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The Use of Deep Learning Algorithms to Realize the Automatic Evaluation of Paintings and the Analysis of the Quality of Artwork

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Abstract: - The public now has easier access to photos of items in museums and galleries because to the digitization of fine art collections. This produced a need for software tools that can quickly retrieve and categorize art. In this manuscript, the use of deep learning algorithms to realize the automatic evaluation of paintings and the analysis of the quality of artwork (AE-PQA-HDMHNN)is proposed. Initially, the images collected from the WikiArt dataset are given as input. Afterward, the collected image is fed to pre-processing. In pre-processing, Multimodal Hierarchical Graph Collaborative Filtering (MHMHNN) is used for remove the background noise and enhances the quality of image. Then the pre-processed output is fed to Feature Extraction Using Multi-Objective Matched Synchrosqueezing Chirplet Transform (MOMSCT) is constructed for the extracting the histograms features. After extraction the output is fed to High-Dimensional Memristive Hopfield Neural Network(HDMHNN)for the Classification of Fine-Art Paintings. In general Fine-Art Paintings was given for classification using Tyrannosaurus optimization algorithm (TOA)to optimize the High-Dimensional Memristive Hopfield Neural Network(HDMHNN)for classifying Australian Aboriginal Art, Expressionism, Impressionism, Post Impressionism, Realism and Romanticism. The proposed AE-PQA-HDMHNN approach is implemented in python. The performance of the proposed AE-PQA-HDMHNN approach contains 14.09%, 22%, and 14.4% high accuracy,28.51%, 18.21% and 22.98% higher precision and 0.12%, 0.41%, and 1.44% high F1−scorewhen analysed to the existing methods like Two-Stage Deep Learning Approach to the Classification of Fine-Art Paintings (TS-FAP-SVM),image classification approach for painting using improved convolutional neural algorithm (ICP-CNN),End-to-End Artworks Generation Via Deep Convolutional Based Generative Adversarial Networks (EEAG-GAN)methods respectively.

Keywords: fine art, High-Dimensional Memristive Hopfield Neural Network, Multimodal Hierarchical Graph Collaborative Filtering, Multi-Objective Matched Synchrosqueezing Chirplet Transform, painting, Tyrannosaurus optimization algorithm, WikiArt dataset.

I. INTRODUCTION

A multi-phase machine learning method for FAP picture semantic classification [1]. The suggested method shows how a computer can effectively identify creative styles. The semantic gap is a persistent problem in machine-based picture retrieval and recognition that is investigated in this study [2, 3]. The process of giving a picture a name that enables it to be categorised may be thought of as image classification in general [4]. Depending on the kind of labels used, images can be categorised based on "what they depict". It is referred to as object recognition [5]. The second kind of labelling is determined by the "meaning" of the image. Differentiating between distinct kinds of pictures, such as joyful and sad, safe and harmful, and aesthetically beautiful and unpleasant, is known as semantic categorization [6]. While object recognition tasks may be solved effectively by current machine learning approaches, semantic categorization [7], which is person-dependent and subjective, is still extensively unexplored [8]. After years of examining and studying the subtleties of the items, highly qualified and seasoned art researchers are able to identify creative styles in FAP[9]. For years, these skills were considered elite and required extensive visual experience to master [10, 11]. The rise of online galleries and other sources of fine art have made it more accessible to the broader public [12]. This has led to a need to make art expertise more accessible. Transferring the subjective knowledge of human specialists to robots is one way to address this issue [13]. Machines can learn to recognize artistic styles and label unknown images after being trained with labeled images of fine art by human experts [14]. Art schools, automatic picture retrieval, and the labelling of unsigned artworks at auction houses are among applications of machine-based art expertise [15]. It can help identify lost masterpieces and create robots with human-like aesthetics and appreciation for art. Style is a commonly used semantic criterion for painting classification. In the visual arts, style refers to the distinctive components connected to a specific creative movement, school, or era. Even an expert can find it difficult to

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classify a painting's unique stylistic category [16]. Difficulties in art include the presence or lack of characteristics that belong to several styles, seamless transitions between art eras, uncertain interpretation of abstract and aesthetic components, and fluctuations in an artist's style [17]. Transfer learning reuses a network model trained on a large dataset for a related task with a smaller dataset.

A sophisticated network model may be readily adjusted for style painting categorization after it has been pre-trained on a substantial natural picture dataset [18]. Smaller datasets can be used and training time is decreased as a result. Although deep learning techniques have demonstrated encouraging outcomes in the categorization of painting styles, they fall short of visual object classification in terms of accuracy.

The drawback of this paper presents while the paper displays a novel TS- DLM for fine art style classification, one limitation is a lack of detailed analysis on the proposed method's generalizability across different datasets. The evaluation focuses primarily on three standard fine-art classification databases, which may limit our understanding of the approach's performance across a broader range of artistic styles and image characteristics. Furthermore, the paper could benefit from a more in-depth discussion of the two-stage classification system's computational efficiency and scalability, which would provide insights into its practical applicability in scenarios other than the specific datasets.

The two-stage deep learning approach in fine art classification was motivated by the need to address the complexities of high-resolution art images and the subsequent loss of detailed characteristics during resizing. The method aims to improve fine art style categorization accuracy by segmenting images into patches and using deep neural networks for patch classification, which are then integrated into a decision-making module. Its advantages include the reduction of geometric distortions, the preservation of detailed texture and composition information, and the potential for improved classification performance over traditional full-image analysis methods. This pioneering methodology, which incorporates the High-Dimensional Memristive Hopfield Neural Network, offers a promising avenue for overcoming the challenges posed by traditional CNN architectures in handling fine art datasets.

Below is a summary of this research work's principal contributions.

- In this research, the use of DL algorithms to realize the automatic evaluation of paintings and the analysis of the quality of artwork (AE-PQA-HDMHNN)is proposed.
- The proposed AE-PQA-HDMHNN method integrates multiple advanced techniques, including Multimodal Hierarchical Graph Collaborative Filtering (MHMHNN) for pre-processing, Feature Extraction using MOMSCT for feature extraction, and High-Dimensional Memristive Hopfield Neural Network (HDMHNN)
- Unlike traditional HDMHNN approaches, which lack optimization methods for computing optimal parameters, the proposed method incorporates Tyrannosaurus optimization algorithm (TOA). TOA optimizes the weight parameters of HDMHNN, improving its performance in classifying Fine-Art Paintings and enhancing overall accuracy.
- By automating the classifying Fine-Art Paintings and enhancing, the proposed method contributes to quality of artwork.
- The method implementation in Python provides a practical and accessible framework for researchers and practitioners in the field of evaluation of paintings and quality of artwork. The validation of the AE-PQA-HDMHNN method using performance metrics effectiveness and reliability in real-world applications.

