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Therapeutic Effect of Visual Expressive Arts Based on Deep Learning

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Abstract: - Art therapy is an innovative and versatile form of psychotherapy that utilizes the creative process of art making as a therapeutic tool to address emotional, psychological, and social challenges. This approach acknowledges the inherent connection between art and human expression, dating back to ancient times when art was used for healing and self-discovery. In this manuscript, Therapeutic effect of visual expressive arts based on deep learning (TE-VEA-DHNN) is proposed. Initially, the images are collected from WikiArt Emotions dataset are given as input. The input images are fed to pre-processing using Confidence partitioning sampling filtering (CPSF) for remove the background noise from the input image. Afterward the pre-processed image is given to Synchro Transient Extracting Transform (STET) for extracting the texture features such as entropy, contrast, correlation and Homogeneity. Then the extracted features are given to Dense Hebbian Neural Network for predicting the artistic expressions and provide therapists with insights into their emotional states. In general,18:05:24 Dense Hebbian Neural Network (DHNN) does not express adapting optimization strategies to determine optimal parameters to ensure accurate prediction based on visual expressive arts therapy. Hence, the Archerfish Hunting Optimizer (AHO) is to optimize to DHNN which accurately predict the visual expressive arts therapy. The proposed TE-VEA-DHNN approach is implemented in Python. The performance of the proposed TE-VEA-DHNN approach attains 23.26%, 24.37% and 25.97% higher accuracy and 21.73%, 23.84% and 25.87% higher recall compared with existing methods such as application of deep learning in art therapy (AT-CNN), An art therapy evaluation method based on emotion recognition using EEG deep temporal features(ATEM-LSTM) and A Portrait of Emotion: Empowering Self-Expression through AI-Generated Art (ESE-AI-GA) respectively.

Keywords: Therapeutic Effect, Visual Expressive Arts, Emotion, Art Therapy, Wikiart, Confidence Partitioning Sampling Filtering, Texture Features, Dense Hebbian Neural Network.

I. INTRODUCTION

The increasing speed of life and the quickening growth of civilization have brought mental health issues to the forefront of public discourse [1]. The accelerating pace of life and the rapid advancement of civilization have elevated mental health concerns to the fore of public conversation [2, 3]. Traditional psychotherapy is useful, but it has drawbacks as well, including a lengthy treatment period, significant side effects, and an unpredictable cure [4-6].Through the expression and production of art forms, expressive arts therapy (EXAT), a novel kind of psychotherapy, and painting therapy can help patients better understand and express their feelings, reduce stress, and enhance their mental health [7-8]. Creative works gain importance during the EXAT process due to the client's relevance and meaning for them [9-12]. Psychotherapy, rehabilitation nursing, education, and other sectors have made extensive use of the treatment approaches due to their wide range of applications, mild side effects, and speedy therapeutic impact.

The use of painting and other creative expression to enhance mental health in individuals is known as art therapy [13]. People can use colors, lines, and forms to represent their inner feelings and experiences when they are producing art. It is thought that this type of artistic self-expression aids in inner balance, better emotional control, stress reduction, and self-awareness [14-16]. Numerous psychological conditions, such as anxiety disorders, depression, PTSD, and challenges with self-esteem, have been effectively treated using art therapy. Traditional art therapy still has a number of difficulties, though [17, 18]. First of all, because art therapy needs specialized education, licensing, and training in both psychology and painting, there aren't many licensed painting therapists in some places or underdeveloped areas. This makes it challenging for people to get possibilities for art therapy in certain places [19]. Second, there is a lack of standardization and clear guidelines regarding the painting therapy therapeutic process and assessment techniques. Because every person has different requirements and circumstances, inconsistent treatment procedures and evaluation methods might lead to inconsistent treatment outcomes and a lack of comparability [20]. Finally, painting therapy may not be a good fit for typical quantitative assessment techniques because of the subjective and individualized character of artistic expression.

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Therapeutic effect of visual expressive arts based on deep learning (TE-VEA-DHNN), addresses several key challenges in traditional art therapy while introducing novel methods for assessment and optimization. By utilizing deep learning techniques and advanced algorithms, your proposed system offers a promising solution to improve the effectiveness and accessibility of art therapy. Integrating the WikiArt Emotions Dataset into the therapeutic effect of visual expressive arts based on DHNN significantly enriches the approach by offering a nuanced understanding of how different artistic expressions evoke specific emotions, enhancing the personalization of therapeutic interventions based on individual preferences and emotional responses. With access to annotations on emotional responses, preferences regarding depictions of faces or bodies, and individual ratings of liking or disliking, TE-VEA-DHNN can fine-tune its recommendations, ensuring a tailored therapeutic experience. Additionally, the dataset facilitates research-driven optimization, contributing to ongoing studies in emotions, art, and human psychology, thereby advancing our understanding of art therapy's underlying mechanisms. This integration holds promise for revolutionizing art therapy by enhancing its accessibility and effectiveness for individuals seeking mental health support.

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

- In this research, Therapeutic Effect of Visual Expressive Arts Based On Deep Learning (TE-VEA-DHNN) is proposed.
- Develop a Confidence partitioning sampling filtering (CPSF) based pre-processing method for remove the remove the background noise from the input image.
- Texture Features are extracted using Synchro Transient Extracting Transform. Dense Hebbian Neural Network (DHNN) is constructed to predict the artistic expressions and provide therapists with insights into their emotional states. Propose an Archerfish Hunting Optimizer (AHO) to optimize the weight parameter of DHNN.
- The competence of the suggested approach is analysed with the current methods like AT-CNN, ATEM-LSTM, and ESE-AI-GA models respectively.

The remaining manuscripts are arranged as follows: Part 2 provides a brief overview of the previous study, Part 3 outlines the suggested technique, Part 4 discusses and confirms the findings, and Part 5 wraps up the paper.

