Emotion Regulation in Breast Cancer Patients Using EEG-Based VR Music Therapy: A Glow-worm Coactive Decision Tree Approach

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Virtual reality (VR) technology is currently being used in emotion management and musical environment modeling to improve mental and emotional wellness through psychological advantages and a flexible musical environment. The purpose of the study is to utilize the Glow Worm Coactive Decision Tree (GW+DT) classifier to develop a technique for controlling feelings and creating authentic musical situations. An electroencephalogram (EEG) wave signal is collected in participant when they listen to VR-based music. Recursive Feature Elimination (RFE) is an extraction technique for extracting the collected EEG recording signals from the patients. Then the Improved Glow Worm Swarm Optimization (IGSO) method has been employed to determine an optimal set of characteristics for accurate emotion classification. Emotion is classified using the Decision Tree (DT) method depending on the feature selected in the EEG wave signal. The valence and arousal levels were measured using the self-assessment manikin (SAM). The GW+DT method achieved a greater accuracy (95%), recall (82.10%) and F1-Score (80.52%), significantly outperforming traditional methods. The findings highlight the probable involvement of VR and music therapy as a therapeutic approach to enhance mental health and emotional stability in clinical settings.

Povzetek: Predlagasna je metoda GW+DT za EEG-podprto glasbeno terapijo v VR okolju za pacientke z rakom dojke. Metoda izboljšuje čustveno regulacijo, kar pokaže terapevtski potencial VR glasbene terapije.

1 Introduction

Emotional management is a significant factor of the psychology science that involves techniques for modifying and adapting emotion to achieve preferred outcomes [1]. Virtual reality (VR) is a cutting-edge technology that creates immersive, embodied experiences by combining computer-generated multimodal displays, improving human sensorimotor skills, and boosting interaction with virtual worlds [2]. Companies worldwide are transforming into innovative factories using advanced technology systems and Augmented Reality (AR), embracing Industry 4.0 for faster product discovery, information transmission, and reduced labor-intensive activities [3]. VR technology makes immersive learning possible by using stereoscopic head-mounted displays and sensors to give spatial immersion and hands-on activities. VR is used to simulate a three-dimensional world on the screen [4]. VR enables users to engage with complicated Personal Computer (PC) data naturally, using their senses such as vision, hearing, and touch. Sensors that measure human activities as well as visualization tools are essential components. VR apps have several benefits, making them one of the most immersive technologies, giving the user a genuine experience [5]. Music is an essential constituent of human beings and has been shown in studies to activate the whole reward network and the anterior hippocampus, shedding light on the neurological correlates of emotion. However, the prominence of research into the hippocampus for cognitive functioning raises concerns regarding its consistency with larger studies [6]. Emotion management is an essential component of a person's existence and is critical for overall well-being. A method for studying how emotion are controlled from the regulator's perspective is described, which involves recreating social support situations in VR [7]. The strategy could be used to guide research on groups that struggle to regulate their emotion, such as young people with autism. Emotional control is critical in a variety of situations, particularly for those with neurodevelopment issues who frequently experience difficulty with emotion management [8].

Objective of the study: The research aims to reduce anxiety and stress and then improve their mental health using VR-based musical simulations. The study aims to determine the influence of VR music therapy on emotional knowledge and mental health.

2 Literature review

This section summarizes the research conducted to assess the influence of VR-based musical simulations on reducing anxiety and stress with a focus on improving mental health and emotional awareness. Table 1 gives an overview of the related study.

Table 1: Literature summary

Related study	Methodology	metrics	Results
[9]	PAD emotional model, music impact	Emotional state influence, assessment scores	Music had minimal impact on communication; warm-toned environment scores.
[10]	Heuristic optimizer for VR emotion model	Efficiency of relaxing experience	The sequence of modifications influenced relaxation; effective for emotion-based adaptive VR
[11]	Emotion-regulating improvisational music therapy	Depression indicators, emotion control	Significant improvement in emotion control and depression; limitation in generalisability noted.
[12]	Electronic intervention program	Flow state, performance anxiety	Increased flow state and control; did not enhance social skills
[13]	Music listening during COVID-19 pandemic	Affect management, stress coping	Positive mood shift; variability in individual responses based on despair and anxiety
[14]	Brain-computer interaction music therapy	Emotional control feedback	Effective emotional control via EEG impulses; limitations in Western medication addressed.
[15]	Machine-learning emotion analysis	Emotion prediction accuracy	Reliable emotion analysis using physiological signals; potential for enhancing mental and physical wellness.

