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Optimization of Digital Media Art Creation Process Based on Dual Transformer Residual Network (DTRN) and Lotus Effect Optimization Algorithm (LEA)



Abstract: - In response to the problems of lack of intelligence, low recognition, loss of brightness, and unclear design objects in the comprehensive material painting of installation art, when materials enter the field of artistic creation, they can assist in artistic creation, but constantly updating materials is also a challenge for artists. This manuscript proposes an image processing technology in the digital media art creation based on dual transformer residual network (DTRN) and lotus effect optimization algorithm (LEA) (DMAC-DTRN-LEA) is proposed. Initially, the extracted images from the multimedia are collected from MSCOCO2014 dataset. Collected images are preprocessed to resize the image using federated neural collaborative filter (FedNCF). Later, resized images are given to feature extraction; morphological features like shape, structure, colour, pattern, and size are extracted based on synchro spline-kernelled chirplet extracting transform (SSCET). Finally, the extracted features are fed to Dual Transformer Residual Network (DTRN) for effectively classify the art images. In, general Dual Transformer Residual Network classifier does not express adapting optimization strategies to determine optimal parameters to ensure accurate art images detection system. Hence, the proposed method examined utilizing performance metrics like accuracy, precision, fl-score, sensitivity, peak signal to noise ratio (PSNR), error rate, and Structural similarity index (SSIM). Proposed DMAC-DTRN-LEA method attains 97% higher accuracy and 0.7% low error rate analysed to the existing methods respectively.

Keywords: Digital Media, Art Creation, Synchro Spline-Kernelled Chirplet Extracting Transform, Federated Neural Collaborative Filter, Education, Image Processing Technique.

I. INTRODUCTION

Art and technology come together to create digital media art, where "digital art" is defined as art produced or displayed through the use of digital technologies. To our visual experiences, professionals like animators, graphic designers, photographers, videographers, and game designers contribute. Artificial Intelligence (AI) aims to replicate human intelligence in computers, enabling machines to learn and solve problems like humans [1]. Visual communication encompasses the use of visual elements, such as animated GIFs, images, movies, diagrams, canvases, and slide deck presentations to communicate concepts or information [2]. Digital media education encompasses digital color art education as well, and knowledge of the state of digital media art research today offers insights examination of the state of digital color art education at the moment [3]. Additionally, educational technology programs have begun incorporating audiovisual art as a fundamental course [4]. Although interest in digital media art has grown the swift advancement of digital media technology in education and other fields has led to a growing demand for media design professionals with higher skill requirements [5].

Currently, many graduates with majors in digital media, animation, and education technology are facing challenges in adapting to societal demands [6, 7]. The main reason behind this issue is the difficulty in achieving the educational goals of digital media art within colleges and universities. Both subjective and objective elements, such as instructional concepts and techniques, are present in the classroom, including the environment, resources, and conditions, hinder the effective teaching of digital media art [8, 9]. Some students tend to focus solely on technology while neglecting the artistic aspect, or struggle to strike a balance between artistic expression and technical skills [8, 9]. Although there are schools that prioritize art education, they often separate it from media technology education [10]. Consequently, students may have a good understanding of traditional art but lack comprehension of digital media art, hindering their ability to apply their knowledge to the planning and creation of digital media projects [11, 12].

The current higher education system has integrated a number of new technologies into its teaching, accompanied by significant investments in human, material, and financial resources [13]. However, the necessary innovations and adjustments have not been made to the educational resources, instructional techniques, curriculum, or instructional concepts [14]. While Photoshop, 3ds Max, and Flash are among the software tools introduced in digital media art education, the artistic design is often neglected in favor of technological usage. This deviation from the original intention of education technology hinders the development of art [15].

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Compared to other forms of media, digital media art possesses unique characteristics that transcend the limitations of time and space. It offers immersive and interactive experiences, enabling individuals to appreciate and comprehend art without being bound by temporal or spatial constraints [16]. Furthermore, in digital media art, computer technology is employed to present virtual representations of actual images without compromising the genuine emotional connection during the appreciation process [17]. The essence of image processing lies in identifying patterns and characteristics within an image. Ultimately, the utilization of digital media art aids in broadening the horizons of artistic creation, expanding the scope and content of artistic expression [18].

The main contribution of this manuscript includes;

- This manuscript, DMAC-DTRN-LEA is proposed. Initially input images are collected from MSCOCO2014 dataset. Afterward, the collected images are fed to pre-processing by utilizing federated neural collaborative filter (FedNCF).
- In pre-processing segment, it eliminates the noise from the image. The output of pre-processing is directed towards the feature extraction segment.
- Following the pre-processing and feature extraction processes, the resulting output is inputted into the classification method.
- The proposed technique is executed and the efficiency of proposed DMAC-DTRN-LEA art image classification is evaluated by several performances analysing metrics like accuracy, precision, f1-score, recall, PSNR, and SSIM.
- From the result, it concludes that the proposed approach is better compared with existing approaches like DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA [23] respectively.