II. RECENT RESEARCH WORK: A BRIEF REVIEW

Numerous studies were have presented before in literatures were depending on visual expressive arts based on deep learning. Few of them were mentioned here.

Kim et al. [21] have presented A deep learning technique for art therapy based on CNNs (Convolutional Neural Networks). Natural language processing and computer vision researchers have been examining deep learning (DL) models for image classification and caption generation. In particular, the state-of-the-art (SOA) has been achieved through the use of pre-trained models for transfer learning and CNN-based image DL models on massive datasets. a CNN model that determines drawings to identify symbolic elements that serve as hints during the art therapy procedure.

Specifically, apply the image captioning and attention techniques of DL to identify psychological features in each drawing. After key features in drawings have been identified and summarized through the presented methodology, a psychotherapist can make consistent and standardized interpretation based on this in more efficient way.psychological elements in every illustration. A psychotherapist may more effectively analyze drawings using a consistent and standardized approach after the process has been used to identify and summarize essential aspects.

Zhichuan Tang et al. [22] have developed an art therapy evaluation technique based on the electroencephalogram (EEG) that might assess the therapeutic impact by looking at emotional shifts that occurred both before and after the art therapy. In a two-step experiment (drawing treatment step and emotion stimulation step), twelve individuals were recruited, and self-assessment ratings and EEG signals were recorded. The long short-term memory (LSTM) network was utilized to extract the deep temporal aspects of the EEG in order to distinguish emotions; the self-assessment model (SAM) was employed to acquire and categorize the real emotional states. Additionally, a comparison and analysis was conducted among the categorical results in various sequence lengths, time-window lengths, and recurrence configurations.

Yoon Kyung Lee et al.[23] have developed the ways in which generative artificial intelligence (AI) may mirror writers' cognitive processes through artistic expression, as well as its limits. The capacity of the AI-generated art to comprehend human intent (alignment) and visually depict emotions based on standards like originality, aesthetics, novelty, enjoyment, and depth was the main focus. The writers' emotional descriptions of the imagery were preferred above the key events, according to the results. Additionally, it discovered that visuals that overly emphasize stereotypes or certain components had a detrimental effect on AI alignment.

Ying Wei and Shijin Yu [24] have presented College and university art students frequently had to balance the demands of both cultural studies and painting classes. They are at a higher risk of developing mental health issues and bear a significant psychological load. To help them navigate, mitigate, and resolve their psychological issues, they must put in more effort. The instruction of art students' mental health was incorporated with expressive art therapy. Students can actively express their inner feelings, experiences, and feelings through painting, music, sand tables, ceramic art, OH cards, psychodrama, and other media. This helps them to achieve the goals of reducing negative emotions, growing in self-awareness, and encouraging the healthy development of their personalities.

Megan Beerse et al. [25] have presented College students' long-term mental and physical health, as well as their academic performance, are threatened by stress and anxiety. However, because of the demanding academic schedule, it is challenging to provide even short-term mental health interventions. An online platform was primarily used to recruit a convenience sample of full-time students at a public institution for a 5-week research. Random assignments were made to place participants in either the Neutral Clay Task (NCT) or the Mindfulness-Based Art Therapy (MBAT) intervention. Measures were taken of salivary cortisol levels, anxiety, and perceived stress.

Lennart Jütte et al. [26] have developed to offer an extra tool for art therapy in the disease treatment of melanoma—a well-trained image style transfer model capable of producing original artwork from individual dermoscopic melanoma pictures in a timely manner. Appreciating visual art is a popular type of art therapy used in disease management that quantifiably lowers psychological discomfort. to create a network for style transfer that is based on the cycle-consistent generative adversarial network that produces customized and one-of-a-kind artworks from photos of dermoscopic melanoma.

Kai-Lung Hua et al. [27] have developeda novel method for classifying digital painting photos according to the creator. From a painting image, we build a multi-scale pyramid to take into account the information included in the image both locally and globally. We train a CNN model to get the class label for each layer. Use Markov random fields (MRFs) to optimize the Gibbs energy function, which is defined by the data term (which measures how well a label matches the provided data) and the smoothness term (which penalizes assignments that label adjacent patches differently), in order to construct the relationship within local image patches.

III. PROPOSED METHODOLOGY

In this sector, therapeutic effect of visual expressive arts based on deep learning (TE-VEA-DHNN) is deliberated. Block diagram of suggested TE-VEA-DHNN method is in Figure 1. It covers such stages as Confidence partitioning sampling filtering, Synchro Transient Extracting Transform, Dense Hebbian Neural Network and Archerfish Hunting Optimizer.

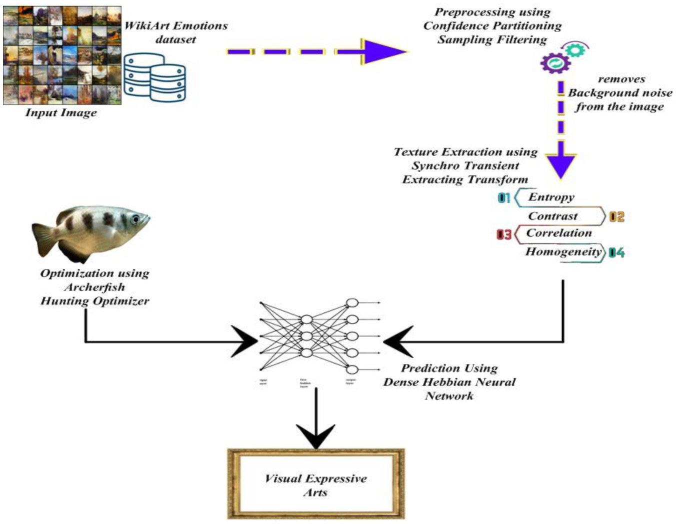

Figure 1: Block diagram of suggested TE-VEA-DHNN method

This manuscript utilizes a multi-step process to leverage the WikiArt Emotions Dataset for predicting artistic expressions and understanding emotional states. Initially, images were collected from the dataset and subjected to pre-processing using Confidence Partitioning Sampling Filtering (CPSF) to remove background sound. Subsequently, the pre-processed images feelSynchro Transient Extracting Transform (STET) to extract texture features like as entropy, difference, correlation, and sameness. These extracted features serve as input for a Dense Hebbian Neural Network (DHNN), which predicts artistic expressions and provides insights into emotional states. To enhance prediction accuracy, the AHO is employed to optimize DHNN parameters. The entire TE-VEA-DHNN method is applied in Python, demonstrating its practical feasibility.