Research gap: There are still several gaps in the field of emotion identification and therapeutic interventions [9], music had little effect on emotional states, which emphasizes the need for more potent music-based interventions. Although they did not provide dynamic adaptation for different emotion [10] showed the advantages of customizing VR experiences to emotional states. The efficiency of EIMT was demonstrated by [11], however small sample numbers limited the generalisability of the findings. The study [12] addressed anxiety reduction and flow improvement, but social skills were not addressed. The study [13] discovered that music improved mood, although they ran across problems with individual variability. A possible alternative to EEG-based music therapy was offered [14], although it was constrained by particular technological needs. Machine learning was utilized by [15] to analyze emotion; however, they encountered difficulties integrating several physiological inputs. To ensure wider applicability and effectiveness, the suggested solution integrates adaptive VR interventions with a dynamic, real-time emotion detection system. It positions itself as a breakthrough in the field by combining multi-modal data for full emotional understanding, improving emotional and social results, and streamlining real-time emotion tracking.

3 Methodology

The study attempted to investigate the usefulness of a VR-based music training system in enhancing emotional regulation in patients. It combines VR technology and musical therapy, assessing the influence of emotional recognition using EEG data. The proposed approach focuses on data collection and analysis. The data collection unit gathered EEG measurements of participant while listening to the VR music teaching method, as depicted in Figure 1.

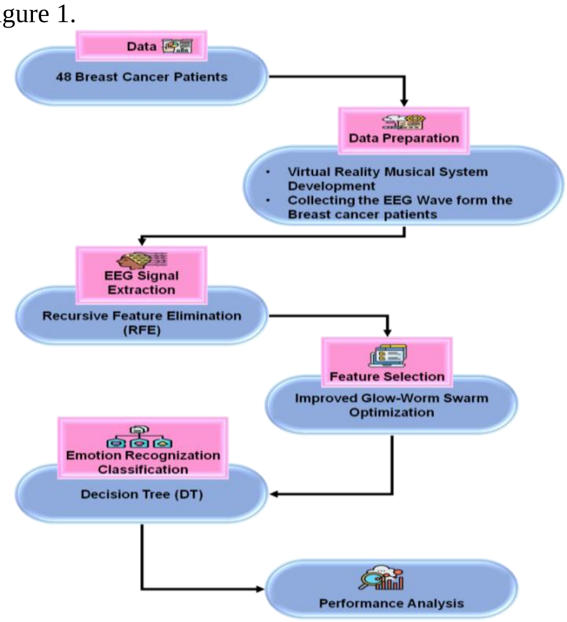

Figure 1: Methodological flow

3.1 Data samples

The study included 48 female patients with breast cancer who were chosen based on their age, diagnosis, and past medical history; individuals with epilepsy, drug addiction, metastases, eyeglasses, or ports were not included. Its goal was to find out how musical therapy affected patients' outcomes. The study found that there were notable differences in patients' mental states according to age: younger patients (36–40 years old) experienced more stress about their bodies, employment, and fertility; middle-aged patients (40–55 years old) found it difficult to balance therapy with responsibilities to their families or jobs; and older patients (56–70 years old) worried about comorbidities, dependency, and quality of life. For people of all ages, therapeutic methods like music therapy and emotional support are essential in managing the psychological effects of breast cancer. Table 2 depicts the demographic character of the breast cancer patients.

