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Clothing Design Style Recommendation Using Optimized Semantic-Preserved Generative Adversarial Network

JES

Journal of Electrical Systems

Abstract: - Recommendations for clothing design styles provide a tailored and efficient buying experience, decreasing consumers' decision fatigue and boosting interest. There are a number of obstacles to implementing clothing design style recommendations, including the requirement for diverse and accurate data to train efficient algorithms, the possibility of biases in recommendation systems, the complexity of comprehending subtle customer preferences, and the ever-changing nature of fashion trends. To overcome this complication, Clothing Design Style Recommendation Using Optimized Semantic-Preserved Generative Adversarial Network (ICMA-SPGAN-SFOA-CD) are proposed. Initially, the images collected from the clothing dataset are given as input. Afterward, the data are fed to pre-processing. In pre-processing, Reverse Image Filter (RIF) is used for redundant of data and noise removal. The pre-processing output is fed to Pyramidal Convolution Shuffle Attention Neural Network (PCSANN) for clothing design style recommendation. The recommended clothing design style was given for classification using Semantic-Preserved Generative Adversarial Network (SPGAN) optimized with Sheep Flock Optimization Algorithm (SFOA)for classifying clothing design style as Basic clothing, Looseness Season for clothing, Collar type, Colour and Advanced clothing . MATLAB is used to implement the proposed ICMA-SPGAN-SFOA-CD method. The performance of the proposed ICMA-SPGAN-SFOA-CD approach attains 25%, 21.5%, and 22.5% high precision,25.3%, 27.5%, and 21.8% high recall and 27.6%, 24.8%, and 23.2% high F1-Scorecompared with existing methods such as RCNN Framework Using L-Softmax Loss (CAR-RCNN-LSL) ,Clothing Attribute Recognition Based on Clothing fashion style recognition with design issue graph (CFSR-DCNN-DIG), Personalized Smart Clothing Design Based on Multimodal Visual Data Detection (PSCD-DNN-MVDD) models respectively.

Keywords: Clothing Design, Reverse Image Filter,   Pyramidal Convolution Shuffle Attention Neural Network, Semantic-Preserved Generative Adversarial Network, Sheep Flock Optimization Algorithm, Style Recommendation.

I. INTRODUCTION

The process of designing clothing is complex and dynamic, encompassing the ideation, sketching, and development of clothing and accessories [1]. Designers choose materials according to their color and texture, make exact construction blueprints, supervise the sewing process, and take inspiration from a variety of sources. Appropriate sizing is guaranteed by fittings and adjustments, which result in the creation of prototypes and test samples. The finished products are frequently displayed in fashion presentations or shows, and in order to remain relevant in the rapidly changing fashion business, successful designers constantly conduct market research and work on their brands [2-4]. A combination of technical skill, artistic vision, and a deep understanding of market trends are needed in this sector. In the field of clothing design, image color matching algorithms play a crucial role in guaranteeing precise portrayal of apparel in digital spaces [5-7]. By utilizing methods like color correction, histogram matching, and color space translation, these algorithms compensate for differences in lighting, screens, and camera settings to match digital colors to actual garment colors. The precision of matching is improved by machine learning and computer vision, and ongoing improvement is facilitated by the integration of user feedback and dynamic illumination adjustment [8, 9]. These algorithms are essential for giving customers accurate and consistent representations of garment colors, which improves the overall digital buying experience as virtual try-ons and online retail become more common [10, 11].

Deep neural networks employed in fashion style recognition may struggle with semantic gaps and ambiguities, hindering accurate classification. Clothing customization systems relying on multitask deep convolutional neural networks may face challenges in engaging users for innovative design [12-14]. The RCNN framework for clothing attribute recognition could be computationally intensive and may not fully address the complexities of diverse clothing styles. Dependency on region proposal techniques in recognition tasks and the sensitivity to dynamic environments pose limitations [15]. The Siamese network-based method for matching time sequence images might struggle to adapt swiftly to changes. The proposed deep learning method for detecting copy-move forgeries may be sensitive to evolving tampering techniques. Style recommendation systems based on body attributes could face challenges in capturing the intricacies of fashion preferences. Evolutionary algorithms for procedural placement may be computationally intensive, limiting their practicality [16, 17].

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These drawbacks highlight the need for further refinement and consideration in the application of these methods. Clothing design lies in the style industry's potential impact on the surroundings, including issues related to fast fashion [18, 19]. The rapid turnover of trends and the pressure to produce clothing at a high pace contribute to overconsumption, excessive waste, and environmental degradation [20]. The weaknesses of the existing methods inspired this development. This study aims to investigate which method is more effective in recommendation of clothing design style and its classifications.

"The following is an outline of the paper's main contributions:"

- In this research, Clothing Design Style Recommendation Using Optimized Semantic-Preserved Generative Adversarial Network (ICMA-SPGAN-SFOA-CD) is proposed.
- Develop aReverse image filtering based preprocessing method for redundant of data and noise removal in the collected data.
- Pyramidal Convolution Shuffle Attention Neural Network (PCSANN) is constructed for the recommendation of clothing design style.
- Propose a SFOA to optimize the Semantic-Preserved Generative Adversarial Network (SPGAN).
- ICMA-SPGAN-SFOA-CD model is implemented at MATLAB and effectiveness examined with several performance metrics.
- The efficiency of the proposed model is analyzed with the existing methods like CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.

Rest of these manuscripts is organized as follows: Part 2 examines the survey of the literature. Part 3 provides an explanation of the proposed strategy, Part 4 proves the results, and This manuscript has concluded in Part 5.

