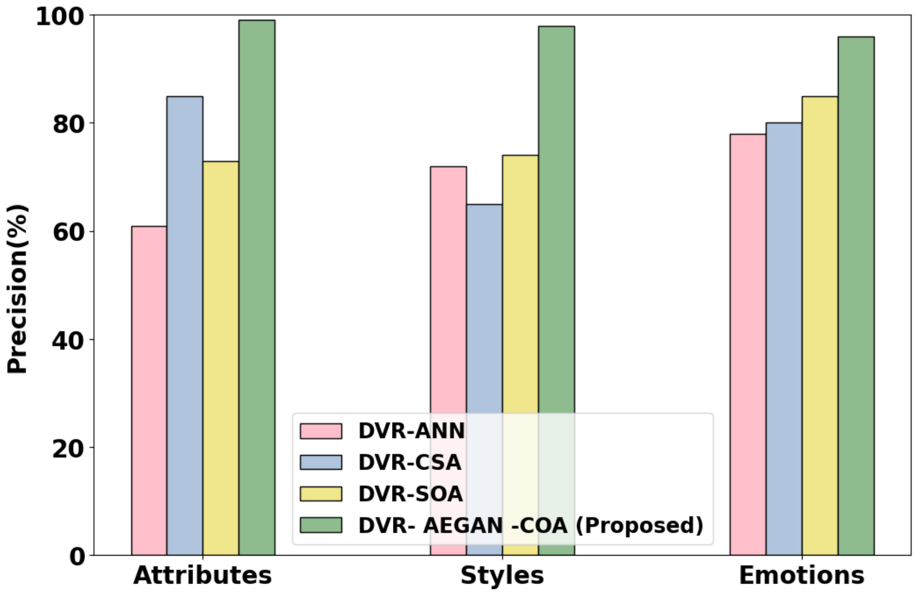

Fig 6: Precision performance analysis using suggested and current methodologies

Precision performance analysis using suggested and current methodologies is displays in fig 6. A measure of a prediction model or algorithm's accuracy is called precision. The figure provides the model's effectiveness in identifying and analyzing the dance action. The precision of proposed DVR-AEGAN-COA methods becomes 29% for attributes, 28% for styles and 25% for emotions. The existing methods DVR-ANN, DVR-CSA, DVR-SOA method of precision are 30%, 30%, 35% for attributes, 45%, 35%, 35% for styles and 30%, 31%, 30% for emotions. The proposed DVR-AEGAN-COA method shows high precision compared with other existing methods.

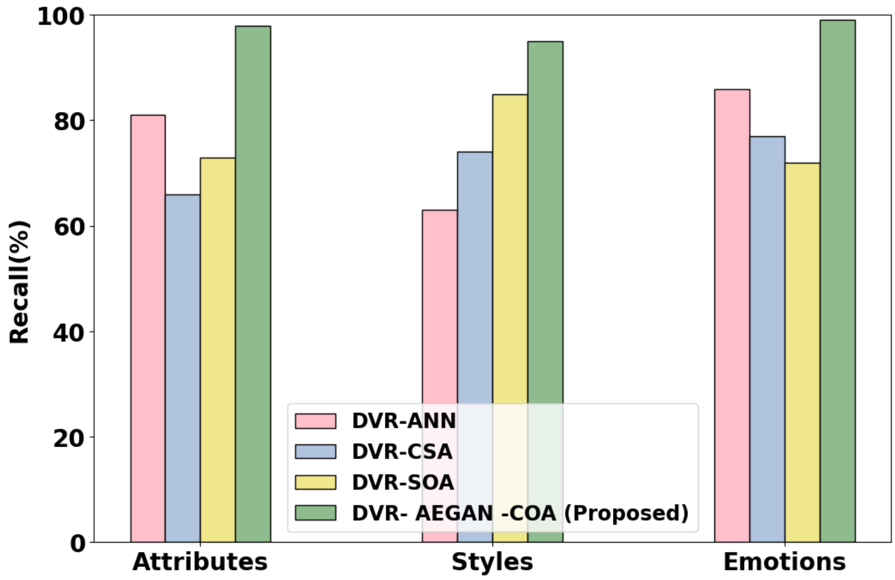

Fig 7: Recall analysis using proposed and existing techniques

Recall analysis using proposed and existing techniques is displays in fig 7.The existing DVR-ANN, DVR-CSA, DVR-SOA method attains 20%, 22%, 10% for attributes, 31%, 20%, 32% for styles and 35%, 30%, 35% for emotions. The proposed DVR-AEGAN-COA method recalls are 28% for attributes, 25% for styles and 29% for emotions. The proposed DVR-AEGAN-COA method of higher recall compared with other existing methods.