The order of the remaining text is as follows: Segments 2 and 3 present the literature review, segment 4 shows the results, segment 5 provides the conclusion, and segments 3 and 4 describe the proposed approach.

II. LITERATURE SURVEY

This section included an assessment of some of the most recent studies conducted on deep learning-based digital media art prediction.

Wu [19] have introduced a CNN-based partial-pixel interpolation method. By using supervised training, this method calls for the input and output targets of the network, commonly referred to as the fractional and integer pictures, should be predetermined. To address the challenge of obtaining subpixel samples, the imaging principle of digital images is first analyzed, and subsequently, an algorithm for generating subpixel samples is proposed. This algorithm is based on a combination of Gaussian low-pass filtering and polyphase sampling.

Gong [20] have presented the application of virtual reality teaching techniques to the art form of digital media creation. Virtual reality education offers distinct advantages in terms of its immersive and autonomous nature. In terms of teaching modes and design, it emphasizes enhancing the overall teaching experience for both teachers and students. This approach encourages a departure from traditional teaching concepts and methods, ultimately leading to more efficient and effective learning outcomes. Technical advantages of artificial intelligence for digital media art creation are also highlighted through the use of VR teaching methods.

Lei [21] have introduced a system for processing visual data in applications for optimizing digital media, based on deep neural networks. The system starts with the creation of a master algorithm that manages the system's automated workflow. A back propagation neural network structure is then used to classify resources intelligently according to different user preferences and behaviours. Leveraging the powerful information processing capabilities of deep neural networks, this system enables the optimization of business scheduling and operations within digital media applications.

Dai [22] have suggested significant advancements in the field of virtual reality creation technology to enhance digital media art. With the convenience and continuous emergence of creative forms, virtual reality technology has become increasingly popular. This technology's widespread adoption undoubtedly drives progress and development in our era, providing digital media art with new dimensions and possibilities. The goal was to show off the potential of virtual reality technology for producing digital media art by offering readers and writers alike perceptive analysis and creative inspiration.

Li and Lu [23] have developed image processing technology, particularly for the digital media era, served as inspiration for the creation of an installation art material painting design system. The objective was to enhance restoration, reduce noise, and intelligently restore brightness balance in integrated material paintings using image processing techniques. This system was designed to address issues related to incorporate painting with

materials into installation art. This article carried out pertinent system tests to validate the efficacy of the all-inclusive image processing technology-based framework for designing material paintings for installation art.

Meng and Liu [24] have explored the evolution and creative possibilities of Visual Content Description (VCD) within the realm of digital media art, with a focus on utilizing AI techniques. The first step in the study was gathering a dataset of digital media art. Next, normalization techniques were used to preprocess the raw image data. The preprocessed 2D data was then converted by a Selective Deep Generative Adversarial Network (SD-GAN) into 3D format.

Xia and Zhou [25] have concentrated on the fundamental advancement of fusing digital media art with AI technology. They assess how technology and art in digital media are developing now and suggest new paths and trends for the future. As one of the foundational technologies of the new era, china is currently experiencing a prosperous phase of ongoing advancement in artificial intelligence technology. People's daily lives and jobs have changed significantly as a result of this technology. As society evolves, individuals are seeking a balance between material and spiritual needs, and art, as a distinct field, has garnered considerable attention. AI presents new challenges for the creative community, encouraging the development of innovative artistic expression through the intersection of technology and art.

A. Research Background

The recent research work reveals that, digital art presents unique challenges as it requires a different skill set compared to traditional art forms. One of the concerns in digital art is the perception that it lacks originality and can be easily altered, leading to questions about its craftsmanship. Additionally, as the focus on creativity increases, there may be a lack of awareness regarding the technological aspects involved, particularly in the context of social networking sites. Despite significant advancements in recent years, generating images from descriptions remains a difficult task, often lacking in-depth information. Certain types of information, such as policy and regulations, cannot be effectively conveyed visually, leading to potential misinterpretation of data. Moreover, creating charts, graphs, and animations can be expensive, especially when complex machinery is involved. Apart from the initial investment, the maintenance and upkeep costs can also be substantial. The researchers' motivation to do this work stems from these shortcomings in the existing methodologies.

