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Article

Biometric painting: Integrating biosensor data into the creative process

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Abstract: Art has been a medium of self-expression, evolving with technological advancements. Using physiological signals, biometric painting directly affects the artistic process. By bridging the gap between the artist's internal emotional state and the visual depiction of the painting, this fusion provides an innovative approach to examining and expressing human emotions. The objective is to investigate biometric painting, integrating biosensor data into the creative process. To expand the creative process of biometric painting by utilizing biosensor data to establish emotion recognition in biometric painting. A biometric painting system was created that used users' real-time biosensor data to gather visual components that represented their emotional and physical states. The data is preprocessed using a median filter to remove noise from the sensor data. Then, the features are extracted using wavelet transform (WT). The research introduces an Intelligent Remora Optimized Flexible Deep Belief Network (IRO-FDBN) to recognize emotion in biometric painting using biosensor data. The results indicate that the established model outperforms an emotion recognition model. The approach emphasizes the smooth combination of visual and affective feedback, allowing audiences to engage with the artwork on an advanced level. This provides a foundation for incorporating biosensor data into the creative process, advancing artistic exploration and effective content development.

Keywords: biometric painting; biosensor; creative process; intelligent remora optimized flexible deep belief networks (IRO-FDBN)

1. Introduction

Biometric painting is an innovative and creative method that combines physiological information attained by biosensors into the creative process. The emotional state of the artist is reflected by biosensors, which measure concurrent signals including heart rate, brainwave activity (EEG), galvanic skin response, and even breathing patterns. Following their dispensation by software algorithms, these signals are rehabilitated into visual components like colors, patterns, and shapes. This results in artwork that vigorously depicts feelings or physical states Ibsen et al. [1]. By converting physiological information, such as heart rate, skin conductivity, and brainwave activity into optical components, biometric data enhances artistic expression. Through this relationship, artists dynamically externalize their feelings and creative work that mirrors their inner emotions. It provides a fresh method for examining the emotional state of artistic procedures by bridging the gap between inspiration and knowledge Saeed [2]. Biosensors are used in concurrent emotion revelation to trace physiological information, like heart rate and brain activity, and exchange them into active visual patterns. This system enhances artistic emotions by enabling artists to characterize their emotional states quickly. It generates an immersive experience by fusing emotion and technology, strengthening the bonds between artists and their audiences Hasnine et al. [3]. The perfect mapping of physiological information to optical out puts is made possible by complex biometric painting technologies, including machine learning (ML) and signal processing. This method ensures particular evaluation and important adaptation of emotions into dynamic artwork. They turn the creative process into an active, emotionally attractive experience with superior accuracy and adaptability Ozkara and Ekim [4]. **Figure 1** shows the emotion analysis using biometric paintings.

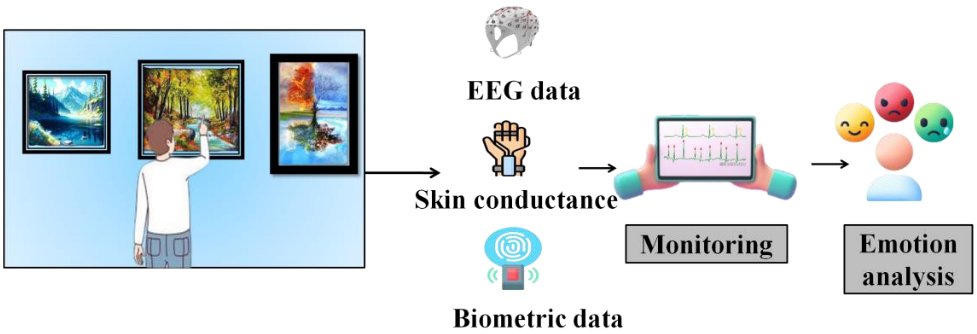

Figure 1. Unlocking emotions: Harnessing biometric data for real-time emotion Recognition.

Through concurrent emotion recognition, biometric painting fosters a mutual emotional experience between the artist and the viewer. Dynamic images permit the audience to recognize the artist's inner feelings, hopeful understanding, and contribution. The intensity and consequence of artistic meets are improved by this creative system that connects public expression with group knowledge Lin et al. [5]. Applications for biometric painting enlarge beyond the domain of art and comprise interactive activity, educational property for the growth of emotional aptitude, and treatment applications, including stress reduction and mood regulation. It offers a novel method of understanding and interacting with human emotions in a range of contexts by illustrating them artistically Morse et al. [6]. Biometric integration currents face challenges like controlling signal noise, ensuring accurate emotion-to-visual mapping and maintaining prominent stability between artistic autonomy and data-driven restrictions. While maintaining the artist's creative freedoms within a controlled, data-informed structure, it is challenging to understand multifaceted physiological signals, requiring complicated dispensation equipment Gnacek et al. [7].

Simulations of biosensors have served as a major source of encouragement for solving challenging human issues. In particular, the biomechanics have been several reports of attempts in the domain of robotics to enhance mechanical components by imitating organic structures. Tendons are composed and have been a key source of motivation in these physiological models for improving stabilizing joints and transferring force to the skeletal muscle Kim et al. [8]. The vast majority of people on the planet reside in cities, and it is predicted that within the next 30 years, three-quarters of the global population will live in metropolitan areas. They are caused by the use of new toxic substances in building substances, decorations, and consumer goods, as well as by poor design and improper care. Although this is mainly unknown, it would seem that as individuals expend more time in enclosed spaces and air circulation rates decrease due to buildings having been more airtight for energy effectiveness, amounts of exposure to the compounds in daily life should raise Persiani et al. [9].

