STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
*Stat., Optim. Inf. Comput.*, Vol. **x**, Month 202x, pp 0–18.
Published online in International Academic Press (www.IAPress.org)

# Advanced Emotion Recognition: A Heuristic Approach Applied to EEG Signals Using Machine Learning

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**Abstract** Emotion analysis through electroencephalographic (EEG) signals has become a prominent research focus due to its applications in fields such as marketing, education, and mental health. Despite numerous methods available for emotion recognition, there remains a lack of robust metrics to validate the accuracy of these analyses against the actual emotional states. This study presents a novel heuristic approach for emotion analysis using EEG signals, employing an advanced algorithm that improves the normalization of Valence and Arousal values through the Emotiv Epoc+ device. The algorithm not only refines these critical variables, but also incorporates context-specific adjustments within an improved database schema, allowing for a more adaptive and precise evaluation of emotional states. Comparisons were made with the Self-Assessment Manikin (SAM) test, a validated tool in psychology, to verify physiological responses recorded by EEG signals. The initial findings demonstrated an accuracy of 76.47%, which increased to 79.45% after implementing the proposed enhancements, validated using the DBSCAN clustering algorithm. This study effectively demonstrates the algorithm's capacity to classify emotional states in a sample of 15 participants aged 16 to 25 years, highlighting the potential of this heuristic approach in improving the reliability and applicability of EEG-based emotion recognition. The proposed methodology not only improves the accuracy of emotion detection, but also establishes a foundation for integrating specific contextual factors into EEG analysis, thereby expanding its application in brain-computer interfaces, mental health monitoring, and other advanced research areas. These findings underscore the value of combining physiological data with validated psychological assessments, which offers a significant advancement in the field of emotion recognition.

**DOI:** 10.19139/soic-2310-5070-2211

## 1. Introduction

### *General Context*

Emotion recognition using electroencephalographic (EEG) signals has emerged as a significant research focus at the intersection of artificial intelligence, neuroscience and biomedical informatics [1]. EEG-based emotion analysis provides a non-invasive and real-time window into neural activity, facilitating the interpretation of emotional states. This capability is particularly valuable in domains such as brain-computer interfaces (BCI), mental health monitoring, and affective computing. Emotions play a central role in human cognition, influencing behavior, decision making, and mental well-being [2]. As such, the ability to accurately detect emotions has profound implications, especially in areas such as psychological evaluation, education, and adaptive human-computer interaction.

### *Motivation*

Despite advances in deep learning methods, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have improved classification accuracy [3, 4], many emotion recognition models still

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

lack adaptability to contextual variations and often depend on extensive labeled datasets and high computational resources [5]. In addition, traditional approaches often overlook personalized normalization mechanisms, which can undermine classification reliability in real world settings. This study is motivated by the need to design a more robust, context-aware framework for EEG-based emotion analysis that can operate efficiently with limited data and hardware constraints. By focusing on heuristic-based techniques, we aim to bridge the gap between precision and practicality in emotion classification.

### *Literature Review*

Recent research in emotion recognition has explored both data-driven and heuristic approaches. Deep learning architectures such as 2D CNNs and hybrid RNNs have demonstrated superior performance over conventional algorithms such as support vector machines (SVMs) [6, 7]. However, these approaches require large training datasets, which are not always feasible in clinical or mobile settings. In contrast, heuristic models emphasize rule-based mechanisms that improve signal segmentation and normalization, offering advantages in adaptability and interpretability [8]. Furthermore, affective computing, particularly in unimodal and multimodal systems, has leveraged EEG signals to achieve nuanced emotion classification [7]. Despite these advancements, few studies have incorporated validated heuristic strategies that align the interpretation of EEG data with self-assessed emotional states, such as those measured using the Self-Assessment Manikin (SAM) test (Figure 1) [9].

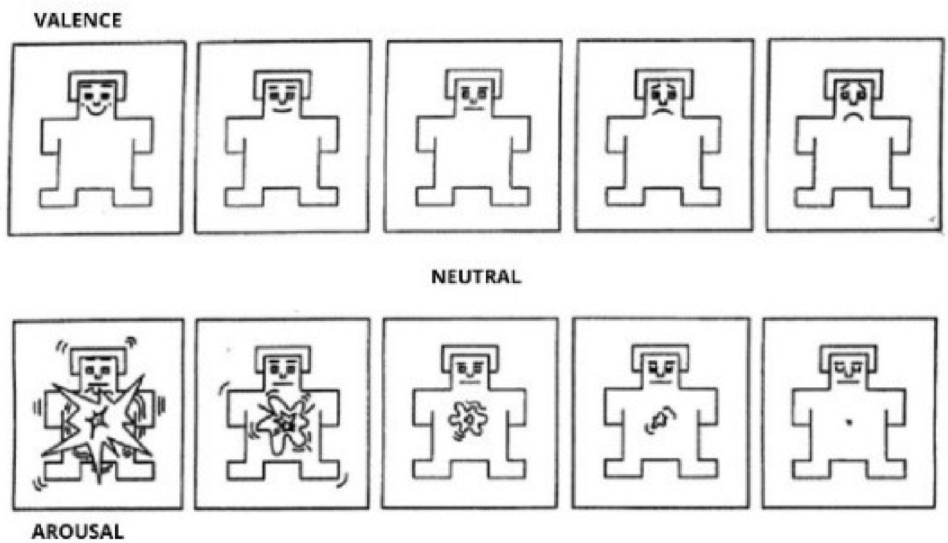



Figure 1. SAM test.

### *Contribution and Scope*

This work proposes a novel heuristic algorithm designed to improve the classification of emotions from EEG signals. The main contributions are as follows.

- A contextual normalization method for valence and arousal values, improving the representativeness of emotional states.
- A database structure that records historical values, enabling the model to self-adjust based on prior emotional contexts.
- A validation framework using the DBSCAN clustering algorithm, which increased the classification accuracy from 76.47% to 79.45%.

The model was developed and tested using EEG data acquired through the Emotiv Epoc+ headset, with the SAM test used to ground truth emotional responses. This approach addresses current limitations in personalization and contextual awareness, offering a scalable solution for emotion analysis in healthcare care and human-computer interaction.

***Document Organization***

The remainder of this article is organized as follows: Section 2 presents the reference framework for EEG-based emotion analysis. Section 3 details the normalization procedures applied to the valence and arousal values. Section 4 defines the measurement settings and the error estimation methodology for the proposed metric. Section 5 describes the experimental setup and reports the results. Section 6 presents a sensitivity analysis of the DBSCAN parameters. Section 7 compares the proposed heuristic with other approaches in the literature. Section 8 explores potential real-world applications of the model. Section 9 outlines suggestions for future research, and Section 10 concludes the article with a summary of the findings and final remarks.