Table 2: Patients demographic factors

Categories		**No. of individuals (n=48)**	**Percentage (%)**
Gender	Female	48	100%
Age	36–40	12	25
	40–55	20	42
	56–70	16	33
Treatment history	Chemotherapy	16	33.4
	Radiation therapy	13	27.0
	Surgery	10	20.8
	Hormone therapy	9	18.8
Comorbidities	Diabetes	22	46
	Hypertension	12	25
	Heart disease	6	13
	None	8	17
Stage of cancer	Stage 1	14	29
	Stage 2	18	38
	Stage 3	12	25
	Stage 4	4	8

3.2 Feature extraction using recursive feature elimination (RFE)

The RFE method is frequently employed considering its flexibility and adjusting options, as well as its efficacy in selecting features in datasets for training that is useful for predicting target variables and discarding weak features. The RFE approach is used for selecting the characteristics that are most significant by recognizing a strong association between particular features and the goal (labels). The RFE process can be represented by Equation (1).

$$Importance\ (F_i) = Model_{train}\ (X, Y) \quad (1)$$

F_i Represents the i^{th} feature, X is the medium of the feature, Y is the target variable and $Importance\ (F_i)$ denotes the importance score of the feature F_i as determined by the model.

The method enhances model performance by selecting the most relevant features, preventing overfitting and ensuring that findings accurately reflect real-world therapeutic effects. It also simplifies the dataset by reducing computational complexity, improves interpretation by pinpointing critical elements of the therapy and supports personalized interventions by identifying individual patient characteristics that influence better outcomes. Figure 2 depicts the steps involved in RFE feature extraction.

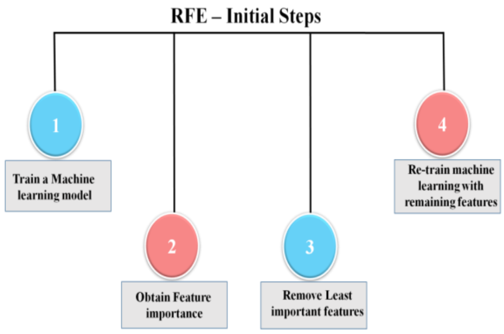

Figure 2: Feature extraction method

3.3 Feature selection and classification of emotional reorganization using glow worm coactive decision tree (GW+DT)

The Glow-worm Coactive Decision Tree (GW+DT) combines the Improved Glow-worm Swarm Optimization (IGSO) and Decision Tree (DT) methodologies to improve feature selection and emotional categorization. IGSO simulates the luminous activity of glow-worms by improving feature selection using luciferin-based calculations, allowing the algorithm to progress to optimal solutions. Each glow-worm modifies its location in response to the luciferin levels of its neighbors, hence enhancing local and global search capabilities. The DT method uses this optimized feature set to classify emotional states by splitting data recursively based on attribute values. The combination of IGSO for feature selection and DT for classification yields an efficient and accurate technique for emotional reorganization prediction.

3.3.1 Feature selection using improved glow-worm swarm optimization algorithm (IGSO)

After the feature extraction feature selection was employed using IGSO. The IGSO technique mimics the actual glow-worms' luminescent behavior. Using a bionic approach, the program calculates the benefits and drawbacks of each glow-worm individual's position using luciferin. Every person has a unique perception or decision range, and they can only progress to exceptional people who have high luciferin values. Repetitive selection is used to traverse through the search space to apply optimization. Every glow-worm sends data to the neighborhood to inform regional choices while the algorithm is running. The initializing choice scope of the IGSO method under the circumstances is the intended function definition area. The decision domain range is then updated by Equation (2):

$$w_x^h(a = 1) = min\{w_e, max\{0, w_x^h(s) + \beta(n_a - |N_h(a)|)\}\}, \quad (2)$$

β is a constant parameter, while m_s is a parameter that controls the number of neighbors. Each glowworm will be drawn to its neighbors, who glow brighter, by the IGSO algorithm principle. As a result, glowworms employed a tendency to go in the direction of their neighbors with greater luciferin levels than did throughout the migration phase as given in Equation (3).

$$i_{hu}(a) = \frac{j_u(a) - j_h(a)}{\sum_{U \epsilon N_h(s)} j_u(a) - j_h(a)} \quad (3)$$

Consequently, the glow-worm movement's discrete-time model can be expressed as Equation (4).

$$q_h(a + 1) = q_h(a) + r\left(\frac{q_u(a) - q_h(a)}{||q_u(a) - q_h(a)||}\right) \quad (4)$$