The objective is to incorporate biosensor data into biometric painting so that emotions are recognized using physiological signals in real-time, enhancing the creative method. The research generates a system for emotion recognition utilizing Intelligent Remora Optimized Flexible Deep Belief Networks (IRO-FDBN). By including emotional and optical feedback, the method improves the creative practice and promotes a stronger emotional connection between the audience and the artwork.

Contribution of the research

By including biosensor data in the creative method, it investigates the integration of art and technology to provide a new method of emotional visual expression utilizing biometric painting. It fills the void between the emotional condition of the artist and the work they create. Key contributions are given below:

- To improve the emotional depth and interaction of the artwork by giving artists a new platform to express their innermost feelings in real time.
- The research uses wavelet transform (WT) for feature extraction after using sophisticated pretreatment methods, including median filtering, to clean sensor data. This ensures the accuracy and reliability of the data utilized for emotion recognition.
- It explores the limits of emotion recognition in a biometric painting by introducing a unique Machine Learning (ML) technique called IRO-FDBN to identify emotions from biosensor data.
- The outcomes show that the proposed method improved emotion identification, providing improved accuracy in recognizing emotional states through biometric information.

To create the foundation for future developments in art, emotional expression, and affective content creation by integrating biosensor data into the creative process, creating new opportunities for audiences and artists alike.

The remaining of the article is separated as follows: Section 2 summarizes the related article. Section 3 shows the method flow. Section 4 demonstrates the findings. Section 5 provides the discussion and Section 6 offers a conclusion.

2. Related work

This section provided earlier research on the integration of biometric information into creative processes, with an emphasis on biosensor-based emotion identification. It presents current strategies, techniques, and tools for bridging the gap between creative expression and physiological information.

Macruz et al. [10] explored new technologies to improve well-being by developing biophilic 2D geometries and utilizing EEG biosensors and facial micro expression analysis to measure human reactions. Applications in architecture and interior design were made possible by the results, which rank geometries according to emotional valence, meditation levels, and preferences, highlighting technology-driven, human-centered methods for improved surroundings.

Wu et al. [11] suggested BioFace- three-dimensional (3D), a portable, single-earpiece bio-sensing device that continually records facial motions and produces 3Dfacial animations. It does 3D facial reconstruction from bio-signals without visual input by using cross-modal transfer learning. Numerous tests demonstrated excellent facial tracking accuracy, user authentication, and resilience to threats.

Zhang et al. [12] created an academic painting sentiment dataset, and five deep learning (DL) approaches were tested to determine which one worked best. The final training accuracy of 54.17% was attained by refining the selected model. It improved knowledge of traditional academic painting and showed the promise of DL in Chinese cultural studies.

Guo et al. [13] examined the sentiment expression of oil painting topics in communal settings using neural network (NN) algorithms and big data identification technology. It created a framework for using these technologies to create oil paintings. High-resolution images were displayed in the experiment, but the image optimization procedure took a long time roughly an hour.

Bian and Shen [14] used an optimized Squeeze Net model for sentiment analysis along with the aesthetic qualities of Chinese paintings. The model's classification accuracy was improved by two optimizations adding a residual network and widening the model. The results of the research demonstrated improved generality and categorization accuracy in the emotion analysis of Chinese paintings.

Zhang et al. [15] suggested Inkthetics, a DL outline for evaluating the aesthetics of Chinese ink artworks. It outperformed present techniques by including handcrafted descriptions with a deep multi-view equivalent CNN (DMVCNN), improving artistic outcomes prediction by 5.7% and attaining a Pearson correlation of 0.843.

Cheng [16] suggested a new method for predicting the distribution of emotions in abstract paintings by applying the weighted nearest neighbor algorithm. In addition to using encoder-decoder architecture with a blank attention mechanism, emotional features were extracted. With an accuracy of 80.7%, the system surpassed existing categorization methods.

Liu et al. [17] examined immersive art in recent paintings, with exacting attention to substance semantics, protrusion mechanisms, and immersion. It draws attention to anthropology, semiotics, and psychology. It also examined the deficiency of education evaluation and the need for more systematic assessments. It concluded that enhanced learning potential and precision were presented by DL-based image design.

Wang [18] suggested a conditional random field-based sentiment analysis system that synthesized emotional polarity weights and extracted key lines from lengthy artwork. When it comes to sentiment analysis, it showed greater accuracy and efficiency than conventional techniques. Experiments demonstrated its efficacy and stability through increased F-value, accuracy, and recall.

Duan et al. [19] examined the growing desire from users for personalized design and suggested an imitative design approach based on AI sentiment analysis. It investigated the integration of AI emotion identification with personalized design, providing creative alternatives for future art derivative design, and validated the viability of this approach using a personalized design system powered by facial emotion features.

Muratbekova and Shamoi [20] presented a fuzzy set method that takes human subjectivity into account when classifying emotions in art. It developed the Wiki Art Dataset to remove fuzzy color-emotion relations utilizing 120 colors and 10 emotions. The outcomes enhanced emotion analysis by indicating strong associations, like fear with gray and support with orange, brown, and green.

Xu and Nazir [21] emphasized how art design utilized artificial Intelligence (AI) and ML to generate artistic competence and coherent emotions. By enabling interactive, superior designs, these techniques have transformed the construction, allotment, and education of art. It offered how AI and ML were impacting art design in the present situation.

Wędołowska et al. [22] created an ML technique that utilized the colors of images and videos to forecast emotions. It entails examining color extraction models, selecting superior techniques for analyzing the emotions in movies, and verifying the outcomes using an online survey. The system used baseline models and DL to unite clustering and histograms.

