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RESEARCH ARTICLE

Emotion Recognition in Gaming Dataset to Reduce Artifacts in the Self-Assessed Labeling Using Semi-Supervised Clustering

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ABSTRACT Popular comments suggest that continuous exposure of children and adolescents to video games yields a non-benefit behavior in the players' mental health. Contrarily, several studies have proven that commercial and serious games improve mental activity; some are used in treating psychological and physical disorders. This paper presents a method based on electroencephalogram signals analysis to classify multiple emotions recorded from subjects' gameplay seasons. In the core of this study, a self-assessed labeling method is evaluated using the Force, EEG, and Emotion Labelled Dataset (FEEL) for emotion recognition tasks. Besides, a 1-D Local Binary Pattern (LBP) method transforms the EEG temporal behavior to extract time-frequency features. Complementarily, the database artifacts were removed using a novel Conflict Learning approach for machine learning models, associating the extracted samples with the subjects' emotion labeling. A semi-supervised clustering method was employed to show the similarity between self-assessed subjects' labels. Finally, numerical results suggested a conflict between 23 original labels, improving the classification by over 92% in accuracy for 19 self-assessed classes.

INDEX TERMS Emotion recognition, gaming, conflict learning, clustering, machine learning.

I. INTRODUCTION

Video games are a comprehensive entertainment platform used generally for children and adolescents, but yielding a growing research field to understand human motivations and learning processes [1].

People usually think violent video games could yield more aggressive behavior in young game players [2]. However, a meta-analysis reported that only a tiny group presented the violent effects of long-time video game exposure [3]. Contrary to many beliefs, several video games helped treat medical conditions, teach, and improve coordination skills and even cognitive behavior. These types of video games are usually called *Serious Games* [1]. Thus, recent findings suggest that these therapeutic video games improve children's well-being by helping them overcome real-life issues, producing different beneficial scenarios that trigger emotional responses [4].

Furthermore, serious games presented a less invasive but enjoyable learning process, achieving attention, motivation, and extensive training seasons. However, other games developed for physical movements, such as exergames, require players' strength, balance, and flexibility [5].

In a scientific sense, these video games improve or stimulate the cognitive functions of older people with specific neurological disabilities [6]. Additionally, these video games

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are used in treating subjects with autism for training sports and promoting physical, cognitive, linguistic, social, emotional, and affective skills [7]. In practice, several researchers have tried to measure and analyze the positive impact of commercial video games, particularly those requiring high-stress tolerance and cognitive skills [8]. For instance, video games like Starcraft can improve mathematical skills, Minecraft for math, and Assassin's Creed for history playfully [1].

Indeed, video games' influence on subjects' emotions is remarkable and measurable. In literature, several methodologies focused on Emotion Recognition (ER) have been proposed to classify primary or secondary emotions [9]. One of the principal ER approaches concentrated on the primitive emotions classification is based on the valence, arousal, or dominance of subjects' emotional stimuli. This type of method develops a particular Machine Learning (ML) or Deep Learning (DL) model per primitive emotion [10], [11]. It is especially noteworthy how these models present a high stimuli detection and a low primary emotion detection due to the self-assessed stimuli. Nevertheless, other methods are based on Positive, Negative, and Neutral (PNN) emotions, avoiding the drawbacks of self-assessed emotion stimuli [12], [13]. The significant advantages of these approaches are remarkable, mainly involving the high accuracy rate achieved in a single model by reducing the target's dimension.

In close connection, models based on primary or secondary emotions classification are challenging to train and validate. Even so, thorough models have been successfully tested as the method proposed by [14], whereby DL techniques achieved an accurate ER model using a frequency Electroencephalogram (EEG) band decomposition, concluding that β and γ bands are the most significant. Similarly, [15] attained a four-class single model for primary emotions classification using different subject-dependent Long Short-Term Memory (LSTM) architectures and discriminant features as input data into the neural network. In contrast, accurate models based on ML frameworks have also been developed, such as the study of [16], where findings emphasize the importance of local brain activations and connectivity of neural networks. Finally, [17] showed a data combination using EEGs and eye movement to classify primary emotions. They discussed a frequency-dependent and frequency-independent classification method for the EEG sub-bands.

Concretely, gameplays and their influence on subjects' emotions are a fertile field of research in video game influence and the difference in labeling emotion stimuli. Remember that this paper uses the Force, EEG, and Emotion Labelled Datase (FEEL) [18] as input data to study the self-assessed emotion perception in subjects playing video games.

The most representative contribution of this work is based on the self-assessed labeling reduction using two approaches: the CL developed by [19] and the clustering emotion perception. Both techniques yield a reduced labels space where the CL reduces almost 50% of labels. Besides, the clustering technique provides eleven, seven, and three clusters per lever tree.

The main contributions of this work are summarized as follows:

- A novel and robust emotion recognition electroencephalographic signals dataset, FEEL, is used as input data.
- A 1-D Local Binary Pattern (1D-LBP) to transform the original EEG signals behavior is computed, achieving a semi-periodical EEG pattern.
- According to the 1D-LBP coefficients, a conflict learning (CL) based on Hamming, Tanimoto [20], and Dixon-Koehler [21] metrics are computed as mean and maximum conflict learning coefficients between samples for artifacts reduction.
- A clustering method based on extracted features to significantly evaluate the self-assessed labels was implemented for labeling reduction and clusterization.