A. Data Acquisition

The input image for this section was gathered from the WikiArt Emotions Dataset [28]. WikiArt feelings is a dataset including annotations for the feelings elicited in the viewer for 4,105 artworks, the majority of which are paintings. The paintings were chosen from the twenty-two categories (impressionism, realism, etc.) of four western genres (Renaissance Art, Post-Renaissance Art, Modern Art, and Contemporary Art) inside the collection of WikiArt.org. WikiArt.org features a Featured page with significant artwork from each category. From each category's highlighted page, we chose 200 articles. Crowd sourcing is used to annotate the artwork with one or more of the twenty emotion categories (including neutral). Apart from the emotions expressed in the artwork, annotations are made on its facial representation and the degree to which the viewers find the piece appealing.

B. Pre-Processing Using Confidence Partitioning Sampling Filtering

In this section, Pre-Processing using CPSF [29] is discussed. The suggested CPSF is used to remove the background noise from the input image. In the method incorporating Confidence Partitioning Sampling Filtering, numerous advantages emerge. Firstly, personalized therapy is facilitated through deep learning algorithms, enabling tailored interventions based on individual responses. This approach fosters more effective outcomes by addressing specific needs. Secondly, the method offers an objective analysis, reducing dependence on subjective interpretations and ensuring consistent assessments of progress. Thirdly, efficiency is enhanced as automated analysis streamlines evaluation, allowing therapists to allocate more time to personalized support. Additionally, the method harnesses the power of pattern recognition inherent in deep learning, uncovering complex relationships within data to provide valuable insights for therapy practice and research. Furthermore, scalability is ensured, with deep learning models capable of analysing large volumes of artwork across diverse settings and populations. Lastly, the iterative nature of continuous improvement enables on-going refinement of the models, ensuring adaptability to emerging insights and evidence, thus further enhancing effectiveness.

$$\omega_d = \frac{q(\hat{j}_d)}{\sum_{d=1}^{D} q(\hat{j}_d)} \tag{1}$$

Where q represents the sampling interval, $\hat{j}$ is used as a dimension for sampling interval, $q(\hat{j}_d)$ is the partitioning sampling input and D is the maximum space under the probability information, the probability space can be greatly compressed into a bounded probability space ω_d with losing a negligible amount of probability information.With just a little loss of probability information, the probability space may be significantly compressed into a limited probability space, ω_d .The noise removal from the input image is given in equation (2),

$$i(j) = \sum_{d=1}^{D} \omega_d \delta(j - \hat{j}_d) \tag{2}$$

Where $\sum_{d=1}^{D}$ represents the weighted impulse function, ω_d represents the bounded space, $(j - \hat{j}_d)$ represents the variety of noise and distortion, δ is the probability datadefined by their weights, d is the input of the noisy image and $i(j)$ is the minimized image frame from the given image. The partial prior impulse function is given in equation (3),

$$i_f(j_g \mid n_{1:g-1}) = \int i\left(j_g \mid j_{g-1}\right) \omega_{g-1,f} \delta(j_{g-1} - \hat{j}_{g-1,f}) dj_{g-1} \tag{3}$$

Where j_g represents the filtering of process noise, j_{g-1} denotes the additive property of the impulse function, ω_{g-1} is the sequences of prospect density function, δ is the increase in the accuracy and reliability of the grading system and i_f is the partial prior impulse function. Then resizing of the input images were given in equation (4),

$$\overline{O}^{\alpha}_{i(j_g|n1:g-1)} = \overset{R_{g-1}}{\underset{r-1}{\cup}} \left(\vec{j}_{g,r} + O^{\alpha}_{iw}\right) \tag{4}$$

Where $\overline{O}_{i(j_g|n1:g-1)}$ represents the weighted parameters which merged the flat files into a image frame of the given image, $\vec{j}_{g,r}$ is the sampled input image, $\overset{R_{g-1}}{\underset{r=1}{\cup}}$ represents the variable for resizing the image, O^{α}_{iw} is the image size reduces undesired changes and $\overline{O}^{\alpha}$ denotes the number of image frames from the given input image. Finally the input image is preprocessed successfully by removing the noise from the input image using CPSF. The preprocessed image is fed intoSynchro Transient Extracting Transform for extracting the texture features.

C. TextureExtraction Using Synchro Transient Extracting Transform

In this section, Feature Extraction using Synchro-Transient-Extracting Transform (STET) [30] is discussed. The proposed STET used to extracting texture features such as entropy, contrast, correlation and Homogeneity for better prediction. Moreover, STET's inherent interpretability allows therapists to gain insights into the underlying characteristics of the artwork contributing to therapeutic effect, fostering more informed therapeutic interventions. Additionally, STET exhibits robustness to variability in artistic style and expression, ensuring the generalizability of predictive models across diverse populations and artwork types. By integrating STET with deep learning techniques, the resulting models leverage the representational power of neural networks while benefiting from the texture features extracted by STET, thereby improving overall model performance and predictive accuracy in assessing the therapeutic impact of visual expressive arts. It is given in equation (5)

$$V(t, b+ct) = S_f(t)\sqrt{2\pi\beta(1-i\beta c)^{-1}} \tag{5}$$

Here, V is denotes the extraction of the feature image; $S_f(t)$ is denotes the partial derivative of the image extraction and $(1-i\beta c)$is denotes the accurately locate the image extraction. The reversibility is clearly retained by the STET, which just reassigns the extracting coefficients in the image direction. Points where two or more edges converge are called corners, and they are distinguished by a sudden shift in edge direction. Thus it is using equation (6)

$$c = \mu - \hat{s}^{[2]}(s,\mu)\left(\delta_\mu \hat{\mu}(s,\mu) / \delta_\mu \hat{s}(s,\mu)\right) \tag{6}$$