III. PROPOSED METHODOLOGY

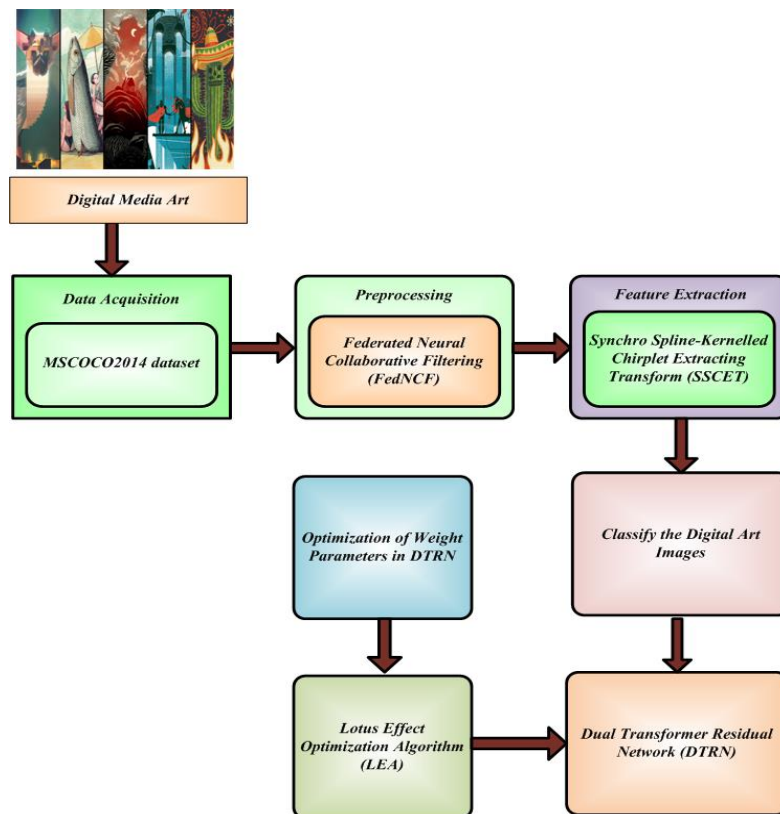


Figure 1: Block diagram for the proposed DMAC-DTRN-LEA method

In this section, digital media art creation process based on dual transformer residual network and lotus effect optimization algorithm is proposed. Block diagram of proposed DMAC-DTRN-LEA is presented in Figure 1. The proposed DMAC-DTRN-LEA takes the extracted images from the multimedia. The preparation of the dataset, pre-processing, feature extraction, classification, and optimization are the five steps in this process. Accordingly, detailed description of all step given as below,

A. Data Acquisition

The MSCOCO2014 dataset, which consists of 328,000 photos broken down into 91 categories, is used in this study. The stochastic gradient descent algorithm with a loss function can be used to combine network parameters for digital and multimedia generation. A noisy image must be entered into the network that combines digital and multimedia generation as part of the training process. Through network operations such as convolution and de-convolution, images of the same size are obtained. Using the content map and a particular merging digital and multimedia image from the MSCOCO dataset, the discriminative network mixes digital and multimedia. Afterwards, an algorithm is used to feed the computation results back into the network that combines digital and multimedia generation, adjusting the weights and parameters of each layer in order to reduce the total loss cost. Strong generalization skills enable the combining digital and multimedia generation network to apply the combining digital and multimedia style to any unknown image after post-training. This is due to the large dataset used for training the network.

B. Pre-Processing Using Federated Neural Collaborative Filtering

The FedNCF executes image pre-processing. In order to remove the noise from the image FedNCF is evaluated [26]. The image pre-processing in this step is carried out by FedNCF, which is used to lower the noise in the dataset. The primary issue pertains to the process of updating the image profile. The agreed-upon samples are subsequently employed to produce a random matrix IR_{ij} , which is determined by the image profile's size, where $j \in C, j \neq i$.

Finally, the updated image profile is expressed by:

$$MI_{t+1}^i = I_{t+1}^i + \sum_{i \in C; i < j} IR_{ij} - \sum_{i \in C; i > j} IR_{ji} \tag{1}$$

When i and j in a pair that is in order $(i, j), i < j$ agree on images, a random matrix called IR_{ij} is formed, and the marked estimated weights are represented by MI_{t+1} . The coordinated image computes the following after gathering each MI_{t+1}^C .

$$I_{t+1}^{SUM} = \sum_{i \in C} MI_{t+1}^i \tag{2}$$

The I_{t+1}^{SUM} parameter, which is generated, comprises the total updates for weight associated with the image that requires aggregation. The image can generate the aggregated weights in the following manner in the most basic form of an aggregation step:

$$I_{t+1} = \frac{MI_{t+1}^{SUM}}{|C|} \tag{3}$$

However, $|C|$ indicates the count of chosen participants at time-step t . But still, this form of aggregation fails to account for individual image adjustments, which leads to slower convergence.