Lu et al. [23] examined ML-based painting emotion prediction, tackling the struggles connected to the nuance of visual signals. The research restricted performance by emphasizing semantic fundamentals. A model used feature fusion to combine object information with facial emotion and position features. Tests using open datasets demonstrated that the suggested approach was more effective than baseline techniques.

Tashu et al. [24] characterized emotions in art using a hybrid sentiment identification design that combined feature-level and modality attention. Through improved feature extraction and modality synthesis, the method facilitated genre-specific searches suggested paintings based on mood, and efficiently classified artworks. WikiArt experiments confirm its effectiveness in three different ways.

Chen et al. [25] integrated color classification models to present a quantitative approach to image emotion analysis. It provided consumers with thorough emotion analysis findings by combining important color attributes, assessing brightness saturation and black-and-white filling, and applying design principles to statistically analyze emotions.

Nolazco-Flores et al. [26] used the EMOTHAW database to examine temporal, spectral, and cepstral properties from tablet-captured signals for the identification of stress, anxiety, and depression. Using fast correlation-based feature selection the accuracy of classification was enhanced via filtering and data augmentation. The accuracy of an SVM with a radial basis and leave-one-out approach was 4%–34% greater than that of baseline models.

Kumar et al. [27] suggested a safe soft-biometric system that used AlexNet to classify age, gender, expressions, and spoofing and a 5-layer U-Net for emotion detection. Tested on six datasets, it beat current techniques and obtained 96.9% accuracy for expressions, improving patient-doctor interactions and medical data accessible worldwide.

Martínez-Díaz et al. [28] assessed three lightweight face recognition models for masked face recognition, with an emphasis on periocular images and fine-tuning with masked faces. It used both simulated and actual datasets for experiments. The findings demonstrated that fine-tuning masked images produced improved outcomes than the particular system and it was more efficient than modern methods.

Particularly in the area of biomechanics tracking, the medical field is presently undergoing a substantial transition from central healthcare structures to residence-based and customized surveillance approaches. Utilizing cutting-edge nanostructures to create innovative biosensors that are mobile for applications in cardiology is gaining traction. With an emphasis on their uses in blood pressure measurement, acceleration of pulse waves assessment, cardiac activity monitoring, and biosensors detection, it offers a thorough examination of the products to design ideas, working processes, and most current developments associated with such sensors Chen et al. [29].

Glaucoma is a leading cause of irreversible vision loss due to its complex relationship with intraocular pressure (IOP). These technological advancements are incorporated into clinical practice, highlighting their practical uses, patient-centered approaches, and opportunities for further advancement in IOP control. By combining theoretical ideas, cutting-edge medical technology, and useful clinical discoveries. These contribute an integrated and complete view of the IOP biosensor's involvement in glaucoma, acting as a guide for ophthalmological academics, physicians, and professionals Wu et al. [30].

3. Methodology

The research gathers data from biometric paintings and biosensor data (heart rate, EEG, etc.). Median filtering is used for data preprocessing to reduce noise and then feature extraction employs Wavelet Transform (WT) for time-frequency analysis and the IRO-FDBN is used for emotion detection to facilitate the development of emotion-based artwork. **Figure 2** shows the methodological flow.

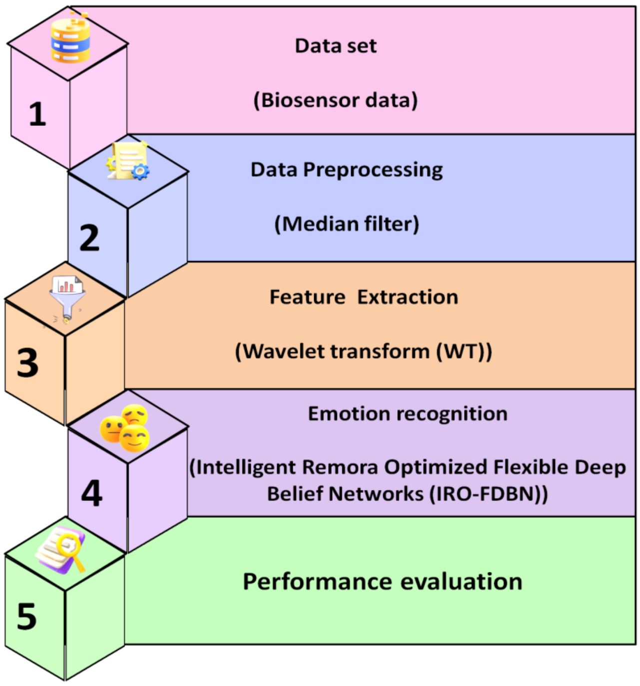

Figure 2. A novel methodological flow for biometric painting analysis using (IRO-FDBN).

3.1. Dataset

The dataset used in this research combines extensive biosensor information, including heart rate, skin conductance, EEG, and respiratory rate, which reveal information about the user's mental and physiological states. These biological cues are essential for real-time comprehension of the user's state of stress and emotional reactions. Together with the biomedical readings, the collection also contains dynamically produced biometric images, which are visual elements derived from the biomedical data points. Through the use of colors, textures, and structure, the paintings graphically depict the user's psychological emotions; each visual component is linked to a certain physiological reaction. To provide a comprehensive knowledge of how changes in emotions appear in the biological artwork, information is included with the visual data to document the connections between these graphical components and the fundamental state of mind. Thorough examination of the relationship between bodily reactions and artistic depiction of emotions is made possible by the integration of physiology data and graphic outputs, which facilitates a more thorough examination of recognizing feelings.