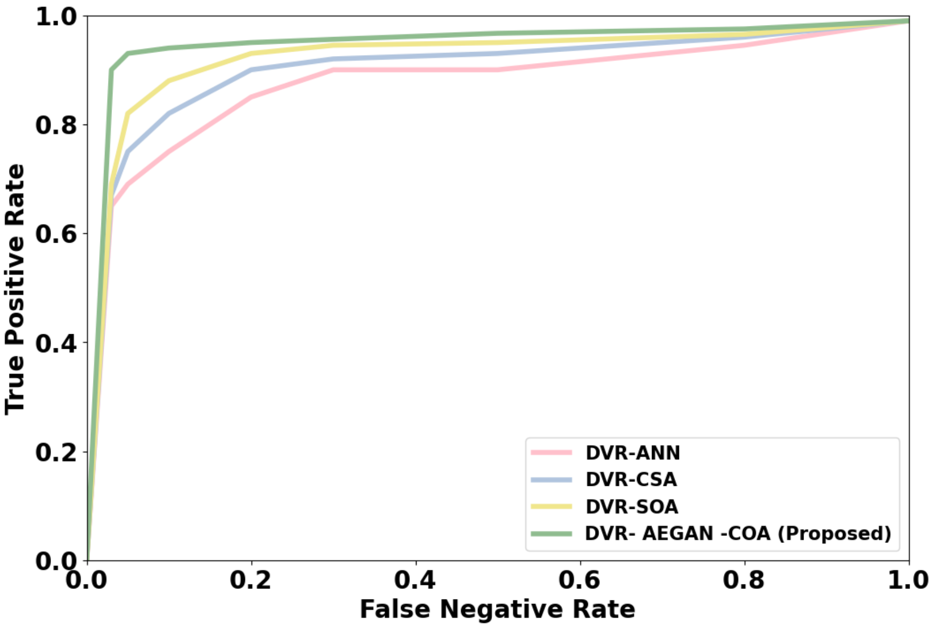

Fig 8: Performance Analysis of ROC

The performance analysis of ROC is shown in fig 8. Each point on the curve represents a different threshold value, and the curve is created by connecting these points. The closer the curve is to the graph's top -left corner, the better the prediction system performs. The higher ROC indicates better performance in distinguishing between positive and negative instances. The proposed DVR-AEGAN-COA methods the ROC provides higher analysis in dance action identification compared with other existing methods. The existing methods like DVR-ANN, DVR-CSA and DVR-SOA of the ROC become lower compared with the proposed DVR-AEGAN-COA technique.

