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Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning

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Abstract: - The objective is to investigate the role of neural networks and vision in painting and design webs, and to provide a technique for automatic painting and design element extraction and computer-aided design (CAD) reconstruction from recurrent patterns. In this manuscript, Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning (DAIG-IPS-DHNN-MBGIO) are proposed. Initially, the input image is gathered from the ModelNet40 - Princeton 3D Object Dataset. The input image is then pre-processed using Orthogonal Master-Slave Adaptive Notch Filter (OMSANF) to be used toenhance the image and size adjustment. The pre-processed images undergo feature extraction, employing the Local Maximum Synchrosqueezing Chirplet Transform (LMSCT) to extract effective features like Function, Quality, and Design from the images. The extracted features are given to Dense Hebbian Neural Network (DHNN) for detecting Artistic Image Generation and it classifies such as Academic Art, Art Nouveau, Baroque, Expressionism, Japanese Art,Neoclassicism,Primitivism,Realism,Renaissance,Rococo,Romanticism,Symbolism and Western Medieval. In general, there is no adaptation of optimization techniques using DHNN to identify the ideal parameters to provide precise classification. In order to precisely categorize, the Artistic Image Generation DHNN classifier is optimized using the Multiplayer Battle Game-Inspired Optimizer (MBGIO).The proposed method is implemented in Python. The efficiency of the proposed DAIG-IPS-DHNN-MBGIO approach is evaluated using a number of performance criteria, including Accuracy, precision, recall, F1value and Error rate. The proposed DAIG-IPS-DHNN-MBGIO method attains 28.26%, 21.41% and 22.26% higher accuracy, 24.36%, 15.42% and 20.27% higher precision and 22.36%, 15.42% and 18.27% higher recall is compared with existing methods, such as State of the Art in Defect Detection Based on Machine Vision (SADD-MV-DNN), Art Teaching Innovation Based on Computer Aided Design and Deep Learning Model (ATI-CAD-CNN), and Automatic Extraction and Reconstruction of Drawing Design Elements Based on Computer Vision and Neural Networks (AE-RDDE-RNN), respectively.

Keywords: Dense Hebbian Neural Network, Local Maximum Synchrosqueezing Chirplet Transform, ModelNet40 - Princeton 3D Object Dataset, Multiplayer Battle Game-Inspired Optimizer and Orthogonal Master Slave Adaptive Notch Filter.

I. INTRODUCTION

Artists that engage in painting design create drawings by hand or create designs [1]. Neural networks and computer vision have become increasingly popular in the realm of art due to their quick advancement [2, 3]. The crystallization of human culture and understanding is art; however its nuanced style and intricate details can make its analysis and diagnosis difficult. We have the chance to investigate the mysteries of art using fresh viewpoints and approaches. By using these cutting-edge technologies, design elements may be automatically extracted from artwork photos and combined with CAD tools to create 3D reconstructions of artwork [4, 5]. Use algorithms to automatically identify elements like colors, textures, and lines in artwork photos. They provide the foundational information needed for further picture analysis. Classify artwork photos automatically based on factors like author, style, time, and more by using neural network models that have been trained. Potential signs of damage, repair, or counterfeit can be automatically found by analyzing the variations between artwork images and regular images. CAD optimizes and mimics the product manufacturing process, which can significantly increase production quality and efficiency. The manufacturing process is a customer-focused approach to production that lowers inventory costs and can react swiftly to market demand [6, 7]. Combining CAD with pull production technologies can enhance production efficiency and quality by facilitating a more accurate and effective extraction of design components from landscape painting designs [8, 9]. Using techniques similar to lean manufacturing and just-in-time, the pull production method is a customer-focused approach to manufacturing that aims to cut inventory costs and promptly respond to market demand [10]. Pull production places a strong emphasis on adaptability, promptness, and process improvement. To streamline the production process, a particular manufacturer of landscape paints implemented the aforementioned technique [11, 12]. By merging the pull production with CAD procedure, the business has succeeded in producing design elements and

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manufacturing management that are more accurate and efficient [13]. When used in conjunction with deep learning, it significantly improves the quality of tasks like target recognition, image production, and image identification. In industries like manufacturing, engineering, and architecture. Nevertheless, the process of creating a typical CAD model frequently necessitates manual input and adjustment [14, 15].

By automatically extracting design features from drawings, we may recreate CAD models and increase design productivity [16].One of the most important processes in recreating CAD models is the extraction of deformable surface mesh. In order to extract the distorted surface mesh, computer vision analysis of the drawings is first required [17]. We selected a real-world example to test the computer vision method for automatically extracting drawing design elements that is recommended in this paper. The experiment successfully recreated CAD models by extracting distorted surface meshes from drawings [18]. This technique lowers mistake rates and significantly increases design efficiency when compared to conventional manual input approaches [19].

Although they have limitations, recurrent neural networks (RNNs) are an effective tool for processing sequential data. These include short-term memory constraints, computational complexity, parallelization challenges, vanishing/exploding gradient problem, and difficulty capturing long-range interdependence. Furthermore, RNNs have difficulty with varying-length sequences, are sensitive to initialization, and may be unstable throughout training. They may have difficulty capturing complicated contextual information and demand a large amount of memory and processing power. RNNs are still frequently utilized despite these drawbacks, and research is still being done to find solutions. Although they have limitations, convolutional neural networks, or CNNs, are efficient for tasks like image categorization. Among these are an excessive number of parameters, a poor grasp of space, and a lack of rotation and scale invariance. Information loss may result from pooling procedures, and CNNs have trouble identifying long-range dependencies. In addition, they need a lot of resources and are less interpretable and hyperparameter-sensitive. CNNs are nevertheless frequently employed and studied in computer vision problems in spite of these drawbacks. Deep Neural Networks (DNNs) have revolutionized many fields, but they face challenges. These include issues like vanishing/exploding gradients, overfitting, high computational demands, and interpretability concerns. DNNs require large datasets and careful hyperparameter tuning, and they can be sensitive to training instability. Additionally, they may still rely on feature engineering and are vulnerable to adversarial attacks. Despite these challenges, ongoing research aims to address these drawbacks and enhance the capabilities of deep learning models.

The following sums up this research work's primary contribution:

- In this investigation, Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning (DAIG-IPS-DHNN-MBGIO)are proposed.
- In pre-processing the images aims to collect paintings images, including image enhancement and size adjustment using Orthogonal Master-Slave Adaptive Notch Filter (OMSANF).
- LMSCT method is extracting the features such as Lines, Shapes, Colors and Textures.
- Dense Hebbian Neural Network (DHNN) for detecting Artistic Image Generation and it classifies like Surrealism, Impressionism, Realistic, Abstract, and Symbolist paintings, among others.
- The obtained results of proposed DAIG-IPS-DHNN-MBGIOalgorithm is comparing to the existing models such as AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNNmethods respectively.