Here, c is denotes the purely impulses of the extraction; $(s,\mu)$is denotes the partial derivative of the image extraction; $\hat{s}$ is denotes the transient image and δ_μ is denotes the number of extracted image. Then the STET can accurately characterize the transient properties of diseases modulated to extracting small information and undetectable patterns from images. Blobs are areas of a picture with comparable hue or intensity. They are frequently employed to find spherical or round items. The Homogeneity is given in equation (7)

$$Homogeneity = \sum_{i,j} q(j,i) \Big/ 1 + |j-i| \tag{7}$$

The texture is described as an outward expression of how natural objects seem to human vision systems. Everyone can easily identify it, but figuring out the texture in a matrix might be challenging. However, it appears in a section of the matrix where texture has been examined using both quantitative and qualitative analysis. To discern the texture of an input picture, a statistical measure of randomness is applied. it is given in equation (8).

$$Entropy = -\sum\sum q(i,j)\log q(i,j) \tag{8}$$

where q stands for the quantity of GLCM gray level co-occurrence matrices. This scale's purpose is to calculate the likelihood of the designated pixel pairings as in Equation (9).

$$Correlation=\frac{\sum_{i=0}^{M-1}\sum_{i=0}^{M-1}(i-n_j)(j-n_i)q(i,j)}{\sigma_i\,\sigma_j} \tag{9}$$

Here $q(i, j)$ represent the pixel at position (i, j) and σ represent the standard deviation of the image. Finally Synchro-Transient-Extracting Transform (STET) has extracted the texture features such as entropy, contrast, correlation and Homogeneity from the pre-processed image. Then the extracted features are given to expressive art therapy prediction.

D. Expressive Arts Therapy Prediction Using Dense Hebbian Neural Network

In this section predicting Expressive Arts Therapy using Dense Hebbian Neural Networks (DHNN) [31] is discussed. DHNN is used to predicting the artistic expressions and provide therapists with insights into their emotional states. Firstly, the DHNN's architecture, inspired by Hebbian learning principles, allows it to capture intricate patterns and associations within the data, enabling more accurate predictions of therapeutic outcomes. This adaptability and learning capability are particularly beneficial in the background of EXAT, where the subtleties of artistic expression play a significant role in therapeutic effect. Secondly, DHNNs are known for their efficiency in learning complex relationships from large datasets, making them well-suited for handling the diverse and extensive data often encountered in expressive arts therapy research. This efficiency streamlines the analysis process and facilitates the extraction of meaningful insights from the artwork. Moreover, by choosing this method, therapists can leverage the power of deep learning to gain deeper insights into the therapeutic potential of visual expressive arts, ultimately enhancing the efficacy and precision of therapeutic interventions it can be expressed in equation (10).

$$\Re(\xi_j^v)=\frac{1}{2}\left[\delta_{\xi_j^v,-1}+\delta_{\xi_j^v,+1}\right] \tag{10}$$

Where $\Re(\xi_j^v)$ represents the probability distribution function for the variable, $\delta_{\xi_j^v,-1}$ represent a specific value of the negative direction and $\delta_{\xi_j^v,+1}$ represent a specific value of the positive direction. In order to achieve this, The input leak-augmented scalograms were convolved with different filters in the convolutional layer. Because the AE shots were 3D, the convolution technique was applied to each channel separately. The related archetypes can be expressed in the given equation (11)

$$\Re(\eta_j^{\mu,b}\,|\,\xi_j^v)=\frac{1+s}{2}\delta_{\eta_j^{\mu,b},+\xi_j^{\mu}}+\frac{1-s}{2}\delta_{\eta_j^{\mu,b},-\xi_j^{\mu}} \tag{11}$$

Whereas $\Re(\eta_j^{\mu,b}\,|\,\xi_j^v)$ is in the Hebbian synaptic tensors, $\delta_{\eta_j^{\mu,b},+\xi_j^{\mu}}$ is the information that is allotted in the intensity of the neuronal interactions, and $\delta_{\eta_j^{\mu,b},-\xi_j^{\mu}}$ is the associated archetype, s functions as a nonlinear activation function. Technically speaking, It is important to note that we all work under the conventional replica-symmetry assumption, which is to say that we assume that all order parameters exhibit vanishing fluctuations around their means in the thermodynamic limit. It is possible to convey the creative feeling in the given equation (12)

$$\mathrm{B}_{M,K,N,s,\beta}^{(Q)}=\frac{1}{M}E\log\aleph_{M,K,N,s,\beta}^{(Q)}(\eta) \tag{12}$$

Where $\mathrm{B}_{M,K,N,s,\beta}^{(Q)}$ this likely represents some functions, M represent a parameter or a variable, η this might represent another variable and $\log$ is the natural logarithm function. It is specifically constructed over a collection of patterns that together make up a disturbed form of certainindefinite archetypes, which the net must deduce, store, and potentially recover. The quenched average can be expressed in the given equation (13)

$$\omega[(.)]:=\frac{1}{\aleph_{M,K,N,s,\beta}^{(Q)}(\eta)}\sum_{\sigma}^{2^M}(.)A_{M,K,N,r,\beta}^{(Q)}(\sigma|\eta) \tag{13}$$