II. LITERATURE SURVEY

Several works have presented previously in literatures were depending on the development of the clothing design style recommendation. Few of them were mentioned here,

Yue et al. [21] have investigated CFSR-DCNN-DIG. In this paper, the method was nevertheless challenging because different clothes photos in the same style may have distinct visual elements. Presented fashion style identification systems recognize garment photographs based on pixel- or region-level criteria by utilizing deep neural networks. However, due to these geographical differences, style recognition lacks the semantics of fashion issues and was susceptible to changes in garment appearance. DIGs with garment attributes were used to generate global and semantic representations of fashion styles in order to tackle this problem. Low accuracy and great precision are provided by this procedure.

Deng and Liu [22] have suggested PSCD-DNN-MVDD. When faced with a variety of styles in this paper, the user simply continually arranges and combines the styles without realizing their own unique look. Using the standard suit style as the starting population, the fitness value was given a score via the human-computer interface in order to carry out the evolution process. The genetic algorithm generates a binary string representing the suit style, which was then decoded using the decoding method and rules to produce a visual style drawing of the suit style. The style drawing was then automatically created. This method provides high recall and low F1-Score.

Xiang et al. [23] have investigated CAR-RCNN-LSL. In this paper, the process was difficult, nonetheless, because of the wide variances in apparel appearance and style as well as the intricate formation requirements of the image. For the recognition problem, a novel strategy based RCNN framework rather of employing CNNs for classification was suggested. First, the region suggestion using the improved selective search technique was extracted. Then, in order to represent images and determine their categories, the L-Softmax Inception-ResNet V1 model was utilized. A basic neural network to rectify the region box boundary following Soft-NMS was employed. This method provides high accuracy and low F1-Score.

Tao et al. [24] have suggested "A Time Sequence Images Matching Method Based on the Siamese Network" . One of the most important parts of activities in dynamic environments was processing time sequence photos to accomplish image matching, like dynamic gesture recognition and multi-object tracking, in this research. A Siamese network-based matching technique for time sequence images was suggested. To create the correlation matrix, the input picture pairings were compared in the first section. To determine the similarity, the correlation matrix the result of the 1st comparison part was compared with a template in the second section. This method provides high F1-Score and low ROC.

Elaskily et al. [25] have investigated a "novel deep learning framework for copy-move forgery detection in images". In this paper, theDigital images were a common sight in modern life, and a vast array of hardware and software tools were available to create and modify them. This research proposes a novel deep learning-based

solution for automatic detection of copy-move forgeries. CMFD was the exclusive domain of Convolutional Neural Networks (CNNs). From the input images, the CNN was utilized to learn hierarchical feature representations in order to distinguish between manipulated and original photographs. This method provides low computation time and low precision.

Hidayati et al. [26] have suggested "Learning Style From Joint Deep Embedding of Clothing Styles and Body Shapes". In this paper, theBody shape was all about proportion, and dressing a body to appear its best was all about fashion style. A new style recommender in this paper that was based on the user's physical features was introduced. For this, a wealth of fashion styling expertise gleaned from social big data was utilized. 'Using a reference dataset classified according to fashion norms, first generate a combination embedding of clothing types and human body measurements via deep multimodal representation learning'. This method provides high F1-Score and low recall.

Yan and Ma, [27] have investigated "Garment Design Models Combining Bayesian Classifier and Decision Tree Algorithm". Based on the decision tree method and Bayesian classifier, this research provides a garment design model to examine how computer technologies could be used to represent knowledge of garment design. It arises from our concept of garment design being vague and imprecise. Personalization of apparel takes into account a broad range of style preferences in order to understand the garment's overall design state. Both high accuracy and long computation times are offered by this method.

III. PROPOSED METHODOLOGY

ICMA-SPGAN-SFOA-CD is discussed in this part . This section provides a full explanation of the research approach that was applied to the clothing design style recommendation. The block diagram of ICMA-SPGAN-SFOA-CD is showed in Figure 1. Thus, the detailed description about ICMA-SPGAN-SFOA-CD is given below,
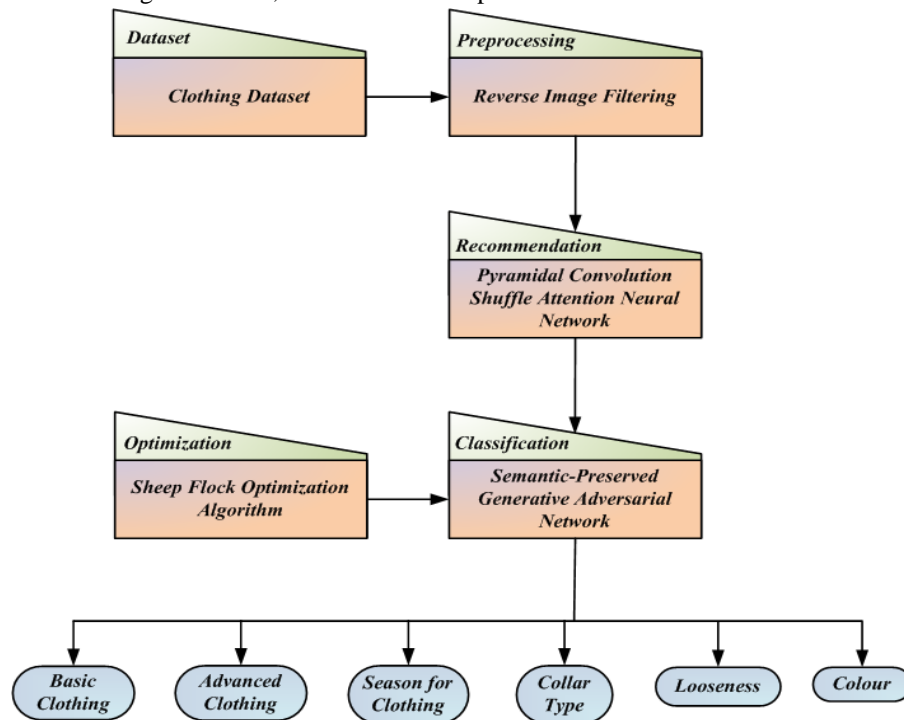