Where $a(> 0)$ denotes the magnitude of the step and the operator for the Euclidean standard. Following the migration to a new place with glow-worm, the luciferin informs regulation is provided by Equation (5).

$$l_h(a) = (1 - \rho)l_h(a - 1) + \gamma w(q_h(a)) \quad (5)$$

Where $\rho \in (0, 1)$, is the rate of luciferin degradation constant, γ is the enhancement constant of luciferin. The distance between the glow-worms steadily decreased due to the glow-worm progressively moving to the neighborhood of the limited excessive particular, this stage in the latter repetition of the IGSO procedure. The position update Equations (6 and 7) states that when glow-worms' attraction to one another gradually increases, each glow-worm will go too far and either miss or arrive at the ideal location, which will lead to oscillation issues close to the extreme point. The position update equation turns into:

$$q_h(a+1) = \omega(n)q_h(a) + t(\frac{q_u(a)-q_h(a)}{||q_u(a)-q_h(a)||} \quad (6)$$

$$\omega(b) = \omega_{max} - (\omega_{max} - \omega_{min}) \times \frac{n}{n_{max}} \quad (7)$$

Where the highest weight is denoted by ω_{max}, and the minimum weight by ω_{min}. The current iteration step is$m$ and the maximum iteration step is $_{max}$. An important component of a glow-worm's swarm optimization process is its inertial weight. It balances the glow-worm's ability to hunt both locally and globally, as well as how far it can migrate. A greater effect of the present location on the next move is achieved by increasing the weight value, which improves global search capability but detracts from local search capability. On the contrary, a lower weight value improves local search performance while degrading global search capability. This adaptive technique increases the study's capacity to determine the best VR music treatment circumstances for improved mental health results by ensuring thorough exploration and preventing unsatisfactory convergence.

3.3.2 Emotion classification prediction using Decision Tree (DT)

A selected feature was classified using Decision Trees (DT). It classifies data objects based on how well their properties are valued. First, a decision tree is built with a pre-classified set of data. For every node in the tree, a set of characteristics is chosen to separate the data into different groups. This partitioning process separates subsets of data items into smaller groups recursively, according to attribute values, until all of the data items in each group are from the same class. The DT divides the data based on the specified characteristics at each node, with edges labeled according to the parent attribute. The decision values on the decision tree's leaves aid in categorization. One popular classification strategy employed by DTs is a statistical classifier. The classification procedure incorporates certain criteria and recursively determines classes that differentiate the target application on all dimensions. Here, let W represent a feature of a data point and Z represent the class. The decision is made by calculating the W | Z ratio, which helps choose the appropriate class for the data point given in Equation (8).

$$\mathrm{RATIO}\,(\,Q \mid L) \;=\; F\,(\,Q\,) \;-\; F(\,Q \mid L)\,F\,(Q) \quad (8)$$

The uncertainty of variable Q given variable L is estimated by the conditional entropy, represented by the symbol $F(\,Q \mid L)$. In contrast, the marginal entropy does not account for any other variables; rather, it quantifies the uncertainty of variable Q only by calling this $F\,(Q)$. Equation (9) defines the train data.

$$C \;=\; \{(q1, l1), (q2, l2), \dots, (qN, lN)\} \quad (9)$$

As a consequence, the regression model can be expressed as follows Equation (10).

$$l \;=\; w(q) \;=\; \Sigma\, su * J(q \in WK) \quad (10)$$

where dl is the specific result associated with area WK, l is the expected output variable, w(q) represents the regression function, and $J(q \in WK)$ is an indicator function that evaluates to 1 when the input q falls inside region WK and 0 otherwise revalue using Equation (11).

$$w(q) = \sum_{k=1}^{k} S_k H(q \epsilon WK) \quad (11)$$

The following optimization problems must be solved to ascertain the values $foundr$ies given in Equations (12 and 13)

$$\min u, r \lfloor \min s1 \sum_{wi \epsilon W1} (u, r)(lh - s1)2 + \min s1 \sum_{qu \epsilon W2} (u, r)\,(lh - s2)2 \rceil \quad (12)$$

$$S1 = \mathrm{ave}((lu|qh \in Wh(u,s),), S2 = \mathrm{ave}((lh|qh \in W2(u,r)) \quad (13)$$