Where $\omega[(.)]$ defines a function ω acting on some argument, $\aleph^{(Q)}_{M,K,N,s,\beta}(\eta)$ It seems like a partition function that varies with the settings, $A^{(Q)}_{M,K,N,r,\beta}$ this appears to be an additional function A that depends on the inputs and $(\sigma|\eta)$ this notation implies that σ is dependent upon η. The pooling layer's feature maps are fundamentally organized as illustrated in Equation (14)

$$G^{(un\sup)}_{i_1 \dots i_p} = \frac{1}{P^{R/2} N} \sum_{\mu=1}^{K} \sum_{b=1}^{N} \eta^{\mu,b}_{i_1} \dots \eta^{\mu,b}_{i_p} \tag{14}$$

When $P^{R/2} N$ is the same archetype prior to exposing them to the network, $G^{(un\sup)}_{i_1 \dots i_p}$ represents the role of the instructor in Hebbian learning. $\eta^{\mu,b}_{i_1}$ is the standard Hopfield model and $\eta^{\mu,b}_{i_p}$ is the supervised and unsupervised settings. Finally the DHNN has detected theleak. In this work, AHO is employed to optimize the DHNN optimum parameters ξ^{v}_{j} *and* $\aleph$. Here AHO is employed for turning the weight and bias parameter of DHNN. For this an optimization algorithm is used which is shown in following section.

E. Optimization Using Archerfish Hunting Optimizer

In this section, AHO [32] is utilized to enhance the parameter ξ^{v}_{j} and $\aleph$ of suggested a DHNN. The Archerfish Hunting Optimizer uses archerfish hunting techniques' natural precision and efficiency to improve targeted search algorithms. This algorithm, which mimics the fish's ability to use water jets to properly take down prey, promises to improve search and targeting procedures by rapidly recognizing and eliminating irrelevant possibilities while focusing on the most relevant targets. The goal is to improve the effectiveness and speed of numerous optimization tasks, including as data mining and resource allocation, search engine algorithms, and focused marketing campaigns, by replicating the archerfish's strategic approach. Any issue with a well-defined objective function may be solved using the gradient-free optimization technique known as AHO.

1) Stepwise Procedure for AHO

Here, a step-by-step procedure based on AHO is provided for obtaining the ideal DHNN value. To start, AHO creates a population that is evenly distributed in order to maximize the DHNN's ideal parameter.

Step1: Initialization Phase

The first phases The shooting and leaping motions of archerfish while chasing insects served as inspiration for the exploration and exploitation stages of AHO. With the right formulation of the objective function, AHO, a gradient-free optimization technique, may solve any optimization problem.

$$H = \begin{bmatrix} z_1^1 & z_2^1 & \cdots & z_m^1 \\ z_1^2 & y_2^2 & \cdots & z_m^2 \\ \vdots & \vdots & \cdots & \vdots \\ z_1^n & z_2^{EHS} & \cdots & z_m^n \end{bmatrix} \tag{15}$$

Here, H is represent the range of allowed values; n is represent the iteration; m is represent the space of dimension.

Step2: Random Generation Phase

the input parameters generated after setup at random. The selection of ideal fitness values was contingent upon a clear hyperparameter scenario.

Step 3: Fitness Function

The initial assessments are used to construct an arbitrary solution.It is given by equation (16)

$$FitnessFunction = Optimization\left(\left[\xi^{v}_{j}\ and\ \aleph\right]\right) \tag{16}$$

Where, ξ^{v}_{j} represent increasing the accuracy; $\aleph$ decreasing the loss.

Step 4: Search Space Estimation ξ^{v}_{j}

Diversification or global optimization are terms used to describe the exploration. Metaheuristic algorithms can avoid local optimums by exploring new search space regions. Excessive exploratory operations can waste work and divert attention away from improving the quality of the current solution.

$$W^{\langle h,s+1\rangle} = W^{\langle h,t\rangle}\xi_j^v + f^{-\left\|W_{prey}^{\langle j,s\rangle} - W^{\langle h,s\rangle}\right\|^2} \tag{17}$$

Here, $W^{\langle h,s+1\rangle}$ is represent the next location of archerfish h ; V^m is represent the denotes the binary complex; $W^{\langle h,s\rangle}$ is represent the current location of archerfish h ; $\|\cdot\|$ is represent the Euclidean distance; $W_{prey}^{\langle j,s\rangle}$ is represent the prey's location.

Step 5: New Location $\aleph$

Local optimization or intensification are terms used to describe the exploitation. Exploitation is one way that metaheuristic algorithms may concentrate on certain problems and find the best answer. The algorithm may converge too soon and become stuck in local optimal regions as a result of overuse of exploitation operations. They are employed in the assessment of AHO's exploitation potential.

$$W_{prey}^{\langle j,s\rangle} = W^{\langle j,s\rangle}\aleph + \left(0,\ldots,\frac{u^2}{2f}\times\sin 2\theta_0,\ldots 0\right) + \varepsilon \tag{18}$$

Here, $\frac{u^2}{2_f}\times\sin 2\theta_0$ is represent the random number in the range; ε is represent the A vector; $t(s)$ is represent the membrane potential of the postsynaptic neuron.

Step 6: Termination

The AHO is used to improve the value of the ξ_j^v *and* $\aleph$ generator weight parameter from Attention Spiking Neural Networks; and it Continue with step 3 until the halting requirement is met. The proposed TE-VEA-DHNN algorithm efficiently predicts the visual expressive arts therapy.

IV. RESULT AND DISCUSSION

The suggested TE-VEA-DHNN technique's results have forecast the healing potential of visual expressive arts. This suggested approach is put into practice using Python, and it is assessed using a number of performance analysis measures, including score, recall, accuracy, precision, and loss analysis. Comparisons are made between the outcomes of the suggested TE-VEA-DHNN methodology and those of other approaches, including AT-CNN, ATEM-LSTM, and ESE-AI-GA.

A. Performance Metrics

Accuracy, precision, recall, F-measure, loss, and ROC are examples of performance metrics. It is determined to scale the performance parameters using the confusion matrix.