3.2. Data pre-processing

The data is pre-processed using a median filter. The most recognized order-statistics filter, which substitutes the median of the gray levels surrounding a pixel for the pixel's value is given in Equation (1).

$$\hat{e}(y,x) = \underset{(t,s)\,\in\,T_{yx}}{median}\{h(t,s)\} \tag{1}$$

$\hat{e}$Represents a function, that takes in two variables, $yandx$, the $median$ is being calculated over the pair of indicates (t,s), where (t,s)belongs to a set T_{yx}. $h(t,s)$ represents a function or value that depends on the pair (t,s), potentially derived from some observations.

The initial value of the pixel is used to compute the median. Due to their significantly lower blurring compared to linear smoothing filters of the same dimension, median filters are frequently utilized for certain types of random noise.

3.3. Feature extraction

The noise-removed data features are extracted using Wavelet Transform (WT). WT is a mathematical field that combines numerical analysis, harmonic analysis, Fourier analysis, and functional analysis. In domains like speech, images, and signal processing, as well as nonlinear sciences, it has emerged as a crucial technique. When used in conjunction with Fourier analysis, WT is regarded as an efficient time-frequency analysis method. WT offers localized analysis in both the temporal and frequency domains. WT employs multi-scale analysis, which addresses issues that the Fourier transforms, by scaling and translating signals to obtain detailed information. WT is computed using Equation (2).

$$ged_i = ged_{i+1}g_1; ked_i = ked_{i+1}k_1, (i = 0, \dots . m-1) \tag{2}$$

where g_1 represents the high-pass filter and k_1 is the low-pass filter;ged_i and lfcj stand for the high and low-frequency portions of the i^{th} layer, respectively. WT predicts the high-frequency and low-frequency components independently and the predicted outcome for each of these components that are recreated. Furthermore, Equation (3) displays the wavelet reconstruction expression.

$$ged_i = ged_{i+1}g_2 + ked_{i+1}k_2, (i = m-1, \ldots, 1,0) \quad (3)$$

where k_1 opposing computation is represented byk_2 and g_1 opposing calculation is represented by g_2. Through the provision of time-frequency localization, multi-scale analysis, and effective management of non-stationary data, it improves feature extraction.

3.4. Emotion recognition using intelligent remora optimized flexible deep belief networks (IRO-FDBN)

This section presents the IRO-FDBN for emotion identification, specific to biometric painting applications where user emotion recognition is essential for producing meaningful and customized artwork combined with FDBN and IRO algorithms.

3.4.1. Flexible deep belief networks (FDBN)

After the feature extraction, the data is classified using FDBN. A FDBN is an enhanced version of the traditional DBN designed to be more adaptable while learning challenging data. To better suit particular tasks, it is composed of layered Restricted Boltzmann Machines (RBMs) with movable layer connections and activation functions. Unsupervised pre-training using untagged data and supervised fine-tuning using labeled data are both components of the learning process. FDBNs are energy-based models with weighted undirected linkages connecting the visible and buried layers. For a binary RBM, the energy function $F(u,g;\theta)$ and the probability distribution model $q(u,g;\theta)$ are given in Equations (4) and (5).

$$q(u,g;\theta) = \frac{1}{w(\theta)} \exp\bigl(-F(u,g;\theta)\bigr) \quad (4)$$

$$F(u,g;\theta) = -\sum_{j=1}^{C} b_j u_j - \sum_{i=1}^{E} a_i g_i - \sum_{j=1}^{C}\sum_{i=1}^{E} z_{ji} u_j g_i = b^S u - a^S g - u^S Z g \quad (5)$$

where $w(\theta)$ is the regularization factor, u is the visible layer's key vector, g is the hidden layer's output vector,θ are the parameters of the model, $F(u,g;\theta)$ is a function of the inputs and parameters, $b_j and u_j$ represents a set of variables, a_i is the coefficients, C is the total number of elements, E is the sum of the elements in the locate, z_{ji} represents a set of iteration coefficients, Z is the weight vector, $g = (z,b,a)$is the set of internal parameters,b^S is the summary of the coefficient, $a^S$is an aggregated or transformed version, and u^S represents a vector, respectively. The following Equation (6) defines each unit's parameters:

$$\begin{cases} u = (u_1, u_2, \ldots., u_{j'})^S j' \in M * \\ g = (g_1, g_2, \ldots., g_{i'})^S i' \in M * \\ \omega = (\omega_{j'i'})^S j' \in [1, n'], i' \in [1, m'] \\ b = (b_1, b_2, \ldots, b_{n'})^S \\ a = (a_1, a_2, \ldots, a_{m'})^S \end{cases} \quad (6)$$

u, g, ω, b, and a are all sets of parameters, M is a set that defines the allowable indices for u and g, ω is a matrix that models interactions between two sets of indices j and i, with its dimensions being $[1, n']$ for j and $[1, m']$for i, b and$a$ are additional sets of parameters, indexed by n and m respectively. Let the numbers for the visible and hidden layers be $|U|$ and $|G|$, respectively. It is possible to determine the provisional prospect distributions of the concealed layer and the perceptible layer, respectively calculated by Equations (7) and (8).

$$q(g_i|u; \theta) = \sigma\left(b_i + \sum_{j=1}^{|U|} U_j Z_{ij}\right) \quad (7)$$

$$q(g_i|g; \theta) = \sigma\left(a_i + \sum_{i=1}^{|G|} g_j Z_{ij}\right) \quad (8)$$

The sigmoid function is where Training the k-step contrastive divergence yields the internal parameter vector $g = (z, b, a)$ the activation function is $\sigma(y) = (\frac{1}{1+f-y)})$.A DBN then be created by stacking multiple RBMs. The visible layer u^S joint probability distribution is written as follows in Equation (9).

$$q(u; \theta) = \sum_g \frac{f^{-F(u,g;\theta)}}{\sum_{u,g} f^{-(u,g;\theta)}} = \frac{1}{w(\theta)} \sum_g \exp\,(u^S zg + a^S u + b^S g) = \frac{1}{w(\theta)} f^{(a^S u)} \prod_{i=1}^{E} (1 + \exp\,(b_i + \sum_{j=1}^{C} z_{ji} u_j)) \quad (9)$$

Unsupervised feature learning makes use of the FDBN. It offers enhanced generalization, flexibility, and representation learning through training and model architectural adaptation. Their proficiency in managing multi-modal data and non-linear interactions makes them perfect for intricate jobs like biometric painting's emotion recognition. In particular, FDBNs improve performance while dealing with unlabelled, noisy, or missing data.