Following local training, to produce $2(|C|-1)$ arbitrary matrices and $|C|-1$ random vectors, from which, $|C|$ specifies that count of participants in the current cycle. The number of parameters in accordance with the quantity of images $|I|$ and the profile's designated dimension, size D . A single linear layer and a single processing unit power the GMF model's various outputs.

$$(|C|-1).(D.|I|+D+1+|I|) \tag{4}$$

The factors are determined based on the art image. In this context, $D.|I|$ implies the count of values in the image profile, $D+1$ represents the count of biases an inputs in the neural structure, and $|I|$ represents the count of factors comprising the arbitrary interaction vector. When the neural design is exceeded the model transforms

into conventional MF, and the count of the produced factors reduces to $(|C|-1) \cdot (D+1+|I|)$. In contrast, the MLP model incorporates a framework that consists of a minimum of a single hidden layer. The quantity of factors that must be produced consequently escalates in accordance with the count of processing units in every hidden layer and the specified hidden layers. With greater precision, an individual produces a designated quantity of parameters.

$$(|C|-1) \cdot \left(D \cdot |I| + 2D + h_1 + \left(\sum_{i=1}^{n-1} h_i \cdot h_{i+1} \right) + h_n + \left(\sum_{i=1}^n h_i \right) + 1 + |I| \right) \tag{5}$$

These parameters include $2D \cdot h_1$, which represents the input size of image, which represents the count of weights, and $\sum_{i=1}^n h_i + 1$, which represents the network bias. The value of h_i represents the count of processing units on the i^{th} hidden layer. Particularly necessary parameters pertain to the image profile $2D \cdot I$ in the NeuMF model, which is formed by concatenating GMF and MLP.

$$(|C|-1) \cdot \left(2D \cdot |I| + 2D + h_1 + \left(\sum_{i=1}^{n-1} h_i \cdot h_{i+1} \right) + D + h_n + \left(\sum_{i=1}^n h_i \right) + 1 + |I| \right) \tag{6}$$

In the training phase of a federated recommender, before any computation begins, the dimensions size D , the number of images $|I|$, and the number of processing units h_i are set. Finally, the pre-processed image is fed into feature extraction phase.

C. Feature Extraction Using Synchro Spline-Kernelled Chirplet Extracting Transform (SSCET)

In this section, feature extraction is discussed. The SSCET is used to extract morphological features like shape, structure, colour, pattern, and size respectively [27]. SCT's frequency-rotating and frequency-shifting operators were improved by the MSEO, upon which the SSCET technique is based. The spline-kernelled chirplet transform's (SCT) mathematical expression is as follows:

$$\begin{cases} SCT(t_0, \omega) = \int_{-\infty}^{\infty} G_{\sigma}(\tau - t_0) \cdot r(\tau) \cdot \phi^S(\tau) \phi^R(\tau) \cdot e^{-j\omega\tau} d\tau, t_0 \in [t_K, t_{K+1}] \\ \phi^S = e^{j\kappa - j} \sum_{n=1}^N P_{K,n}(\tau - t_K)^{n/n} \\ \phi^R = e^{j\tau} \cdot \sum_{n=1}^N P_{K,n}(t_0 - t_K)^{n-1} \end{cases} \tag{7}$$

Where ϕ^S and ϕ^R represent the operators for spline frequency shifting and rotation, correspondingly. $P_{K,n}$ denotes as the spline-kernel function coefficient matrix. The shape of morphological features in digital art can be expressed as;

$$Shape = \frac{1}{\sqrt{2\pi\sigma}} \cdot e^{-\frac{1}{2} \left(\frac{t}{\sigma} \right)^2} \tag{8}$$

Where σ represent the window function's resolution argument.

The structure of morphological features in digital art can be expressed as;

$$Structure = \int_{-\infty}^{\infty} G_{\sigma}(\tau - t_0) \cdot r(\tau) \cdot \phi^S(\tau) \phi^R(\tau) \cdot e^{-j\omega(\tau - t)} d\tau \tag{9}$$

The initial estimated IF trajectory ω_0 is redefined by a new one based on the equation above. In digital art, the color of morphological features can be expressed as

$$colour = -j \cdot \frac{\partial_t SCT_e(t, \omega)}{SCT_e(t, \omega)} \tag{10}$$

A MSEO replaces $\tilde{\omega}_0$ based on this new two-dimensional IF trajectory, and its expression is as follows:

$$\delta(\omega - \tilde{\omega}_0) = \begin{cases} 1, & \omega = \tilde{\omega}_0 \\ 0 & \omega \neq \tilde{\omega}_0 \end{cases} \quad (11)$$

With the MSEO, the SSCET technique, the size of morphological features in digital art can be expressed as

$$Size = SCT_e \cdot \delta(\omega - \tilde{\omega}_0) \quad (12)$$

Then the extracted features are fed to classification process. The classification process is done by dual transformer residual network. The detail about the classification process is given in the below section.