1) Accuracy

The value of accuracy is calculated as ratio of the count of samples accurately categorized by scheme with total count of samples, which is computed using equation (19),

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{19}$$

Where TP represent the true positive, TN represent the true negative, FP represent the false positive and FN represent the false negative.

2) Precision

It assesses a sample's predictive value, which varies depending on the class for which it is calculated; in other words, it determines the sample's predictive power, which is determined by equation(20).

$$\Pr ecision = \frac{TP}{(TP+FP)} \tag{20}$$

3) Recall

The recall of a machine learning model measures how well it can recognize good samples. Put another way, it measures the likelihood of getting a favorable result. Equation provides that (21)

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{21}$$

4) F-Measure

The F-measure or F1 score are other names for the F-score. It is a measure employed to assess a machine learning model's performance. It generates a single score by merging recall and accuracy.

$$F - Measure = \frac{2*(precision*recall)}{precision + recall} \tag{22}$$

5) ROC

It is provided by the equation and is the ratio of the real positive area to the fake negative area. (23)

$$ROC = 0.5 \times \left(\frac{TP}{TP + FP} + \frac{TN}{TN + FP} \right) \tag{23}$$

6) Loss

The loss curve indicates the values of the models loss over time. The loss graph serves as a tool for understanding how well the deep learning model is capturing patterns or features relevant to therapeutic outcomes.

B. Performance Analysis

The imitation outputs of TE-VEA-DHNN method are shown in figure 2 to 7. The proposed TE-VEA-DHNN method is associated to current AT-CNN, ATEM-LSTM and ESE-AI-GA models respectively.

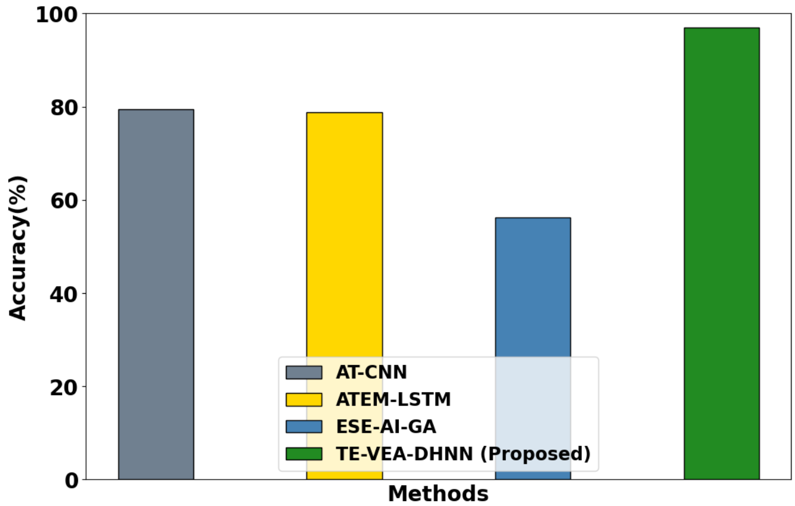

Figure 2: Accuracy performance analysis

Figure 2 shows theAccuracy performance analysis. The bar graph illustrates the performance comparison of four different deep learning methods used for therapeutic visual expressive arts, evaluated based on their accuracy percentages. The proposed method compared with AT-CNN, ATEM-LSTM and ESE-AI-GA respectively. The proposed TE-VEA-DHNN method, demonstrates superior performance in enhancing the therapeutic effects of visual expressive arts compared to the other methods analysed. With an accuracy of 22.54%, 26.36% and 25.95% it significantly outperforms of existing AT-CNN, ATEM-LSTM and ESE-AI-GA. This suggests that TE-VEA-DHNN is exceptionally effective in providing personalized and adaptive therapeutic outcomes, making it a highly promising approach for integrating deep learning into art therapy practices. The results highlight the potential for deep learning models, particularly TE-VEA-DHNN, to revolutionize the field of art therapy by offering more accurate, adaptive, and personalized therapeutic interventions.

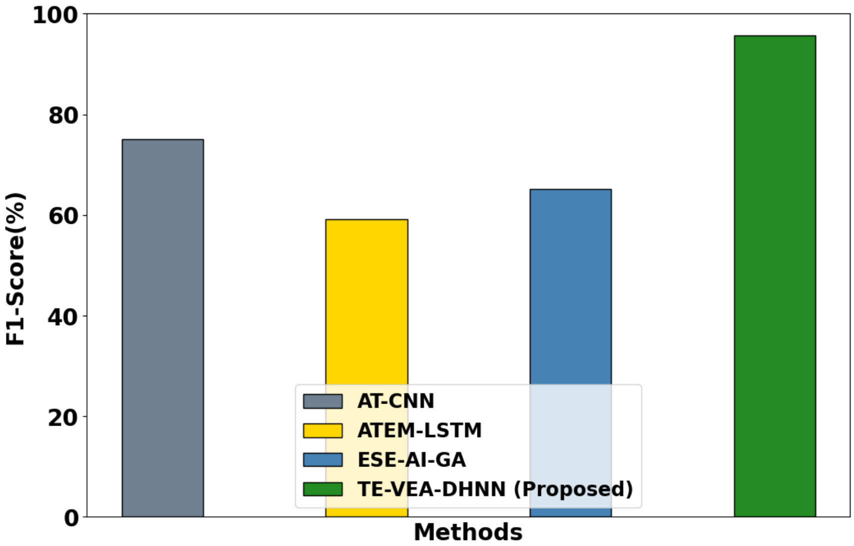

Figure 3:F1-score performance analysis

Figure 3 shows theF1-score performance analysis.The bar graph illustrates the performance comparison of four different methods based on their F1-scores. The methods compared are AT-CNN, ATEM-LSTM and ESE-AI-GA respectively. The proposed method, TE-VEA-DHNN, demonstrates superior performance in enhancing the effectiveness of visual expressive arts therapies compared to the other methods analysed. With anhigher F1-score of 21.56%, 24.35% and 25.98%. This suggests that TE-VEA-DHNN is exceptionally effective in achieving a balance between precision and recall, making it a highly promising approach for integrating deep learning into art therapy practices. The results highlight the potential for deep learning models, particularly TE-VEA-DHNN, to revolutionize the field of art therapy by offering more accurate, adaptive, and personalized therapeutic interventions.