Figure 1: Block Diagram of the proposed ICMA-SPGAN-SFOA-CD Clothing Design Style Recommendation

A. Data Set

In this section, images are gathered from the Clothing dataset [28]. This data set is a collection of over 5000 images of 20 different classes. Any usage, including commercial ones, is permitted for this dataset. The images in the dataset are given a unique ID values and also sender ID for the person who contributed the image. The type of the clothes in the images is labelled under various labelled names. This dataset also contains images of clothes for the all aged person.

B. Pre-processing using Reverse image filtering

In this step, the pre-processing of clothing dataset images by using Reverse Image Filtering (RIF) [29] is proposed. The objective of reverse image filtering, given an image filter, is to eliminate or suppress the filter effects using simply the filter. In clothing image processing method the RIF is a recent and most capable, by

giving the image as an input the Reverse image filtering will remove the unwanted creation from the image by using the filter itself. The output of the Reverse image filtering method is represented in given equation (1)

$$\left\| M(y) - x \right\|^2 \to \min \tag{1}$$

Here , $M(\cdot)$ is a linear filter, $M(y) = Z_y$, then it seems natural to restore y by applying the standard Land weber iterations the terms contains detail of x removed by the filter $M(\cdot)$. It is given in equation (2)

$$y_{i+1} = y_i - \tau Z^*(Zy_i - x) \tag{2}$$

Where Z^* adjoin in the operator Z and τ is sufficiently small step size parameter x are filtered image. $y_i \ and \ y_{i+1}$ Here, estimating an original clothing images. The first two processes (1) and (2) involve a straightforward gradient descent for quadratic energy, while the general modifications include widely used methods for a variety of linear and nonlinear problems, such as convolution. It is given in equation (3)

$$\left\| GY - X \right\|^2 \to \min \tag{3}$$

Where G is a transfer function, here $Y \ and \ X$ deal with a linear convolutional filter and it is fixed, $\min$ is noisy by the frequency space and the land-weber (2), and gradient descent for (3) are given in equation (4)

$$Y_{i+1} = Y_i - \tau(G^*(GY_i - X)) \tag{4}$$

Where G^* indicates the complex of conjugate of $G \ and \ \tau$ is a size. Now joining the (4) with the estimating transfer function G, iteration is given in formula (5)

$$G_i = E(y_i)/Y_i \tag{5}$$

Equation (6) can be obtained by referring to E as the Fourier transform of the pictures represented by the corresponding lowercase letters.

$$Y_{i+1} = Y_i - \tau G_i^*(E(y_i) - X) \tag{6}$$

Here, from the frequency space and, the each step exactly with nonlinear filter by a linear convolution filter which the transfer function. Finally the RIF is removed the noises among the clothing images and this process will take to the next step for recommendation of clothing design style.

C. Clothing Design Style Recommendation using Pyramidal Convolutional Shuffle Attention Neural Network

In this section, design style of clothing recommendation using Pyramidal Convolution Shuffle Attention Neural Network (PCSANN) [30] is discussed. The design style of clothing was recommended based on the characteristic of the clothing and user information data using the proposed PCSANN. Pyramidal convolution allows the neural network to learn features at various granularities by capturing data at several sizes. 'The backbone network uses a residual network model with pyramidal convolution to learn the multi-scale discriminative of pathological abnormalities'. To improve representation power, the discriminative characteristics are then added to the shuffle attention module, which focuses more on pathological abnormality discrimination. It starts with the convolution loss defined in equation (7) in its generic form.

$$\tilde{g}(c \mid I) = 1/\left(1 + \exp\left(-g_p(c \mid I)\right)\right) \tag{7}$$

Here , I indicates the input data. $\tilde{g}(c \mid I)$ denotes the probability score of I belongs to the category c which expressing the probability score. Subsequently, the shuffle attention module receives the discriminative features in order to boost representation power and number of thread categories is given in equation (8)

$$A(W) = -\frac{1}{C}\sum_{c=1}^{c} f_c \log(\tilde{g}(c \mid I)) + (1 - f_c)\log(1 - \tilde{g}(c \mid I)) \tag{8}$$

Where, C indicates the total number of thread categories and the true label of category c is indicated by the f_c. $A(W)$ the sigmoid activation functions are provided in equation (9) and A pyramidal convolution residual network model is used by the backbone network to learn the multi-scale discriminative characteristics of clinical abnormalities are optimized by minimizing the binary cross entropy loss function.

$$T_{l1}' = \sigma(l_c(r)) \cdot T_{l1} = \sigma(W_1 r_1 + b_1) \cdot T_{l1} \tag{9}$$

Where, l_c indicates the linear function, σ indicates the function of sigmoid activation, r_1 indicates 'the average pooled feature', and the two parameters W_1, b_1 can be obtained by the network training. T'_{l1} and T_{l1} Are the two different directions of the channel weights to enhance that features. The fully connected layer's output vector travels via a nonlinear activation layer and group norm normalization function is given in equation (10)

$$T'_{l2} = \sigma(W_2 \cdot NG(T_{l2}) + b_2) - T_{l2} \tag{10}$$

Where, NG indicates the normalization function of the group norm, then T'_{l2} and T_{l2} is the two spatial attention weights to emphasize a feature's importance for a particular area. The design of clothing recommendation can be obtained through network training. Finally the PCSANN recommended the design for the clothing based on the attributes of the clothing and user information data. In this work, SPGAN is employed for the classification of the PCSANN recommended clothing design style.