D. Classify the Digital Art Images Using Dual Transformer Residual Network (DTRN)

In this sector, DTRN is discussed. Three pairs of token embeddings, a convolutional transformer block (CTB), and an up sample block for dimension restoration are all included in the transformer branch. This branch uses the multi-head attention in the CTB to extract and organize global contextual information [28]. Normalization layers, reshaping operations, and cascaded convolutional layers make up the token embedding module. The token embedding module's output can be described mathematically as

$$F_{out} = LM(Reshape(conv(F_{in}))) \quad (13)$$

Where F_{in} and F_{out} are denoted as the token embedding's input and output correspondingly. LM represent layer normalization. $Reshape(.)$ and $conv(.)$ represents the reshape and the convolutional operators of image correspondingly.

The long-range spatial data from the LR inputs is intended to be captured by the CTB module. It uses a number of techniques, such as layer normalization, multi-head attention, convolutional projection, and multi-layer perceptrons, to accomplish this. More specifically, three convolutional projection blocks process the inputs first in order to accelerate the multi-head attention calculation. Prior to adding the output of the multi-head attention module, the CTB's input images pass through a skip connection. A multi-layer perceptron is used once the total has been through a normalization layer. Ultimately, the normalization layer's input and the multi-layer perceptron's output are combined. The CTB's output image can be expressed mathematically as follows:

$$CTB_{out} = MLP(LM(Htt_{out})) + Htt_{out} \quad (14)$$

$$Htt_{out} = Htt_{multi}(CP(CTB_{in})) + CTB_{in} \quad (15)$$

Where CTB_{in} and CTB_{out} being the input and output image of the CTB correspondingly. Htt_{out} represent the output of multi-head attention. Convolutional projection and multi-layer perceptron are denoted by the letters CP and MLP, respectively, in this instance.

To address the task of generating an optimal subpixel reference block, the objective is to make the most accurate prediction about the block that will be encoded next. The result of the resblock can be expressed mathematically as follows:

$$Res_{out} = conv(ReLU(conv(Res_{in}))) \times R + Res_{in} \quad (16)$$

Where Res_{in} and Res_{out} are the residual block's input and output images and R is denoted as the residual scale respectively.

In this manuscript, provide a solution to the aforementioned regression problem using DTRN model training. The DTRN model's structure defines the function space, and a group of network model parameters represents the regression function.

$$\xi^* = \arg \min_{\xi} \sum_j G\{(Z_j / \xi), X_j\} \quad (17)$$

Where ξ represent the CNN model parameters, Z_j and X_j represent the regression function's function space and G represent the DTRN model.

The generating function is difficult to mathematically characterize due to the range of motion vectors present in natural video. As a result, make the problem mentioned above into a looser one by stating that the integer pixel translation is invariant to the subpixel reference generation function. Finally DTRN classify the art images. Artificial intelligence depend optimization technique is considered by the DTRN classifier due to practically and efficacy. In this work, lotus effect optimization (LEA) is assigned to enhance DTRN. LEA is assigned for tuning weight ξ parameter DTRN.

E. Stepwise Process for Lotus Effect Optimization Algorithm (LEA)

Here, step-by-step procedure for utilizing LEA to get ideal DTRN values is explained. The Lotus Effect Algorithm (LEA) is a novel approach inspired by the unique properties of the lotus leaf [29]. The lotus leaf exhibits exceptional water repellence, self-cleaning ability, and resistance to dirt and contaminants. The comprehensive step's technique designated below:

Step 1: Initialization

Initialize population of LEA weight parameter values of generator R from DTRN. It expressed in equation (18)

$$Z = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \dots & Z_{1,H} \\ Z_{2,1} & Z_{2,2} & \dots & Z_{2,H} \\ \dots & \dots & \dots & \dots \\ Z_{n,1} & Z_{n,2} & \dots & Z_{n,H} \end{bmatrix} \tag{18}$$

Here Z denotes the LEA population matrix, n is denotes the quantity of lotus leaf, H is denotes the quantity of decision variables, correspondingly.

Step 2: Random Generation

After initialization, input fitness function developed randomness via LEA method

Step 3: Fitness Function

An initialization value, result is random solution. Assessment of fitness values utilizes outcomes of weight parameter optimization ξ . It expressed in equation (19),

$$fitnessfunction = Optimizing[\xi] \tag{19}$$

Step 4: Exploration Phase

LEA uses dragonflies for global pollination, mimicking their intelligent behaviour through separation, alignment, and cohesion principles. These ensure collision avoidance, velocity matching, and movement towards the swarm's centre. Mathematically modelled with five factors, these behaviours update positions in the swarm. The step, also known as the velocity vector, is defined as follows and shows the dragonflies' direction of travel:

$$\Delta Z_j^{t+1} = (rR_j^t + bB_j^t + dD_j^t + eE_j^t + hH_j^t) + v\Delta Z_j^t \tag{20}$$

Where r stands for separation coefficient, R_j^t for the j th individual's separation degree, b for alignment, B_j^t for the j th individual's alignment, d for cohesion, D_j^t for the j th individual's cohesion, e for food factor, E_j^t for the j th individual's food source, h for enemy, H_j^t for the j th individual's enemy, w for inertia weight, t for iteration counter, and Z_j^t for the current individual position.