II. RELATED WORKS

Emotions play an essential role in people's life, where anxiety, depression, and anger affects them physically and psychologically [22]. After the pandemic outbreak of COVID-19, emotional health took profound relevance. In fact, [23] described the crucial importance of Facebook, TikTok, and social media platforms during this period. As a consequence of this pandemic period, one of the most profitable sectors was the video games industry. Proof of this is the Twitch platform showing an increase of 53% in users' watched hours and 63% in streamers' numbers between December 2019 and December 2020. Besides, video games showed an emotional impact on children and adolescents, enabling the manifestation of socio-emotional responses due to the social characteristics content of video games [24]. In this way, parents expressed concern about the harmful effects of violent video games on the young population. However, recent findings have established that only a few video game users can present negative behaviors or violent responses directly related to video games' influence [3].

In another study, [25] documented the importance of Cognitive-Behavioral Therapy (CBT) in video games while helping overcome barriers to improve mental health. Such a study also emphasized the importance of gaming by showing a reduction in depressive moods and an increase in emotion regulation, proving that left frontal brain activity is associated with the same process. Furthermore, another favorable response to playing video games was studied by [1], using serious games as a treatment for Attention Deficit Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD). Also, [26] found a positive influence of video games on neurodevelopmental and trauma-related disorders using meta-analysis while studying several commercial video games on gamer emotions. Similarly, [27] pointed out the positive effects of violent video games; the players showed better control for inhibitory emotional stimuli, developing non-distractions to emotional contents and control tasks.

ER can classify primitive or primary emotions based on the emotion stimuli. So, it is known that the methods based on primitive or PNN emotion classification are highly associated with the self-assessed emotion triggered in the subjects. Meanwhile, primary or secondary emotions are instead related to diverse cognitive processes. For example, primary emotions (anger, fear, joy, sadness, disgust, and surprise) are expressed in the first six months of life. In contrast, the secondary emotions use somatic makers to provide an accurate emotion from the primary ones. Thereunto, the secondary emotions are specially activated by the ventromedial Prefrontal Cortex (vmPFC) [9].

Reference [28] highlighted the importance of the amygdala in emotion generation and propagation; meanwhile, they confirmed with a channel selection method that FC1 and CZ EEG channels are the most relevant in classification tasks and present strong amygdala influence. In addition, previous ER models obtained 80% Broadening EEG channel selection discussion, [29] found five channels (P3, FC2, AF3, O1, and FP1) influence compared to the explored 32 channels available in the Dataset for Emotion Analysis using Physiological (DEAP) [30]. Similarly, [31] conducted a channel selection analysis for each primitive emotion, finding eight significant channels for valence and ten for arousal using the Normalized Mutual Information (NMI) algorithm. Likewise, [32] found that using only 10-EEG channels, most located in the frontal lobe, the classification methods are highly accurate concerning those that exploit 62 or 32 channels while identifying four different primary emotions.

On their side, [33] presented a novel classification method testing different ER datasets, achieving high accuracy in detecting primary emotions. Correspondingly, [34] used a feature extraction process combined with Principal Components Analysis (PCA) to train a DL architecture to recognize four primary emotions. Finally, [35] studied and implemented a brain network correlation with EEGs, where primary emotions' identification remarkably showed to be accurately modeled. In our previous findings [36], we systematically evaluated a Conflict Learning (CL) method [19] to avoid dataset artifacts and substantially increase the accuracy. This study uses the same method to reduce the artifacts in the self-assessed labeling dataset.

III. MATERIALS AND METHODS

As said before, emotions during gameplay are an interesting study field, and according to recent research, the number of positive study cases is much higher than negative gamer effects. Consequently, an efficient and reliable emotional stimuli analysis is needed in real applications.

The FEEL is a sixteen-subject self-assessed labeling dataset for emotion recognition supported by EEG signals [18]. In such a database, electroencephalogram data is recorded in gameplaying seasons, including the joystick-keypress force data, which is unnecessary for this study. The EEG activity is saved in a Comma Separated Values (CSV) format as a table, $\boldsymbol{\xi} \in \mathbb{R}^{m\times n}$, where m is the variable for indexing each EEG channel per gameplay, and n is the length of each EEG signal. Several gameplay trials per subject were stored in the nth dimension differently. Therefore, the CSV labels file contains the elapsed time per subject trial, so the matrix $\boldsymbol{\xi}$ is organized for better management as

$$\boldsymbol{\xi} = \begin{pmatrix} \xi_{1,1} & \xi_{1,2} & \cdots & \xi_{1,n} \\ \xi_{2,1} & \xi_{2,2} & \cdots & \xi_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \xi_{m,1} & \xi_{m,2} & \cdots & \xi_{m,n} \end{pmatrix}^{\mathsf{T}} \tag{1}$$

The proposed framework, including the signal processing, conflict learning criteria, and clustering using the Hamming distance, is represented in Figure 1.