D. Classification using Semantic-Preserved Generative Adversarial Network

In this section, the classification using SPGAN [31] is discussed. The recommended clothing designs were accurately classified as Wearing simple clothes, stylish clothes, Time of year for clothes, Utilizing the proposed SPGAN, collar type, looseness, and color. SPGANs can be very helpful in situations where keeping certain qualities is crucial, including artistic content generation. The goal of SPGANs is to produce data representations that are more task-translatable. The recommended clothing designs were classified as classic style, elegant style, light style, sports style, leisure style, neutral style, fashion style and national style of adversarial loss is given in equation (11)

$$L_{SPGAN}(G, F, D_S, D_T, I_S, I_T) = N_{zt \sim C_T}[\log D_T(z_t)] \tag{11}$$

Where, D_S and D_T are the two adversarial discriminators of the classification in recommended clothing designs, G and F are the innovation architecture of recommended clothing designs and I_S the ultrasound imagery and corresponding pixel-level labels are marked, then N and I_T are the ultrasound images marked as unlabelled. Then $z_t \sim c_T$ are the purpose is to map the source of ultrasound images separated as the channels in recommended clothing designs. The ultrasound figure consistency loss is given in equation (12)

$$L_{img}(G, F, I_S, I_T) = N_{z_t \sim C_T}[\|G_{img}(F(z_t)) - z_t\|_1] \tag{12}$$

Where, G_{enc} is denoted as purple colour, then the translation of source-to-target images with semantic preservation using our proposed SPGAN. L_{img}, is represents the loss of the source to targeted ultrasound images. The representation invariant loss are given in equation (13)

$$L_{rep}(G, F, I_S, I_T) = N_{z_t \sim C_T}[\|G_{enc}(z_t) - G_{enc}(G_{img}(z_t))\|_1] \tag{13}$$

Where, L_{rep} is represents the loss of representative invariant for the ultrasound image consistency. G_{img}, indicates the source to target generator. The same distribution must be applied to the intermediate representations of the 2 opposing generative networks. The generator produces images that are far closer to the target in distribution, ensuring that features are retained. The Semantic-Preserved Loss is given in equation (14)

$$L_{sem}(G, I_s) = [j(G_{sem}(y_s), x_s)] \tag{14}$$

Where, y_s indicates the predicted probability, $j(\cdot)$ represents the cross-entropy loss function that is frequently used, x_s indicates the source domain's label. Our SPGAN's total loss function is provided in equation (15) based on the terms of loss mentioned before.

$$L_{SPGAN}(G, F, D_S, D_T, I_S, I_T) = \lambda_1 L_{img}(G, F, I_S, I_T) \tag{15}$$

Where, λ_1 represents the training epochs which means typically set to the value within $[10, 20]$. Finally the images are classified into Advanced clothing, Basic clothing, Season for clothing, Collar type, Looseness and Colour. In this work, SFOA for recommended clothing design classification, this method optimizes the SPGAN optimum parameter D_T and D_S. In this case, the weight and bias parameters of the SPGAN are adjusted using SFOA.

E. Optimization using Sheep Flock Optimization Algorithm (SFOA)

The weights parameter of SPGAN is optimized using the SFOA [32], which precisely optimize the classifications of the recommended clothing designs. Initially, SFOA creates the uniformly dispersed populace for optimizing the initialization parameters of SPGAN parameters. Sheep are ruminant mammals with four legs that are commonly raised as livestock. Because a sheep's grazing radius may not include the global maximum location, the shepherd attempts to transfer the flock to the maximum place by observing other sheep behaviour. A sheep desire to keep grazing within its own grazing radius.

Step 1: Initialization

Initialize the input parameter, here the input parameter are the gain parameters of SPGAN which was denoted as D_T, D_S.

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d-1} & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d-11} & a_{1,d} \\ \vdots & \vdots & a_{u,v} & \vdots & \vdots \\ a_{m,1} & a_{m,2} & \dots & a_{m,d-1} & a_{m,d} \end{bmatrix},$$ (16)

Where, $a_{u,v}$ and m indicates the count of sheep in a mound indicates where the vth dimension of the uth population.

Step 2: Random generation

Weight parameters are created at random after setup. Best fitness values are chosen based on an explicit hyperparameter scenario.

Step 3: fitness function

Initialized assessments, random results generated. The function of fitness is increased with values of parameter optimization for weight parameters D_T, D_S are generator. It's expressed as equation (17)

$$Fitness\ function = Optimizing\ [D_T, D_S]$$ (17)

Step 4: Exploration phase

Initial values are defined as population size, maximum iteration, limitations, cost function, dimensions, and maximum velocity. The quantity of goats and sheep in the pastures is known as the population size. The count of optimization iterations is max iteration. One function that gives the value of input variables is the cost function. The quantity of problem dimensions is known as dimensions. Maximum velocity is obtained in equation (18).

$$V_{Max} = 0.1 * (upperbound - lowerbound)$$ (18)

Where, *upperbound and lowerbound* are each variable's bounds and V_{Max} indicates The maximum possible velocity for sheep and goats. Every individual in the population is given a random position, and their kind is allocated. Every individual in the population is given a random position, and their kind is allocated. The area within which a sheep can search is known as the grazing radius, and it is determined by method development and growing congestion. Equations (20) and (21) can be used to determine the grazing radius for sheep and goats.

$$d_x = (2 * r_{G(sheep\ or\ goat)}) * Rand - r_{G(sheep\ or\ goat)}$$ (19)

$$r_{Gsheep} = 0.001 * (upperbound - lowerbound) * T$$ (20)

$$r_{Ggoat} = 0.1 * (upperbound - lowerbound) * T$$ (21)

Where, d_x denotes the sum added to the existing position, r_{Gsheep} and r_{Ggoat} are the sheep and goat grazing radius and T denotes the progress of algorithm iterations. The flowchart of Sheep Flock Optimization Algorithm is shown in Figure 2.