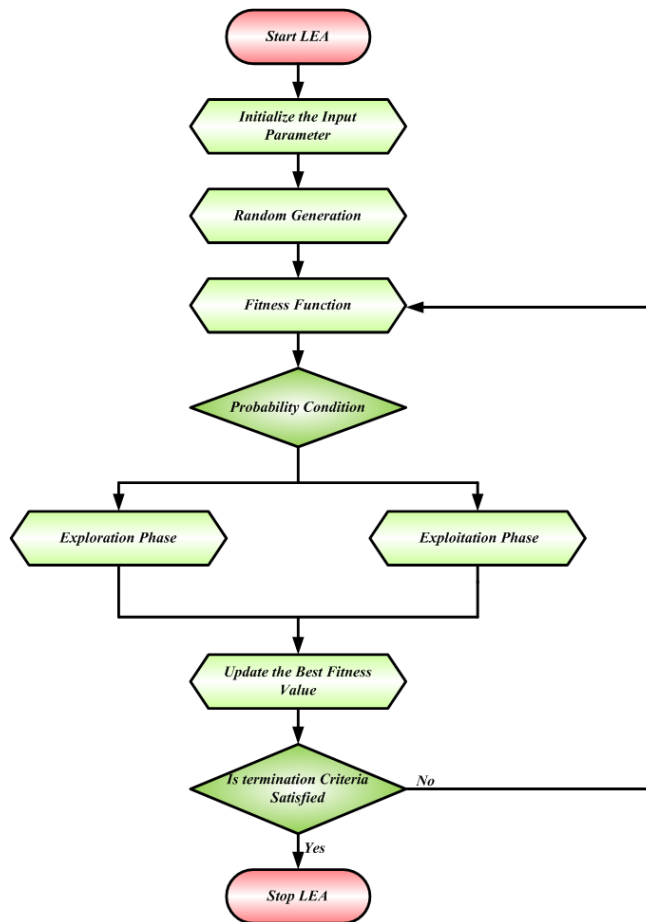


Figure 2: Flowchart of LEA

Step 5: Exploitation Phase by optimizing ξ

The algorithm's extraction phase is known as local pollination or self-fertilization. In this type of pollination, the size of each flower's growth area surrounding the best-found flower is determined by a coefficient. The movement of other solutions is influenced by the best-found solution, with steps getting shorter as the movement algorithm progresses and longer at the start.

$$Z_j^{t+1} = Z_j^t + Q(Z_j^t - s^*) \tag{21}$$

Where Z_{t+1} represent the location of the pollen, Q represent the growth area and s^* denotes the best pollen location.

Step 6: Termination Criteria

Verify the termination criteria; if it is met, the best possible solution has been found; if not, repeat the procedure. The weight parameter is ξ from DTRN is optimized with LEA, for effectively for classify the art images. Figure 2 illustrate the flowchart of LEA.

IV. RESULT AND DISCUSSION

This section discusses the experimental results using the proposed approach. The proposed technique simulated utilizing python based numerous performance measures comprising accuracy, precision, F1-score, Recall, mean square error (MSE), structural similarity index (SSIM), and peak signal to noise ratio (PSNR). Obtained results of proposed DMAC-DTRN-LEA method are analysed with existing methods such as DI-ML-MAD [21], VR-AI-DMAC [22] and DNN-VDPS-DMOA [23] respectively.

A. Performance measures

This is an important step in selecting the best classifier. Metrics including accuracy, precision, F1-score, recall, error rate, PSNR, and SSIM are examined in order to evaluate performance. It is decided to use the confusion matrix to scale the performance measures.

1) Accuracy

The capacity to measure a value with accuracy, or accuracy, is represented by equation (22),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{22}$$

TP Represent true positive, *TN* Denotes true negative, *FP* denotes false positive, *FN* Represents false negative.

2) Precision (*P*)

Precision is a metric which quantifies the count of correct positive prediction made. This is scaled by equation (23),

$$Precision = \frac{TP}{(TP + FP)} \tag{23}$$

3) F-Score

The F-score, a composite metric shown in equation (24), rewards strategies with higher sensitivity and presents challenges for strategies with higher specificity.

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \tag{24}$$

4) Specificity

The percentage of true negatives that the method correctly identifies is called specificity. It is determined by equation (25),

$$Specificity = \frac{TN}{TN + FP} \tag{25}$$

5) Error Rate

This can be ascertained using equation (26).

$$ErrorRate = 100 - Accuracy \tag{26}$$

B. Performance Analysis

Fig 3 to 9 portrays simulation results of DMAC-DTRN-LEA method. Then, the proposed DMAC-DTRN-LEA method is likened with existing DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA method.