The remaining manuscript is structured as follows: Portion 2 outlines the Literature Survey, Portion 3 displays the proposed methodology, Portion 4 presents the results with discussions, and Portion 5 accomplishes the manuscript.

II. LITERATURE SURVEY

The literature presents a amount of research projects on deep learning-based Artistic Image Generation; this section evaluated some of the most recent studies.

Huang, et al. [20] have presentedDrawing design elements are automatically extracted and recreated using computer vision and neural networks. The purpose of the study was to find out how neural networks and vision operate in painting and design. It also proposes a method for reconstructing computer-aided design (CAD) utilising recurrent networks and automatically retrieving portions of painting and design. It was intended that by using this technique, painting design aspects can be automatically extracted and rebuilt, resulting in more creative inspiration. This paper investigates the automated extraction of design and painting elements with RNN, including line, color, composition, and other element identification and extraction. Furthermore, the research delves further into the process of using CAD to recreate the aspects of the painting design that were deleted and create a parametric representation of those features for future editing and change. The pre-improvement rate was between 9% to 10%, while the enhanced matching error rate ranged from 3% to 5%. The success of the improvement was further confirmed by the fact that the greatest error rate following the improvement was 4.5%, compared to the lowest error rate of 9% before to the improvement approach.Both high and low precision are provided by it.

Cai, et al. [21] have presentedDeep learning models and computer-aided design are the foundation of innovative art education. Teaching art was a challenging and innovative field that was vital to developing students' creative, aesthetic, and practical abilities. This paper organizes and evaluates the Deep Learning (DL) models used in art education, and creatively builds a CAD and DL model-based art education system. With the system's ability to automatically extract, categorize, and forecast the qualities and styles of artistic works, pupils they receive more precise and objective aesthetic guidance. Additionally, the system incorporates artistic practice, enables a variety of learning modalities, integrates teaching resources, and adds an evaluation mechanism all of which enhance the quality of art instruction. The findings demonstrate how well the system may raise students' output quality, level of skill mastery, and learning impact. It can use the benefits of computer technology and artificial intelligence (AI) to support students in developing more innovative and practical skills, expanding their creative ideas, and improving design efficiency. It provides high precision and it provides low accuracy.

Ren, et al. [22] have presented cutting edge of machine vision-based flaw detection. Defect identification becomes much more reliable, accurate, and efficient with the use of machine vision. A thorough examination of the state of the art in optical illumination, image acquisition, processing, and analysis in the field of visual inspection was conducted, along with a brief history of the field. This article introduces advances in machine vision-based industrial defect detection. Great optical illumination platforms and suitable image acquisition devices were required for visual inspection in order to produce high-quality images. Deep learning was having a significant impact on the fiThe field of visual inspection they continue to grow, and deep learning applications they become more crucial. So, after talking about conventional defect detection techniques, a thorough explanation of how deep learning was used to defect classification, localization, and segmentation was given. Lastly, potential directions for the advancement of technology related to visual examination were discussed. It provides high recall and it provides low precision.

Canet Sola, et al. [23] have presented Dream Painter: Investigating artistic potential of AI-assisted speech-to-image synthesis within the framework of interactive art. This article discusses Varvara& Mar's interactive robotic art piece, Dream Painter. The exhibit allows spectators to creatively interpret their own dreams, resulting in a collective painting made possible by artificial intelligence (AI), a KUKA industrial robot, and interface technologies.The exhibit consists of four main components: a design for audience participation, AI-driven, multicoloured drawing software, communication with an arm robot, and a kinetic element that, once each dream picture is completed, is an autonomous paper progression.Two floors of a cultural center were taken up by an art installation that was the result of all these interconnected pieces working together to create an autonomous and interactive system.Additionally, the research explores the imaginative possibilities of speech-to-AI-drawing transformation, a robot's translation of diverse semiotic spaces, as a tool for audience engagement inside an art show. It provides high F1value and it provides low recall.

Yu, et al. [24] have presentedDigital sculpture using computer-aided design: the use of machine learning and computer graphics. Digital sculpture has gained popularity as an art form thanks to computer-aided design (CAD) technology. Computer graphics technology was essential to the CAD design of the digital sculpture. Thanks to technology, digital sculpture artists may more readily create and update sculpture models by utilising computer graphics, as well as produce rendering and animation of excellent quality. In this work, the CAD design of digital sculpture incorporates picture feature fusion technology. A sculpture effect that was more vibrant and lifelike was produced by combining the texture and picture aspects of the model. The test findings demonstrate that the Atrous Convolution Neural Network (ACNN)-based method outperforms the other two in terms of running efficiency and extraction precision features of sculptural texture. This technique can offer a novel and useful tool for this industry and support digital sculpture's CAD design in an efficient manner. It provides high recall and it provides low F1 value.

Zhang, et al. [25] have presentedThe creation of fractal art graphics using intelligence driven by deep learning. Not only have science and technology significantly advanced social progress, but they have also had a significant effect on the arts and design. Inspired by artificial intelligence (AI), this piece suggests a fractal art image model generation using deep learning (DL). The model minimises the total loss function of style and content information in order to continuously optimise an image with random noise. Both the texture information from the style map and the content information from the content map are ultimately retained by the random picture. To actualize the fusion creation of fractal art pictures, the random gradient descent technique was also applied to iteratively update the pattern producing effect. This was achieved by designing loss functions with different fusion degrees to meet the needs of diversified feature extraction. The suggested model performs better and was more practically based than other traditional DL models. It also has a certain level of reliability. It provides further groundwork for fractal art graphic development on DL using CAD. It offers a poor recall rate and a high mistake rate.

Zhao, et al. [26] have presented Neural network vision valve-driven interactive art design powered by artificial intelligence. The natural fusion of technology and art was known as interactive art design, or IAD. AI robots have undergone phases of command, graphical, and multimedia interfaces, as may be seen from the perspective of how they have developed throughout time. The creation of interactive art has been ongoing for some time. It improves and enriches people's lives, meets the needs for human-computer connection, increases the efficacy of creative design, and fosters human-human interaction because it is a form of art. The intention was to influence people's psyche and the works by introducing various emotions and sensations. Specifically, the use of AI in IAD has not only significantly altered the landscape for designers. Additionally, it results in the interplay of behavioral limbs, which enhances the audience's experience and interaction improving the interactive impact.It offers both low mistake rates and excellent precision.