The remaining manuscripts are arranged as: Part 2 Literature Review, Part 3 Proposed Methodology, Part 4 Results and Part 5 Conclusion.

II. LITERATURE REVIEW

Several work suggested in the literature related to TS-FAP-SVM, a few recent works were divulged here,

Sandoval et al. [19] has presented TS-FAP-SVM. The public now has greater access to photos of items in museums and galleries because to the digitization of fine art collections. to generate a need for software solutions capable of efficiently retrieving and classifying artwork. The technique divides the input image into five patches, and then uses a deep CNN to train and classify each patch independently. The decision-making module uses a shallow neural network trained on the probability vectors of the first-stage classifier to aggregate the results of the five separate patches in the second stage. The method attains higher Accuracy and lower precision.

Yu et al. [20] have presented an ICP-CNN. Effective software solutions are becoming more and more necessary as a result of the increasing availability of digital fine art collections in galleries and museums. Art picture retrieval and semantic categorization are made possible by these technologies. Many different picture attributes may be extracted using conventional image classification techniques, which are frequently based on shallow structure learning algorithms. However, due to the possibility of losing certain features, a thorough understanding of fundamental painting knowledge was requiring Romanticism throughout the process. The Convolutional Neural Network (CNN) algorithm was used to assign class labels on the pyramid at every level. To join localised picture patches, maximise the Gibbs energy function, and Touse Markov Random Fields. The method attains higher precision and lower recall.

Turhan, et al. [21] have presented EEAG-GAN.AI technologies were widely used in various fields, including health, education, and art. Informatics and law were also exploring new AI solutions. The demand for a legal framework that can keep up with the quick speed of social change has grown in recent years, in addition to the challenges associated with legal rules. In respect to intellectual and artistic works legislation, the study looks at and assesses the technological phases of digital artworks produced through contested producer networks utilising deep learning algorithms. The uniqueness of an output is influenced by the quantity of photos in a dataset. The method attains higher precision and lower recall.

Muratbekova, et al. [22] have presented Color-emotion associations in art: Fuzzy approach.Art objects can elicit specific emotions. Color was a key component of vwasual art and influences how it was perceived. A fuzzy sets method for categorising emotions in artwork. They use a fuzzy approach because it was appropriate for the imprecate and subjective nature of human judgments. They transform them back into a domain and build a fundamental colour knowledge base of color-emotion correlations. Strong relationships were discovered in the study between some emotions and colours, such as appreciation and Australian Aboriginal art's use of brown and orange. Brown is associated with wrath, orange with embarrassment, yellow with pleasure, and grey with fear, among other colours. The method attains higher F1-score and lower recall.

Mohammadi, et al. [23] have presented Hierarchical classification of FAP using DNN. Recent years have seen a significant increase in interest in the automated categorization, indexing, and retrieval of FAP. Artworks were much more difficult to classify than natural objects. To enhance DNN's art style classification performance, we propose a hierarchical classification approach. We organise similar styles in the approach into several super-styles known as presentations. Next, we create a parent classifier and many child classifiers to categorise both the style and the super-style. The method attains higher F1-score and lower AUC.

Geng, et al. [24] have presented an MCCFNet: for cognitive classification of traditional Chinese paintings. Traditional Chinese paintings were computationally modelled and analyzed using vwasual perception-based cognitive classification. The technique was crucial to comprehending and differentiating works of art by different art wasts. Nevertheless, there hasn't been much research done on how to include visual perception into AI models. Moreover, a number of obstacles must be overcome for Chinese painting classification research to be successful, including a lack of study on the unique character traits of painted pictures for author identification and categorization. We introduce MCCFNet, a novel framework for extracting vassal features from various color perspectives, to address these was sues. The method attains higher Accuracy and lower AUC.

Lu, et al. [25] have presented creating representations of emotions for FAP using numerous painting techniques. The task of using ML to provide emotion descriptors for FAP was becoming more and more common. However, the artistic as well as nuanced quality of the relying on visual hints made transcribing the emotions shown in paintings challenging. Prior research on emotion painting captioning has mostly concentrated on semantic elements that are content-oriented, which has led to poor results. Adding facial expression and human position features to the painting emotion captioning model, two more features, in recognition of the fact that human emotions may be reflected in facial expressions and body language. The method attains higher accuracy and lower recall.

III. PROPOSED METHODOLOGY

In this section, the use of deep learning algorithms to realize the automatic evaluation of paintings and the analysis of the quality of artwork (AE-PQA-HDMHNN) is proposed. The proposed AE-PQA-HDMHNN revolutionizes the automatic evaluation and quality analysis of fine art by taking a multifaceted approach. Starting with images from the WikiArt dataset, the process goes through meticulous pre-processing with Multimodal Hierarchical Graph Collaborative Filtering (MHMHNN) to remove background noise and improve image quality. Next, Feature Extraction Using Multi-Objective Matched Synchrosqueezing Chirplet Transform (MOMSCT) extracts shape features from histograms. These features are then fed into the High-Dimensional Memristive Hopfield Neural Network (HDMHNN) to classify fine art. The HDMHNN uses the Tyrannosaurus optimization algorithm (TOA) to classify a variety of art styles, including Romanticism, Realism, Impressionism, Post Impressionism, and Australian Aboriginal Art. Implemented in Python, this methodology improves performance significantly, with higher accuracy, precision, and F1-score than existing methods such as TS-FAP-SVM, ICP-CNN, and EEAG-GAN. Figure 1: shows that Block Diagram of the proposed AE-PQA-HDMHNN.