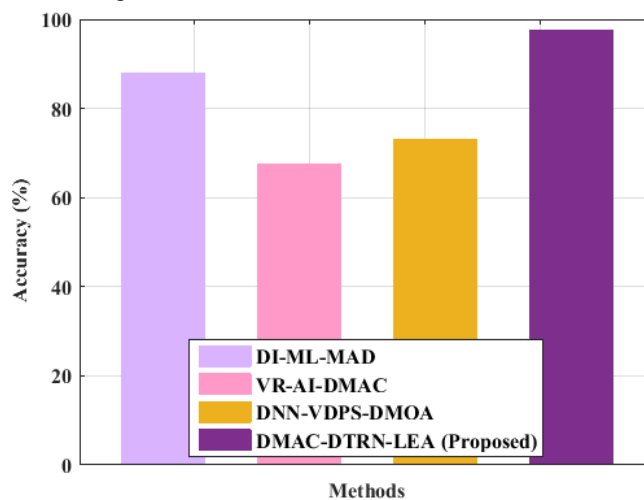


Figure 3: Performance Analysis of Accuracy

Figure 3 demonstrates the performance analysis of accuracy. The performance accuracy of different models or approaches used to analyse digital media art. This could involve comparing statistical models, machine learning algorithms, or any other methods used for this. The proposed DMAC-DTRN-LEA method of accuracy is 97%. The existing methods DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA, the accuracy become 88%, 67%, and 74%. The proposed MTM-HGRNN-LOA method shows higher accuracy compare with existing methods.

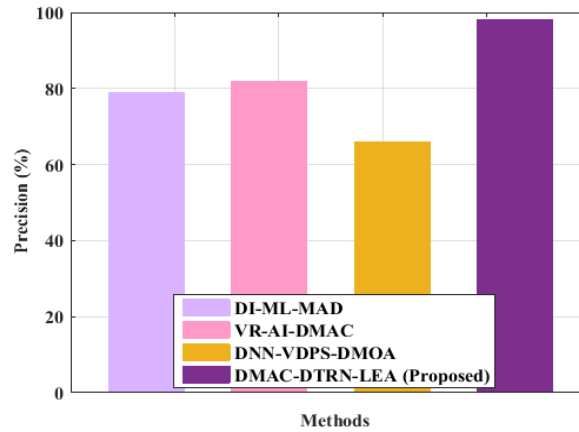


Figure 4: Performance Analysis of precision

Performance Analysis of precision is illustrated in figure 4. Precision is a metric used to evaluate the accuracy of a predictive model or algorithm. The precision of proposed DMAC-DTRN-LEA methods becomes 98%. The existing methods DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA the precision attain 79%, 82%, and 65%. The proposed DMAC-DTRN-LEA method shows higher precision value compare with existing methods.

Performance analysis of f1-score is depicted in figure 5. The proposed DMAC-DTRN-LEA method provides 97%. The existing methods DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA the f1-score become 60%, 84%, and 75%. The proposed DMAC-DTRN-LEA method shows higher F1-score value compare with existing methods.

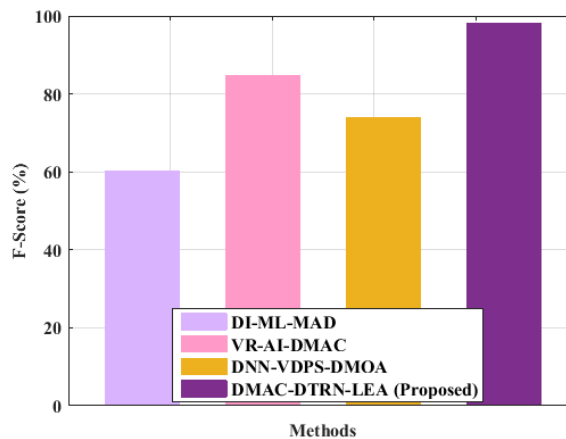


Figure 5: Performance analysis of f1-score

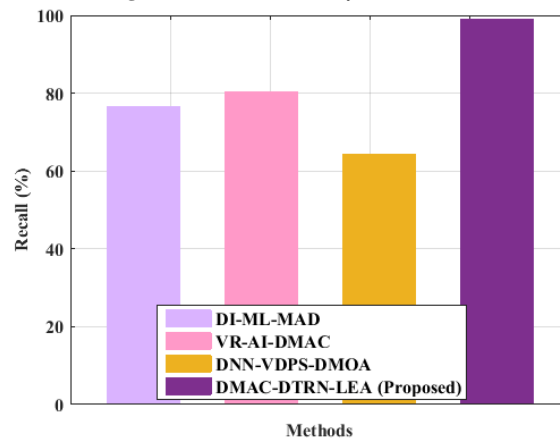


Figure 6: Performance analysis of Recall

Performance analysis of Recall is illustrated in figure 6. In Recall the proposed DMAC-DTRN-LEA methods provide 98%. The existing methods DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA the recall becomes 76%, 80%, and 63%. The proposed DMAC-DTRN-LEA method shows higher recall compare with existing methods.