A. EEG SIGNAL PROCESSING

The EEGs record the brain's bioelectrical activity according to a stimuli response. This study's signal magnitude per EEG channel is stored in the matrix $\boldsymbol{\xi}$ and extracted from the FEEL dataset. Consequently, using the following criteria, a 1D-LBP algorithm is used to compute a periodicity pattern per EEG.

$$\alpha_i = \left[\xi_{\psi_{(w+i-8)}}, \xi_{\psi_{(w+i-7)}}, \ldots, \xi_{\psi_{(w+i-1)}}\right], \quad \forall i \in [0, \upsilon],\ \upsilon \in \mathbb{Z}^+ \tag{2}$$

$$f(\alpha_i) = \begin{cases} 1, & \alpha_i \geq \xi_{\psi_c} \\ 0, & \alpha_i < \xi_{\psi_c} \end{cases}, \forall \xi_{\psi_c} = \xi_{\psi_{(w+i-4)}} \tag{3}$$

$$\xi_{LBP}(n) = \sum_{j=0}^{7} 2^j \times f(\alpha_i), \tag{4}$$

where $\upsilon = (n - w)/w$ represents the number of windows according to the length of ξ, and $w = 9$ is a constant window size for the 1D-LBP analysis. Plus, a min-max normalization process is applied, yielding an array $\boldsymbol{\xi}_{LBP_{norm}}$, as shown in Figure 2. Next, an $F \in \mathbb{R}^{37696\times 13}$ feature extraction matrix is computed; the first dimension corresponds to the number of trials for all subjects, and the second is the number of computed features in [36]. Finally, the Minimum Redundancy Maximum Relevance (MRMR) [37] feature selection algorithm is applied to the feature matrix $\mathbf{F}$ to extract a feature-reduced matrix $\mathbf{F}_\zeta \in \mathbb{R}^{37696\times 3}$. Hence, the data were arranged into 45 self-assessed subject-labeled targets, as shown in Figure 3. It was noticed that some labels were quite similar, which led us to use a clustering algorithm to reduce the number of labels merging the correlated data. Hence, the standardized Euclidean distance (cf. Section III-C) is applied to the F_ζ matrix to improve the recognition rate of the whole process.

B. CONFLICT LEARNING ALGORITHM

The main drawback in classifying EEG signals is a low Signal-to-Noise Ratio (SNR), i.e., artifacts significantly

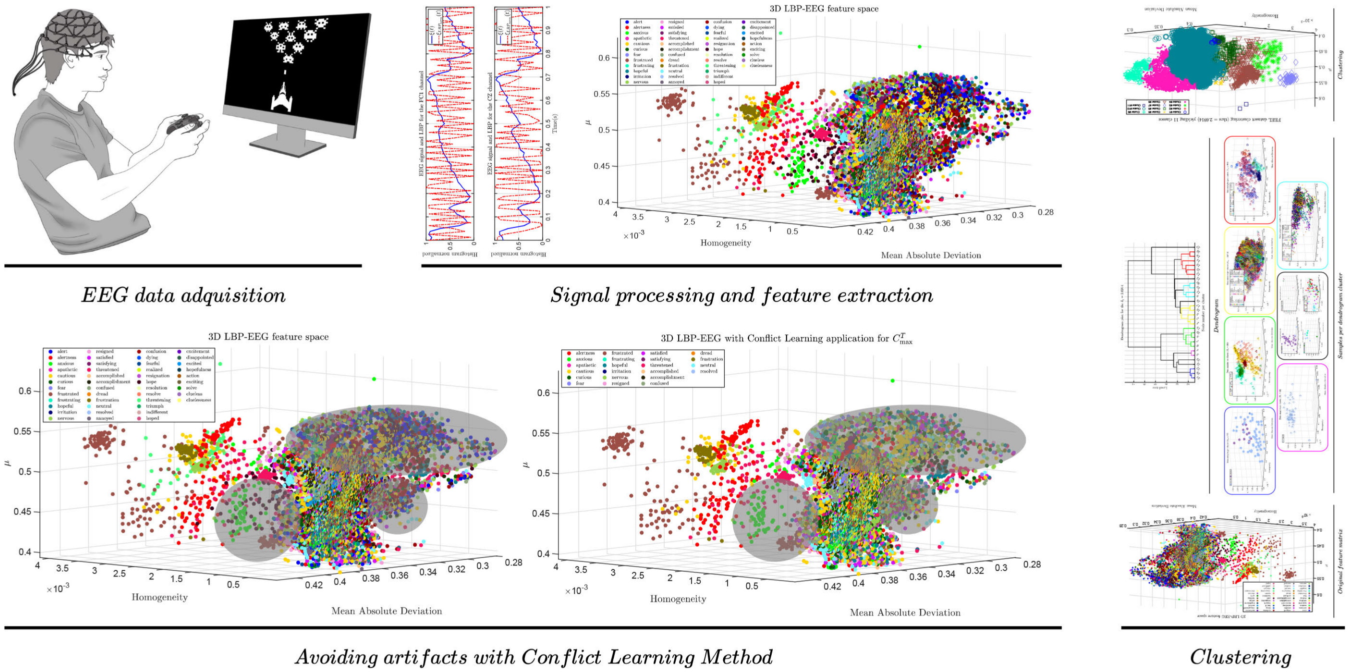

FIGURE 1. General methodology diagram using the FEEL dataset for CL and clustering.