Step 5: Exploitation for optimizing D_T, D_S

The shepherd uses the worldwide best position in the move section to try and shift the flock to the best location, however the sheep don't understand why they are in this order, therefore they still make an effort to go in the direction of other sheep and their finest experience. Regarding convergence, the move sections for goats and sheep differ as well; each is split into two halves. All iterations are split into two sections in this section; in part one, convergence has not yet occurred and the herd is dispersed ($T > 0.3$). Equation (22) computes the movement brought on by the sheep's desire to remember the best past experience.
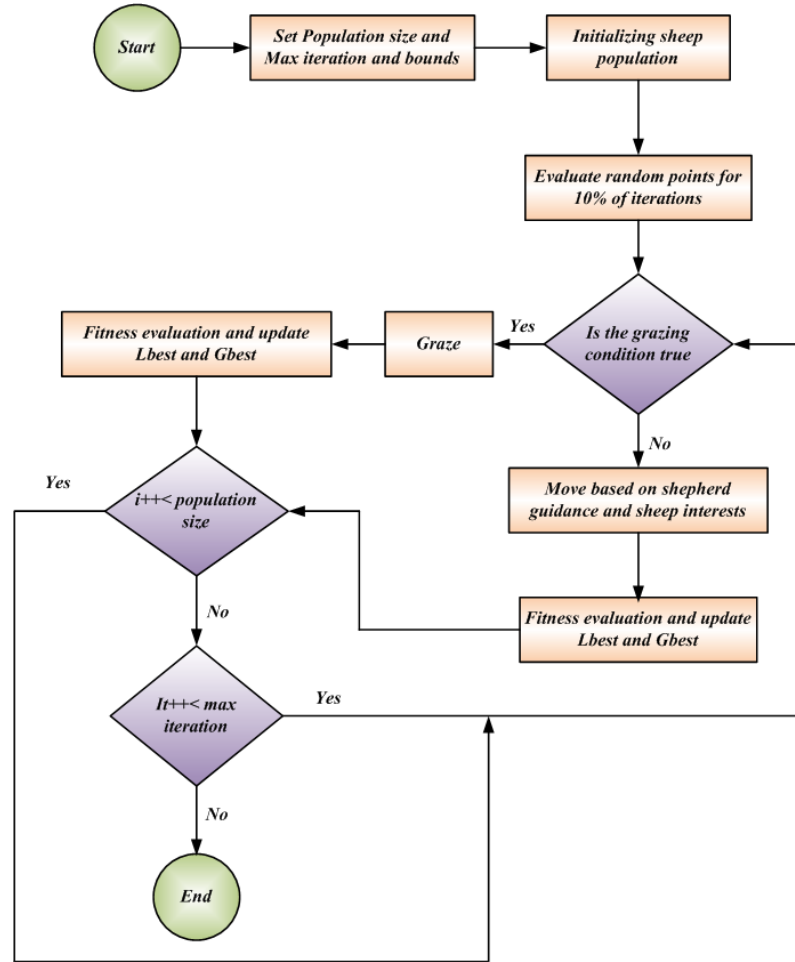
Figure 2: Flow chart of Sheep Flock Optimization Algorithm (SFOA)

$$V_{Lbest,1} = C * Rand(1, Dim) * (X_{Lbest} - X) \tag{22}$$

Here , X denote the sheep's current position, X_{Lbest} is the best fitness discovered by present ship, *Dim* represent the dimension of the problem and C denotes a random number between 0 and 3. When the herd dispersion diminishes (ttt) in the second section. Equation (23), which calculates movement from the shepherd's command to the optimal position, is used. When the herd dispersion diminishes ($T \leq 0.3$) in the second section. Equation (23), which calculates movement from the shepherd's command to the optimal position, is used.

$$V_{sh2,1} = C1 * (1 - T) * (X_{GBest} - X) \tag{23}$$

$$\begin{cases} V_{m,1} = V_{sh1,1} + V_{LBest,1} + V_{other,1} & T > 0.3 \\ V_{m,1} = V_{sh2,1} + V_{LBest,1} & T \leq 0.3 \end{cases} \tag{24}$$

Where, X_{GBest} denotes the best fitness, $V_{m,1}$ is the shepherd order speed. The future position of the sheep is determined by adding the calculated speed to the current positin. After the new position has been assessed, the sheep move to it. If the cost value of the new position is higher than either the sheep local best cost or the flock worldwide best cost, it is also assigned to them.

Step 6: Termination Condition

In this stage, the weight parameter D_T, D_S Semantic-Preserved Generative Adversarial Network are optimized with the help of SFOA, will iteratively repeat the step 3 until the halting $Y = y + 1$ is met**.** Then, the ICMA-SPGAN-SFOA-CD was ultimately proposed , which classifies recommended clothing design style images with a higher degree of accuracy into Basic clothing, Collar type ,Advanced clothing, Looseness, Season for clothing, and Color.

IV. RESULT WITH DISCUSSION

The experimental results of the proposed system are covered in this part . The proposed method is then simulated in MATLAB using the mentioned performance indicators. In MATLAB, the proposed ICMA-SPGAN-

SFOA-CD method is implemented into practice. The obtained outcome of the proposed ICMA-SPGAN-SFOA-CD approach is analyzed with existing systems like CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL correspondingly.