To ensure clarity and consistency throughout this article, Table 1 presents a summary of the main acronyms and parameters used in the study. This nomenclature facilitates the understanding of key concepts, particularly those related to EEG signal processing, emotion classification, and clustering methodologies.

| **Acronym/Parameter** | **Description** |
|---|---|
| EEG | Electroencephalography |
| BCI | Brain–Computer Interface |
| DBSCAN | Density-Based Spatial Clustering of Applications with Noise |
| CNN | Convolutional Neural Network |
| RNN | Recurrent Neural Network |
| Valence | Measure of emotion along the positive–negative axis |
| Arousal | Level of emotional activation |
| Emotiv Epoc+ | EEG device used in the study |
| Silhouette Score | Clustering validation metric |
| eps | Distance parameter in DBSCAN |
| min_samples | Minimum number of points to form a cluster in DBSCAN |

Table 1. Nomenclature used throughout the article.

## 2. Reference Framework

### *2.1. Recognition of Emotions Using a Machine Learning Algorithm*

*T*he classification of emotions from biological signals like EEG has inspired numerous studies in recent years. Such studies propose a variety of models and methods to accomplish the task of classification, including machine learning algorithms, which are among the most popular ones, given their high performance and capacity to learn and improve data collection. For example, [10] proposed an innovative multimodal framework that employs a Random Forest algorithm to classify or score consumer items using three data sources, entailing EEG signal measurements, while an individual observes a product on the screen. Similarly, [11] suggested an emotion classification process from EEG signals using a progressive graphical convolutional neural network. Their focus was on capturing key features in EEG signals with the objective of classifying emotions within a hierarchical system based on their relation to EEG signals. The results obtained from this model are promising as they confirm the relationship between human emotions and high-frequency EEG signals.

### *2.2. Analysis of Emotions*

*I*n this work [12] a comprehensive analysis of the dataset was conducted using power law analysis, allowing the classification of features according to their importance in the classification model. This approach enabled the precise identification of content with mixed sentiments in social web forums, where posts express both positive and negative emotions. This work discusses the impact of profanity data on deep learning-based sentiment classification. With the rise of social media, sentiment analysis has become crucial, relying heavily on data reliability. This study examines whether profanity acts as noise data that reduces classification accuracy. Using movie review data, simulations compared model performance before and after profanity removal. Results showed a 2% decrease in accuracy when profanity was treated as noise, highlighting the importance of handling such data in sentiment analysis[13].

### *2.3. Analysis of Emotions Using Emotiv Epoc+*

*E*ven though the market offers a wide variety of devices to capture EEG signals, the evidence from research demonstrates a preference for Emotiv Epoc+ as a brain–computer interface. For example, Correa employed Emotiv Epoc+ to detect physical activity, referring to Emotiv Epoc+ as “a slightly invasive wireless EEG device” that allows the capture of 14 channels based on the international system 10/20 [14]. On the one hand, the author detailed the development of a model to detect physical activity through EEG signals, carrying out tests with different classification algorithms, namely, k-nearest neighbors (KNN), support vector machine (SVM), naïve Bayes (NB), and random forest. On the other hand, the research highlights the performance of the first and last algorithms and restates the established relationship between human emotions and high-frequency bands of EEG signals (Alpha, Beta, and Theta). Harrison, in his work, employed Emotiv Epoc+, together with the “Affective Suite” package, to determine the grade of assertiveness based on both detected emotions and those reported by the participant during the test; these findings were further applied to an intelligent tourism system [15]. Taken as the basis for the work entitled “Heuristic Design for the Analysis and Measurement of Emotions using Electroencephalographic Signals (EEG)” [16], some challenges were found during the development of this study. After an exhaustive review of the algorithm and considering the directions provided by the authors for further improvements, two modifications were identified to enhance the metric measurement and increase reliability.

## 3. Normalization of the valence and excitation values

*I*n [16], the authors introduced an algorithm divided into components that can be grouped into three categories, as shown in Figure 2. The first improvement proposed in this work focuses on modifying the processing box, particularly with regard to the value normalization V.E. process, which involves deriving valence and excitation values from frequency analysis of encephalographic (EEG) signals. Then, these values are mapped on a valence-excitation plane with limits of 1 (minimum) and 9 (maximum) using Equation 1, where Zi represents the value (excitation or valence) to be mapped, and X denotes the set of values measured by Equation 1. This process is discussed in the context of data normalization [14].

$$EmotivEpoc.Z_i = \frac{(X_i - \min(x))}{(\max(x) - \min(x))} \times 100 \tag{1}$$

The purpose of the procedure is to accurately compare the measured values of Emotiv Epoc+ in contrast with those measured with the SAM test, which employs whole numbers between 1 and 9 for the application. According to the values $\max(x)$ and $\min(x)$ used to perform the mapping, different Zi values can be found. This aspect also highlights a potential area for improvement in the aforementioned algorithm. The authors calculated the Max and Min values (excitation or valence) under normalization, as shown in Figure 3(a).

A disadvantage of this approach is that the result may be biased if the maximum and minimum values in the set represent values other than the highest and smallest ones, respectively. This implies that, in extreme cases, when an individual is experiencing mental health issues, certain emotions might be suppressed, resulting in a high valence