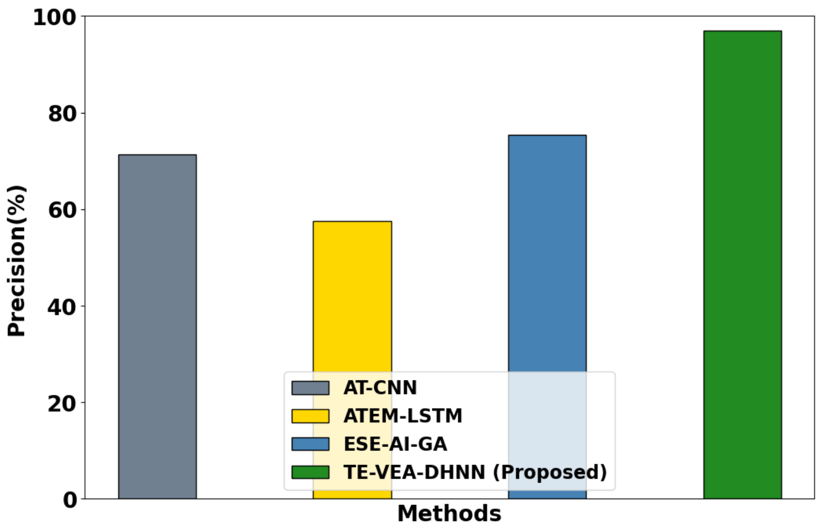

Figure 4: Precision performance analysis

Figure 4 shows thePrecision performance analysis.The bar graph illustrates the performance comparison of four different methods based on their precision percentages. The methods compared are AT-CNN, ATEM-LSTM and ESE-AI-GA respectively. The proposed method, TE-VEA-DHNN, demonstrates superior performance in enhancing the precision of visual expressive arts therapies compared to the other methods analysed. With an high precision of 21.62%, 22.95% and 25.98%. This suggests that TE-VEA-DHNN is exceptionally effective in accurately identifying and delivering relevant therapeutic outcomes, making it a highly promising approach for integrating deep learning into art therapy practices. The results highlight the potential for deep learning models, particularly TE-VEA-DHNN, to revolutionize the field of art therapy by offering more accurate, adaptive, and personalized therapeutic interventions.

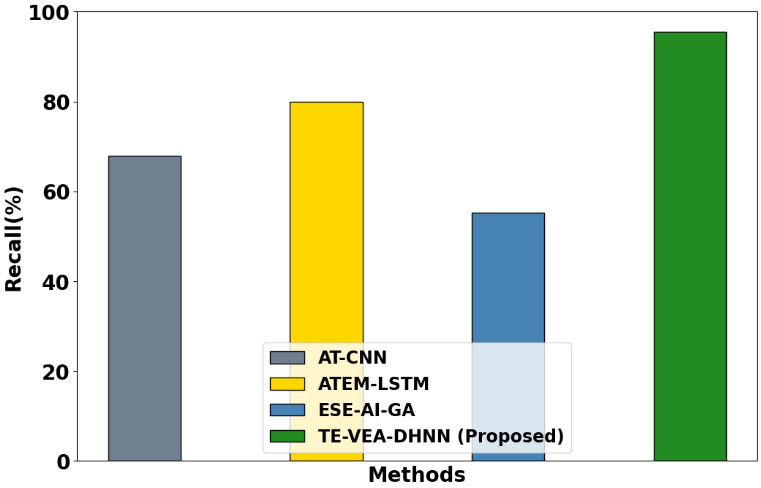

Figure 5: Recall performance analysis

Figure 5 shows theRecall performance analysis.The bar graph illustrates the performance comparison of four different methods based on their recall percentages. The methods compared are AT-CNN, ATEM-LSTM and ESE-AI-GA. The proposed method, TE-VEA-DHNN, demonstrates superior performance in enhancing the recall of visual expressive arts therapies compared to the other methods analysed. With a recall of 21.73%, 23.84% and 25.87% is higher. This suggests that TE-VEA-DHNN is exceptionally effective in identifying and addressing all relevant therapeutic outcomes, making it a highly promising approach for integrating deep learning into art therapy practices. The results highlight the potential for deep learning models, particularly TE-VEA-DHNN, to revolutionize the field of art therapy by offering more accurate, adaptive, and comprehensive therapeutic interventions.

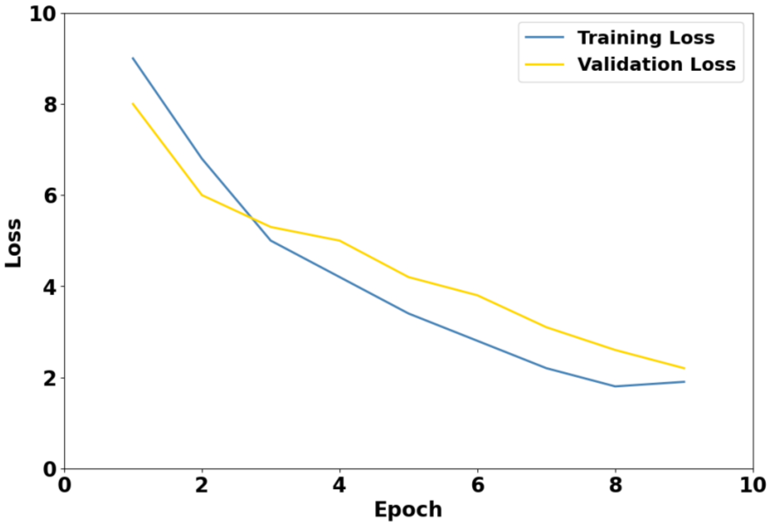

Figure 6: Performance analysis of loss

Performance analysis of loss is illustrated in figure 6. The bar graph illustrates the performance comparison of four different methods based on their loss percentages. The methods compared are AT-CNN, ATEM-LSTM and ESE-AI-GA respectively. The proposed method, TE-VEA-DHNN, demonstrates superior performance in minimizing loss compared to the other methods analysed. This suggests that TE-VEA-DHNN is exceptionally effective in reducing errors of 2%, making it a highly promising approach for integrating deep learning into art therapy practices. The results highlight the potential for deep learning models, particularly TE-VEA-DHNN, to revolutionize the field of art therapy by offering more accurate, adaptive, and error-free therapeutic interventions.