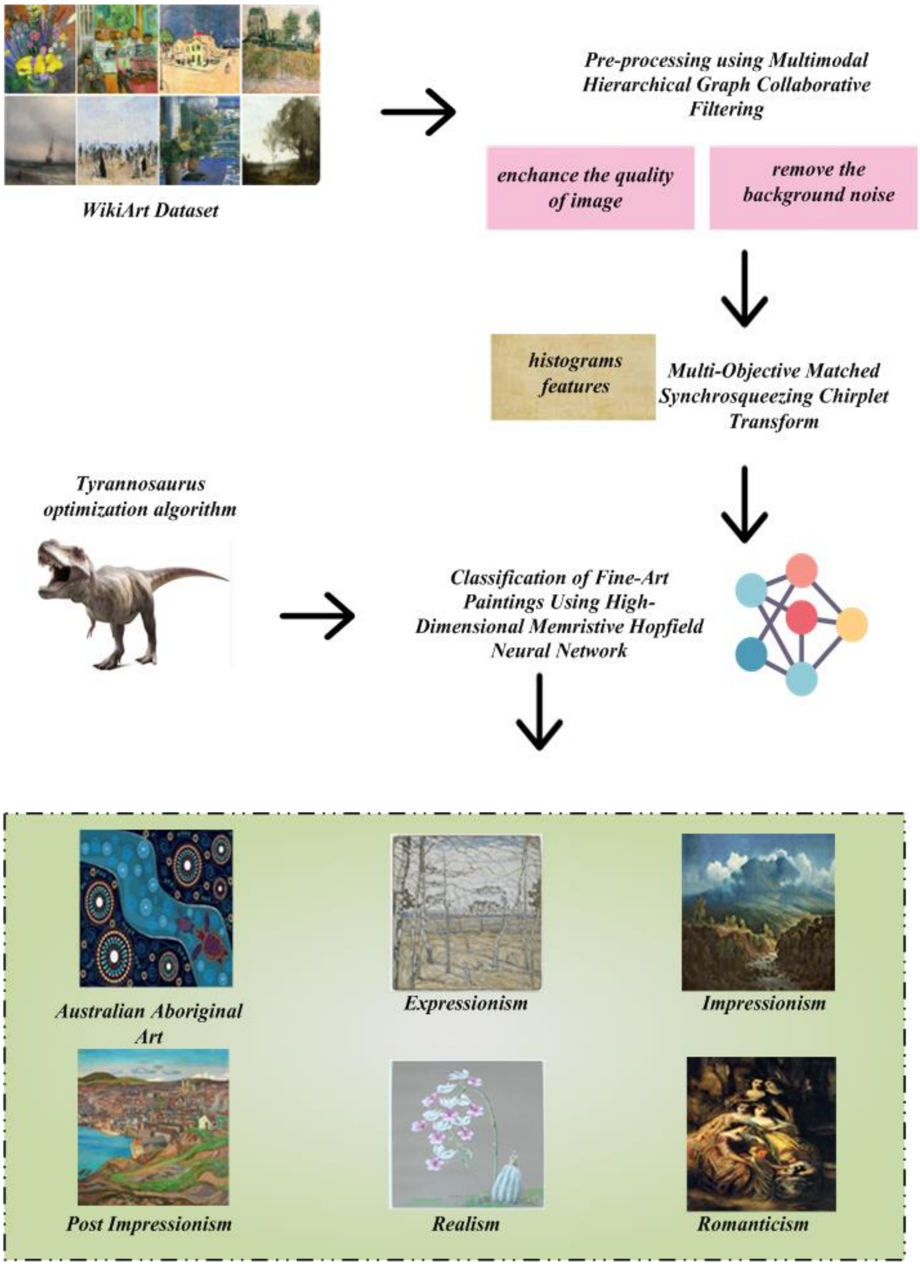


Figure 1: Block Diagram of the proposed AE-PQA-HDMHNN

A. Image Acquisition

In this section input image is taken from WikiArt Dataset [26]. Initially 30870 pictures that cover six different artistic genres. There was balance among the stylistic classes, with 5145 images (16.66% of the total) representing each class. Romanticism, Realism, Impressionism, Post Impressionism, and Australian Aboriginal Art were among the styles. Being the only styles with an equal amount of pictures to those in the Aboriginal style, the final five styles were selected from the WikiArt collection, which was otherwise bigger. Rather of being labelled by art specialists, WikiArt photographs were annotated by volunteers from the broader public, so the images had to be manually checked to make sure the labels were accurate as well as to remove any that did not depict fine art paintings or were of poor quality.

B. Pre-processing using Multimodal Hierarchical Graph Collaborative Filtering

In this section, Multimodal Hierarchical Graph Collaborative Filtering (MHGCF) [27] is discussed. For pre-processing, the MHGCF collected data from the WikiArt Dataset to remove the background noise and enhances the quality of image. Multimodal Hierarchical Graph Collaborative Filtering improves recommendation accuracy by combining multiple data sources and capturing complex user-item interactions. It uses deep learning algorithms to facilitate automated evaluation of paintings, allowing for nuanced analysis of artwork quality based on factors such as style, composition, and historical significance, thus enriching our understanding of art appreciation.

$$o_{t_1}^{(k)} = \sum_{h \in M_{t_1} \cup h_1} \frac{|M_h|^{\alpha}}{|M_{t_1}|0.5\||M_h|^{0.5}} \cdot o_h^{(k-1)} \tag{1}$$

Here, $o_{t_1}^{(k)}$ represent the art work, $k-1$ represent the layer of artwork, $o_{t_1}^{(k-1)}$ represent the painting layer, $|M_t|$ & $|M_h|$ denotes the size, h denotes the image, α represent the co-efficient and $\frac{|M_h|^{\alpha}}{|M_{t_1}|0.5\||M_h|^{0.5}}$ denotes the popularity-aware norm. Canvas, with each row representing a user and each column representing an artwork.

$$p_{d_1}^{(k)} = \sum_{h \in M_{d_1} \cup d_1} \frac{|M_h|^{\alpha}}{|M_h|^{0.5}|M_{d_1}|^{0.5}} \cdot p_h^{(k-1)} \tag{2}$$

Here, $p_{d_1}^{(k)}$ represent the latent features of users in artwork, $k-1$ represent the layer, $p_h^{(k-1)}$ represent the image at layer, $|M_h|$ & $|M_{d_1}|$ denotes the size of image, h denotes the item, α represent the relationships between artworks as edges in anart,

$$g_{l,h_1}^{(1)} = \frac{|M_{h_1}|^{\alpha} V_l g_{l,h_1}^{(0)}}{|M_{h_1}|} + \sum_{t \in M_{h_1}} \frac{|M_{h_1}|^{\alpha} h_{l,t}^{(0)}}{|M_{h_1}|^{0.5}|M_t|^{0.5}} \tag{3}$$