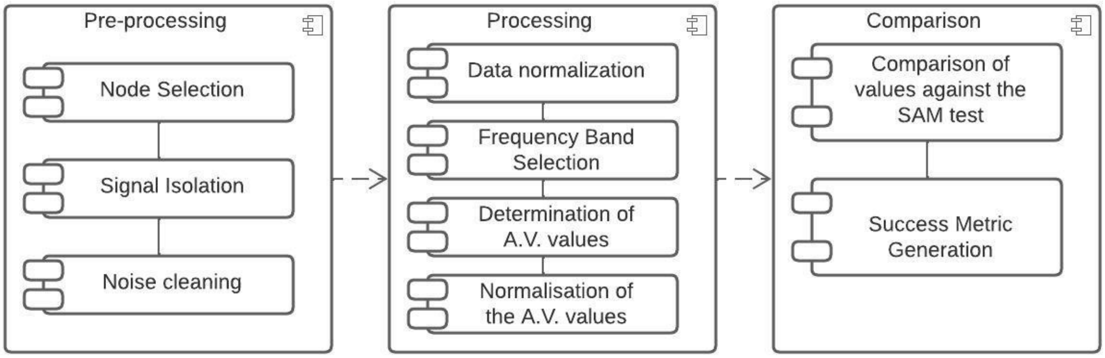
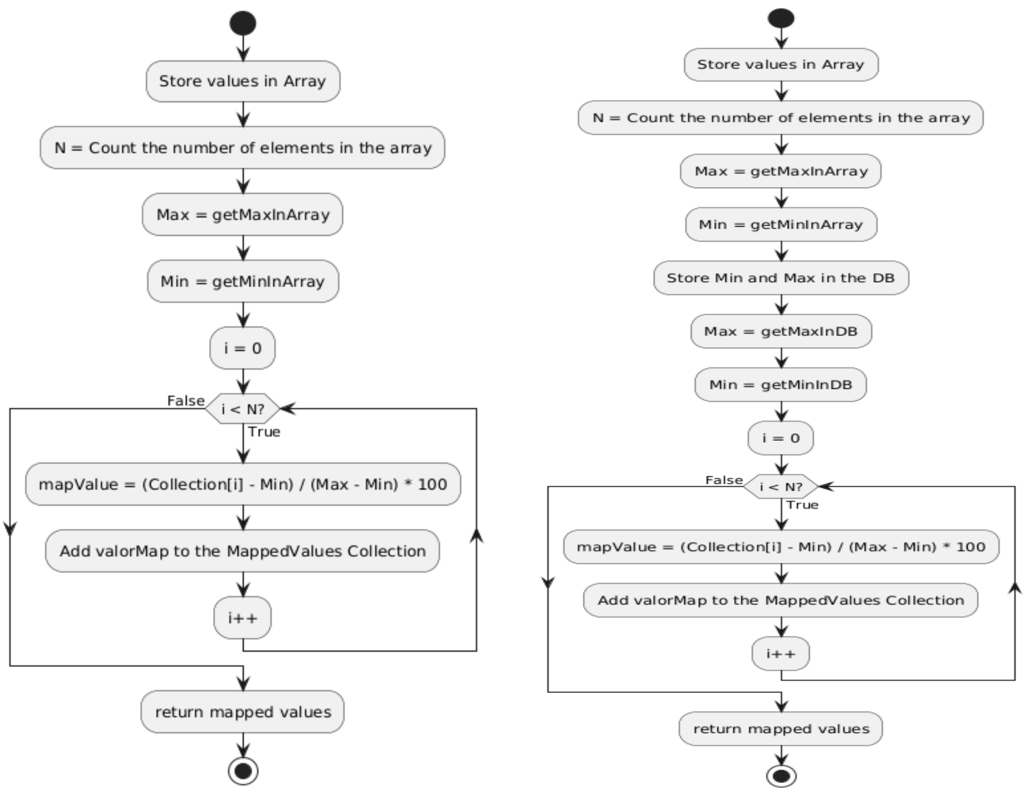



Figure 2. Diagram of the algorithm's components [16]




(a) (b)

Figure 3. Flow chart of the current process. Own authorship.

value (e.g., happiness). In this scenario, when mapping the excitation and valence values, the result can produce extreme elements (maximum valence, maximum excitation), representing the maximum excitation -valence point, which can be interpreted as the individual having experienced a state of extreme happiness when it never occurred. To address this issue, it is suggested to replace the 'Normalization of Values VE'. component with another method that obtains the maximum and minimum values when collecting excitation and valence values, as carried out in [16]. However, instead of using these values directly within the algorithm, they should be stored in a database table to allow obtaining the valence and excitation values for all existing records in the database, as shown in Figure 3(b).

The proposed strategy ensures that the maximum and minimum values are surveyed every time the algorithm is executed, considering the widest extremes in all the tests, without limiting the current execution. The reason behind choosing to keep the maximum and minimum values in all executions, even if they surpass the current records in the table, lies in the capability of maintaining a record. This guarantees that the record is eliminated without affecting execution when tagged as incorrect or inadequate, employing previous values to include in the erroneous record.

In addition, it is proposed to add a label column to each record to identify the context (social, geographic, and demographic) in which the measurement was made. This allows us to obtain maximum and minimum values in that specific context, ensuring that the algorithm is adaptable to the applied context and that the values of other contexts do not influence the measurement of the current context. Developing an optimal database scheme depends

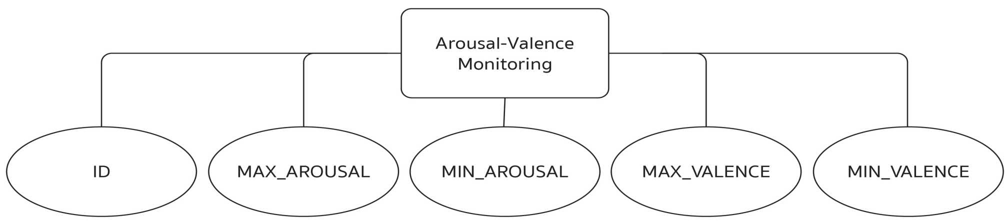



Figure 4. Entity–relationship flowchart. Own authorship

on a suitable understanding of the data model used. In this sense, various tools are helpful for this process. One of the most popular tools is the entity–relationship diagram, which, according to [17], is used in software engineering to model data to optimize software development. The entity–relationship diagram is shown in Figure 4 and consists of a unique entity (table) with four attributes that are followed in the algorithm: Max_Excitation, Min_Excitation, Max_Valence, and Min_Valence, and a primary key to identify each record in the table to ease the process of modification or elimination.

## 4. Setting of Measurements for Grade of Error in the Metric

*T*he authors employed a non-supervised algorithm in [16]. However, the tests lacked a percentage of the error to evaluate the reliability of the algorithm used. The DBSCAN algorithm offers specific validations that help determine its reliability According to [18], DBSCAN allows validation employing the following techniques:

- External validation: This compares the cluster structure with existing ones that require labeled data.
- Internal validation: This is based on intrinsic data information and is used to evaluate the procedure.
- Relative cluster validation: Finally, this type of validation consists of varying the parameters of the grouping method when performing the analysis.