3.4.2. Intelligent remora optimization (IRO)

Classified data is optimized using IRO to improve accuracy and reliability. It is a nature-inspired optimization technique that mimics the symbiotic relationship between remora fish and larger marine animals like sharks and turtles. In this algorithm, the remora fish represent smaller agents that seek to attach themselves to larger hosts in a search space. The phases of free travel and eating thoughtfully in IRO correspond to the stages of exploration and exploitation. The method uses one small step to try to transition between the exploration and exploitation stages.

Exploration:

The global search is carried out by the IRO using the sailfish optimization (SFO) approach, which is based on the elite technique employed in the swordfish algorithm. The following is an expression for the position updating in Equation (10).

$$U_j(s+1) = Y_{best}(s) - (uand \times \left(\frac{Y_{best}(s) + Y_{uand}(s)}{2}\right) - Y_{uand}(s) \qquad (10)$$

And the j^{th} remora's nominee location is denoted by$U_j(s+1)$. The best position is$Y_{best}(s)$. Remora's random position is denoted by$Y_{uand}(s)$. $s$is an Iteration number. A random number between $0\ and\ 1$ is called$uand$.

Furthermore, remora switches hosts based on its experiences. In this instance, a fresh candidate post is created by Equation (11).

$$U_j'(s+1) = U_j(s+1) + uandm \times (U_j(s+1) - Y_i(s)) \qquad (11)$$

And the j^{th} remora's nominee location is determined by$U_j'(s+1)$. The j^{th} remora's previous position is represented by$Y_i(s)$. Moreover, a correctly dispersed random integer is created utilizing a distribution of algorithm.

Exploitation:

To obtain food, remora clings to humpback whales. Remora's moves are equal to humpback whales. In ROA, the local search is carried out using the whale optimization algorithm (WOA) approach. More precisely, the WOA bubble-net attack technique is utilized. The following are the updated position updates in Equations (12)–(15).

$$U_j(s+1) = E \times d^b \times \cos(2\pi b) + Y_{best}(s) \qquad (12)$$

$$E = |Y_{best}(s) - Y_i(s)| \qquad (13)$$

$$b = uand \times (a-1) + 1 \qquad (14)$$

$$a = -(1 + \frac{s}{S}) \qquad (15)$$

where E is the division among the fare and the remora, it is evident from Equations (10) and (11) that is a random number between $2\ and\ 1$. Additionally, a drops linearly from $1\ to\ 2$.

Furthermore, the surrounding prey process in WOA is explained as follows, the remora produces a small stride to improve the superiority of the explanation given in Equations (16)–(19)

$$Y_j(s+1) = U_j(s+1) + B \times E' \qquad (16)$$

$$B = 2 \times A \times uand - A \qquad (17)$$

$$B = 2 \times (1 - \frac{s}{S}) \qquad (18)$$

$$E' = U_j(s+1) - D \times Y_{best}(s) \qquad (19)$$

where the j^{th} remora's recently produced position is defined by $U_j(s+1)$, the remora feature, denoted by B in IRO, is set to 0.1. It increases the effectiveness of optimization by robustly managing nonlinear, multi-modal issues in dynamic situations. It enhances convergence speed, performs exceptionally well in multi-objective optimization, and fits well with real-time applications. Model performance and accuracy are improved by IRO's adaptability and capacity of the methods.

IRO-FDBN enhances emotion recognition using real-time biosensor data by fusing the capabilities of IRO with FDBN. The model successfully navigates complex, hierarchical data by optimizing FDBN parameters with IRO, which improves its capacity to precisely identify and categorize emotional states. Higher performance results from the model's ability to avoid local minima and converge more quickly due to this optimization process. By modifying the artwork according to the user's emotional state, this method enhances the interaction between the user and the art and allows for dynamic emotion-driven feedback in applications, such as biometric painting. This results in individualized and captivating experiences. Algorithm 1 shows the IRO-FDBN algorithm.

Algorithm 1 Intelligent remora optimized flexible deep belief networks (IRO-FDBN)

```
START
 Step 1: Initialize Parameters
     Initialize FDBN parameters (weights, biases, and other network parameters)
     Initialize IRO parameters (U, Y_best, and, s)
 Step 2: Pre-training using Unsupervised Learning (FDBN)
     For epoch in range (max epochs):
         Forward pass through FDBN
     For data in the dataset:
 u, g = FDBN forward (data, FDBN parameters)
         Loss = Compute loss (u, g)
     Back propagate and Update FDBN weights
         FDBN update (FDBN parameters)
Step 3: Optimization using IRO
         Phase 1:  Exploration Stage
             For iteration in range (max iterations):
         Phase 2: Remora Optimization—Exploration (using SFO approach)
             For remora in remoras:
                 Update position exploration (remora, Y_best, uand, s)
         Phase 3: Remora Optimization—Exploitation (using WOA approach)
             For remora in remoras:
                 Update position exploitation (remora, Y_best, Y_i, s)
         Phase 4: Update FDBN parameters based on the optimized position from IRO
             FDBN parameters = Update FDBN parameters with optimized positions (remoras)
 Step 4: Fine-tuning using Supervised Learning
     For epoch in range (fine-tuning epochs):
     Forward pass through FDBN
         For labeled data in the labeled dataset:
 u, g = FDBN forward (labeled data, FDBN parameters)
         Loss = Compute loss (u, g)
     Back propagate and Update FDBN weights with supervised data
         FDBN update (FDBN parameters)
 Step 5: Final Evaluation and Emotion Recognition
     Predicted emotion = Predict emotion (training data, FDBN parameters)
     Print (predicted emotion)
   END
```