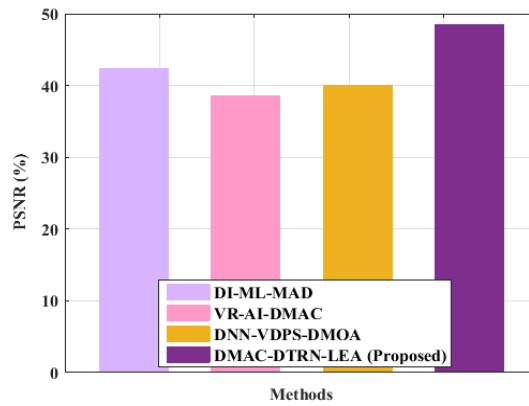


Figure 7: Performance analysis of PSNR

Performance analysis of PSNR is illustrated in figure 7. In PSNR the proposed DMAC-DTRN-LEA methods provide 47%. The existing methods DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA the PSNR become 43%, 38%, and 40%. The proposed DMAC-DTRN-LEA method shows higher PSNR compare with existing methods.

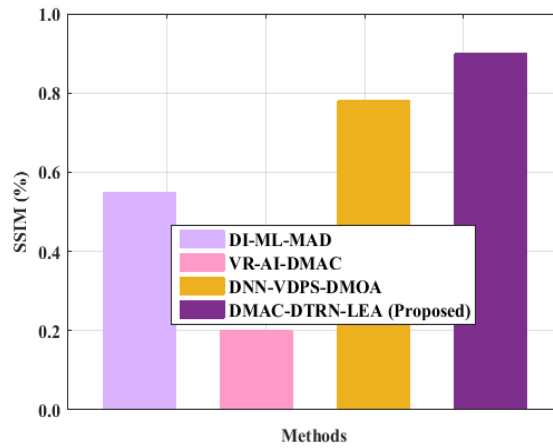


Figure 8: Performance analysis of SSIM

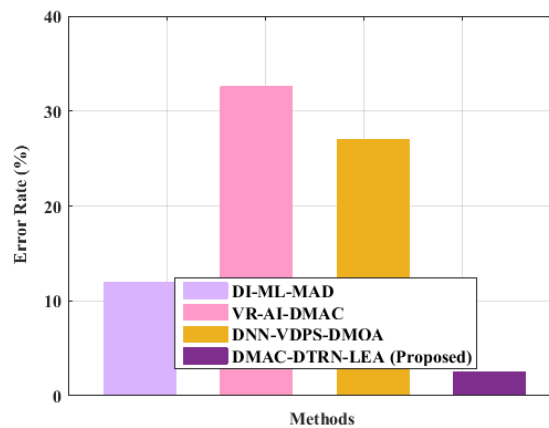


Figure 9: Performance analysis of Error Rate

Performance analysis of SSIM is illustrated in figure 8. In SSIM the proposed DMAC-DTRN-LEA methods provide 0.9%. The existing methods DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA the SSIM become 0.55%, 0.2%, and 0.78%. The proposed DMAC-DTRN-LEA method shows higher SSIM compare with existing methods.

Performance analysis of Error Rate is illustrated in figure 9. The proposed DMAC-DTRN-LEA error rate is 3%. The existing methods MTM-CNN, MTM-BPNN and MTM-GNN, the error rate become 32%, 23%, 34% best, 41%, 11%, 17% good, 20%, 35%, 21% normal, 16%, 41%, 38% satisfactory and 33%, 24%, 15% poor music teaching mode. The proposed MTM-HGRNN-LOA method shows lower error rate compare with existing methods

V. CONCLUSION

In present study, an image processing technology in the digital media art creation based on dual transformer residual network (DTRN) and lotus effect optimization algorithm (LEA) (DMAC-DTRN-LEA) is successfully executed. Python is used to implement the proposed DMAC-DTRN-LEA method using the MSCOCO2014 dataset. The main suggestion made in this paper is an approach that uses the DTRN to improve feature extraction and classification for art images. This paper addresses the issue of inadequate research on the classification of current multi-class art images by achieving superior classification results for art images when compared to existing network models and conventional classification techniques. Performance of proposed DMAC-DTRN-LEA approach contains 97% high accuracy is analysed with existing methods likes DI-ML-MAD, VR-AI-DMAC and DNN-VDPS-DMOA method respectively.

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