Here, $g_{l,h_1}^{(1)}$ represent the user Fine art, $|M_{h_1}|$ & $|M_{t_1}|$ denotes the size, V_l represent the Artistic style, h denotes the Modern art, α represent the co-efficient of an artist, l represent the Art movements, t_1 denotes the target user and h_1 denotes the Art expertise. Thus, equation (4) is displays to remove the background noise.

$$K_1 = \sum_{(t,h,i) \in N} -km\sigma\left(\left(o_t^{(K)}\right)^S \cdot o_h^{(K)} - \left(o_t^{(K)}\right)^S \cdot o_i^{(K)}\right) + \lambda\left(\|O\|_2^2\right) \tag{4}$$

Here, $(t,h,i) \in N$ represent the training image, K_1 Texture information of matrix O, t denotes the user artist, $\sigma(.)$ represent the sigmoid function and $o_t^{(K)}$ & $o_h^{(K)}$ represent the target art at k^{th} layer. Thus, equation (5) displays to enhances the quality of image.

$$K = K_1 + K_2 + K_3 \tag{5}$$

Here, K represent the style of image, K_1 objective function of initialized image matrix O, K_2 objective function of initialized Artistic features P and K_3 objective function of initialized Artistic datasets G. After the output picture has been filtered by the MHGCF, the pre-processed image is sent to the feature extraction process so that features may be extracted.

C. Feature Extraction Using MOMSSCT

This section, MOMSSCT [28] is discussed. This MOMSSCT method is extracting the histogram features. When combined with deep learning algorithms, the MMSCT provides a number of benefits for automatic painting evaluation and artwork quality analysis. First of all, MMSCT makes it possible to precisely localize time-frequency information, thereby capturing fine details and subtleties in artwork signals. As a result, deep learning models are better able to extract meaningful features, improving classification and evaluation task accuracy. Second, because of its multi-objective approach, multiple aspects of artwork quality, including texture, color distribution, and composition, can be considered simultaneously, resulting in a more thorough analysis. Furthermore, MMSCT's robustness in evaluating a variety of artwork styles and genres is suited to the dynamic nature of artistic expressions due to its ability to handle non-stationary images.

$$A(s)=\sum_{p=1}^{P} B_p(s)e^{j\varphi s(s)} \tag{6}$$

Where, p is the To get patch sizes that meet the input requirements, the image must be scaled up by the proper amount, $A(s)$ and $\phi\, s(s)$ stands the p^{th} sections of the picture on the top left, top right, bottom left, and bottom right, B_p represent the higher order expression and e^{j} denotes the image .

$$W(p,v)=\int_{-\infty}^{+\infty} a(v)\, f(v-t) \tag{7}$$

Where, $W(p,v)$ denotes the phase function, $a(v)$ denotes the modulation rate and $f(v-t)$ denotes the window function width.

$$\varphi_k(u)=\varphi_k(t)+\varphi_k'(t)(u-t) \tag{8}$$

Where $\varphi_k(u)$ denotes identify the authenticity of artworks, $\varphi_k(t)$ denotes the $k-th$ component's art historians, $\varphi_k'(t)$ denotes the image art frequency and $(u-t)$ denotes a evaluation of paintings, in equation (9) the histogram features are extracted,

$$\Delta_{\varpi}(t)=\sum_{k=1}^{K}\sqrt{[\varphi_k''(t)^2]} \tag{9}$$

Where $\Delta_{\varpi}(t)$ denotes the Specify the quality metrics and $\varphi_k''(t)^2$ denotes the It's crucial to remember that judging the quality of an artwork can be arbitrary and dependent on cultural context. To some extent, biases can be reduced by deep learning models trained on a variety of datasets; however, cultural context and human expertise are still essential for accurate interpretation.

$$d=\tan(\beta).\frac{R_s}{2U_s} \tag{10}$$

Where, d denotes the artist rate, β art that defies conventional classification criteria, R_s denotes the paintings of an artist and U_s denotes the painting features. Finally MOMSSCT has extracted the histograms features. The classification phase is then provided with the retrieved characteristics.

D. Classification of Fine-Art Paintings Using High-Dimensional Memristive Hopfield Neural Network

In this section, HDMHNN [29] is discussed. The HDMHNN is used to classify the Fine-Art Paintings such as Romanticism, Realism, Impressionism, and Post Impressionism in Australian Aboriginal Art, There are various benefits to classifying fine art paintings with a high-dimensional memristive Hopfield neural network. First off, the network's memristive quality makes it possible to store and retrieve high-dimensional patterns efficiently, which makes it possible to accurately represent intricate artistic features. Second, by promoting associative memory recall, the Hopfield architecture makes it easier to spot patterns and similarities in paintings. Furthermore, even with complex and nuanced artwork, the network's capacity to handle high-dimensional data improves classification accuracy. Additionally, the compact and low-power hardware implementation made possible by the memristive components makes it appropriate for embedded systems and portable devices. Overall, this method's special fusion of neural and memristive computing paradigms promises reliable and effective fine-art classification.

$$Y_i x_i = -\frac{x_i}{J_I} + \sum_{j=1}^{n} N_{ij} \tanh(x_j) + I_i, (i, j \in N^*) \quad (11)$$

Here, Y_i and x_i J_I could be related to various elements of the artwork, including composition, texture, or color distribution i, both inside and outside the paintings, correspondingly. N_{ij} Reflects the duration spent analyzing each painting. i and j, $\tanh(x_j)$ and I_i stands for both relates to a user or an artwork, correspondingly, and the columns depict various latent characteristics like a preference for a certain genre, a color scheme, or a historical setting. Equation (12) are used to classify Australian Aboriginal Art and Expressionism,

$$\mu_1 N_1(\varphi_1) = \mu_1(i_1 j_1 \varphi_1) \quad (12)$$

Where μ_1 indicates the importance or caliber of the features found. By representing the connections between pieces of art as graph edges, it enables the model to comprehend the creative surroundings of individual paintings and deduce user preferences from a subset of related pieces of art. Equation (13) are used to classify Impressionism and Post Impressionism,

$$\mu_2 N_2(\varphi_2) = \mu_2(i_2 j_2 \varphi_2) \quad (13)$$

Where μ_2 corresponds to the depth of data that the DLM has been able to capture. This illustrates the deep learning model's numerical evaluation of the artwork's quality. It's comparable to a critical assessment or a grade assigned to a painting according to different standards like composition, color harmony, technique, and emotional impact. Equation (14) are used to classify Realism and Romanticism,

$$\mu_3 N_3(\varphi_3) = \mu_3(i_3 j_3 \varphi_3) \quad (14)$$

Where μ_3 represent the memristor coupling strengths. In order to generate the quality score, the deep learning model that combines and processes the input features text features, image features, and metadata is represented by this function. In this work, TOA is employed to optimize the HDMHNN weight parameters $(Y_i x_i, \mu_1 N_1(\varphi_1))$. Here TOA is employed for turning the weight and bias parameter of HDMHNN.