4. Result

On a Lenovo machine running Windows 8.1 and featuring an Intel i7 processor and 8 GB of RAM loaded, the CPLEX Ensemble Software. Using Python 3.10, the emotion analysis for biometric paintings is evaluated by IRO-FDBN. The performance of the IRO-FDBN system is evaluated using important metrics like throughput, processing time, accuracy, F1 score, precision, recall, and error rate. The purpose of these metrics is to evaluate the system's capability to recognize emotions, handle information effectively, and reduce mistakes in real-time emotion recognition.

Performance evaluation

Accuracy: The percentage of outcomes that are accurately anticipated out of all predictions is known as accuracy. The IRO-FDBN model's overall effectiveness in forecasting emotional states using biosensors and biometric painting data is measured by accuracy. It is calculated using Equation (20). **Figure 3** determines the assessment of accuracy.

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

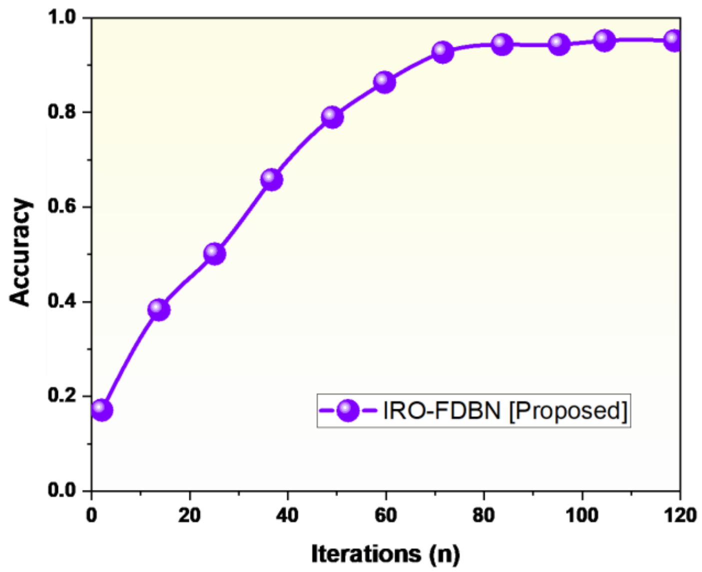

Figure 3. Evaluation of the accuracy of IRO-FDBN in emotion recognition through biometric paintings.

The algorithm's accuracy increases with the number of iterations and ultimately achieves near 0.95 stability. This shows how effective the system is based on how well it performs and converges to high accuracy. As established by the process, the algorithm capably learns from data over time, ensuring enduring learning and optimization for enhanced accuracy and recital in succeeding rounds.

Precision: It establishes the proportion of True Positive (TP)forecast among the entire system positive forecast like TP and True Negative (TF). Reducing False Positives (FP) in biometric emotion detection ensures that the recognized emotional states are relevant. Equation (21) is utilized to calculate precision. **Figure 4** determines the estimation of precision.

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

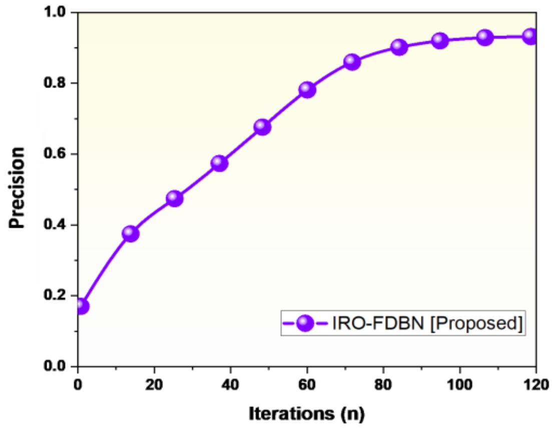

Figure 4. Optimizing emotion recognition with IRO-FDBN for accurate biometric painting.

The model's precision rises and stabilizes at almost 0.95 as the number of iterations increases, offering the method's efficiency. This shows successful convergence and optimization, demonstrating that the system keeps learning and enhancing its predictions over time. The method is reliable for complex tasks due to its long-term learning description, which ensures permanent, accurate results.

Recall: The proportion of values that the system accurately detects is known as recall or sensitivity. To reduce False Negatives (FN) in emotion identification, recall examines the IRO-FDBN's capability to identify emotional states. Recall is computed using Equation (22). **Figure 5** denotes the evaluation of recall rates.

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

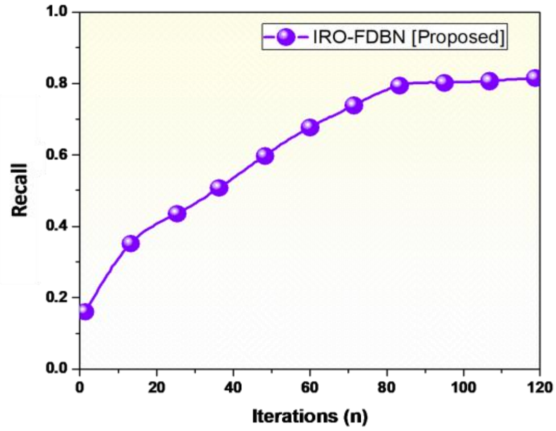

Figure 5. A dynamic evaluation for recall performance in biometric painting.