III. PROPOSED METHODOLOGY

In this section, Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning (DAIG-IPS-DHNN-MBGIO) are proposed. The five processes in this procedure are: pre-processing, image acquisition, feature extraction, classification, and optimisation. In the proposed Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning undergo pre-processing to prepare them for further analysis. Following preprocessing effective features such as Function, Quality, and Design are extracted from each segment. These features are then organized into a feature vector. The final step involves employing a Dense Hebbian Neural Network (DHNN) for Artistic Image Generation classification, with the feature vector serving as input. The Multiplayer Battle Game-Inspired Optimizer method is introduced for training the DHNN. The block diagram of proposed DAIG-IPS approach is represented in Figure 1. Accordingly, detailed description of all step given as below,

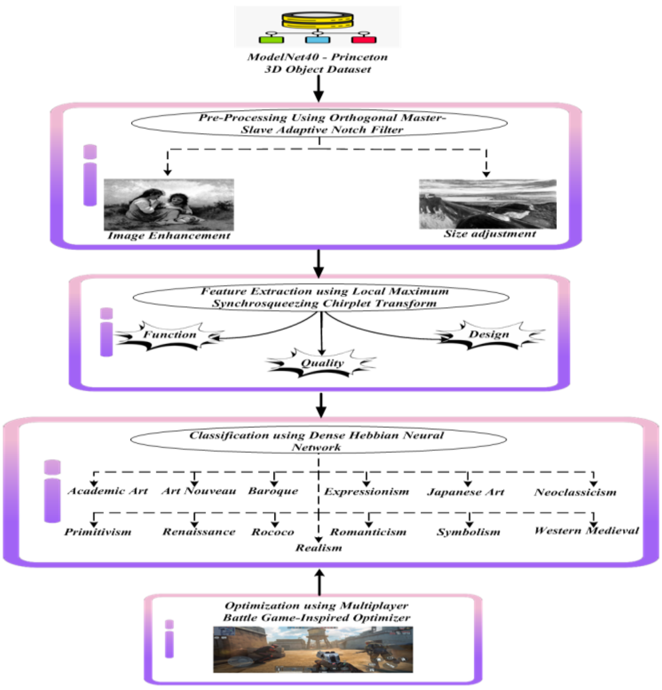


Figure 1: Block Diagram of Proposed DAIG-IPS-DHNN-MBGIO Method

A. Image Acquisition

The original source of the input photos is WikiArt Art Movements/Styles [27], In an effort to build a deep learning model that could identify which pieces of art belonged to specific movements or styles, I constructed this dataset. I choose to share my dataset as I collected the data and have been experiencing problems creating the model. I collected the data by scraping all of the artwork created by certain artists associated with these movements from wikiart.org. Please up vote if you think this dataset is helpful.

B. Pre-Processing Using Orthogonal Master-Slave Adaptive Notch Filter(OMSANF)

In this section, pre-processing using OMSANF [28] is discussed. The OMSANF is used to enhance the image and size adjustment. For artistic rendering, where minute details are important, OMS-ANF can effectively eliminate noise and undesired artifacts in the input signal. Because of its great frequency selectivity, the system can concentrate on particular elements or patterns in the input image that enhance artistic depiction. Because of its adaptive nature, the OMSANF may dynamically modify its parameters in response to the input signal's properties. This flexibility comes in handy when working with various image formats and creative approaches. The main objective is to enhance relevant information using adaptive filtering and reduce noise to improve the quality of generated artistic images. By offering user-friendly interfaces for modifying filter parameters and experimenting with various artistic styles, you may empower users to actively oversee the artistic rendering process. Give users the ability to adjust the OMSANF's different parameters to produce the required visual effects and styles. To create dynamic model is given in equation (1)

$$\dot{\hat{\omega}} = -\frac{\gamma}{2\zeta} x_1 \left(\ddot{x}_1 + \hat{\omega}^2 x_1 \right) \tag{1}$$

Where, $\dot{\hat{\omega}}$ denotes initial stage distribution of OMSANF, x is denoted state transmission function, γ is denoted as the observation model and ζ denotes the dynamic model for OMSANF. The collection of paintings images is followed by the equation (2)

$$\dot{\hat{\omega}} = -\frac{\gamma}{2\zeta} x_1^2 \left(\hat{\omega}^2 - \omega_1^2 \right) \tag{2}$$

Where, $\dot{\hat{\omega}}$ denotes initial stage distribution of OMSANF, x is denoted state transmission function, $\dot{\hat{\omega}}$ will converge quickly at high speeds and slowly at low ones. This causes problems with γ 's tuning is calculated in accordance with the OMSANF is adjustment the size of the input image is followed by the equation (3)

$$x_1 = -\frac{A}{\omega_1} \cos\left(\omega_1 t + \theta_1 \right) \tag{3}$$

Where, A is denoted as the harmonic in x_1^2 essential components distribution of the sums the posterior is approximated by the estimated state x_1^2 is splitting the data and label encoding the data is expressed in equation (4)

$$x_1^2 = \frac{A^2}{2\omega_1^2} \left(1 + \cos\left(2\left(\omega_1 t + \theta_1 \right) \right) \right) \tag{4}$$

Where, A denotes estimated state of harmonic in x_1^2, x_1^2 denotes the data has been splitted and label encoding data to estimated fundamental waves of this axis. ω Is denotes as the convergence of the input image, t is denoted as the time duration of filtered data, θ is denoted as the degree of the angled value. The OMSANF is used to obtain an enhanced image quality is represented in equation (5)

$$\dot{\hat{\omega}} = -\frac{\gamma}{2\zeta\omega_1} \left[A^2 \left(\hat{\omega} - \omega_1 \right) + A^2 \left(\hat{\omega} - \omega_1 \right) COS\left(2\left(\omega_1 t + \theta_1 \right) \right) \right] \tag{5}$$

Where, γ is denoted as the observation model of ζ denotes the dynamic model for OMSANF. Finally the OMSANF has enhanced the image and size adjustment from the input image and proceed with the feature extraction procedure.

C. Feature Extraction using Local Maximum Synchrosqueezing Chirplet Transform(LMSCT)

In this section, Feature extraction using LMSCT [29] is discussed to extract the features such as Function, Quality, and Design. Excellent time-frequency localization is a feature of LMSSCT, which allows for highly accurate signal analysis in both the time and frequency domains. This is essential for faithfully portraying the qualities of creative photographs, which frequently feature intricate textures and patterns. LMSSCT has the ability to depict features at various scales and orientations in an adaptable manner. Because of this, it may be used to analyze and combine different artistic styles and aspects, like shapes, textures, and strokes. Because of its intrinsic noise resilience, LMSSCT can handle noisy data with effectiveness and without significantly losing information. This can assist in preserving the integrity of the created images in the context of creative image generation, even in cases when the input data is erroneous or flawed. Creating algorithms that create new artistic images that imitate the style of a specific reference image using the data gathered by LMSSCT could be another objective Users may be able to dynamically alter and control artistic components like textures, brushstrokes, and color palettes in real-time by integrating LMSSCT into an interactive painting system. Users would have a more expressive and intuitive method to produce digital artworks as a result is given in equation (6)

$$H_b(b,v,\omega)=\int_{-\infty}^{+\infty} p(v)h(v-u)f^{-j\omega(v-y)}f^{\frac{-jb(v-y)^2}{2}}dv \tag{6}$$