It is possible to determine the method or validation methods to apply to improve the algorithm once the definitions are clarified. Initially, external validation is discarded since it requires either having all the data previously labeled or comparing it with a similar model. However, there is no comparable model for this validation, as evidenced in the framework. The internal validation stage involves evaluating the data labeled by the algorithm. Among the multiple metrics used to determine the adequacy of a grouping, the results of the Silhouette coefficient are remarkable, as they represent an essential metric used to assess the efficacy of a grouping technique. According to [19], the Silhouette formula and evaluation are described below. 1: The media groupings are well separated and the media are distinguished. 0: The media conglomerates are indifferent, or the distance between the conglomerates is insignificant. $-1$: The conglomerates are poorly assigned, or, as indicated in [20], ”Negative values typically suggest that a sample has been assigned to an incorrect group since another group shows greater similarity.”

$$l_s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{2}$$

Equation 2 represents the Silhouette index [18]. According to [19], in Equation 2, the indicated parameters are taken as follows: Parameter a represents the average distance between the clusters and parameter b is the average distance between the conglomerates. The following examples are intended to explain the functioning of this coefficient [19]: A value of 1 was obtained when applying the Silhouette coefficient, as the clusters in Figure 5 are grouped individually, showing no evidence of crossing the points of the cluster.

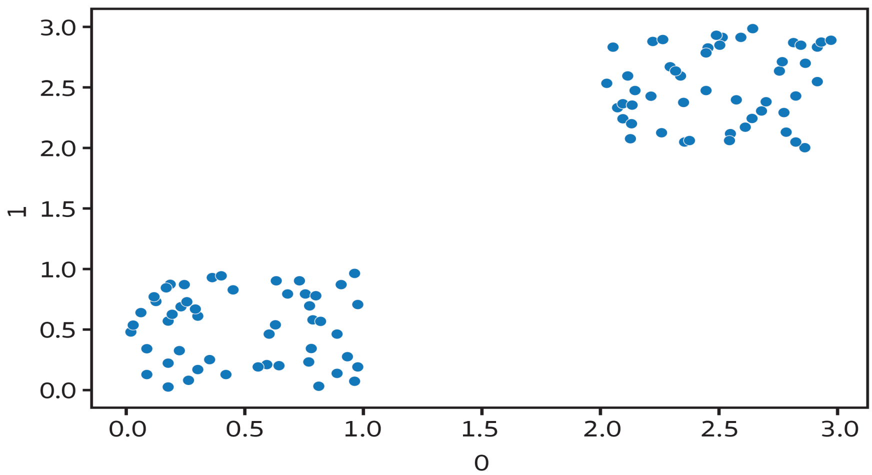



Figure 5. Example 1: Silhouette coefficient [19]

A value of 0.596 was obtained by applying the Silhouette coefficient in Figure 6. This allowed us to determine that despite the proximity of neighboring clusters (clusters 1 and 2), the distance from cluster 0 is sufficient. This calculation determined whether there was any correlation between the data.

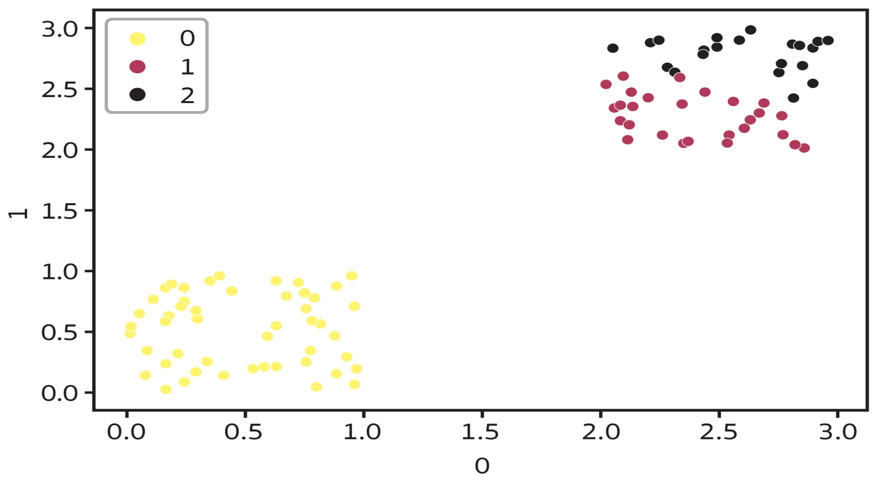



Figure 6. Example 2: Silhouette coefficient [19]

### 4.1. Simulated Tests with the Silhouette Coefficient

*I*n this section, three simulated environments of the Emotiv Epoc+ were taken. The tests were conducted under the premise that the user views an image for 30 s, to determine the suitability of the method for the algorithm. A value of 0.013 was obtained by applying the coefficient in Figure 7. This indicates that the distance between the clusters is insignificant. Thus, the ideal scenario is to improve the result.

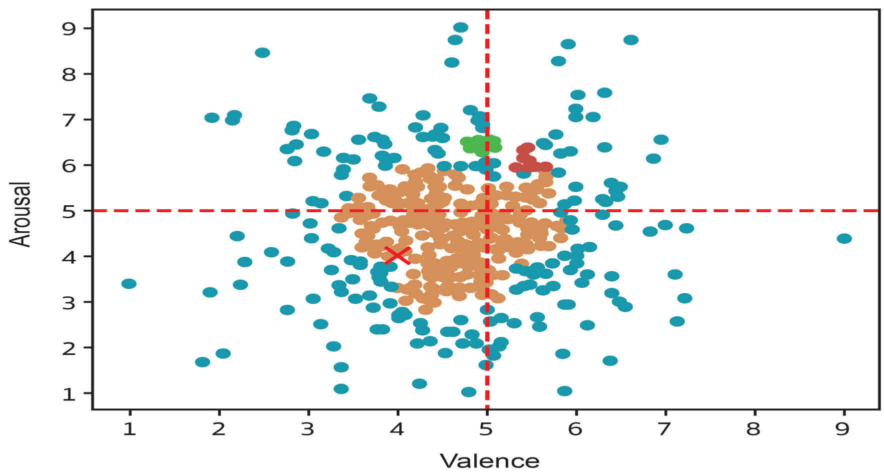



Figure 7. Example 1: Silhouette coefficient test. Own authorship

In Figure 8, the coefficient is closer to 1. For this case, the value obtained was 0.6858, which shows that the clusters are well grouped or separated.