This highlights how recall increases and stabilizes at about 0.8 with other iterations, offering the effectiveness of the proposed system. This reveals competitive learning and optimization for tasks like emotion recognition and biometric analysis, ensuring that the system constantly enhances its potential without experiencing considerable performance loss over time.

F1-Score: F1-Score stabilizes the substitute between precision and recall by fascinating the harmonic mean of the recall and precision. It presents a thorough assessment of the system's recall and precision, primarily in circumstances with unstable data. F1-score is calculated using Equation (23). **Figure 6** Assessments of f1-score.

$$F1 - Score = 2 \times \frac{TP}{TP + FP + FN} \tag{23}$$

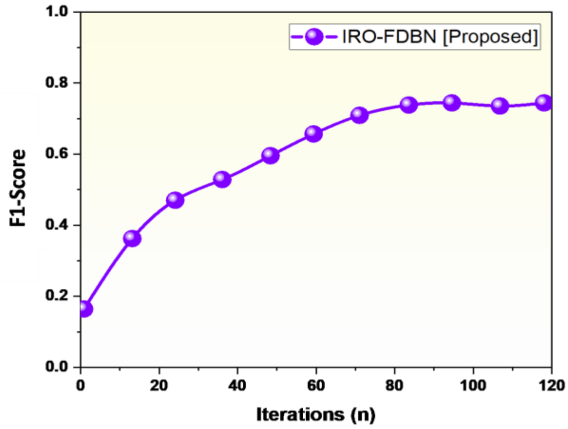

Figure 6. Optimizing emotion recognition with f1-score evaluation.

The F1-score increases and stabilizes at about 0.74 as the number of iterations rises, indicating the method's long-term learning potential and efficient optimization. In addition to efficiently managing unbalanced data and preserving consistency across several iterations, it ensures strong performance in emotion recognition tests.

Throughput: Throughput is the speed at which a system processes information tasks in a persuasive amount of time. It is often expressed in requisites of successful operations per second. The competence of the IRO-FDBN method in processing biosensors and optical data for emotion detection is examined. High throughput interactive biometric painting significance is necessary to identify emotions concurrently while ensuring the system can capably handle huge amounts of data. **Figure 7** represents the assessment of the throughput of the suggested approach.

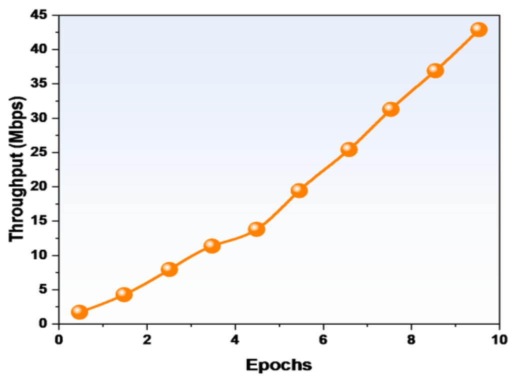

Figure 7. Maximizing efficiency enhancing throughput for real-time emotion recognition in biometric painting.

As the IRO-FDBN model is trained auxiliary, the rising throughput with more epochs demonstrates the system processes data. The processing competence of the model enhances over time, attaining superior throughput ideals by later epochs after starting with a lower throughput at the start. This implies that when the system is trained, its capacity to extract features and identify emotions improves. This illustrates a rise in throughput to measure system performance over time, influential when further training yields deteriorating or when the finest point is reached for the best emotion recognition results. This development underlines the model's development in learning from biosensor data.

Processing time: Processing time is the overall amount of time that a computer system or algorithm needs to finish a given task, including the time needed for data input, processing, and output generation. This assesses the effectiveness of IRO-FDBN in completing tasks including emotion identification, feature extraction, and biosensor data preprocessing based on processing time. The technology is appropriate for concurrent applications, such as the creation of biometric paintings, due to efficient processing that saves time. **Figure 8** shows the processing speed of the proposed system.

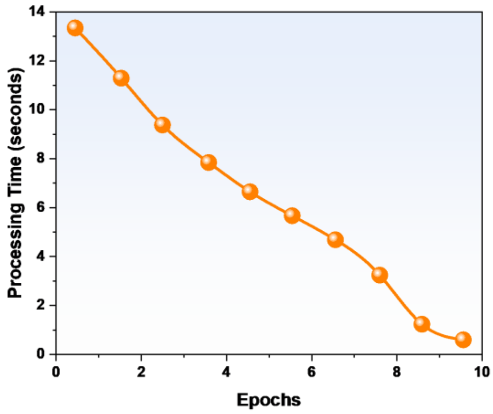

Figure 8. Processing time reduction in IRO-FDBN for efficient emotion recognition.

The processing time is 13.8 seconds at epoch 1 and gradually drops to 0.8 seconds by epoch 10. Efficiency gains become less significant with time, as evidenced by the rate of decline decreasing as training increases. By the last epochs, the processing time has stabilized below 1 second, indicating that the system has reached a point where more preparation output reduces processing time returns. This behavior demonstrates that the model steadily finds a stable, efficient performance stage after initially optimizing quickly.

