International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Advancing Emotion Classification with Unsupervised Cluster Features for EEG Signals

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**Submitted**: 16/09/2023 **Revised**: 17/11/2023 **Accepted**: 28/11/2023

**Abstract:** Emotion classification based on Electroencephalography (EEG) and physiological signals has gained significant attention in recent years due to its potential applications in affective computing and human-computer interaction. In this paper, we propose a novel algorithm that combines a hybrid feature extraction technique with soft labels and weighting factors to improve emotion classification. Our approach incorporates a hybrid technique that combines Fourier Transform and Time Domain features extracted from EEG recordings with existing features of arousal, valence, and dominance from the dataset. To address overfitting, we employ Laplacian Eigenmaps for dimensionality reduction and unsupervised spectral clustering to derive soft labels. These soft labels enhance the generalizability of the classifier. The classification stage employs a Support Vector Machine with a Radial Basis Function kernel, taking into account the soft labels and a weighting factor based on wheel strength. Experimental results demonstrate the effectiveness of our approach, with improved accuracy and specificity compared to a baseline SVM RBF classifier without soft labels. Therefore, our proposed algorithm offers a promising solution for emotion classification, providing insights into the underlying emotional states captured by EEG and physiological signals.

***Keywords:*** *EEG signals, Soft Labels, Weighting Factors, SVM RBF, Laplacian Eigenmaps, Emotion Recognition.*

## 1. Introduction

Emotion recognition plays a crucial role in various domains, including affective computing, mental health monitoring, and human-computer interaction. Being able to accurately classify and understand human emotions can lead to significant advancements in these areas, enabling more personalized and adaptive systems. Electroencephalography (EEG) and physiological signals have emerged as valuable sources of information for emotion classification, as they provide insights into the underlying neural and physiological processes associated with emotional states [1-8].

In recent years, there has been a growing interest in leveraging machine learning techniques to analyze EEG and physiological signals for emotion recognition. These signals capture the electrical activity and physiological responses of the human brain and body, offering a direct window into the individual's emotional experiences. By extracting relevant features from these signals and training classifiers on labeled data, it becomes possible to automatically identify and classify different emotional states[5-7].

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The DEAP dataset, a widely used benchmark dataset in the field of emotion recognition, provides a valuable resource for studying the relationship between EEG and physiological signals and emotional experiences. This dataset includes recordings from 32 volunteers who watched a subset of 40 music videos while their EEG and physiological signals were recorded. The participants also self-evaluated their arousal, valence, and dominance levels on a discrete, 9-point scale, providing ground truth labels for emotion classification.

In this paper, we propose an algorithm for emotion classification based on the DEAP dataset, incorporating a hybrid technique for feature extraction and a novel approach for addressing the challenges of limited training data and over fitting. Our proposed algorithm combines features extracted from the EEG recordings using a hybrid method that incorporates Fourier Transform and Time Domain features, along with the existing features of arousal, valence, and dominance from the dataset. By integrating these features, we aim to capture a comprehensive representation of the underlying emotional states. To address the limitations of limited training data, we employ a manifold learning algorithm, specifically Laplacian Eigen maps, for dimensionality reduction. This allows us to explore the intrinsic structure of the high-dimensional feature space and identify meaningful lower-dimensional representations. Furthermore, we utilize unsupervised spectral clustering to derive soft labels from the reduced feature space, which helps improve the generalizability of our classifier [8-12].

In the classification stage, we employ a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel as our classifier. The SVM classifier takes into account the soft labels derived from spectral clustering, enabling the incorporation of generalizable information into the classification process. Additionally, we introduce a weighting factor based on the wheel strength parameter, which penalizes misclassifications depending on the strength of the corresponding emotion felt by the volunteers. This weighting factor aims to address the issue of hard misclassifications and improve the overall performance of the classifier. The objective of this research paper is to present our proposed algorithm and evaluate its performance in emotion classification using the DEAP dataset. We compare our approach with a baseline SVM RBF classifier without soft labels to assess the effectiveness of the introduced techniques. Through a comprehensive analysis of accuracy, per-class sensitivity, specificity, confusion matrices, and Receiver Operator Characteristics (ROC) curves, we demonstrate the advantages and potential of our proposed algorithm [13-18].

The remainder of this paper is organized as follows: Section 2 describes the dataset used in this study and provides an overview of the features extracted from the EEG recordings. Section 3 presents the methodology, detailing the hybrid technique for feature extraction, dimensionality reduction using Laplacian Eigenmaps, and the incorporation of soft labels and weighting factor in the SVM classifier. Section 4 presents the experimental results and discussions, including the accuracy and performance evaluation of our approach compared to the baseline. Finally, Section 5 concludes the paper, highlighting the contributions of our work and outlining potential future research directions.