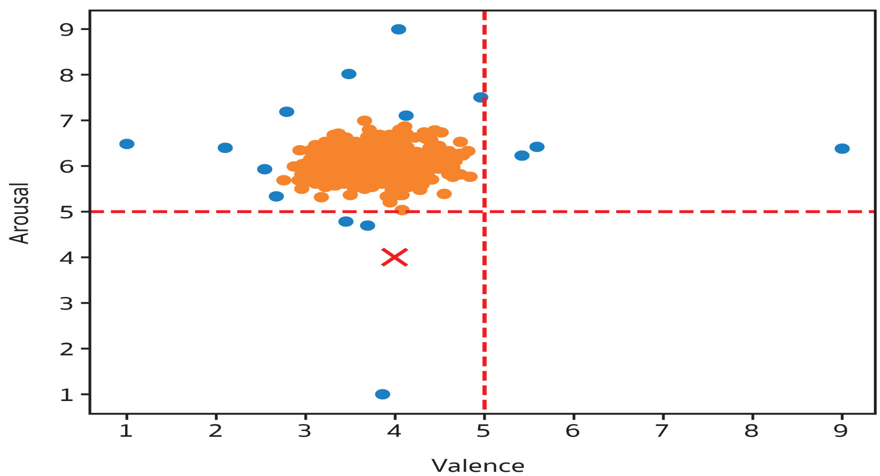



Figure 8. Example 2: Silhouette coefficient test. Own authorship

As evidenced by the previous tests, the coefficient allows one to determine if the data are adequately set; however, more reliability in the data is desired when a value above 0.70 is possible.

### 4.2. Relative Cluster Validation

*A*s mentioned, this method involves varying the parameters of the clustering method [18]. In DBSCAN, Esp and Min_sample are two methods used to test variation. According to [21], Esp is the "observation neighboring", understood as the maximum distance that can be obtained from each observer. Another aspect to consider is the number of neighbors (Min_sample), which represents the minimum number of neighbors to be considered as a central observer. Thus, if the criterion is met, it is regarded as a high-density observation. Likewise, (Datascientest, n.d.) revealed a key factor for the parameter Esp: “If Esp is too small, all the observations in the data set will be considered anomalies”. The case is better illustrated in Figure 9. When using a significantly low Esp value, anomalies are presented. However, when using a significant parameter, “each observation contains in its $\epsilon$ neighborhood all the other observations of the data set” [21].

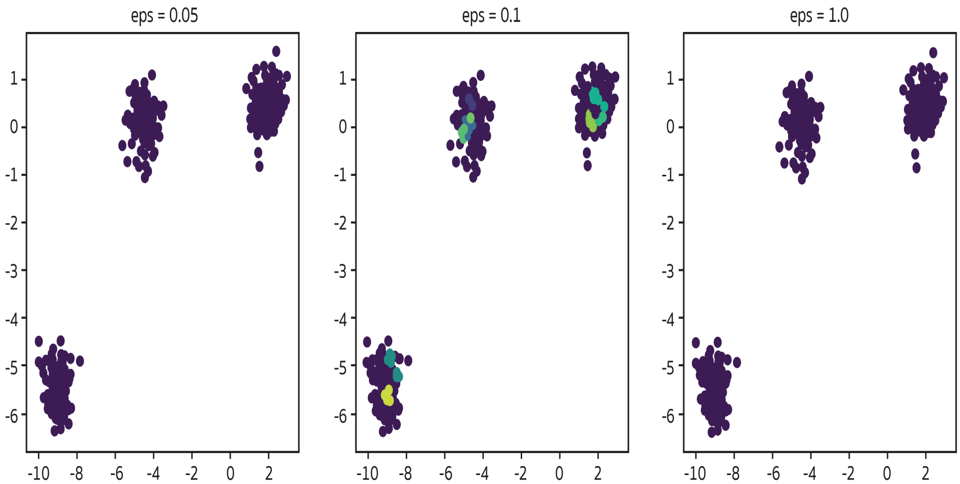



Figure 9. Example of value Esp [21]

Next, tests were conducted to modify these values to guarantee a Silhouette index greater than 0.7. In [16], the authors found that the optimal values are between 0.17 and 0.25, while for the value of Min_sample, it is possible to opt for values between 3 and 12.

### *4.3. Tests with Variations of Esp and Min_Sample*

*A*ccording to the recommendations in [21], the parameters of the DBSCAN algorithm were adjusted. The punctuation criterion established in the Silhouette index was superior to 0.7. The tests were carried out through simulations using the Cortex application programming interface (API) of Emotiv Epoc+. The simulations included signals received for more than 250 s, during which participants were exposed to five images, each shown for 30 s while answering the SAM test with intervals of 15 s between images. For the first test case, the value of Esp was set to 0.25, with a Min_sample of 9, to assess the index behavior, yielding the following results: Figure 10 shows the results, showing well-classified clusters (labels different from $-1$) and noise in the classification (labels equal to $-1$). In addition, the Silhouette index, whose value varied in each test, is presented alongside the results obtained by the metric. A threshold of greater than 0.7 was established for this index, considering the variability of the Silhouette index with each image. An iteration was then implemented for the Esp and Min_sample values, followed by the evaluation of the index; if the desired condition was not met, the parameters were modified accordingly. The initial process was carried out as described in Table 2.

```
<Api.Emociones.Emociones object at 0x7fed8756bee0>
Indice silhouette: 0.606569725776216
Clusters: [-1, 3, 0]:  851
Indice s1.1: 0: 0: 485
Clusters: [1.-1, 3, 501
  0.6026076297575777621616 7
  0.8927908979608163032
  0.8204686763728729 0,20164769334
  0.8140914547696045
Indice silhouette 0.812907378682533
Clusters: 0
  Indicestll: 148
Clusters: [-1, 3, 0]: 501
Indice silhouette: 0,80
Indicesil:Gute 0.59083209008709672
Metrica: 0
Clusters: [-1,3, 0, 0]
Metrica: 0.67305111621414
Metrica: 0.823329482260827
Metrica: 0.776502742201464
```

Figure 10. DBSCAN tests. Own authorship

Table 2. Esp and Min_sample values. Own authorship

| Esp Values | Min_Sample Values |
|---|---|
| 0.17 | 9 |
| 0.27 | 10 |
| 0.37 | 11 |
| 0.47 | 12 |