Here, H_b is represent the number of multiple components; v is represent $p(v)$ denotes even window; ω is represent sufficient frequency interval; h is denotes sampling frequency; $f^{-j\omega(v-y)}$ is denotes a strongly time-varying signal resulting from the modulated operator; the discrete chirp rates can be found using the following expression is given in equation (7)

$$b=\tan(\beta)\cdot\frac{G_p}{2Y_p} \tag{7}$$

Where, b is represent the connection between the degree of rotation; (β) is indicates the rate of chrip; G_p indicates the quantity of distinct chirp rates; $2Y_p$ is represent the lines; thus, it is given in equation (8)

$$|H_b(b,v,\varphi'(v))|=\sum_{m=1}^{M}B_j(v)\frac{\sqrt{1\pi}}{\left(1+(\varphi''_m(v)-b)^2\right)^{1/2}} \tag{8}$$

Where, H_b is represent weakly frequency-varying signal; $B_j(v)$ represent higher order terms are neglected; $\varphi'(v)$ denotes the instantaneous phase of the m^{th} mode; $\varphi''_m(v)$ denotes an increasing contribution of the term; b is represent the spread out in a large are; thus the colors is given in equation (9)

$$\hat{b}(v,\omega)=\arg\min_b\{|H_c(a,v,\omega)|\} \tag{9}$$

Here, $\hat{b}$ represents the window's Fourier transform, H_c denotes impartial approximation provided that the textures thus, it is given in eqn (10)

$$P[g,n]=\sum_{m=0}^{M}p[k]h[k-g]f^{-j\frac{1\pi}{M}[k-n]n} \tag{10}$$

Here, g shows the time variable that is discrete; n represents the variable of discrete frequency. Contrast is defined as the grayscale variations in intensity or between the reference pixel and its neighbour. Contrast is determined by the brightness of the object's colour and by other items in the same display area. Then the styles is given as equation (11)

$$C = \sum_{n}^{N_h - 1} n^2 \left[\sum_{i=0}^{N_h - 1} \sum_{j=0}^{N_h - 1} p_{g,\theta}(i, j) \right] \tag{11}$$

Where, $\sum_{n}^{N_h - 1}$ denoted as the comparable and the diagonal extraction; C denotes the small contrast and $p_{g,\theta}(i, j)$ indicates the neighbour quantity of extracting the semantic information. Finally, LMSCT extracted the features such as Function, Quality, and Design. After completing feature extraction, the extracted features are fed to classification phase.

D. Classification using Dense Hebbian Neural Network (DHNN)

In this section, a Dense Hebbian Neural Network (DHNN) [30] is discussed. The DHNN is used to classify such as Academic Art, Art Nouveau, Baroque, Expressionism, Japanese Art, Neoclassicism, Primitivism, Realism, Renaissance, Rococo, Romanticism, Symbolism and Western Medieval. By taking into account the varied and complicated emotional expressions found in song lyrics, VCANN can offer more sophisticated sentiment analysis. The system can catch fine details and patterns in creative photographs because DHNNs can automatically learn relevant features from the input data. The capacity to understand features is essential for producing visually appealing and high-quality artwork. Hebbian learning is a type of unsupervised learning that enables the DHNN to adjust and arrange its connections purely on the basis of the statistical characteristics of the input data. With this capability, the system may explore the creative image dataset and find intricate links and patterns without explicit supervision. When DHNNs learn to encode important information in the weights of the network, they can provide compact and effective representations of artistic imagery. Faster production and interactivity within the painting system may result from more effective image data processing and storage. The main objective is to create a painting system that can produce artistic images of superior quality that demonstrate originality, diversity, and aesthetic appeal. The goal of the DHNN is to produce visually appealing outputs that represent the artistic qualities of the input data while also learning to capture the essence of different creative styles and genres. Developing an interactive painting system that involves users in the process of creating art is another objective. In order for users to effectively express their creativity, experiment with settings, and explore many artistic possibilities, the DHNN should have responsive feedback systems and intuitive user interfaces. Equation (12) provides a description of the computing time.

$$A\left(\xi_j^{\mu}\right) = \frac{1}{2}\left[\delta_{\xi_j^{\mu},-1} + \delta_{\xi_j^{\mu},+1}\right] \tag{12}$$

Where, A define the channel bandwidth, ξ_j^{μ} define the power of transmission and $\delta_{\xi_j^{\mu}}$ define the channel bandwidth. It makes advantage of the widely accepted replica-symmetry (RS) assumption, which holds that at the thermodynamic limit, all order parameters have vanishing fluctuations around their means. Based on CPU requirements, the node modifies its load as it completes given tasks. The index of a node in the action space represents the task assignment action. The agent assigns the work to a cloud instance (a node with high resources and a high communication cost owing to its remote location is supplied as equation (13), provided there are no unused resources in the fog colony.

$$A\left(\eta_j^{\mu,b} \mid \xi_j^{\mu}\right) = \frac{1+f}{2}\delta_{\eta_j^{\mu,b}+\xi_j^{\mu}} + \frac{1-f}{2}\delta_{\eta_\eta^{\mu,b},-\xi_j^{\mu}} \tag{13}$$

Where, A define the channel bandwidth, f define the queue priority, b $\eta_j^{\mu,b}$ defines the scheduling time, ξ_j^{μ} define the amount of time it takes for a computing node to process the task and $\delta_{\eta_j^{\mu,b}}$ define the computing time.

Tasks are scheduled at the node level according to arrival order and priority. Should the CPU capability of a node be inadequate to manage the subsequent job in the queue, they allocate tasks until no more can fit within its resourcesis given as equation (14).

$$R_{j1.....jl}^{(\mathrm{sup})} = \frac{1}{E^{A/2}N^{A}} \sum_{\mu=1}^{S} \sum_{b1.....ba}^{N,.....N} \eta_{j1}^{\mu,b1} ....\eta_{ja}^{\mu,ba} \tag{14}$$

Where, $R_{j1....jl}^{(\sup)}$ define the task fog nodes, $E^{A/2}$ define the fog colonies, N^{A} define the communication task, S define the load nodes, N define the behaviour nodes and $\eta_{j1}^{\mu,b1}$ define the multiple nodes is given in equation (15)

$$B_{M,S,N,f,\beta}^{(A)} = \frac{1}{N} G \log X_{M,S,N,f,\beta}^{(A)}(\eta) \tag{15}$$

Where, B define encapsulates the behaviour of nodes, N is allocated by the computing node, G define the task priority, X define the queue priority, S define the load nodes, f define the queue priority and β define the task schedule. The distance component represents the communication cost of transmitting a task to a certain node is given in equation (16)

$$\lim_{M \to +\infty} \frac{S}{M^{a}} =: ba < \infty \tag{16}$$

Where, S define the load nodes, ba define the node current load and M^{a} define the node distance. Finally, DHNN classifies the classification of Artistic Image Generation such as Academic Art, Art Nouveau, Baroque, Expressionism, Japanese Art, Neoclassicism, Primitivism, Realism, Renaissance, Rococo, Romanticism, Symbolism and Western Medieval. In this research, MBGIO is employed to optimize the DHNN optimum factors f and G. In this case, MBGIO is used to adjust the DHNN's weight and bias parameter.