The process comprises selecting the optimal split variable (u) after calculating the output values for each of the input variables. Each variable functions as a dividing line, separating the input space into two distinct sections (u, s). After segmenting each region, the process is repeated until a stop condition is met. They are skilled at capturing the intricate interactions between different facets of therapy and their impact on mental health because they can manage non-linear relationships between features. Moreover, DTs provide information about feature relevance, which aids in determining the therapy's most effective elements. Their ability to withstand outliers and eliminate the need for feature scaling makes data preparation easier. Their adaptability enables them to perform well with smaller datasets, which is advantageous if participant numbers are restricted. They can handle both numerical and categorical data with ease. Generally, decision trees provide a simple and efficient way to categorize and comprehend how virtual reality music therapy affects mental health and anxiety reduction.

To improve categorization, Glow Worm Swarm Optimization (GWSO) and Decision Trees (DT) are combined in the Glow Worm Coactive Decision Tree (GW+DT). By fine-tuning settings and feature selection, GWSO maximizes DT while utilizing global search capabilities to increase accuracy. This hybrid technique provides robust performance and clear, actionable insights in data with complicated linkages by leveraging the interpretability of DT and the ability to investigate difficult decision boundaries of GWSO. Algorithm 1 shows the Glow Worm Coactive Decision Tree (GW+DT).

Algorithm 1: Glow Worm Coactive Decision Tree (GW+DT)

Start

1. Set parameters for GW and DT
2. Load data
3. Randomly initialize glow worms' position in the feature space and luciferin values.
4. Evaluate the fitness of GW
5. Update luciferin values: $l_h(a) = (1-\rho)l_h(a-1) + \gamma w(q_h(a))$
6. Update decision domain range: $w_x^h(a=1) = min\{w_e, max\{0, w_x^h(s) + \beta(n_a - |N_h(a)|)\}\}$
7. Update GW positions: $q_h(a+1) = q_h(a) + r(\frac{q_u(a)-q_h(a)}{||q_u(a)-q_h(a)||})$
8. Adjust inertia weight and position: $q_h(a+1) = \omega(n)q_h(a) + t(\frac{q_u(a)-q_h(a)}{||q_u(a)-q_h(a)||}$
9. Extract selected features
10. Train DT
11. Evaluate

END

4 Results

The system was built on a VR-ready gaming laptop with an Intel Core i9-11980HK CPU, 32 GB RAM, NVIDIA GeForce GTX 1080, and Windows 11. Unity served as the software development platform. The HP Microsoft mixed reality headset, a consumer-grade VR headset, was utilized for the head-mounted display. Hand tracking was carried out using leap motion technology. The headset's resolution is 1570 x 1500 per eye, with a refresh rate of 120 HZ and Self-Assessment Manikin (SAM) software for arousal and valence analysis of the patient. The program can work on less powerful devices, such as the Oculus Go. The study examined data from EEG measurements to determine the effect of a VR-based music guidance system on the regulation of emotion. The RFE approach was utilized to extract relevant features from the EEG recordings for classification, resulting in the greatest classification accuracy at each iteration. The proposed method was compared to traditional methods like Support Vector Machine (SVM) [16], Naive Bayes (NB) [16], Visual Geometry Group (VGG 16) [17], conventional neural network with gated recurrent unit (CNN + GRU) [17]. The performance was evaluated utilizing several matrices such as F1-Score, accuracy, and recall. The GW+DT technique was utilized to categorize emotional states, with a classification accuracy of 95%. The findings show that the treatment has a considerable favorable influence on emotional control in patients, underlining its potential as a therapeutic intervention depicted in the brain signals, as displayed in Figure 3.