E. Optimization of HDMHNN Using Tyrannosaurus optimization algorithm

In this section, Tyrannosaurus optimization algorithm (TOA) [30] is described. The Tyrannosaurus optimization algorithm, named after the Tyrannosaurus rex's predatory prowess, seeks to solve optimization problems efficiently by mimicking the ancient predator's hunting behavior. This algorithm aggressively explores the search space while exploiting promising solutions, much like the T. The Tyrannosaurus optimization algorithm uses a combination of exploration and exploitation strategies to efficiently converge on optimal solutions, making it especially suitable for challenging optimisation issues across several fields, including engineering and finance.

Step 1: Initialization

The population-dependency approach known as TOA is used to randomly determine the number of animals in the search space. Let the location of the prey randomly made at search area between lower and upper limits. Then the weight parameter values of generator $(Y_i x_i)$ and $(\mu_1 N_1(\varphi_1))$ from High-Dimensional Memristive Hopfield Neural NetworkThus, it is given in equation (15)

$$Y_i = rand(mp, \dim) * (ua - k\rho_J) + k\rho_J \quad (15)$$

Where, $Y_i = \lfloor y_{1,} y_2, \ldots.. y \rfloor$ denotes prey locations $i = 1,2 \ldots n$ where, m signifies dimension, mp denotes no of position, $\dim$ signifies dimension at search space, kb denotes the lower limit, and ua the upper limit.

Step 2: Random Generation

The settings for the input are entered arbitrarily. It is necessary to have precise hyper parameter conditions before choosing the optimal fitness values.

Step 3: Fitness function

Based on initialised judgements, an arbitrary solution is generated. It is evaluated using parameter optimisation settings for enhancing weight parameter $(Y_i x_i)$ and $(\mu_1 N_1(\varphi_1))$ of generator, given equation (16)

$$Fitnessfunction = Optimizing\ [\ Y_i x_i \ \text{ and } \ \mu_1 N_1 \varphi_1\ ] \tag{16}$$

Where $(Y_i x_i)$ denotes the increasing the accuracy. $(\mu_1 N_1(\varphi_1))$ represent the decreasing the ROC.

Step 4: Hunting and Chasing for Optimizing $(Y_i x_i)$

An apex predator, like a wolf, lion, or other, would claim that a T. Rex hunts by trying to find the nearest prey. It can sometimes fight itself against attackers to flee. Juveniles are involved at search for, capture of prey, therefore when the T-Rex hunts, it acts arbitrarily. Thus, it is given in equation (17)

$$Y_{new} = \begin{Bmatrix} y_{new} & if\ rand() < T\alpha_J \\ Random & else \end{Bmatrix} \tag{17}$$

Where, T denotes estimate of the distance to dispersed prey. Here, the prey starts to disintegrate as the T-Rex starts to hunt by updating its location. Thus, it is given in equation (18)

$$Y_{new} = y + rand() * d\alpha_J * (tpos * yr - target * ar) \tag{18}$$

Here, d denotes success rate of hunting. Target signifies minimum location of prey to T-Rex location; T-Rex running rates are yr ; ar is the prey running rate, running speed lesser than T-Rex speed. Figure 2 shows of TOA for optimizing HDMHNN.

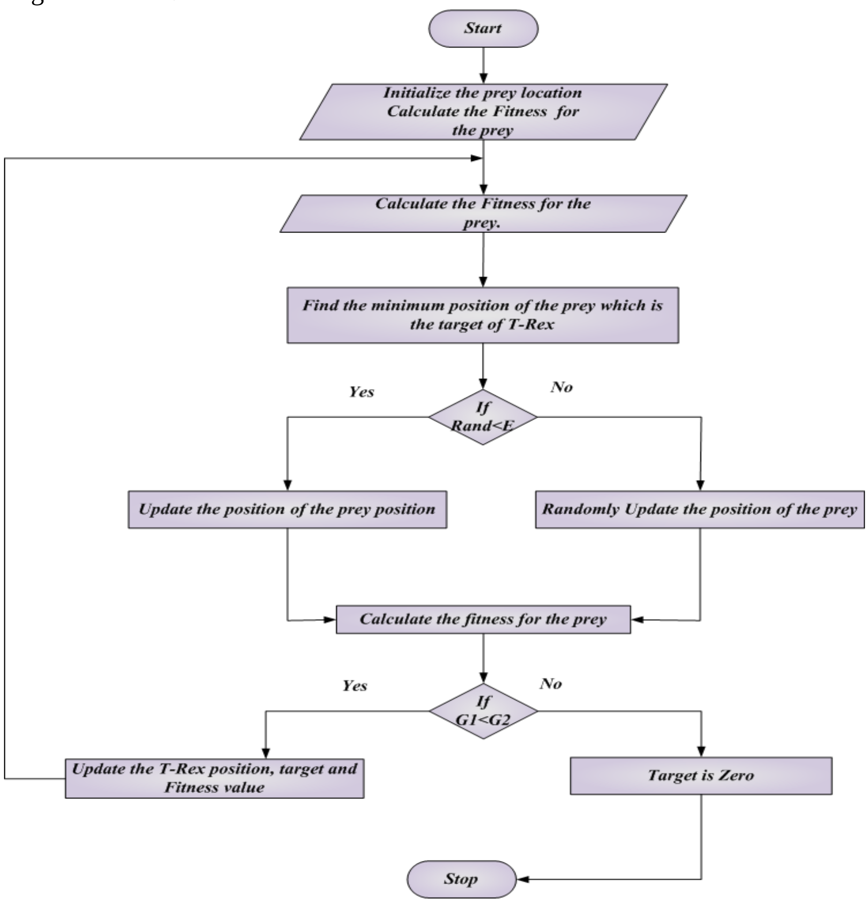


Figure 2: Flowchart of TOA

Step 5: Selection for Optimizing $(\mu_1 N_1(\varphi_1))$

The prey's location that is, it's prior and current locations determines the process of selecting. In the event that prey runs itself against hunting, the prey location becomes zero and T-Rex is unable to hunt. By comparing fitness function, it is realized. Thus, it is given in equation (19)