affect recognition. Therefore, artifact avoidance is a highly recommended task. In this context, the algorithm proposed by [19] is used to reduce the feature dimensions in matrix $\mathbf{F}_\zeta$. Such an algorithm splits off samples with similar or closely related values from those with a different target. Complementarily, three different metrics were systematically evaluated, Hamming δ^H, Tanimoto δ^T [20], and Dixon-Koehler δ^{DK} [21], whereby computing the $f(\alpha_i)$ and $f(\alpha_{i+1})$ vector in (3), the CL is achieved in the same task following the CL criteria given by [38]. These binary metrics are integrated into the distance $\mathbb{D}$ as follows

$$\mathbb{D}^{\alpha}_{i,j} = \begin{cases} \delta^H_{i,j} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} f(\alpha_i) \oplus f(\alpha_{i+1}) \\ \delta^T_{i,j} = \begin{cases} 1 & \text{if } f(\alpha_i) = f(\alpha_{i+1}) = 0, \\ 1 - \dfrac{\sum f(\alpha_i) \cap f(\alpha_{i+1})}{\sum f(\alpha_i) \cup f(\alpha_{i+1})} & \text{otherwise,} \end{cases} \\ \delta^{DK}_{i,j} = \delta^H_{i,j} \times \delta^T_{i,j} \end{cases} \tag{5}$$

where $\oplus$ is the XOR operation, and $\times$ means the single product between the normalized Hamming and Tanimoto metrics. Plus, representative values as the maximum and mean value for each metric are computed to construct the matrix $\mathbb{C}$ as follows

$$\mathbb{C} = \begin{pmatrix} {}^{\max}C^H_1 & {}^{\mu}C^H_1 & {}^{\max}C^T_1 & {}^{\mu}C^T_1 & {}^{\max}C^{DK}_1 & {}^{\mu}C^{DK}_1 \\ {}^{\max}C^H_2 & {}^{\mu}C^H_2 & {}^{\max}C^T_2 & {}^{\mu}C^T_2 & {}^{\max}C^{DK}_2 & {}^{\mu}C^{DK}_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ {}^{\max}C^H_i & {}^{\mu}C^H_i & {}^{\max}C^T_i & {}^{\mu}C^T_i & {}^{\max}C^{DK}_i & {}^{\mu}C^{DK}_i \end{pmatrix}, \tag{6}$$

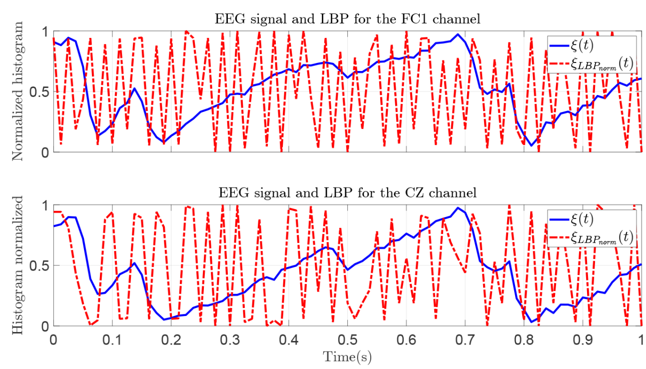

FIGURE 2. EEG signal (blue line) and LBP (red dotted line) behavior for two different EEG channels in a single sequence.

by using the following weighted criterion,

$$C_i = \frac{1}{N}\sum_{\substack{j=1 \\ i \neq j}}^{N} \left|\tau_i - \tau_j\right| \exp\left\{-\frac{\delta_{i,j}}{2\sigma^2}\right\}, \tag{7}$$

where τ_i are the normalized numeric labels, and σ is set at 0.01, as developed by [19].

C. CLUSTERING ALGORITHM

It is worth noting that the targets in the FEEL dataset exhibit label redundancy due to self-assessment by the subjects, as illustrated in Figure 3. Consequently, a clustering algorithm has been employed to group samples with different labels. A standardized Euclidean distance, often used in

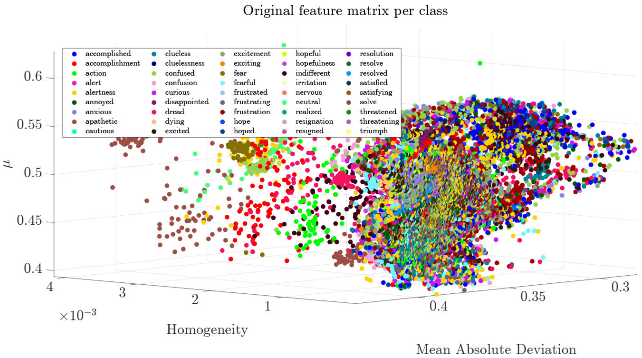

FIGURE 3. Original feature matrix based on signals from the FEEL dataset.