The values of Esp and Mi_sample were changed with an inter-value of 0.1 and 1, respectively, following the approach reported in [1], [20]. Although this test drastically improved the behavior and reliability of the algorithm, it also showed errors in some cases. Each block in Figure 11 shows the algorithm response, showing variations in Esp. The observations allow us to conclude that variations in Min_sample rarely occur; nevertheless, it was also observed that the Esp interval was too short, leading to flaws in specific cases of the algorithm. Consequently, the decision was made to increase the interval value from (0.17, 0.50) to (0.17, 0.70) to achieve a superior algorithm response.

```
Clusters: {0: 488}
Indice silhouette: 1
Mejor esp: 0.4700000000000001
Mejor min_samples: 9
Metrica: 0.8096823041570085

Clusters: {0: 488}
Indice silhouette: 1
Mejor esp: 0.27
Mejor min_samples: 9
Metrica: 0.8104186529325066

Clusters: {0: 488}
Indice silhouette: 1
Mejor esp: 0.27
Mejor min_samples: 9
Metrica: 0.7710607306497762

Clusters: {-1: 1, 0: 487}
Indice silhouette: 0.7006661257648895
Mejor esp: 0.4700000000000001
Mejor min_samples: 9
Metrica: 0.7765695793123951
```

Figure 11. Algorithm test. Own authorship

The operation of the algorithm after the adjustment applied to the intervals is depicted in Figure 12, ensuring a Silhouette index level greater than 0.70 in each test run. The reliability of the algorithm is demonstrated by meeting the conditions of this index, as shown in Equation 3. 3 was used for the DBSCAN algorithm tests.

$$\text{Error} = 1 - \text{indiceSilhouette} \tag{3}$$

As a final adjustment, the increment of the interval was modified. Despite initially increasing the values by 0.1, a decrease was observed in those cases where an optimal response was achieved. Therefore, smaller increments of 0.01 were applied to improve the response in the process. No additional adjustments were made to avoid increasing the complexity of the algorithm, which could result in longer response times.

```
Clusters: {-1: 1, 0: 503}
Indice silhouette: 0.7536700525944943
Mejor esp: 0.27
Mejor min_samples: 9
Metrica: 0.7570237223501981

Clusters: {-1: 29, 0: 459}
Indice silhouette: 0.7441206499256366
Mejor esp: 0.37
Mejor min_samples: 9
Metrica: 0.8103968800140403

Clusters: {-1: 33, 0: 455}
Indice silhouette: 0.7065372153301526
Mejor esp: 0.27
Mejor min_samples: 9
Metrica: 0.8073230131728146

Clusters: {0: 488}
Indice silhouette: 1
Mejor esp: 0.17
Mejor min_samples: 9
Metrica: 0.7708894188882607

Clusters: {-1: 41, 0: 447}
Indice silhouette: 0.7012254005306002
Mejor esp: 0.37
Mejor min_samples: 9
Metrica: 0.7772165382727336
```

Figure 12. DBSCAN algorithm tests. Own authorship

## 5. Experiment and Results

Various resources used by the authors in [16] were applied to conduct both the testing and the validation of the changes applied to the algorithm. For instance, the API Rest was modified for the back-end case by adding labeled endpoints according to the required metric version. This allowed results from both the original and proposed versions to be obtained through the same API. In addition, certain user interfaces were adapted to the new endpoints developed for the latest metric version on the front-end.

The selected sample consisted of 50 students aged 16 to 25 years of age from the Faculty of Engineering of the Universidad Distrital Francisco José de Caldas. The rationale for selecting this population group includes the following factors:

- **Emotional development of young adults:** The age range of 16–25 years represents a crucial stage in the emotional development of individuals. According to numerous references, this stage is characterized by significant changes in emotional regulation and perception of visual stimuli. For example, a study by Steinberg [22] highlighted the relevance of brain and emotional development during late adolescence and emerging adulthood.
- **Receptivity to visual stimuli:** The response of this demographic group to visual stimuli is essential. Research such as that conducted by Nummenmaa et al. [23] has shown that visualization of images can elicit specific emotional responses that vary depending on age and emotional state.
- **Aptitude for technology and cognition:** University students in this age range are typically more familiar with technology and quickly adapt to using devices such as the Emotiv Epoc+ headset. This facilitates participation in experimental protocols, as shown in studies such as Vessel and Haber [24].
- **Homogeneity and control of variables:** Restricting the sample to students within this age range reduced variability in the study group, making it easier to control confounding variables and obtain more transparent and comparable results, as discussed by Reichert and Carpenter [25].
- **Relevance of practical application:** Understanding the emotional responses of this demographic in visual environments has significant implications in various fields such as education, marketing, and psychology. The research by Lang et al. [26] emphasized the importance of decoding emotional responses to visual content.
- **Ethics and informed consent:** All participants provided informed consent according to the ethical guidelines for research involving human subjects. Participation was voluntary and was carried out with institutional ethical approval.

Although the total sample used in this study consisted of 50 participants, a focused sub-sample of 15 individuals was selected for the EEG-based emotion analysis component. This decision is consistent with established practices in the field, where small sample sizes are commonly used due to the complexity of EEG data collection and the high sensitivity required for experimental control. Previous studies have shown that working with sample sizes ranging from 5 to 20 participants can still produce valid and meaningful insights.

For example, Marco et al. [27] developed an emotion recognition system based on EEG signals with only 5 participants, achieving a classification precision of 76%. Tejada Bustillos [28] conducted a similar analysis with 12 individuals using machine learning models, and Olivares Cortés et al. [29] found strong correlations between emotional states and brain activity in a group of 10 subjects. The selection of 15 participants in our study ensures a balance between the feasibility of experimental implementation and the statistical reliability of the results. Furthermore, a smaller cohort allows for rigorous supervision during the data acquisition phase, reducing potential artifacts and improving the quality and interpretability of the recorded EEG signals.

Only 15 students from the original 50 individuals who agreed to participate in the experiment were selected. This reduced selection was motivated by the need for participants to meet specific physical and environmental conditions that ensured optimal EEG data quality. These conditions included:

- Having short hair, to facilitate proper sensor calibration.
- Ensure that the hair was free of cosmetic products, which can interfere with signal conduction and device performance.

- Avoid the use of metallic or electronic accessories during the session, to prevent electromagnetic interference with the Emotiv Epoc+ headset and its USB dongle.
- Conduct the experiment in a dedicated quiet space free of external noise to help participants maintain focus and avoid environmental artifacts in the EEG recording.

### *5.1. Algorithm Transparency and Pseudocode*

To ensure reproducibility and methodological transparency, this section provides a structured overview of the heuristic algorithm implemented in this study. The algorithm comprises four main stages, each contributing to the pre-processing, feature extraction, normalization, and clustering of EEG-derived emotional data. The pseudocode presented in the following offers a clear reference for replicating the proposed method.