$$Y_i^{l+1} = \begin{cases} update\ \ the\ \ target\ \ \ position\ \ \ if\ g(Y) < \alpha_J\ (Y_{new}) \\ \qquad target\ is\ zero \qquad\qquad otherwise \end{cases} \tag{19}$$

Here, $g(Y_{new})$ stands for the fitness function for the revised target location and $g(Y)$ for the fitness function for the original arbitrarily assigned target location.

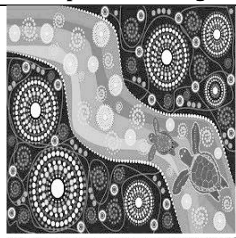
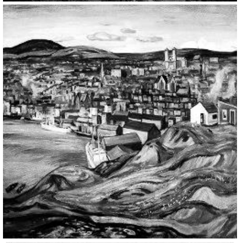
Step 6: Termination

This stage, the weight parameter $(Y_i x_i, \mu_1 N_1(\phi))$ High-Dimensional Memristive Hopfield Neural Network is improved with the use of TOA, repeat step 3 repeatedly until the stopping point is reached. HDMHNN is optimized with TOA for classify the Fine-Art Paintings as Romanticism, Realism, Impressionism, Post Impressionism, and Expressionism in Australian Aboriginal Art in order to improve the Fine-Art Paintings to classifying which type of painting is classified. The TOA flowchart is shown in Figure 2.

IV. RESULT AND DISCUSSION

This section presents the actual outcomes of the proposed approach. The proposed AE-PQA-HDMHNN method is implemented Python platform on a PC running Intel ®core (7M) i3-6100CPU @ 3[U1] with 12 GB of RAM. Processor operating at 70 GHz the number of iterations under certain performance measures is equal to the number of batches needed to finish an epoch. Evaluated using a number of performance metrics, including F1-score, AUC, recall, accuracy, and precision. The result of AE-PQA-HDMHNN approach was compared with existing TS-FAP-SVM, ICP-CNN and EEAG-GAN techniques. The output of the proposed PHD-TMLD-VCANN technique is displayed in Table 1.

Table 1: Output of the Proposed PHD-TMLD-VCANN Method

Input image	**Pre-processed image**	**Classification**
		Australian Aboriginal Art
		Expressionism
		Impressionism
		Post Impressionism
		Realism

		Romanticism

A. *Performance* Measures

This is a crucial stage in determining the exploration of optimization algorithm. Performance measures to evaluate to access performance likes Accuracy, precision, Recall, F1-score and AUC.

1) Accuracy

The accuracy value found in equation (20) is calculated by dividing the entire amount of samples by the amount of samples that each scheme correctly classified.

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{20}$$

Here, TP signifies true positive, TN signifies true negative, FN means false negative and FP signifies false positive.

2) Precision

Precision estimation how many positive labels had expected with high accuracy, it expressed equation (21),

$$precision = \frac{TN}{FP + TN} \tag{21}$$

3) Recall

Recall is intended by dividing entire amount of true positive, false negative predictions by amount of true positives. The model's capacity to collect all pertinent instances is measured. It is shown in equation (22),

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{22}$$

Here, TP represent true positive and FN represent false negative.

4) F1-score

Measured by the F1-score used to assess the effectiveness of a deep learning model. Precision and recall are combined into a single score (F1-score). Thus it’s give this equation (23),

$$F1 - score = \frac{\mathrm{Pr}ecision * \mathrm{Re}call * 2}{(\mathrm{Pr}ecision + \mathrm{Re}call)} \tag{23}$$

5) Area under Curve

The AUC score evaluates the model's overall performance. A flawless classifier is rated at 1.0, but an arbitrary classification is rated at 0.5. A greater AUC score denotes superior model performance. This is calculated by equation (24)

$$AUC = \frac{1}{2}\left(\frac{TP}{TP + FP} + \frac{TN}{TN + FP}\right) \tag{24}$$

B. Performance Analysis

The proposed method's simulation results are displayed in Fig. 3 to 7. Then, the proposed AE-PQA-HDMHNN technique is likened with existing TS-FAP-SVM, ICP-CNN and EEAG-GANmethods respectively.