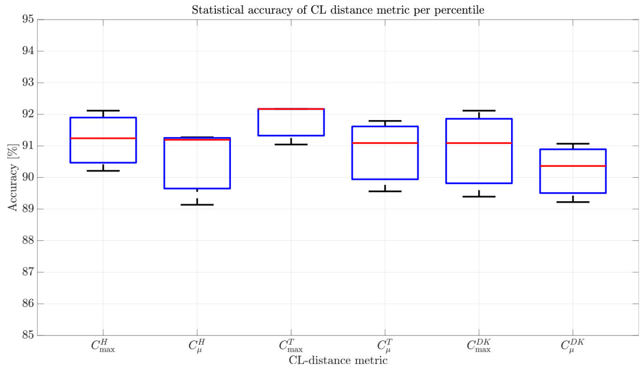

FIGURE 4. Statistical classification results per CL distance metric and percentile threshold.

statistical clustering models, is applied as follows:

$$d_{st}^2 = (x_s - x_t)^\intercal \, V_s^{-1} \, (x_s - x_t) \,, \tag{8}$$

where s and t represent two different index vectors for distances (per dimension). Additionally, the weighted matrix V_s is defined as follows:

$$V_s = \begin{pmatrix} \sigma_{s,1}^2 & 0 & \dots & 0 \\ 0 & \sigma_{s,2}^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{s,n}^2 \end{pmatrix}, \tag{9}$$

where n represents the number of features in the matrix F_ζ, and V_s is a diagonal matrix derived from each element of feature dimension in F_ζ.

Furthermore, the cophenetic is commonly used in the hierarchical cluster tree as the linear correlation coefficient between a computed distance and the cophenetic distances obtained from the dendrogram plot tree. The cophenetic correlation coefficient is computed as

$$c = \frac{\sum\limits_{i<j} \left(d_{ij} - \mu_d\right) \left(z_{ij} - \mu_z\right)}{\sqrt{\sum\limits_{i<j} \left(d_{ij} - \mu_d\right)^2 \sum\limits_{i<j} \left(z_{ij} - \mu_z\right)^2}}, \tag{10}$$

where d_{ij}, μ_d, are distance and mean coefficients from (8), as well as z_{ij} and μ_z represent the distance information about the linkage. This function returns a distance value between two subclusters that emerged by a link, and the output should be close to 1.0 for high-quality solutions.

IV. NUMERICAL RESULTS

Numerical results were obtained using an Intel Xeon Silver 4210R (10 digital cores, 2.4 GHz) and 208GB RAM running in Windows 11 OS. The algorithms were coded and tuned in the ML toolbox of MATLAB V-2022b. In practice, two approaches were tested to solve the self-assessed labeling in the FEEL dataset. Additionally, three classification methods were implemented: the first exploits the matrix $\mathbf{F}_\zeta$, the second uses the $\mathbf{F}_{CL}$, and the third, the target fusion merges the suffixes targets samples $\mathbf{F}_{TF}$.

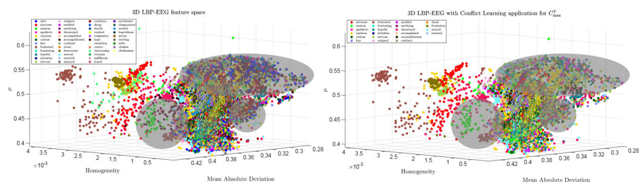

FIGURE 5. 3D Conflict learning comparison between samples per class.

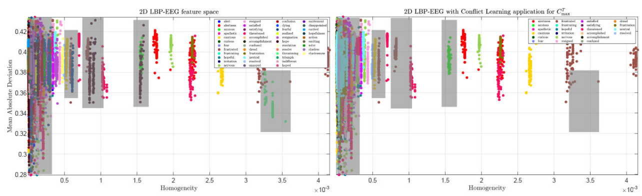

FIGURE 6. 2D Conflict learning comparison between samples per class.

A. CONFLICT LEARNING IN THE FEEL DATASET

The classification results using the direct matrix $\mathbf{F}_\zeta$ gave under 30% accuracy. From such results, it was detected that the data contains many artifacts. Considering this, the CL method was tested to reduce data artifacts and increase accuracy.

Thus, six classification models were systematically tested based on the maximum and the mean per CL distance. Figure 4 shows the estimated classification results, where the method using the ${}^{max}C_i{}^T$ achieved the best performance, a reduced dimension feature matrix $\mathbf{F}_{CL} \in \mathbb{R}^{29312\times 3}$, and 22.24% of redundant samples were eliminated from the original $\mathbf{F}_\zeta$ matrix.

Figure 5 shows the 3D samples reduction, whilst Figure 6 presents the corresponding 2D samples reduction. Finally, results using the proposed evaluation binary metrics for the ${}^{max}C_i{}^T$ trained model are summarized in Table 1. According to Figure 6, the original feature matrix has 45 self-assessed labels. Meanwhile, the CL model retained only 22 of them, separating off those targets in conflict.

B. CONFLICT LEARNING WITHOUT SUFFIXES LABELS

Similarly to the method described above, a new model based on the CL is implemented by merging the samples with those

TABLE 1. Results obtained from the evaluation metrics for the ${}^{max}C_i{}^T$ trained model using the $\mathbf{F}_{CL}$, where μ and σ are the typical mean and standard deviation per class.

Evaluation metrics for the CL method [%]						
Precision		Recall		F1		Accuracy
μ	σ	μ	σ	μ	σ	
92.60	02.64	92.35	02.37	92.47	02.33	92.17

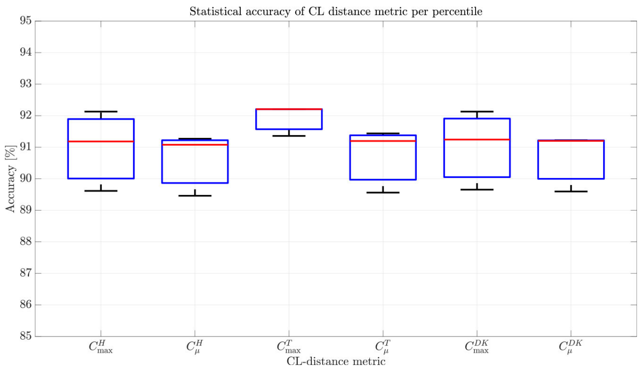

FIGURE 7. Classification results per CL metric and percentile threshold using the $\mathbf{F}_{TF}$.