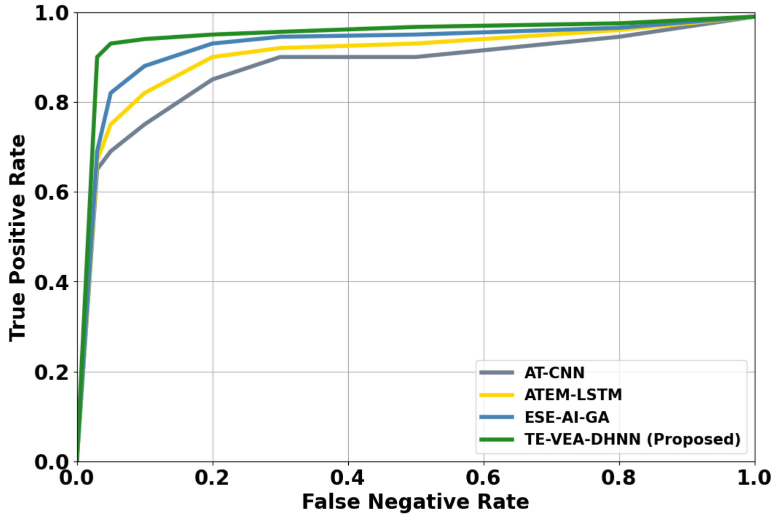

Figure 7: Performance analysis of ROC

Performance analysis of ROC is illustrated in figure 7. The bar graph illustrates the performance comparison of four different methods based on their ROC (Receiver Operating Characteristic) analysis. The methods compared are AT-CNN, ATEM-LSTM and ESE-AI-GA respectively. The proposed method, TE-VEA-DHNN, demonstrates superior performance in ROC analysis compared to the other methods analyzed. With a ROC score of 0.97%, 0.92% and 0.95% is higher. This suggests that TE-VEA-DHNN is exceptionally effective in distinguishing between different therapeutic outcomes, making it a highly promising approach for integrating deep learning into art therapy practices. The results highlight the potential for deep learning models, particularly TE-VEA-DHNN, to revolutionize the field of art therapy by offering more accurate, adaptive, and reliable therapeutic interventions.

C. Discussion

The proposed TE-VEA-DHNN approach revolutionizes art therapy by employing advanced deep learning techniques to analyse visual expressive arts. Through CPSF removes background noise from the input images, ensuring that the subsequent analysis focuses on the relevant artistic elements, Synchro Transient Extracting Transform (STET) for extracts critical texture features such as entropy, contrast, correlation, and homogeneity from the pre-processed images. These features are essential for understanding the emotional and psychological content of the artworks and Dense Hebbian Neural Network (DHNN) optimized with Archerfish Hunting Optimizer (AHO) for accurate prediction, TE-VEA-DHNN significantly improves therapy outcomes. Compared to existing methods like AT-CNN, ATEM-LSTM, and ESE-AI-GA, proposed TE-VEA-DHNN achieves remarkable enhancements across various performance metrics. It attains 23.26%, 24.37%, and 25.97% higher accuracy and 21.73%, 23.84%, and 25.87% higher recall rates respectively, indicating its superior ability to identify and address therapeutic outcomes. Moreover, TE-VEA-DHNN demonstrates balanced improvements in precision and recall, with F1-score enhancements of 21.56%, 24.35%, and 25.98%. Additionally, the model reduces errors by 2% and achieves higher ROC scores of 0.97%, 0.92%, and 0.95%, showcasing its reliability in distinguishing between therapeutic states. These advancements make TE-VEA-DHNN a promising tool for offering more accurate, adaptive, and personalized interventions in art therapy, addressing the challenges of traditional methods and widening accessibility to effective mental health treatments.

V. CONCLUSION

In this manuscript, Therapeutic effect of visual expressive arts based on deep learning (TE-VEA-DHNN)was successfully implemented. The proposed TE-VEA-DHNN approach is implemented in Python. The WikiArt Emotions Dataset offers valuable insights into the emotional responses evoked by visual art, shedding light on the impact of various factors such as artistic style, content, and observer perception. The consistent annotations of dominant emotions like fear, happiness, love, and sadness across different art styles provide a robust foundation for further analysis. Additionally, the dataset highlights the significant influence of the artwork title on emotional interpretation, emphasizing the interconnectedness of visual and textual elements in art perception. The performance of the proposed TE-VEA-DHNN approach contains 22.54%, 26.36% and 25.95% higher accuracy and 21.56%, 24.35% and 25.98% higher F-measure when analysed to the existing methods like AT-CNN, ATEM-LSTM and ESE-AI-GA respectively. In future research entails refining ML algorithms to enhance the accuracy of predicting emotions suggested by art. This involves exploring the synergy between textual descriptions and image features for emotion detection and investigating visual attributes contributing to art's evocativeness. Advancements in deep learning for altering artwork's affective impact could yield sophisticated tools for generation and manipulation. Integrating emotion-based search into online art platforms and conducting user studies to validate technologies while addressing ethics are crucial.

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