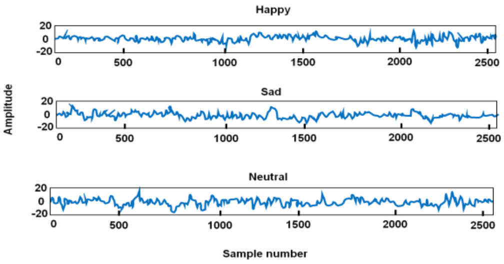

Figure 3: Emotional recognized brain waves

Participant's arousal and valence levels were assessed with a SAM. SAM is a multimodal visualization assessment approach that assesses the individual's emotional reaction in three different categories: valence (from happy to unhappy), arousal (from aroused to calm), and domination (from emotional uncontrolled to control), as illustrated in Figure 4. Table 3 summarizes the outcomes of SAM.

Table 3: Outcomes of SAM

Emotion	Valence	Arousal
Fear	-0.5 to -0.1	0.1 to 0.5
Neutral	-0.5 to -0.3	-0.5 to -0.1
Anger	0.1 to 0.3	0.4 to 0.8
Joy	0 to 0.3	0.5 to 0.9
Tenderness	0.3 to 0.5	-0.5 to -0.2
Sadness	0.5 to 0.8	-0.5 to -0.2
Disgust	0.6 to 0.9	-0.7 to -0.3
Depressed	0.6 to 0.9	-0.7 to -0.3

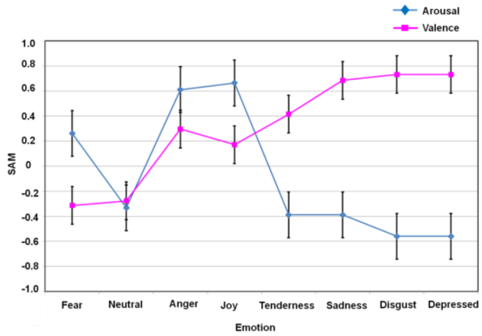

Figure 4: SAM Outcomes

Patients who fell below or over the threshold were assessed as having a cheerful, sad, or neutral mentality. The outcomes demonstrated that true positive (TP) predicted yes (patients do move physically and express their emotion), true negative (TN) predicted no act of kindness, false positive (FP) predicted yes (patients do move physically and express their emotion), and false negative (FN) predicted no facial expression. The system's accuracy was evaluated for each average and gesture of affection. The study analyzed multi-variable correlation analysis which is shown in Figure 5.

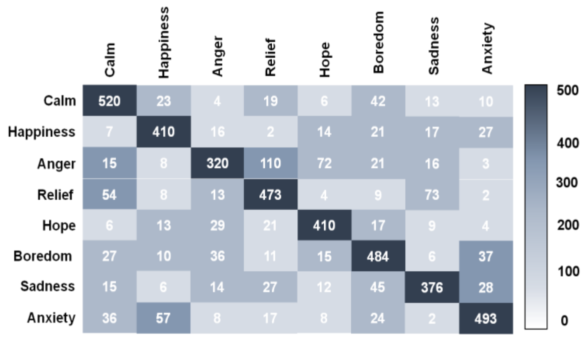

Figure 5: Correlation matrix

A method's accuracy is examined by the sum of TP and TN, or properly categorized items. The aforementioned are positioned on the predominant diagonal and ought to be reduced with the overall amount of forecasts, excluding misclassifications. The accuracy is constant throughout all classes. Figure 6 and Table 4 depict the accuracy of existing and proposed classification methods: accuracy of the SVM is 86%, NB is 61%, VGG 16 is 56.45%, CNN + GRU is 82.23% and the proposed GW+DT approach is 95% recognized the participant's emotion. GW+DT surpasses the other algorithms, achieving the best accuracy in classification.