E. Optimization using Multiplayer Battle Game-Inspired Optimizer (MBGIO)

In this section, Optimization using Multiplayer Battle Game-Inspired Optimizer (MBGIO) [31] is discussed. By utilizing the widespread appeal of multiplayer battle games, one can draw in a sizable user base and promote involvement and interpersonal communication. By introducing competitive components, users are encouraged to explore their imagination and produce a wide range of inventive and creative artistic images. The presence of multiplayer capability promotes user cooperation, feedback, and sharing, strengthening the sense of community and improving the overall experience. The main objective is to give people a creative exploration platform so they may use image generating as a creative outlet. Through the gamification of the image generating process, the optimizer hopes to support users' skill development and inspire them to gradually advance their artistic ability. Here the proposed DHNN weight and bias parameters $f\ and\ G$ are optimized using MBGIO.

1) Stepwise procedure of MBGIO

Here, a step-by-step process based on MBGIO is developed to obtain the optimal value of DHNN. MBGIO first distributes the population evenly in order to optimise the DHNN's $f\ and\ G$ parameters. Ideal solution promoted using MBGIO algorithm.

Step 1: Initialization

Initialization is performed once to create the initial population. It uses random initialization, which is the most usual strategy. Assuming a predefined population size of neutral, the initial population can be represented as a matrix. It is given in equation (17)

$$Y = \begin{bmatrix} y_1^1 & y_1^2 & y_1^1 & \cdots & y_1^G \\ y_2^1 & y_2^2 & y_2^3 & \cdots & y_2^G \\ \vdots & \vdots & \vdots & \vdots & \\ y_N^1 & y_N^2 & y_N^3 & \cdots & y_N^G \end{bmatrix} \tag{17}$$

Where y is the uniform distribution that generates G the dimension's initial value, then N denoted as the neutral for population size.

Step 2: Random generation

After start up, input parameters are created at random. The selection of the optimal fitness value is contingent upon their explicit hyperparameter state.

Step 3: Fitness Function

The outcome is determined by initialized judgments and random responses. The fitness is then computed using the equation (18)

$$Fitness\,Function = Optimizing\ [f\ and\ G] \tag{18}$$

Here f represents the increasing accuracy and G represents the lowering mean absolute error.

Step 4: Exploration Phase for optimizing f

The Battle Phase enables exploration and mimics various battle behaviours when players randomly interact in the game. When playing against opponents of differing skill levels, players typically aim to reduce damage and maximize damage in order to win. It is given in equation (19)

$$f_{new} = y_i + dir \times \cos(2 \times \pi \times rand(0,1)) \tag{19}$$

Here $rand\,(0,1)$ represents the arbitrary number between 0 and 1 is produced by the uniform distribution. Here dir denoted the vector connecting the $i-th$ individual with the arbitrarily chosen opponent individual π denotes that to prevent people from achieving local optimality, employ an exclusive vector to impede convergence, and f_{new} exceeds the value of the original single.

Step 5: Exploitation phase for optimizing G

The Movement Phase focuses on exploitation and employs the "safe zone" idea to steer persons to prospective regions. Each game's rules may vary, but the main idea is to designate a safe area and gradually reduce it to promote player gatherings as the game progresses. That's provided in equation (20).

$$G = (|Y_{best} - Y_{worst}| + eps \times rand(0.8,1.2)) \tag{20}$$

Here G represents the safety radius, and eps is a small, non-negative value that guarantees the safe region's radius is not zero. Then $Y_{best} - Y_{worst}$ are the best and worst solutions, this keeps the populace current through the utilisation of the elite selection procedure, which is the last important point to make.

Step 6: Termination Condition

The weight factor values $f\ and\ G$ of generator from Dense Hebbian Neural Networkis optimized with the help of MBGIO, will repeatedly perform step 3 until the halting requirements ($y = y+1$) are satisfied. The DAIG-IPS effectively classifies the Artistic Image such as Academic Art, Art Nouveau, Baroque, Expressionism, Japanese Art, Neoclassicism, Primitivism, Realism, Renaissance, Rococo, Romanticism, Symbolism and Western Medieval by higher accuracy. Figure 2 shows Flowchart for MBGIO Optimizing DHNN.

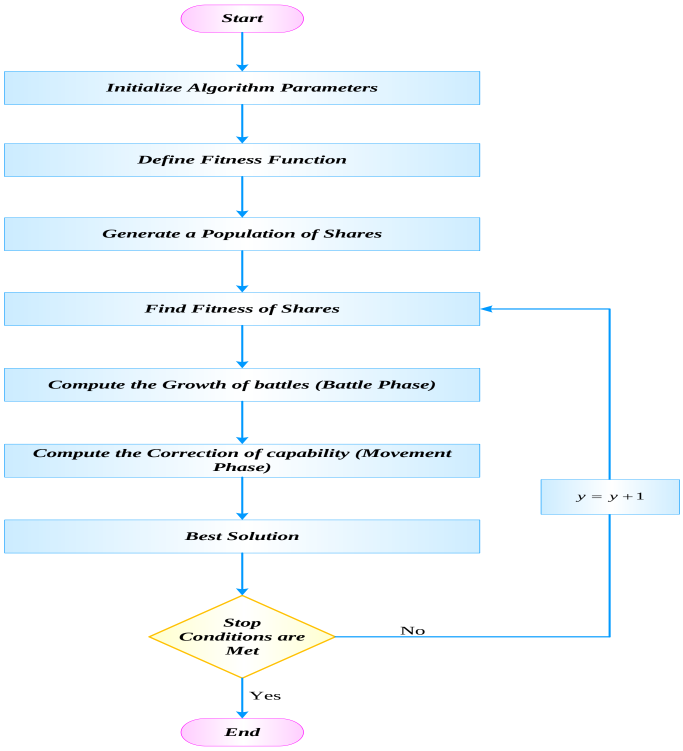
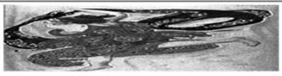
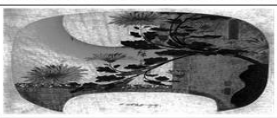
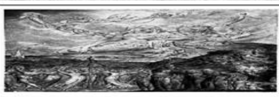