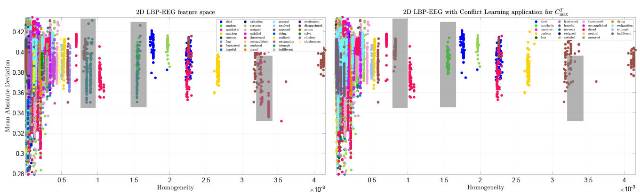

FIGURE 8. 2D Conflict learning comparison between samples per class using the $\mathbf{F}_{TF}$.

TABLE 2. Evaluation metrics results for the ${}^{max}C_i{}^T$ trained model using the $\mathbf{F}_{TF}$,, where μ and σ are the typical mean and standard deviation per class.

Evaluation metrics for the CL method [%]						
Precision		Recall		F1		Accuracy
μ	σ	μ	σ	μ	σ	
92.46	02.32	92.42	01.84	92.43	01.92	92.21

targets that represent the same, varying only in the suffixes. Therefore, the initial feature matrix is modified to the matrix $\mathbf{F}_{TF}$ with a new target space of 30 labels. Next, the CL method is also applied to this target selection, and consequently, the dimension is reduced to $\boldsymbol{\tau}_{TF} \in \mathbb{R}^{19\times1}$.

Figure 7 shows the accuracy rate per distance metric, and Figure 8 presents the CL dimension reduction. In addition, Table 2 shows the evaluation metrics results for the ${}^{max}C_i^T$ trained model using the $\mathbf{F}_{TF}$.

C. CLUSTERING ALGORITHM IN THE FEEL DATASET

So far, a high accuracy rate has been achieved for a classification model based on 22 and 19 targets, $\mathbf{F}_{CL}$, and $\mathbf{F}_{TF}$, respectively. The major problem with self-assessed labels is the term used for a subject to describe an emotion. Some of them can be associated with primary or secondary emotions. With this in mind, the clustering method described in Section III is applied and evaluated. Hence, the cophenetic correlation coefficient is computed for six metrics to obtain a high-quality cluster using the standardized Euclidean distance for optimal results.

TABLE 3. Cophenetic correlation coefficients per distance metric tested (the higher, the better).

Cophenetic coefficients per computed distance					
Euclidean	Std. Euclidean	Mahalanobis	Chebychev	Hamming	Jaccard
0.7390	0.8573	0.8554	0.7148	1.0000	1.0000

Table 3 contains the cophenetic coefficients computed for the six proposed metrics. In addition, results for the Hamming and Jaccard distances using dendrograms were systematically tested. Besides, these two methods yield a cluster per sample in the dataset.

Under such circumstances, the standardized Euclidean was optimal for this case study. Figure 9 shows the dendrogram tree diagram achieved for this model using three thresholds, $\delta = \{2.6914, 3.2682, 4.9423\}$. Eleven clusters were generated using the model depicted in Figure 9a. Seven and three clusters are achieved using the δ_2 and δ_3, shown in Figures 9b and 9c, respectively. Finally, Figure 10 shows the dimension space per cluster obtained using the standardized Euclidian distance.

D. DISCUSSION

In previous findings, [36] proved the benefits of using the CL [19] for avoiding artifacts and enhancing accuracy. This framework has improved the CL, increasing accuracy from 30% to 92.17% and splitting off 22.24% of non-discriminant samples from the original feature matrix. Fig. 5 presents the target dimension reduced from $\boldsymbol{\tau}_\zeta \in \mathbb{R}^{45\times1}$ to $\boldsymbol{\tau}_{CL} \in \mathbb{R}^{22\times1}$, showing that 23 self-assessed labels had high conflicts with other classes. Similarly, the CL-avoiding suffixes was notably reduced to $\boldsymbol{\tau}_{TF} \in \mathbb{R}^{19\times1}$ classes.

Notably, the ${}^{max}C^T$ presented a minor variance per percentile threshold compared to the ${}^{max}C^H$. The high accuracy increase using the original feature matrix is attributed to the self-assessed labels. This kind of labeling depends on the experience of subjects to identify their emotions, where the same emotion in two subjects can be associated with different experiences. To the best of our knowledge, this subject's confusion is also determined in a way by the somatic makers. Secondary emotions provide an accurate emotion that the amygdala can not associate with the primary ones. Due to this, social and physical subjects' knowledge directly influences the target's labeling.