#### *Heuristic Algorithm Implementation*

The heuristic algorithm consists of the following key stages:

1. **EEG Signal Preprocessing**
   - Application of a bandpass filter (0.5 Hz – 60 Hz) to remove physiological and environmental noise.
   - Removal of artifacts using mean and variance-based normalization to reduce signal irregularities.
2. **Feature Extraction**
   - Application of Discrete Wavelet Transform (DWT) to decompose the signal into frequency components.
   - Calculation of energy in the Alpha and Beta frequency bands to represent the characteristics of the emotional state.
3. **Normalization of Valence and Arousal Values**
   - Application of the normalization equation 4:

$$Z_i = \frac{X_i - \min(X)}{\max(X) - \min(X)} \times 100 \tag{4}$$

   - Storage of historical valence and arousal values for longitudinal emotional analysis and model adaptation.
4. **Clustering with DBSCAN**
   - Configuration of optimal parameters (eps = 0.25–0.75, min_samples = 9–12).
   - Clustering of data points in the two-dimensional valence–arousal space using the DBSCAN algorithm.
   - Validation of clusters using the Silhouette coefficient, with values $\geq 0.7$.

This pseudocode and its corresponding description facilitate the full replication of the methodology proposed in this study, thereby enhancing the reliability and transparency of the emotion classification process.

### *5.2. Experiment*

The group of students was exposed to a series of images to evaluate their emotional responses; The images displayed different characteristics and settings, including disheartening scenarios such as natural catastrophes, misuse of power in institutions, and situations of physical abuse between individuals. In this case, the following activities were carried out from the outset of the test:

- Test explanation: This stage included a precise explanation of the test for all participants, including the purpose of the test.
- Device calibration: This occurred right after the test explanation and consisted of starting and calibrating the Emotiv Epoc+ device.

- Test execution: According to the parameters established in [16], the test was performed as follows: A 5 s delay was determined to normalize the signal; later, a random image was shown for 30 s, followed by the SAM test for 15 s. At this stage, the participants chose pictograms that represented the emotions displayed in the image. The process is fully detailed in Figure 13.

Fig. 13. Data capturing in the test. Own authorship.

### 5.3. Results

In Table 3, a comparison of the results obtained using version 2 of the heuristic, which is the version presented in this work, can be observed against the results from version 1 [16].

Table 3. Metric versions comparison

| IMAGE | SAM | | | | EMOTION | | | ERROR |
|---|---|---|---|---|---|---|---|---|
| | VALENCE | | EXCITATION | | NAME | RESULT | | |
| | VERSION 1 | VERSION 2 | VERSION 1 | VERSION 2 | | VERSION 1 | VERSION 2 | VERSION 2 |
| 1 | 4 | 4 | 3 | 3 | Miserable | 0.75 | 0.81 | 0.25 |
| 2 | 6 | 6 | 3 | 3 | Angry | 0.89 | 0.78 | 0.20 |
| 3 | 7 | 7 | 5 | 5 | Annoyed | 0.69 | 0.78 | 0.22 |
| 4 | 3 | 3 | 6 | 6 | Sleepy | 0.75 | 0.84 | 0.24 |
| 5 | 4 | 4 | 4 | 4 | Bored | 0.86 | 0.90 | 0.26 |
| AVERAGE | | | | | | 0.78 | 0.82 | 0.23 |

The results of all the tests indicate a simple and specific statistical analysis, mainly focused on suggestions for improvements to the algorithm, rendering the following results.

*5.3.1. Normalization of the Excitation–Valence Values T*he applied improvement consisted of modifying an existing module, which allowed a comparison of the results for both versions, as detailed in Table 4 (version 2). This version offers superior results compared to the original version. Although the difference in each measurement

Table 4. Statistical analysis results of improvement 1. Own authorship.

| Measurement | Version 1 | Version 2 |
|---|---|---|
| Maximum | 0.95701099 | 0.95789596 |
| Minimum | 0.53053680 | 0.52817684 |
| Median | 0.76470015 | 0.79159017 |
| Standard deviation | 0.11070618 | 0.10319025 |

reached 0.03 in the most suitable cases, this represents a promising advancement that could be extended with additional tests. Specifically, for the median case, it was observed that the average value for version 2 was 0.79, 0.27 units over the result for version 1. This indicates that on average, the proposed modification yields higher values for the metric. This assertion is reinforced by examining the standard deviation: Approximately 0.1031 for the improved version, which is 0.0075 units lower than for version 1. The exact value was used to evaluate the dispersion of the data, demonstrating that the resulting values of the metric, when applying the suggested improvements, are more homogeneous and, on average, higher than those obtained in the first version.

*5.3.2. Measurement Error Estimate* Unlike the first improvement proposed, this did not involve modification of an existing module, instead involving the generation of a new characteristic. Therefore, directly comparing both versions is impractical. Consequently, the statistical analysis was focused only on the results obtained from the second version of the metric, detailed in Table 5.

Table 5. Statistical analysis results of improvement 2. Own authorship.

| Measurement | Value |
|---|---|
| Maximum | 0.29665470 |
| Minimum | 0 |
| Median | 0.03713923 |
| Standard deviation | 0.08400233 |

*5.3.3. Measurement Error Estimate* Regarding the first revision of the first version, the Esp and Min values remained constant and did not allow modifications to identify the algorithm response. In contrast, the new version allows you to find an optimal value from the values that help the algorithm improve its behavior. It enables both finding an optimal response by adjusting the algorithm for each participant and providing more accuracy in the raised metric. This point allows for the reduction of the margin of error in each test.

## 6. Sensitivity Analysis

To evaluate the influence of DBSCAN hyperparameters on clustering performance, a sensitivity analysis was performed by systematically varying the values of `eps` and `min_samples`. This analysis aimed to identify the configuration that yields optimal cluster separation, as measured by the Silhouette coefficient.

### *Methodology*

The experimental setup for the sensitivity analysis was defined as follows:

- The parameter `eps` was varied from 0.2 to 0.8 in increments of 0.1.

- The min_samples parameter was tested with values ranging from 5 to 15.
- The Silhouette coefficient was calculated for each configuration to evaluate the quality of the clustering.

***Results***

Table 6 summarizes the clustering quality obtained for each parameter configuration. The highest Silhouette score was observed at eps = 0.5 and min_samples = 9.

| **eps** | **min_samples** | **Silhouette Score** |
|---|---|---|
| 0.2 | 5 | 0.62 |
| 0.3 | 5 | 0.70 |
| 0.4 | 7 | 0.74 |
| 0.5 | 9 | **0.78** |
| 0.6 | 9 | 0.72 |
| 0.7 | 12 | 0.69 |
| 0.8 | 15 | 0.65 |

Table 6. Sensitivity analysis of eps and min_samples parameters in DBSCAN.