A. Performance measures

Selecting the most effective classifier requires taking this critical step. Performance is assessed using performance metrics, including accuracy, recall, computation time, error rate, precision, sigmoid cross-entropy loss function, F1-Score and ROC. The performance metric is deemed in order to scale the metrics. the False Positive/ Negative, True Positive / Negative, samples are required in order to scale the performance metric.

- True Negative (TN): Presents the count of samples which are correctly predicted as negative.
- True Positive (TP): Presents the count of samples values which are correctly predicted as positive.
- False Positive (FP): Presents the count of positive samples which are incorrectly predicted as positive.
- False Negative (FN): Presents the count of samples which are incorrectly predicted as negative

1) Accuracy

Equation (25), which evaluates accuracy, provides the proportion of samples (positives and negatives) relative to total samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{25}$$

2) Precision

The accuracy of a machine learning model's positive prediction is one measure of the model's performance, along with precision. Equation (26), which gives the count of true positives spit by the entire count of positive predictions, is the definition of precision.

$$\Pr ecision = \frac{TP}{TP + FP} \tag{26}$$

3) Recall

The percentage of data samples that a machine learning model properly classifies as belonging to a class of interest is known as the true positive rate (TPR), also known as recall. The following equation (27) is used to measure it.

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{27}$$

4) F1-Score

A machine learning model's performance is assessed using a metric called the F-score. Equation (28), which combines recall and precision into a single score, describes it.

$$F1 - Score = 2 * \frac{precision * recall}{precision + recall} \tag{28}$$

5) Computational time

The only way to measure an algorithm's execution time that is not totally reliant on the algorithm and its inputs is on time complexity. The computational complexity indicates the amount of time required to run a program. This is scaled by equation (29)

$$CPU\ Time = \frac{IC * CPI}{Clockrate} \tag{29}$$

6) Error Rate

One minus than accuracy is the error rate. A model with a 90% accuracy rate would have a 10% mistake rate. Formula (30) is used to calculate it.

$$Error Rate = 1 - \frac{FP + FN}{TP + TN + FP + FN} \tag{30}$$

7) Sigmoid Cross-Entropy loss function

In binary classification problems, the sigmoid cross-entropy loss function is commonly used, particularly in neural network training. For a binary classification job, it quantifies the discrepancy between the true distribution and the projected probability distribution. The formula for 'sigmoid cross entropy loss function' is given in equation (31).

$$L = -\frac{1}{N}\left[\sum_{i=1}^{N} y_i \log(x_i) + (1-y_i)\log(1-(x_i))\right] \quad (31)$$

Where, denotes the number of data points, represent the true label for the example and is the predicted probability.

8) ROC

Equation (32) provides the ratio of the false negative to the true positive area.

$$ROC = 0.5 \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \quad (32)$$

B. Performance Analyses

Fig 3 to 10 depicts the simulation results of proposed ICMA-SPGAN-SFOA-CD method. Then, the proposed ICMA-SPGAN-SFOA-CD method is likened with existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL methods respectively.
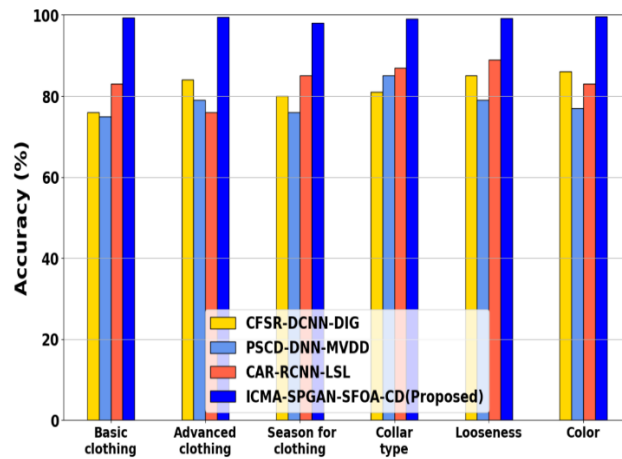
Figure 3: Performance Analyses of Accuracy

Figure 3 displays Accuracy analyses. The proposed ICMA-SPGAN-SFOA-CDmethod attains 29%, 27.5% and 28% higher accuracy for basic clothing; 24%, 28.5% and 26% higher accuracy for advanced clothing; 21.5%, 23%, and 22.5% higher accuracy for season for clothing; 19.5%, 24% and 23% higher accuracy for collar type; 29%, 25% and 24.5% higher accuracy for looseness and 24.5%, 22% and 21.5% higher accuracy for color estimated to the existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
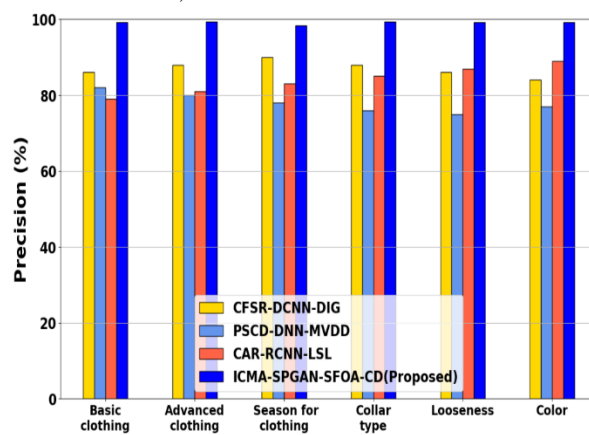