Furthermore, a non-supervised model using a clustering method was presented. Therefore, several samples with different labels are associated with more than one cluster. Most samples in the dataset are located in the single cluster #10 where $\mathbf{F}_{C_{10}} \in \mathbb{R}^{34215\times3}$ achieves $\approx$ 90% of

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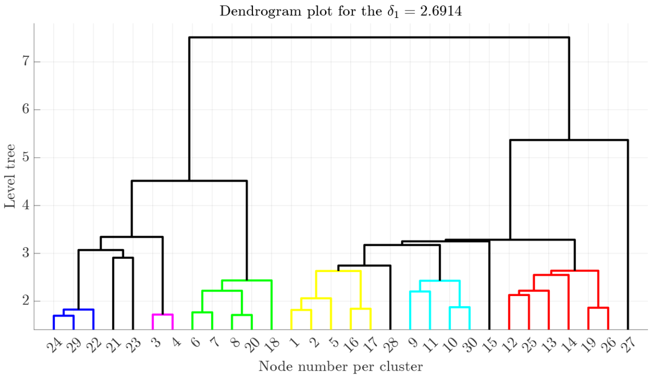
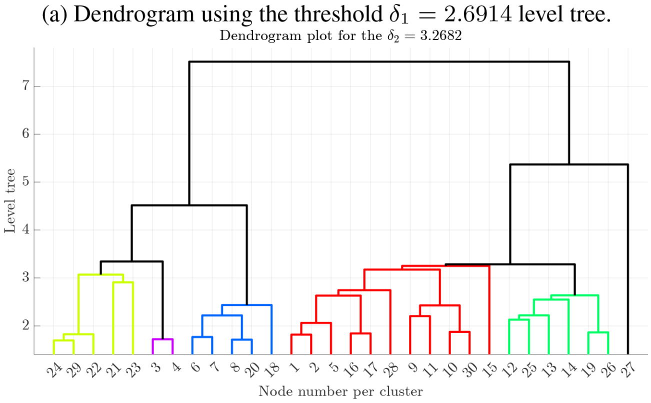
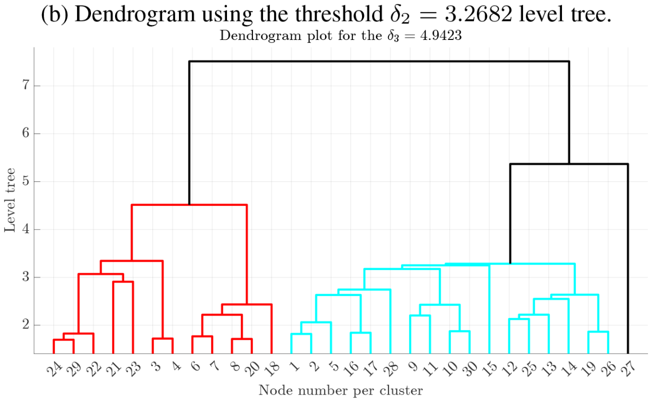


(a) Dendrogram using the threshold $\delta_1 = 2.6914$ level tree.



(b) Dendrogram using the threshold $\delta_2 = 3.2682$ level tree.



(c) Dendrogram using the threshold $\delta_3 = 4.9423$ level tree.

FIGURE 9. Dendrogram plot results per threshold.

the samples in the FEEL dataset, applying a threshold of $\delta = 2.6914$ to the clustering level tree.

As mentioned earlier, clustering metrics like Hamming and Jaccard create a single leaf per sample in the tree, producing a cluster per sample. The standardized Euclidean distance was successfully selected because these last two metrics did not perform well in the non-supervised approach. Figure 10 shows the results using the standardized Euclidian distance, noticing that the clusters with fewer samples are marked in black lines at the tree. Moreover, each clustering box provides the respective leaf number associated with each sample.

The proposed method obtained classification results above 90% accuracy for primary emotions. In addition, it was proven that the LBP-CL method outperforms classification results for non-periodic signals such as EEGs and high dimensional targets. The FEEL dataset has not been used in another literature review, so it is impossible to provide a comparative analysis with other related approaches. Therefore, Table 4 presents only the most representative approaches for emotion recognition.

The approaches developed by [39], [42], and [43] are ER models based on EEG gaming recording seasons. However, only [43] used a novel Database for Emotion Recognition System Based on EEG Signals and Various Computer Games (GAMEEMO) [44], achieving another two models based on primitive emotions from the Emotion Recognition through EEG and ECG Signals from Wireless Low-cost Off-the-Shelf Devices (DREAMER) database [45], and from the Emotion Analysis using EEG, Physiological and video signals (DEAP) [30] dataset. Besides, [39] and [42] developed their database inspired by EEG signal acquisition in gaming seasons.

1) PRINCIPAL FINDINGS

Clustering is a semi-supervised technique tested using six different classical distance metrics. Clustering results suggested using an eleven-cluster space, where the original 45 self-assessed labeling is reduced. If we interpreted the δ_2 clustering threshold as a primary emotions label space, the number of resulting clusters approximates the primary emotions space. However, it is not simple to associate a cluster with a specific primary emotion. So, this was mentioned as a possible interpretation for one space to another. Finally, following the same inference, the δ_3 cluster shown in Figure 9c, each cluster is associated with the Positive, Negative, and Neutral (PNN) classification task.

2) ADVANTAGES

The LBP algorithm performed well by changing the EEG signal time domain to a semi-periodical pattern, improving the classification results. According to the MRMR scores, homogeneity was the best feature descriptor for EEG-LBP. In a previous study, [46] established homogeneity as the top feature descriptor, assuming that this feature is sufficient to achieve a competitive classification model in physiologic signal while combined with LBP. Plus, the CL method finds that only 22 self-assessed labels are significant for studying emotion perception using the FEEL dataset. The CL avoids those samples with different targets and similar magnitude-related behavior; the 23 missing labels are unnecessary and related to another more significant class.