Table 4: Accuracy

Outcomes of Accuracy	
Methods	**Values (%)**
SVM [16]	86
NB [16]	61
VGG 16 [17]	56.45
CNN+GRU [17]	84.23
IGSO-DT [Proposed]	**95**

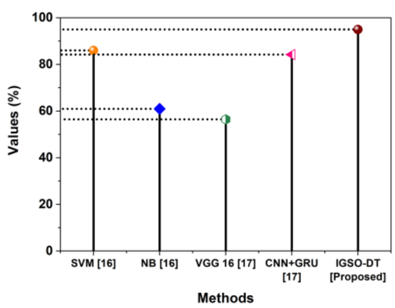

Figure 6: Accuracy

Table 5: Estimation of recall and F1-Score

Methods	**Recall**	**F1-Score**
VGG 16 [17]	72.69	76.4
CNN+GRU [17]	79.63	77.36
IGSO-DT [Proposed]	82.10	80.52

Recall: It is used to calculate a method's efficacy, especially in classification tasks, by gauging the model's capability to exactly recognize every pertinent event. It is resolute by isolating the sum of TN by the sum of FN. Table 5 evaluates the outcomes of Recall. Figure 7 depicts the evaluation of Recall. With a recall of 82.10, the suggested IGSO-DT technique outperformed CNN+GRU and VGG 16, which had recall values of 72.69 and 79.63, respectively, in identifying pertinent instances. This shows that IGSO-DT has a better detection performance and is more successful at reducing missed cases.

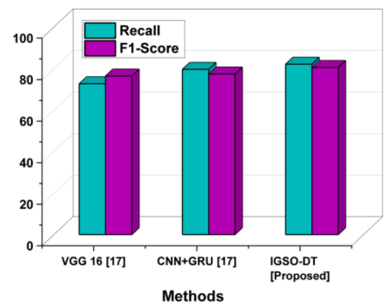

Figure 7: Evaluation of F1 score and Recall

F1- Score: The precision of the capacity to accurately identify positive outcomes and recall the capacity to catch all pertinent instances is taken into account when calculating the F1-Score, which is a metric, used to assess a model's accuracy. The average harmonic of recall and precision is used to calculate it. Table 5 summarizes the estimation of the F1 score. Figure 7 shows the outcomes of F1-Score. The model appears to successfully balance recall and precision if the suggested IGSO-DT approach attains an F1-Score of 80.50. This indicates that the model performs better than the VGG 16 (76.4%) and CNN+GRU (77.36%) methods in recognizing true cases with a little mistake.

5 Discussion

When it comes to classifying emotion, existing techniques like SVM [16] and NB [16] have significant drawbacks. Even while SVM is useful, it frequently has trouble processing high-dimensional data and can need a lot of hyperparameter tweaking to operate at its best. Overfitting and higher processing expenses can result from this. However, as this study's 61% accuracy shows, NB oversimplifies complicated correlations in EEG data, which usually leads to lower classification accuracy. By fusing a decision tree-based classification strategy with feature extraction, the CNN+GRU [17] model, while combining spatial and temporal features, is resource-intensive and prone to overfitting, requiring extensive hyper-parameter tuning. VGG 16 [17], though effective for image classification, has a large computational footprint and model size, making it less adaptable and efficient for varied tasks, the suggested GW+DT method overcomes these drawbacks. By adaptively fine-tuning its classification algorithm and dynamically picking pertinent features, GW+DT achieves a noteworthy 95% accuracy, 82.10% recall and 80.52% F1-score, improvement in handling high-dimensional EEG data. This approach uses decision tree robustness and iterative learning to reduce overfitting, a major problem with SVM. Furthermore, GW+DT does not depend on the feature independence assumption as NB does, which enables it to recognize complex patterns and relations in the data. By taking advantage of these benefits, GW+DT overcomes the shortcomings of current techniques to provide a more precise and effective solution for emotional state classification.

6 Conclusion

This study demonstrates the enormous potential of VR-based music therapy for improving emotional control and well-being among patients receiving chemotherapy. Using modern techniques such as EEG signal processing with RFE and GW+DT, the methodology obtained an impressive 95% accuracy in recognizing emotional states. The VR system revealed significant advantages over traditional approaches, offering a more immersive and engaging therapeutic experience. The findings demonstrate the usefulness of combining VR technology with music therapy as a unique and effective strategy for enhancing mental health and emotional stability in a clinical environment. The findings confirmed that virtual reality can suggest more pleasant, neutral in nature, and anxious feelings than self-imagination, as well as increase singing skills through emotional engagement. The VR training method is regarded as an efficient way to enhance voice music instruction techniques. Future studies ought to examine the broader applicability and long-term effects of this new therapeutic technique.

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