Figure 2: Flowchart for MBGIO Optimizing DHNN

IV. RESULT AND DISCUSSION

In this section, the experimental results of the proposed procedure are shown. Proposed DAIG-IPS-DHNN-MBGIO method is implemented by Python on platform based machine under several performance metrics the number of batches required to finish one epoch is equal to the number of iterations. The obtained outcome of the proposed DAIG-IPS-DHNN-MBGIO approach is analysed with existing systems like State of the Art in Defect Detection Based on Machine Vision (SADD-MV-DNN), Art Teaching Innovation Based on Computer Aided Design and Deep Learning Model (ATI-CAD-CNN), and Automatic Extraction and Reconstruction of Drawing Design Elements Based on Computer Vision and Neural Networks (AE-RDDE-RNN) are the titles of the respective projects. Table 1 depicts Output of the Proposed DAIG-IPS-DHNN-MBGIO Method.

Table 1: Output of the Proposed DAIG-IPS-DHNN-MBGIO Method

Input Images	*Pre-processed image*	*Classification*
		*Academic Art*
		*Art Nouveau*
		*Baroque*
		*Expressionism*
		*Japanese Art*
		*Neoclassicism*
		*Primitivism*
		*Realism*
		*Renaissance*
		*Rococo*
		*Romanticism*
		*Symbolism*
		*Western Medieval*

A. Performance Measures

Accuracy, precision, recall, F1 value, and error rate are examples of performance metrics. It is decided that they scaled the performance parameters using the confusion matrix.

- True Positive (TP): Perfectly classify the Sentiment Analysis into Academic Art.

- True Negative (TN): Perfectly classify the Sentiment Analysis into Art Nouveau.
- False Positive (FP): Imperfectly classify the Sentiment Analysis into Academic Art.
- False Negative (FN): Imperfectly classify the Sentiment Analysis into Art Nouveau.

1) Accuracy

The ability to measure a precise value is known as accuracy. A performance statistic known as accuracy may be used to describe the model's functionality across all classes. It is quantified by the following equation (21)

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{21}$$

2) Precision

Precision, or how well a machine learning model generates positive predictions, is one indicator of the algorithm's efficacy. The following stated equation (22) is used to measure it.

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{22}$$

3) Recall

The recall of a machine learning model measures how well it can recognise positive examples. Put another way, it measures the likelihood of getting a good result. That's provided in equation (23)

$$\text{Recall} = \frac{TP}{(TP+FN)} \tag{23}$$

4) F1value

The harmonic mean of recall and precision is measured using the F1value, frequently employed as a multi-class and binary classification evaluation metric. Here is the F1 value found in equation (24)

$$F1 = 2.\frac{\text{Precision}.\text{Recall}}{\text{Precision}+\text{Recall}} \tag{24}$$

5)Error rate

The degree of prediction error of a model made in relation to the genuine model is measured by the error rate. Equation (25) is used to calculate this.

$$ErrorRate = 100 - Accuracy \tag{25}$$

B. Performance Analysis

The simulation outcomes of the proposed DAIG-IPS-DHNN-MBGIO techniques are shown in figure (3 to 8). The proposed DAIG-IPS-DHNN-MBGIO techniques linked to the AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNN techniques, in that order.

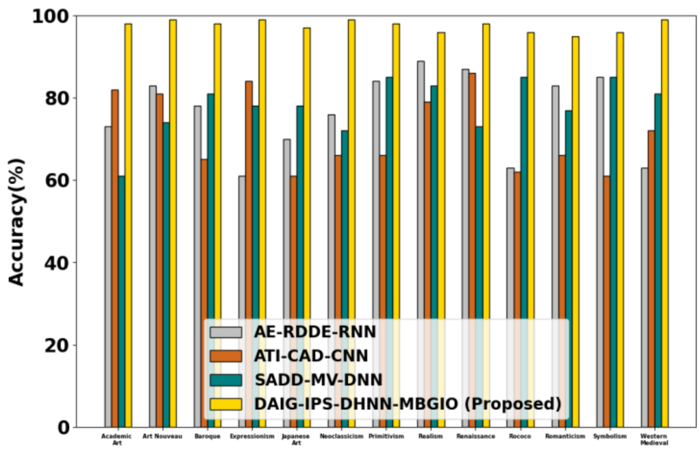


Figure 3: Performance Analysis of Accuracy

Figure 3 displays performance analysis of accuracy. Using vivid colors and dramatic shapes create an abstract artwork that embodies the trends and patterns shown in the accuracy graph. Every data point turns into a bright ball, representing accuracy in both size and intensity. Symbolic components lead the observer through a visual story of advancement by evoking concepts of perseverance and growth. Try varying the texture and composition to imply depth and intricacy. Iteratively improve the design while maintaining data accuracy and aesthetics. Include finishing details to increase impact and coherence, such as delicate lighting effects and textures. Examine how well the artwork conveys the main ideas of the accuracy graph while allowing for discussion and interpretation. In this context the proposed DAIG-IPS-DHNN-MBGIO technique reaches in the range of 22.36%, 25.42% and 18.27% higher accuracy for Academic Art 27.26%, 20.41% and 23.26% higher Accuracy for Art Nouveau 22.36%, 25.42% and 18.27% higher accuracy for Baroque 22.36%, 25.42% and 18.27% higher accuracy for Expressionism22.36%, 25.42% and 18.27% higher accuracy for Japanese Art and 27.26%, 20.41% and 23.26% higher Accuracy for Neoclassicism27.26%, 20.41% and 23.26% higher Accuracy for Primitivism 22.36%, 25.42% and 18.27% higher accuracy for Realism 22.36%, 25.42% and 18.27% higher accuracy for Renaissance 27.26%, 20.41% and 23.26% higher accuracy for Rococo 27.26%, 20.41% and 23.26% higher Accuracy for Romanticism 22.36%, 25.42% and 18.27% higher accuracy for Symbolism 22.36%, 25.42% and 18.27% higher accuracy for Western Medieval and compared to existing techniques such as AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNN respectively.