Figure 4: Performance Analyses of Precision

Figure 4 displays Precision analyses. The proposed ICMA-SPGAN-SFOA-CDmethod attains 23%, 21.5% and 20% higher precision for basic clothing; 14%, 18.5% and 16% higher precision for advanced clothing; 25%, 21.5%, and 22.5% higher precision for season for clothing; 18.5%, 21% and 20.5% higher precision for collar type; 19%, 22% and 20.5% higher precision for looseness and17.2%, 20% and 28.5% higher precision for color estimated to the existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
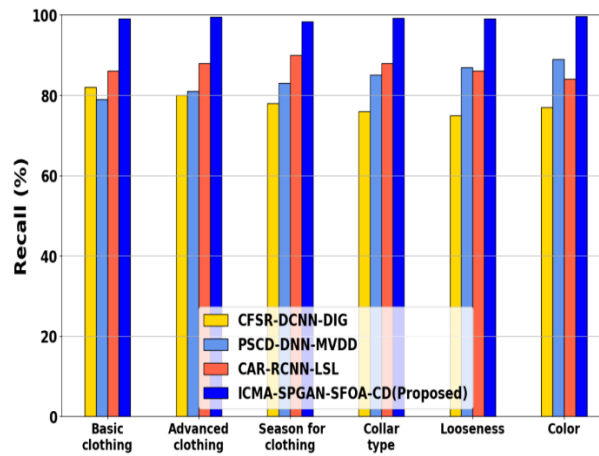
Figure 5: Performance Analysis of Recall

Figure 5 displays Recall analysis. The proposed ICMA-SPGAN-SFOA-CDmethod attains 21.2%, 21.75% and 21.3% higher recall for basic clothing; 12.3%, 17.5% and 14% higher recall for advanced clothing; 25.3%, 27.5%, and 21.8% higher recall for season for clothing; 18.9%, 21.6% and 20.45% higher recall for collar type; 19.9%, 22.2% and 20.5% higher recall for looseness and18.2%, 23.6% and 27.7% higher recalls for color estimated to the existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
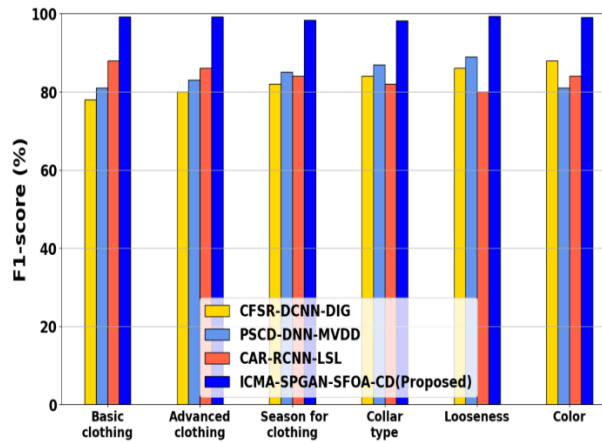

Figure 6: Performance Analyses of F1-Score

Figure 6 displays F1-Score analyses. The proposed ICMA-SPGAN-SFOA-CDmethod attains 23.6%, 27.1% and 25.1% higher F1-Score for basic clothing; 22.3%, 19.8% and 21.3% higher F1-Score for advanced clothing; 27.6%, 24.8%, and 23.2% higher F1-Score for season for clothing; 15.9%, 18.6% and 17.45% higher F1-Score for collar type; 24.9%, 28.4% and 22.5% higher F1-Score for looseness and15.2%, 18.6% and 17.7% higher F1-Score for color estimated to the existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
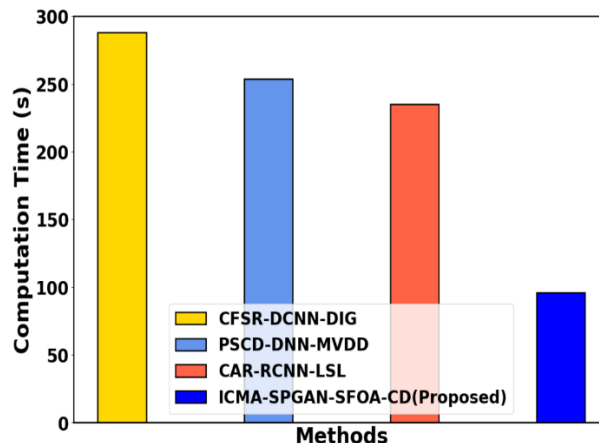

Figure 7: Performance Analyses of Computation Time

Figure 7 illustrates computation time analyses. The proposed ICMA-SPGAN-SFOA-CD method attains 21.3%, 25.1% and 22.3% lesser computation time estimated to the existing method such as CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
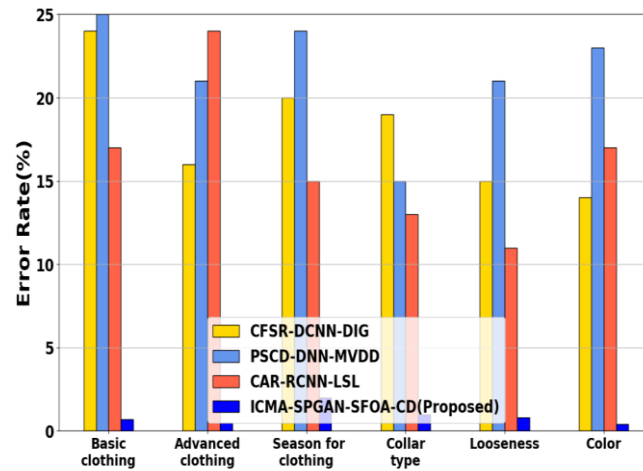