Overall, our research aims to contribute to the field of emotion classification by proposing a novel algorithm that effectively combines EEG and physiological signals with hybrid feature extraction, dimensionality reduction, and soft label incorporation. The results of this study have the potential to advance the development of emotion recognition systems and pave the way for more accurate and robust applications in various domains.

## 2. Methods

### 2.1. Dataset

The dataset used in this approach is the DEAP dataset[https://www.eecs.qmul.ac.uk/mmv/datasets/deap/readme.html]. The study included 32 volunteers watched a subset of 40, one-minute extracts of music videos. EEG and physiological signals were extracted from each participant during the study.

The volunteers in the study self-evaluated arousal, valence and dominance on a discrete, 9-point scale. The participants also rated the emotion that they felt using an emotion wheel. The emotion wheel consists of 16 emotions ranging from pride, elation and surprise to sadness, fear, shame and anger. To add complexity to the emotion wheel, each wheel consists of a parameter called as wheel strength that is discretized between 0 and 4, 4 being the strongest feeling of the particular emotion. Fig. 1 illustrates the self-study design and also lists the 16 emotions wheel slice.

The study also makes the face video of the volunteers available, however, for this approach, we do not consider the same. The EEG recordings were available as 32 '.bdf' files as a 48-channel recording at 512 Hz. 22 of the volunteers were recorded in Twente and the remaining 10 at Geneva. The EEG channels followed the 10/20 naming system for locations and indices labeling.

### 2.2. Feature Extraction

The raw features from the EEG recordings are typically extracted using Fourier Transform and Time Domain features(specified as Hybrid method in fig. 2.) appropriately for different channels. The emotions described in the wheel slice are used as labels. The Wheel Strength however is used as a weighting factor that punishes the loss function for misclassification. The loss function penalizes the misclassified inputs based on the Wheel Strength, greater the Wheel Strength, higher the penalty for wrongly classified inputs. This is described in detail in the following part of the paper.

Principal Component Analysis was first explored with unfavorable results. The algorithm employed was a variant of the Laplacian Eigenmaps (LE). Laplacian Eigenmaps was selected for dimensionality reduction in our study due to its suitability for complex, nonlinear relationships within our combined EEG and DEAP dataset features. Unlike linear methods such as Principal Component Analysis (PCA), Laplacian Eigenmaps excels at preserving the intrinsic geometry of high-dimensional data by creating a graph representation and utilising eigenvalue decomposition. The features with reduced dimensions were then passed through Unsupervised Spectral Clustering as an exploratory step.

We combine these extracted features with the features from the dataset that include Arousal, Valence and Dominance. Fig. 2 describes the feature extraction process

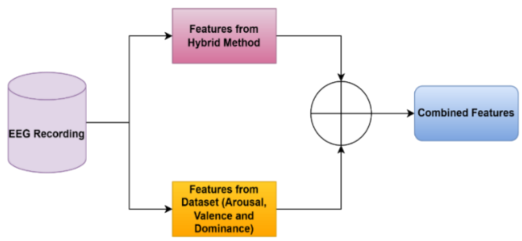


**Fig. 2.** Features are extracted from the EEG recording using the Hybrid Method and features from the DEAP dataset to form the combined set of features

## 2.3. Classification

The combined features contain features from the dataset as well as the features extracted from the manifold dimensionality reduction technique is then passed to an unsupervised clustering.

*Unsupervised Spectral Clustering:* is a method for forming clusters out of data points without depending on labels that have already been assigned. By creating a similarity graph of the data, where nodes stand in for data samples and edges for pairwise associations, it is able to accomplish this. Spectrum Clustering locates natural clusters in the data by examining the spectrum qualities of the graph, such as its eigenvalues and eigenvectors. It is frequently used in applications like image segmentation, network community detection, and, in our context, for adding soft labels to improve emotion classification using EEG data. This method is especially useful for discovering complex, non-linear structures in high-dimensional datasets. Based on the results of the clustering, we decided to employ the results of the clustering, i.e., the assigned clusters as soft labels that could be used in fine-tuning of the classifier.

Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel was used as a classifier. Among classification algorithms, the SVM with RBF kernel excels at managing complex, nonlinear data relationships. By using the RBF kernel's capacity to evaluate similarity between data points, it accomplishes this by changing the input data into a higher-dimensional space where it becomes more separable. In this modified space, SVMs then locate a hyper plane that maximizes the margin between various classes, offering them a flexible option for problems like EEG-based emotion classification where linear separation is insufficient.