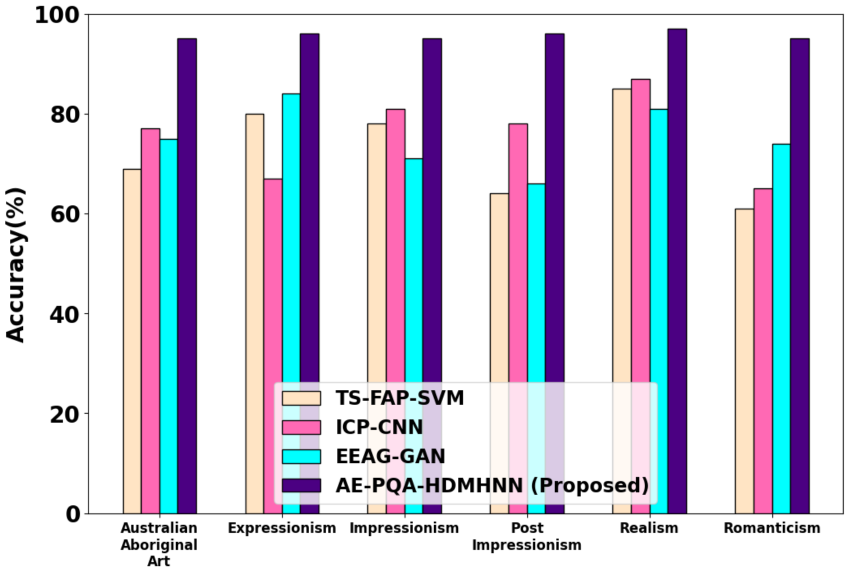


Figure 3: Performance Analyses of Accuracy

Figure 3 displays Performance Analyses of Accuracy. The High-Dimensional Memristive Hopfield Neural Network (HDMHNN) represents significant advances in deep learning algorithms for automatic painting evaluation and quality analysis. This method has demonstrated significant increases in accuracy across a variety of artistic genres when compared to existing models such as TS-FAP-SVM, ICP-CNN, and EEAG-GAN. The proposed method attains 29%, 27.5% and 28% higher accuracy for Australian Aboriginal Art; 14.68%, 26%, and 24.3% higher accuracy for Expressionism; 21.5%, 22%, and 27.5% higher accuracy for Impressionism; 29.5%, 27% and 21% higher accuracy for Post Impressionism; 26%, 29% and 21.5% higher accuracy for Realism 14.09%, 22%, and 14.4% higher accuracy for Romanticism estimated to the existing TS-FAP-SVM, ICP-CNN and EEAG-GAN models respectively.

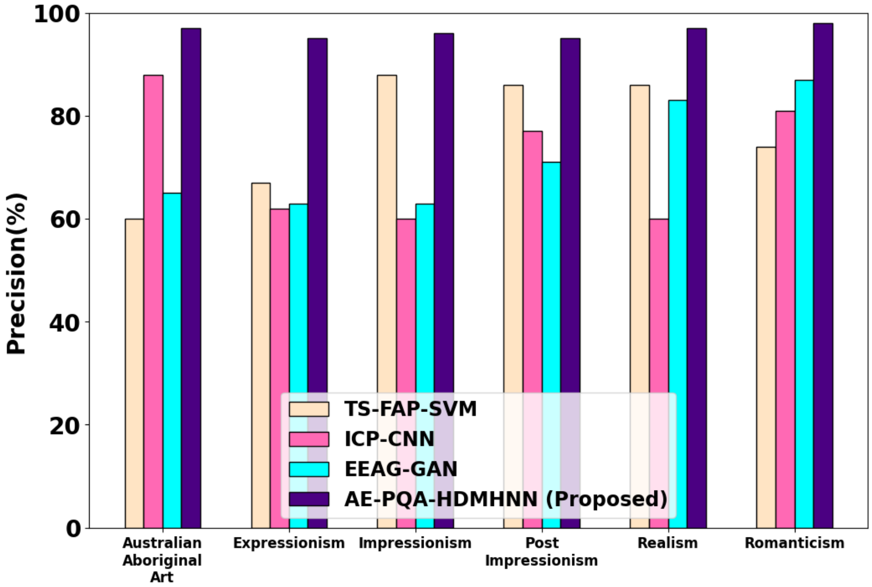


Figure 4: Performance Analyses of Precision

Figure 4 displays Performance Analyses of Precision.Precision across a wide range of artistic styles demonstrates the effectiveness of the AE-PQA-HDMHNN approach. This method, which employs deep learning algorithms, particularly the High-Dimensional Memristive Hopfield Neural Network, not only allows for the automatic evaluation of paintings but also for in-depth analysis of artwork quality, enriching the field of computational art analysis and appreciation.The proposed AE-PQA-HDMHNN method attains 23%, 21.5% and 20% Precision for Australian Aboriginal Art; 24%, 14.5% and 11% higher Precision for Expressionism; 22%, 24.8%, and 26.5% higher Precision for Impressionism; 17.5%, 11% and 20.5% higher Precision for Post Impressionism; 11%, 21% and 26.5% higher Precision for Realism ;28.51%, 18.21% and 22.98%higher

Precision for Romanticism estimated to the existing TS-FAP-SVM, ICP-CNN and EEAG-GANmodels respectively.

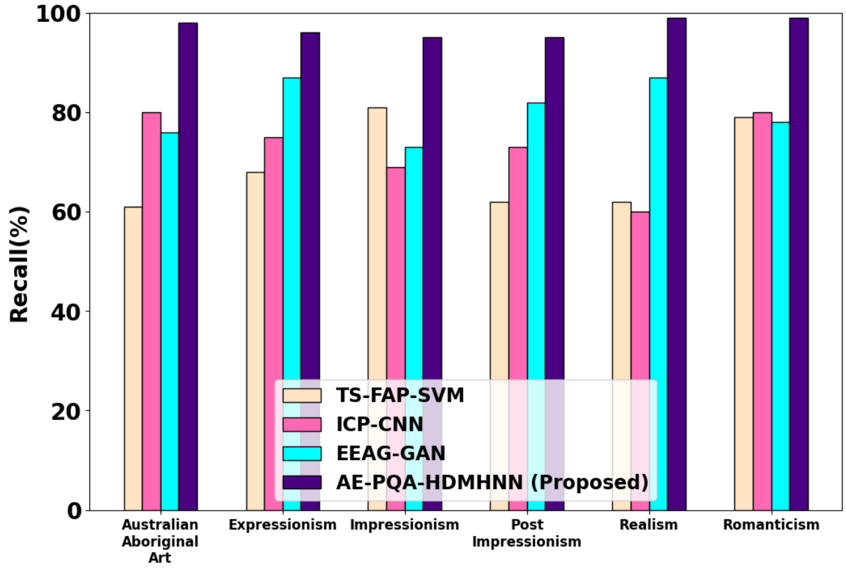


Figure 5: Performance Analyses of Recall

Figure 5 displays Performance Analyses of Recall. The AE-PQA-HDMHNN method has high recall rates, demonstrating its effectiveness in automating the evaluation process and providing valuable insights into the quality and characteristics of artwork from various genres.The proposed AE-PQA-HDMHNN method attains 26.23%, 28.21% and 12.35% higher Recall for Australian Aboriginal Art; 12.3%, 19.8% and 28.3% higher Recall for Expressionism; 16.6%, 24.8%, and 33.2% higher Recall for Impressionism; 13.9%, 28.4% and 18.45% higher Recall for Post Impressionism; 24.9%, 28.4% and 22.5% higher Recall for Realism;26.29%, 28.21% and 11.36% higher Recall for Romanticism estimated to the existing TS-FAP-SVM, ICP-CNN and EEAG-GAN models respectively.