3) LIMITATIONS

The previous target's information is lost when a feature space is clusterized. So, one can only assume or qualitatively approximate each cluster's meaning. The proposed clustering framework represents the feature space using the threshold δ_1; the information related to cluster #4 could be used as a new artifacts reduction space, as shown in Figure 10. However, CL and clustering are complicated to associate and use as

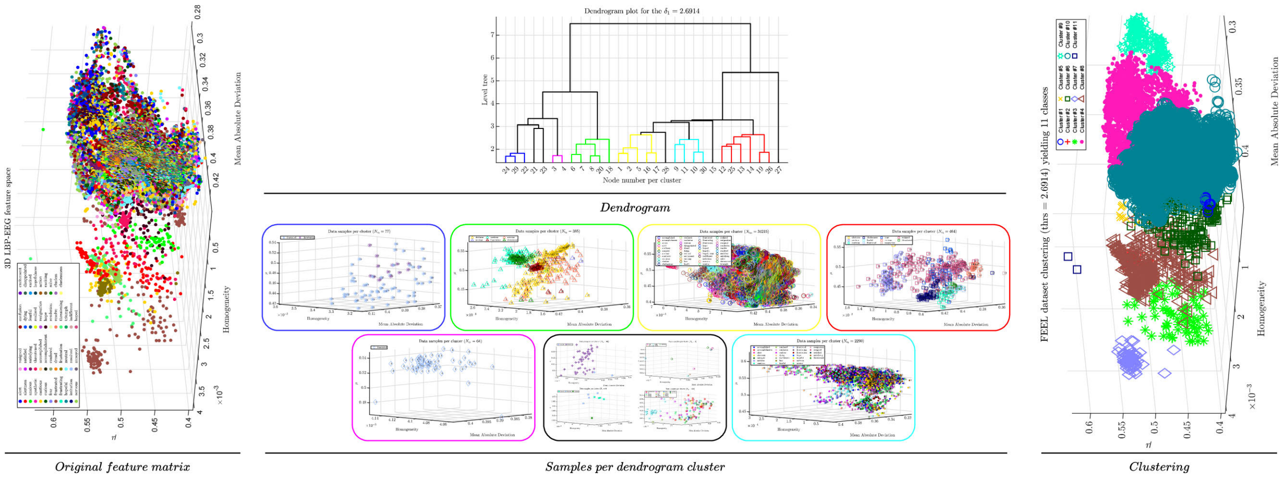


FIGURE 10. Samples and targets per cluster using the standardized Euclidean distance.

TABLE 4. Emotion recognition comparative study with the representative works based on primary or secondary emotions.

ER works in the state-of-the-art					
Reference	Dataset	IA Approach	Classes	Acc. [%]	F1 [%]
[39]	Own	ML-ED[1]	4	81.45	80.71 ± 04.60
[40]	Own	ML-SD[2]	4	83.34	–
[41]	Own	DL-SD[3]	3	92.24	–
[42]	Own	ML-SD	4	98.10 ± 02.73	98.70 ± 01.89
[43]	DREAMER, GAMEEMO, DEAP	ML-CD[4]	VAD[5], 4, VA	100.00, 100.00, 99.00	-
Our approach	FEEL	ML-SI	24	92.17	92.47 ± 02.33
			15	92.21	92.43 ± 01.92

[1] Emotion Dependent, [2] Subject Dependent, [3] Subject Independent, [4] Channel Dependent, [5] Valence, Arousal, and Dominance classification.

artifact reduction combinations. Furthermore, even if the LBP-EEG is a good combination, the computational cost is remarkably high. Despite the simple arithmetic algorithms, exhaustive computation given many window analyses is performed in the LBP and CL.

V. CONCLUSION

Emotions experienced in gameplay provide extensive analysis from different areas. EEGs are one of the most accurate signal-based methods to recognize emotions and use this information in close-related applications. Contrary to popular thought, violent games do not influence players' behavior badly. Instead, it has been proven that the main contribution is based on problem-solving and improving social abilities. Therefore, serious- and exer-games help players to improve their quality of life. Besides, some of these are used in the treatment of mental disorders.

In this research, an AI model based on ML has been developed to classify multiple self-assessed labels. These labels differ between subjects, highlighting that the somatic makers' theory is essential in providing an accurate emotion. The main conclusion in this study is that the secondary emotions can be inferred differently between two players, under the social and physical subjects' knowledge. The classification results concluded that 22.24% of the dataset samples have conflicts with samples from a different label. This effect is attributed to the self-assessed process and suffixes labels.

Furthermore, the clustering method provided a reliable technique to include $\approx$ 90% So, it was found that the clustering behavior is closely related to primary emotions, and the threshold $\delta = 4.9423$ suggested a PNN classification. Besides, $\delta = 3.2682$ produced a seven-cluster space, which could be close to a primary emotions space. Finally, a future classification analysis could be applied to the samples in the $\mathbf{F}_{C_{10}}$ subset to improve results.

AUTHOR CONTRIBUTIONS

All the authors contributed to the study's conception, design, and formal analysis. Data analysis, software design, and first draft were made by O-AC. They read, corrected, and approved the final manuscript.

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