Figure 8: Performance Analyses of Error Rate

Figure 8 displays Error Rate analyses. The proposed ICMA-SPGAN-SFOA-CDmethod attains 13.6%, 17.1% and 15.1% lesser error rate for basic clothing; 12.3%, 9.8% and 11.3% lesser error rate for advanced clothing; 17.6%, 14.8%, and 13.2% lesser error rate for season for clothing; 15.9%, 18.6% and 17.45% lesser error rate for collar type; 14.9%, 18.4% and 12.5% lesser error rate for looseness and15.2%, 18.6% and 17.7% lesser error rate for color estimated to the existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
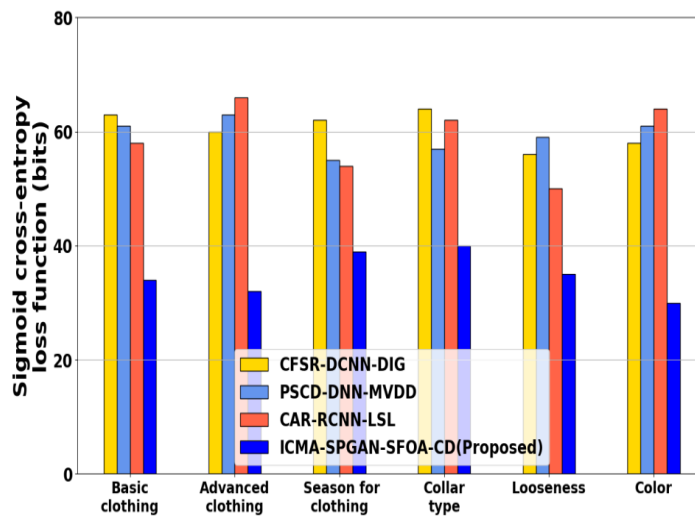

Figure 9: Performance Analysis of Sigmoid Cross-Entropy Loss Function

Figure 9 displays Sigmoid Cross-Entropy Loss Function analysis. The proposed ICMA-SPGAN-SFOA-CDmethod attains 12%, 13% and 14%lesser sigmoid cross-entropy loss function for basic clothing; 16%, 14% and 15% lesser sigmoid cross-entropy loss function for advanced clothing; 14%, 18%, and 16% lesser sigmoid cross-entropy loss function for season for clothing; 13%, 14% and 18% lesser sigmoid cross-entropy loss function for collar type; 13%, 17% and 13% lesser sigmoid cross-entropy loss function for looseness and14%, 17% and 16% lesser sigmoid cross-entropy loss function for color estimated to the existing CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.
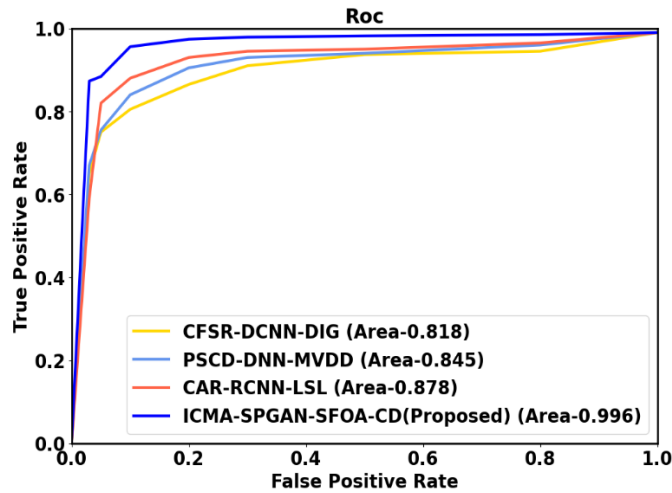
Figure 10: Performance Analysis of ROC

Figure 10 displays ROC analysis. The proposed ICMA-SPGAN-SFOA-CD method attains 0.34%, 0.49%, and 0.44% higher ROC estimated to the existing method such as CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL models respectively.

C. Discussion

A novel Clothing Design Style Recommendation Using Optimized Semantic-Preserved Generative Adversarial Network is developed in this paper**.** Recently, various clothing classification categories are classified based on the recommended clothing design from the clothing dataset. It brought up the issue of their classification, which has grown more difficult as a result of their high similarity in classifying. To solve this issue, it concentrated on the classification of recommended clothing design from the clothing dataset. Sadly, this categorization technique makes the classifications challenging.It was inspired by the idea that classification based on the recommended clothing design could significantly enhance clothing classification. SPGAN, in particular, have shown promise as a deep learning alternative to traditional feature extraction techniques in recent years.

V. CONCLUSION

In this section, Clothing Design Style Recommendation Using Optimized Semantic-Preserved Generative Adversarial Network (ICMA-SPGAN-SFOA-CD) are successfully implemented. The proposed ICMA-SPGAN-SFOA-CD approach is implemented in MATLAB. The performance of the proposed ICMA-SPGAN-SFOA-CDapproach contains 21.5%, 23%, and 22.5% high accuracy; 278sec, 264sec, and 235sec low computation time and 0.34%, 0.49%, and 0.44% high ROC when analyzed to the existing methods like CFSR-DCNN-DIG, PSCD-DNN-MVDD and CAR-RCNN-LSL methods respectively. Recommendation of clothing design style encompasses sustainable fashion, gender neutral fashion, tech wear, 3-D printed clothing and up-cycled fashion, it presents distinct obstacles in comparison to standard clothing design style. Machine learning might be used to create interactive experiences that blur the boundaries between reality and fashion, or it could be used to adapt clothes to your own style and take inspiration from the intricate motifs seen in nature. In future, this proposed ICMA-SPGAN-SFOA-CD method measuring successful start-ups or patent registrations is one thing, but it's much more critical to comprehend how clothing design style recommendation evolves along the design process.

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