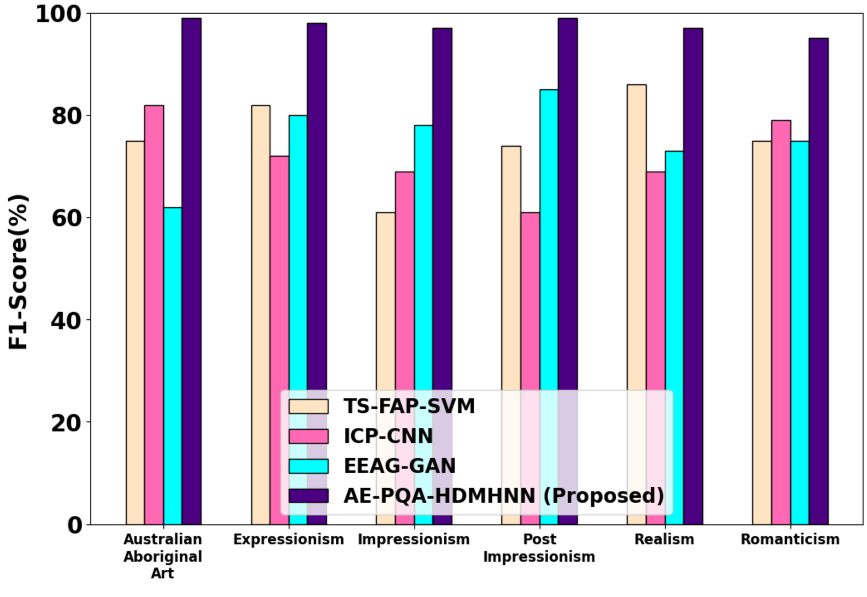


Figure 6: Performance Analyses of F1−score

Figure 6 displays Performance Analyses of F1−score. The observed increases in F1-scores demonstrate the AE-PQA-HDMHNN method's effectiveness in pushing the boundaries of automatic painting evaluation and artwork quality analysis. This approach, which makes use of high-dimensional memristive neural networks and deep learning algorithms, shows great promise for facilitating a deeper understanding and appreciation of various artistic expressions.The proposed AE-PQA-HDMHNN method attains 0.21%, 0.33%, and 1.44% higher F1−score for Australian Aboriginal Art; 22.8%, 23.8% and 21.4% higher F1−score for Expressionism; 22.6%, 15.5%, and 19.4% higher F1−score for Impressionism; 0.24%, 0.39%, and 0.44% higher F1−score for Post

Impressionism; 18.9%, 11.3% and 24.5% higher F1−score for Realism;0.24%, 0.39%, and 3.44%higher F1−score for Romanticism estimated to the existing TS-FAP-SVM, ICP-CNN and EEAG-GANmodels respectively.

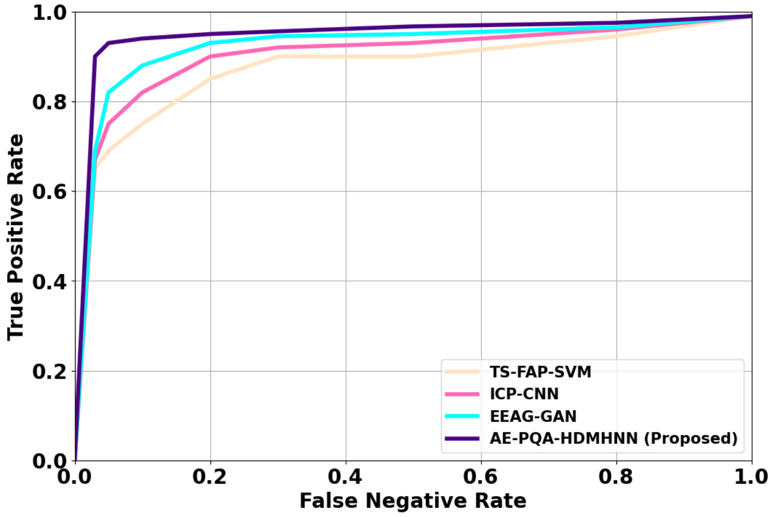


Figure 7: Performance analysis of AUC

Figure 7 displays Performance analysis of AUC.The loss progression is noticeable when the High-Dimensional Memristive Hopfield Neural Network (HDMHNN) is used in conjunction with DL algorithms for the automatic assessment of paintings and the analysis of artwork quality.The proposed AE-PQA-HDMHNN method attains 22.2%, 11.55% and 26.3% higher AUC estimated to the existing TS-FAP-SVM, ICP-CNN and EEAG-GANmodels respectively.

C. Discussion

The paper proposes the use of DL algorithms to realize the automatic evaluation of paintings and the analysis of the quality of artwork (AE-PQA-HDMHNN)based on the WikiArt dataset. To remove background noise and improve image quality, initial preprocessing uses Multimodal Hierarchical Graph Collaborative Filtering (MHMHNN). Next, the Multi-Objective Matched Synchro Squeezing Chirplet Transform (MOMSCT) is used to extract histogram features. The High-Dimensional Memristive Hopfield Neural Network (HDMHNN) is then used to classify Fine-Art Paintings of various styles, including Romanticism, Realism, Impressionism, Post Impressionism, and Australian Aboriginal Art.To improve classification performance, the Tyrannosaurus optimization algorithm (TOA) is used. Evaluation measures, including as accuracy, precision, recall, and F1-score, and AUC are used to evaluate the model's efficacy. While the approach outperforms baseline techniques on standard art classification datasets, its applicability to a wider range of artistic styles and image characteristics calls for further investigation.

V. CONCLUSION

In this section, the use of DL algorithms to realize the automatic evaluation of paintings and the analysis of the quality of artwork (AE-PQA-HDMHNN)are successfully implemented. The proposed AE-PQA-HDMHNN method is implemented in python. The performance of the proposed AE-PQA-HDMHNN approach contains 24.5%, 27%, and 12.5% high accuracy,16.23%, 18.21% and 17.31% higher recalland 0.24%, 0.39%, and 0.11% high F1-score when analyzed to the existing methods like TS-FAP-SVM, ICP-CNN and EEAG-GAN methods respectively. The goal of future directions is to lessen ambiguity between different styles. This research will investigate shallow and deep networks that are interdependent and capable of differentiating between highly similar styles, as well as hierarchical information-sharing systems.

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