Time delay: The outcome of time delay on system performance is investigated through error values and outcomes from delays between input and output. Systems locate more complex to adjust quickly as time delays increase, leading to larger differences between normal and concrete outputs. This looks into how delays impact executive and prediction accuracy with the objective of the best potential equilibrium between reducing time delays and control error values in a significant phase of concurrent systems like communication networks. **Figure 9** shows the error rate for the proposed method.

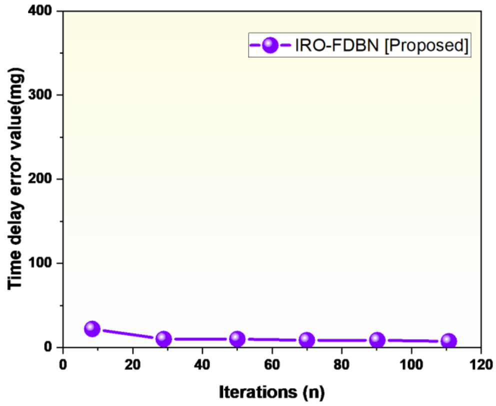

Figure 9. Impact of time delay error on emotion recognition.

As the time delay increases, the system's error number either climbs or stays the same, depending on how successfully the input is processed and emotions are identified. Higher errors, which are caused by data noise or processing limitations, indicate, lower accuracy, whereas lower or consistent errors suggest better accuracy. Since longer delays impair real-time feedback, which damages the artist's creativity and audience engagement, this relationship is essential for system optimization. To amplify the exactness of emotion recognition and make the model more responsive and efficient for real-time artistic creation, delays decreased or data processing improved.

Skin conductance: It is recognized as Galvanic Skin Response (GSR) is a dimension of the skin's electrical conductivity that varies depending on the amount of moisture (sweat) present. Sweat glands regulate this moisture and are impacted by the sympathetic nervous system. Higher skin conductance results from increased sweating production brought by an increase in emotional or physiological arousal. Skin conductance is utilized to monitor physiological or emotional reactions to various situations, such as being exposed to stresses or incentives. **Figure 10** demonstrates the evaluation of skin conductance over time.

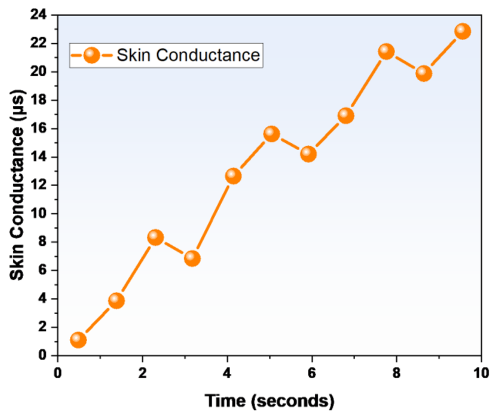

Figure 10. Tracking skin conductance for enhanced biometric emotion recognition.

This is important since it shows the connection between time, raw skin conductance data, and the 3-point rolling average. It reduces the effect of natural differences in the body. In addition to selection to understand how physiological or emotional states change concurrently, this rolling standard assists in the recognition of enduring trends, like a reliable increase in skin conductance over time. It is particularly practical in research involving stress, emotions, or other psychological conditions since it allows for a more precise examination of individuals' mental or physical conditions.

5. Discussion

To investigate the significance of emotion analysis in biometric paintings by using biometric data to analyze and describe emotional conditions. The objective was to enhance the accuracy and emotional affluence of biometric artwork by analyzing physiological conditions that were interrelated between emotional changes, like variations in skin conductance. The IRO-FDBN system capably managed biosensor data, displaying an amplified throughput with time and attaining superior accuracy, F1 score, precision, and recall with each iteration. Furthermore, the model's shorter processing time determined superior efficacy, which qualifies for concurrent applications like dynamic biometric painting, where emotional conditions play a crucial function in the method of creating art. By precisely detecting minute emotional changes in biological sensor data, such as respiration and EEG impulses, the suggested IRO-FDBN overcomes difficulties in identifying emotions from biometric drawing. The IRO enhances model performance by lowering overfitting and improving resolution. It enables immediate handling and adaption to a variety of sensor information, facilitating accurate and variable detection of emotions. As a result, emotion detection techniques become more reliable and effective. In the environment of biometric painting, the suggested IRO-FDBN model has several improvements over alternative models. It provides a more comprehensive depiction of the user's physical and mental reactions by integrating biosensor data, including conductivity of the skin, cardiac rate, and EEG, to precisely record the state of mind. By increasing learning effectiveness, the IRO improves accuracy and speeds up resolution. FDBN adaptability also makes it possible to recognize emotions in real-time, which makes it ideal for dynamic, participatory processes of creativity like biological painting. The resource will be added between the source and destination by the process of introducing.

6. Conclusion

Emotion analysis with biometric paintings was important since it traced and exhibited emotional conditions concurrently, adding to the creative prosperity and genuineness by including physiological information. The aim utilized biosensor data to assess and suggest emotional conditions to create dynamic biometric paintings. The findings showed that the IRO-FDBN method demonstrated enhanced throughput and decreased processing times over time, allowing for successful concurrent applications, and it forecasted emotional states with excellent accuracy, F1-score, precision, and recall. The IRO-FDBN model demonstrated that accuracy achieves 0.95, precision achieves 0.95, recall of 0.80, and F1-Score of 0.74. They showed a balanced efficiency, stabilizing at 0.74. By epoch 10, the processing time has reduced from 13.8 seconds to 0.8 seconds, indicating effective optimization. The influence of exterior variables that prejudiced skin conductance ability and possible issues managing data noise were drawbacks. By adding more physiological sensors, and expanding the systems used to other interactive art forms, future research investigated boosting model resilience and capturing a superior range of emotional expressions.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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