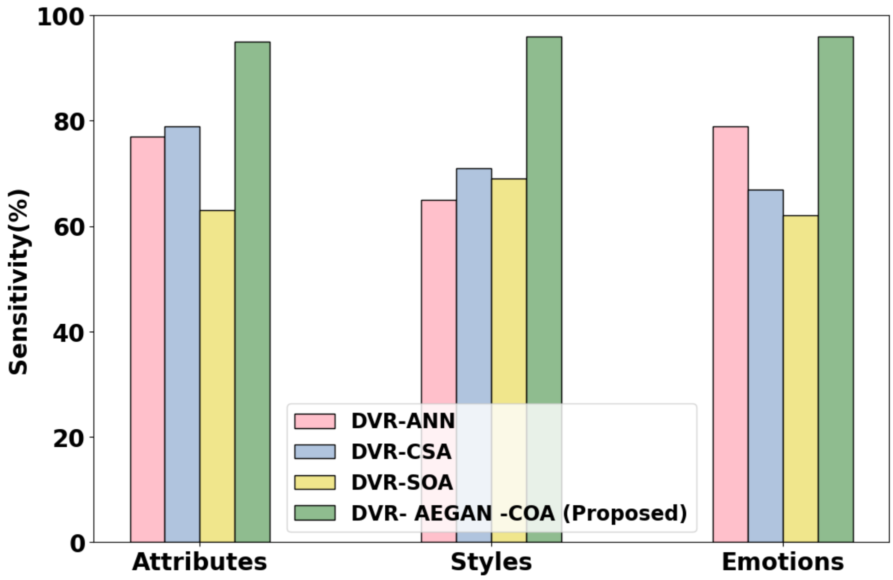

Fig 9: Comparative analysis of sensitivity

The comparative analysis of sensitivity is displays in fig 9. The existing DVR-ANN, DVR-CSA, DVR-SOA method sensitivity attains 26%, 29%, 22% for attributes, 32%, 30%, 38% for styles and 31%, 35%, 30% for emotions. The proposed DVR-AEGAN-COA method sensitivities are 25% for attributes, 25% for styles and 25% for emotions. The proposed DVR-AEGAN-COA method of higher sensitivity compared with other existing methods.

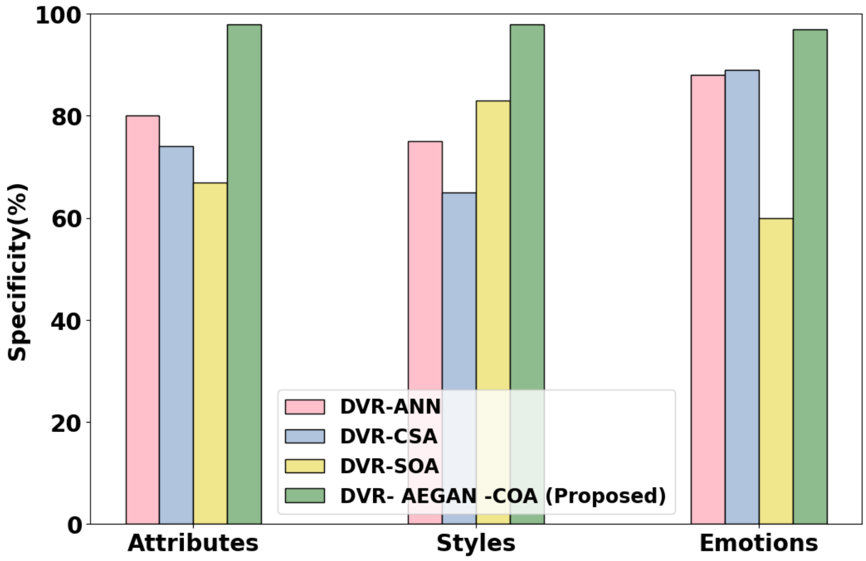

Fig 10: Analysis of specificity performance

The Analysis of specificity performance is shown in fig 10.The existing methods DVR-ANN, DVR-CSA, DVR-SOA method specificity are 30%, 36%,39% for attributes, 45%, 35%, 30% for styles and 38%, 30%, 30% for emotions. The proposed DVR-AEGAN-COA method specificities are 29% for attributes, 29% for style and28% for emotions. The proposed DVR-AEGAN-COA method of higher specificity compared with other existing methods.

C. Discussion

The "Enhanced DVR Classification Utilizing Attentive Evolutionary Generative Adversarial Network" addresses the critical need for accurate and efficient classification of DVR utilizing advanced deep learning techniques. The enhanced method's performance is assessed utilizing standard metrics likes accuracy, precision, recall. Comparisons with baseline models or previous approaches may also be included to demonstrate the improvement achieved through optimization. The proposed method DVR-AEGAN-COA is comparing with existing methods like DVR-ANN, DVR-CSA and DVR-SOA with higher accuracy.

V. CONCLUSION

In this manuscript, Attentive Evolutionary Generative Adversarial Network based Dance rehearsal depend on VR technology is successfully implemented. Over the optimization of AEGAN and utilization of evolutionary generative information, significant improvements in classification performance have been achieved. The performance of the DVR-AEGAN-COA method contains precision, accuracy, F-score, computational time, specificity and sensitivity. The proposed DVR-AEGAN-COA method attains higher specificity 27.32%, 24.43%, 38.24% and higher recall 31.13%, 23.33% and 38.13% for attributes, styles and emotions respectively. The proposed DVR-AEGAN-COA method's performance is compared with that of existing approaches, including DVR-ANN, DVR-CSA, and DVR-SOA.

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