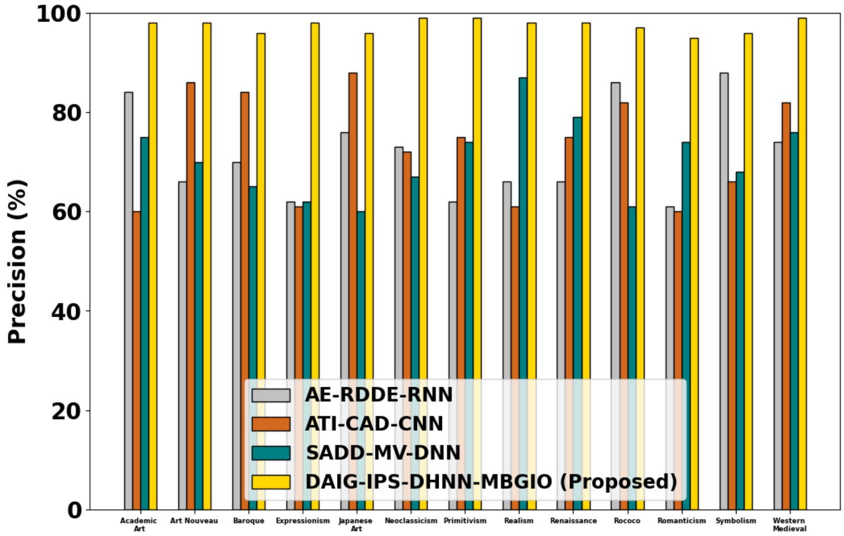


Figure 4: Performance Analysis of precision

Figure 4 displays performance analysis of precision. By use of machine learning and artistic techniques, precision graph explanation is used to generate artistic images. Generating creative graphics is inspired by precision graph explanations that emphasize important aspects in machine learning models. Through the extraction of significant characteristics from these explanations and their application as a basis for artistic production, creators can generate visually captivating artworks that provide insights into intricate decision-making processes within models. This multidisciplinary method bridges the gap between technology and art by combining creative expression with analytical thought to create visually appealing artworks. In this context the proposed DAIG-IPS-DHNN-MBGIO technique reaches in the range of 22.36%, 25.42% and 18.27% higher accuracy for Academic Art 27.26%, 20.41% and 23.26% higher precision for Art Nouveau 22.36%, 25.42% and 18.27% higher precision for Baroque 22.36%, 25.42% and 18.27% higher precision for Expressionism 22.36%, 25.42% and 18.27% higher precision for Japanese Art and 27.26%, 20.41% and 23.26% higher precision for Neoclassicism 27.26%, 20.41% and 23.26% higher precision for Primitivism 22.36%, 25.42% and 18.27% higher precision for Realism 22.36%, 25.42% and 18.27% higher precision for Renaissance 27.26%, 20.41% and 23.26% higher precision for Rococo 27.26%, 20.41% and 23.26% higher precision for Romanticism 22.36%, 25.42% and 18.27% higher precision for Symbolism 22.36%, 25.42% and 18.27% higher precision for Western Medieval and compared to existing techniques such as AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNN respectively.

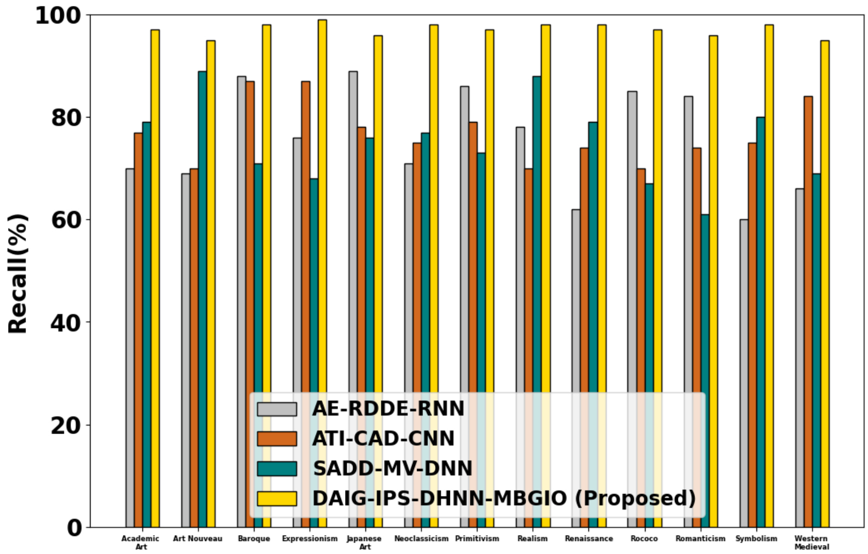


Figure 5: Performance Analysis of Recall

Figure 5displays performance analysis of Recall. Machine learning insights and creativity are combined in the process of creating artistic images from recall graph explanations. Recall graphs identify key components that affect a model's recall capability. These findings are interpreted by artists, who then use color and shape as visual cues. They create visually striking artworks that provide novel insights into data and model behaviour by ingeniously utilizing recall graphs. This combination unites artistic expression with deep analysis, enriching the nexus between technology and the arts. Artists shed light on intricate ideas by using this creative method, encouraging viewers to interact with the artwork's beauty as well as the underlying complexities of machine learning. In this context the proposed DAIG-IPS-DHNN-MBGIO technique reaches in the range of 22.36%, 25.42% and 18.27% higher recall for Academic Art 27.26%, 20.41% and 23.26% higher recall for Art Nouveau 22.36%, 25.42% and 18.27% higher recall for Baroque 22.36%, 25.42% and 18.27% higher recall for Expressionism 22.36%, 25.42% and 18.27% higher recall for Japanese Art and 27.26%, 20.41% and 23.26% higher recall for Neoclassicism 27.26%, 20.41% and 23.26% higher recall for Primitivism 22.36%, 25.42% and 18.27% higher recall for Realism 22.36%, 25.42% and 18.27% higher recall for Renaissance 27.26%, 20.41% and 23.26% higher recall for Rococo 27.26%, 20.41% and 23.26% higher recall for Romanticism 22.36%, 25.42% and 18.27% higher recall for Symbolism 22.36%, 25.42% and 18.27% higher recall for Western Medieval and compared to existing techniques such as AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNN respectively.