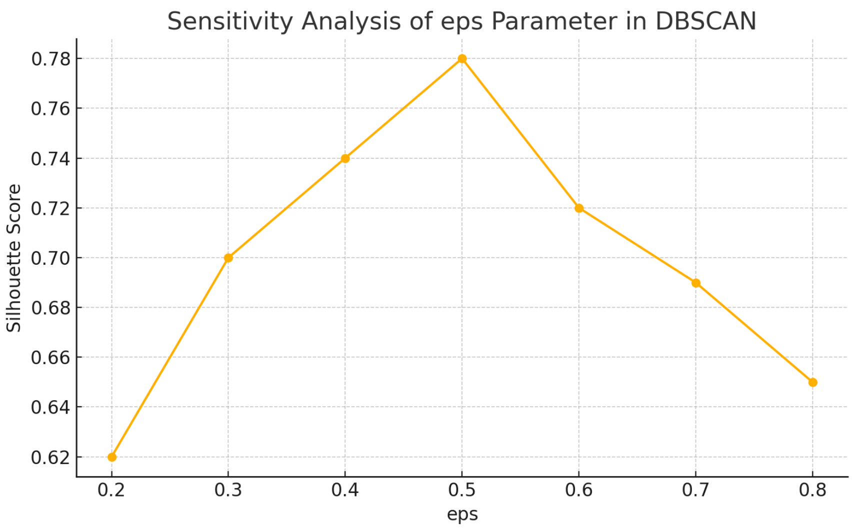



Figure 14. Silhouette Score obtained for different values of eps, with fixed min_samples. The optimal value was eps = 0.5.

## 7. Comparative Analysis

To highlight the relevance and strengths of the proposed method, this section presents a comparative analysis of the heuristic algorithm alongside commonly used deep learning models and heuristic optimization approaches in the context of EEG-based emotion recognition.

| **Method** | **Limitations** | **Strengths / Advantages** |
|---|---|---|
| Convolutional Neural Networks (CNN) [30] | Requires large volumes of labeled data and intensive computational training. | High performance in spatial pattern recognition. |
| Recurrent Neural Networks (RNN) [31] | Suffers from gradient vanishing and dependency on large datasets. | Effective for processing temporal EEG sequences. |
| Genetic Algorithms [32] | Computationally expensive; sensitive to parameter tuning. | Useful for feature optimization and global search. |
| Local Search Methods [32] | Prone to becoming trapped in local optima. | Efficient for fine-tuning parameters in constrained spaces. |
| **Proposed Heuristic Algorithm** | Less suited for highly dynamic or deeply non-linear data patterns. | **Computationally efficient, does not require large labeled datasets, and offers high interpretability due to its transparent structure.** |

Table 7. Comparison of commonly used methods with the proposed heuristic approach.

## 8. Real World Applications

*T*he practical applicability of emotion recognition through EEG signals is increasingly relevant in various domains. The proposed heuristic model, validated under controlled conditions, has the potential to be integrated into multiple real-world contexts. In the following, we outline several implementation areas where this approach could deliver significant value.

- **Mental Health:** EEG-based emotion recognition can serve as a powerful tool in the diagnosis and treatment of emotional and affective disorders. In neurofeedback therapy, patients can learn to self-regulate their emotional states by receiving real-time feedback on brain activity [33]. This technique may also support the rehabilitation of people with neurological impairments by improving the recovery of emotional and cognitive functions [34].
- **Education:** In academic environments, monitoring students' emotional states can provide valuable insights into their engagement, stress levels, and learning effectiveness. Real-time emotion tracking systems can allow educators to dynamically adapt their instructional strategies. For example, signs of frustration could prompt pedagogical adjustments or the suggestion of breaks to improve concentration and retention [35].
- **Marketing and User Experience:** Emotion analysis can inform business strategies by evaluating consumer responses to products, services, or advertising content. EEG-based emotional feedback provides objective data on customer perception, which can guide product development, interface design, and marketing campaigns to better align with user expectations and emotional reactions [36].
- **Brain–Computer Interfaces (BCIs):** Incorporating emotion recognition into BCIs enhances their intuitiveness and personalization. For example, virtual reality systems could dynamically modify content based on the user's detected emotional state, improving immersion, comfort, and overall user satisfaction [37].

## 9. Suggestions for Future Work

*T*o expand and validate the findings of this study, the following research directions are proposed:

- **Sample expansion:** Evaluate the algorithm with a more diverse population in terms of age, sex, and cultural background to determine its applicability in different contexts.
- **Integration with hybrid models:** Combine the proposed heuristic with deep neural networks to improve classification performance without significantly increasing computational complexity.

- **Application in real-world environments:** Implement the model in real-time monitoring systems to evaluate its performance in practical applications such as mental health and personalized education.
- **Longitudinal analysis:** Conduct follow-up studies on participants to evaluate the stability and evolution of emotional patterns over time.
- **Parameter optimization:** Explore the automatic parameter tuning techniques in DBSCAN and other clustering methods to further increase the accuracy of the system.

## 10. Conclusion

*T*his study demonstrates the effectiveness of a heuristic-based approach to emotion classification using EEG signals. The proposed methodology improves the normalization of the valence and arousal values, optimizing the precision of emotion detection. Validation with the DBSCAN clustering algorithm showed an increase in classification precision from 76. 47% to 79. 45%, suggesting that the implemented strategy is effective in segmenting and analyzing emotional states.

Furthermore, the integration of a historical database of valence and arousal values improves the adaptability of the model in various experimental contexts, thus increasing the applicability of the method in real-world scenarios. These findings may serve as a foundation for future developments in brain–computer interface systems and mental health monitoring.

In addition, a sensitivity analysis was performed to evaluate the impact of the DBSCAN parameters `eps` and `min_samples` on clustering quality. The results confirmed that the combination of `eps` = 0.5 and `min_samples` = 9 provided the most stable and well-separated clusters, with a Silhouette coefficient of 0.78. This reinforces the methodological rigor of the proposed model and justifies the selection of these parameters in the experimental phase.

Our heuristic offers a viable and efficient alternative for EEG-based emotion recognition, particularly in contexts where computational resources and labeled data are limited. Although deep learning models and other heuristic algorithms have their own merits, the selection of an appropriate method must consider the specific constraints and objectives of each study.

Finally, although the results obtained are promising, future research should focus on evaluating the model with larger sample sizes and across diverse population groups, as well as exploring hybrid approaches that combine heuristics with deep learning models.

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