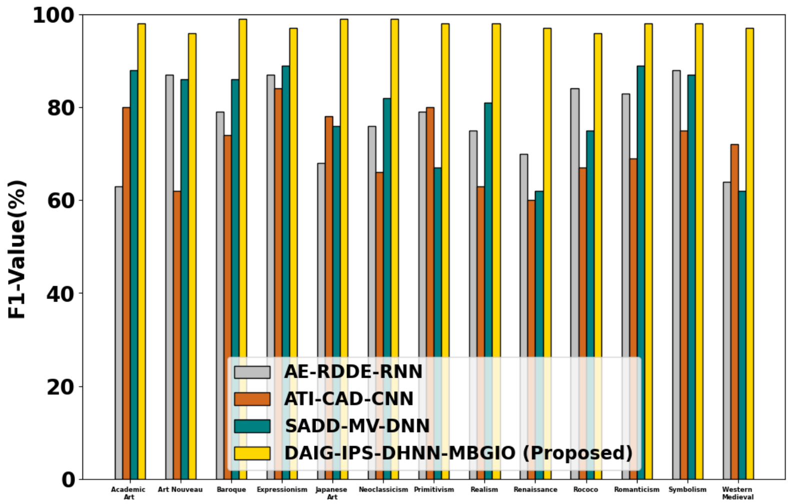


Figure 6: Performance Analysis of F1-value

Figure 6 shows performance analysis of F1-value. Machine learning insights and creative expression are combined in the artistic image generation influenced by F1-value graph explanations. The model's performance's balance between recall and precision is shown by F1-value graphs. These explanations provide patterns that artists can translate into visual elements like geometric shapes and color gradients. Through imaginative interpretation of F1-value graphs, artists create visually arresting pieces of art that present distinct viewpoints on data and model behaviours. This creative combination enhances the meeting point of art and technology by encouraging spectators to consider the underlying complexity of machine learning measures as well as the visual beauty of the artwork. In this context the proposed DAIG-IPS-DHNN-MBGIO technique reaches in the range of 22.36%, 25.42% and 18.27% higher F1-value for Academic Art 27.26%, 20.41% and 23.26% higher F1-value for Art Nouveau 22.36%, 25.42% and 18.27% higher F1-value for Baroque 22.36%, 25.42% and 18.27% higher F1-value for Expressionism 22.36%, 25.42% and 18.27% higher F1-value for Japanese Art and 27.26%, 20.41% and 23.26% higher F1-value for Neoclassicism 27.26%, 20.41% and 23.26% higher F1-value for Primitivism 22.36%, 25.42% and 18.27% higher F1-value for Realism 22.36%, 25.42% and 18.27% higher F1-value for Renaissance 27.26%, 20.41% and 23.26% higher F1-value for Rococo 27.26%, 20.41% and 23.26% higher F1-value for Romanticism 22.36%, 25.42% and 18.27% higher F1-value for Symbolism 22.36%, 25.42% and 18.27% higher F1-value for Western Medieval and compared to existing techniques such as AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNN respectively.

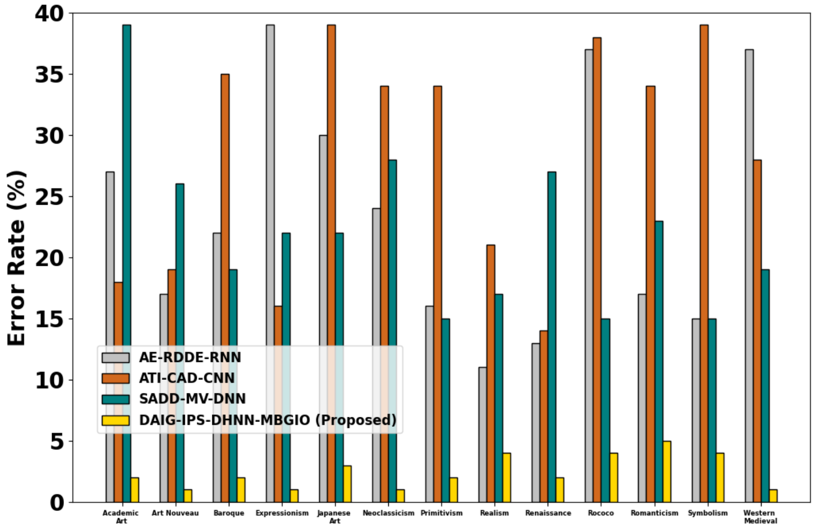


Figure 7: Performance Analysis of Error rate

Figure 7 shows performance analysis of Error rate. In this context the proposed DAIG-IPS-DHNN-MBGIO approach obtains in the range of 22.36%, 25.42% and 18.27% decreased error rate for Academic Art Error rate reductions of 27.26%, 20.41%, and 23.26% for Art Nouveau reduced mistake rate for Baroque by 22.36%, 25.42%, and 18.27% a reduced error rate of 22.36%, 25.42%, and 18.27% for expressionism Error rates for Japanese art were 22.36%, 25.42%, and 18.27% lower, whereas those for neoclassicism were 27.26%, 20.41%, and 23.26% lower. Reduced error rate for primitivism by 27.26%, 20.41%, and 23.26% reduced error rate for realism by 22.36%, 25.42%, and 18.27% Renaissance saw a 22.36%, 25.42%, and 18.27% decreased error rate. error rate reductions of 27.26%, 20.41%, and 23.26% for Rococo Romanticism has a 27.26%, 20.41%, and 23.26% reduced error rate reduced error rates for symbolism, Western Mediaeval, and compared to currently used methods like AE-RDDE-RNN, ATI-CAD-CNN, and SADD-MV-DNN, respectively, were 22.36%, 25.42%, and 18.27% lower.

C. Discussion

A novel DAIG-IPS-DHNN-MBGIO model to Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning. In this paper, data collected from WikiArt Art Movements/Styles Dataset. The model DAIG-IPS-DHNN-MBGIO includes pre-processing of the WikiArt Art Movements/Styles Dataset using Orthogonal Master-Slave Adaptive Notch Filter, feature extraction using LMSCT, and classification using Dense Hebbian Neural Network. Finally, the DHNN model is used to carry out the classification procedure, which divides into thirteen categories as: Academic Art, Art Nouveau, Baroque, Expressionism, Japanese Art, Neoclassicism, Primitivism, Realism, Renaissance, Rococo, Romanticism, Symbolism and Western Medieval. The approach's highest average results were compared to the average results of other approaches, including AE-RDDE-RNN, ATI-CAD-CNN, and SADD-MV-DNN, using the WikiArt Art Movements/Styles Dataset as an example. However, the proposed DAIG-IPS-DHNN-MBGIO method uses the Multiplayer Battle Game-Inspired

Optimizer in conjunction with a quicker DHNN, which leads to a more effective data collection and improved handling of the model over-fitting issue. Compared to current methods, the suggested approach has higher evaluation criteria for accuracy and precision. As a result, the suggested technique is less expensive than the comparative methods. Consequently, the suggested method more accurately and efficiently detects and classifies the Artistic Image Generation.

V. CONCLUSION

In this section, Design of Artistic Image Generation and Interactive Painting System Based on Deep Learning (DAIG-IPS-DHNN-MBGIO) are successfully implemented. Python is used to replicate the proposed strategy. Performance metrics are used to assess a technique's performance. The performance of the proposed DAIG-IPS-DHNN-MBGIO technique offers 23.70%, 23.21%, 25.52% greater F1-value, 21.17%, 25.22%, 25.35% greater recall and 21.17%, 25.22%, 25.35% greater accuracy when compared with existing AE-RDDE-RNN, ATI-CAD-CNN, SADD-MV-DNN methods. Therefore, in order to obtain a more thorough knowledge of the purpose and style of painting works, future study might take into account combining multimodal data.

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