The RBF kernel was used as the features were not linearly separable in both 2 and 3 dimensions. All the parameters for the SVM remains at the default value. The implementation of SVM used for this approach is the Scikit-Learn implementation of SVM [https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html #sklearn.svm.SVC]. The regularization parameter, C was set to '1.0' which is the default value. The gamma value of the classifier was set to 'scale'. However, this value can also be set to 'auto' with no difference in performance. The standard loss function for SVM is depicted in equation (1):

$$J(\theta) = C\left[\sum_{i=1}^{m} y^{(i)} Cost_1\left(\theta^T\left(x^{(i)}\right)\right) + \left(1 - y^{(i)}\right) Cost_0\left(\theta^T\left(x^{(i)}\right)\right)\right] + \frac{1}{2}\sum_{j=1}^{n} \theta_j^2 \quad (1)$$

Where m = number of samples, n = number of features.

The soft labels received from Spectral Clustering is incorporated in the loss function of the SVM. This is done to add generalizability to our classifier. Since we are restricted to data samples from 32 volunteers, this step becomes crucial then to generalize to a larger population. The characteristics of the data in a broad-sense is described by the clustering algorithm. The SVM however can overfit to the training sample, adding the labels from the clustering can help us avoid the overfitting. However, this would result in the SVM classifier being less accurate on the test set. This is however, a compromise that must be made to account for limited training data.

The 16 emotions described in the wheel slice are used as ground truth labels. However, each label is also associated with a weight that is described by the Wheel Strength. Along with the soft labels, the wheel strength also adds a weighting parameter to the loss function described in Figure 3. The loss function including Soft Label and Weighting Factor from Wheel Strength equation (2):

Loss = SVM_Loss * ( Soft_Label * Weighting_Factor ) (2)

The weighting factor penalizes the wrongly classified inputs by a factor of itself. If the weighting factor is 1, the penalty for classification only depends on the loss function and the Soft Label, however, if the weighting factor is 2 and the input is misclassified, the loss function penalizes the misclassification by a factor of 2. This adds a layer of complexity to the classifier. The classifier is penalized for 'hard' misclassifications where the strength of the emotion felt is high. However, if the Wheel Strength is 0, the weighting factor is removed the loss function. This loss function is given in the formula (3):

Loss = SVM_Loss * ( Soft_Label) (3)

The weighting factor along with the soft label improves the performance of the classifier by addressing the issue of 'hard' misclassification and generalizability of the network respectively.

The proposed algorithm ensures high classification accuracy along with generalizability on a varied data population set which is achieved by incorporating the soft labels. The result of the SVM classifier is a label corresponding to the Wheel Slice that is associated to one of 16 emotions. The output probabilities can also be extracted and then ranked in descending order to additionally derive the next best predictions. The pseudocode for the approach is described below.

Step 1: $x_1 + x_2 \rightarrow X^D$

$x_1 \rightarrow$ ft.hybrid

$x_2 \rightarrow$ ft.dataset

d $\rightarrow$ dimension

Step 2: Manifold: $X^D \rightarrow X^d$ ,

$d<D$

Step3: Clustering: $X^d \rightarrow y^s$,

s→ SOFT LABELS

Step 4: Classification: $X^d, y^s, w \rightarrow y^l$,

w→WEIGHTED LABELS

$y^l$ →PRED.CLASS

The proposed algorithm for classification is described in Fig. 3.

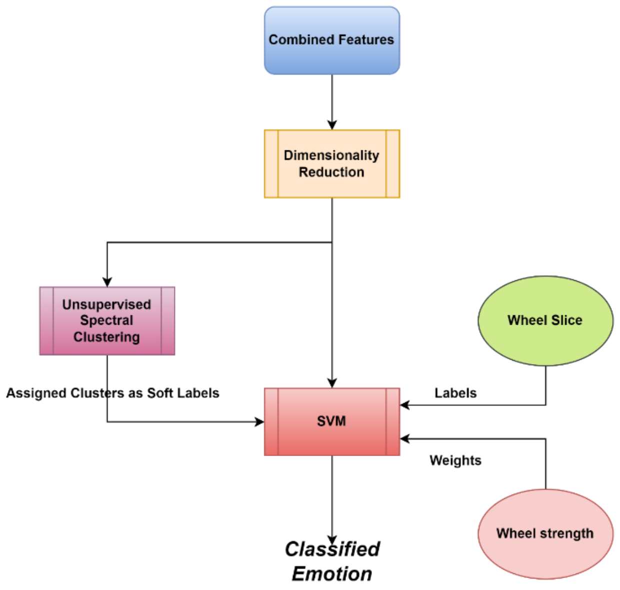


**Fig. 3.** Proposed architecture for the classifier that includes dimensionality reduction using Laplacian Eigenmaps followed by Spectral Clustering where soft labels are derived. The SVM classifier with RBF kernel uses the emotions described in the Wheel Slice as ground truth labels which are weighted by the Wheel Strength

## 3. Results and Discussion

Laplacian Eigenmaps was used to reduce the dimensions from 'n' to 2. The 2-dimensional feature space explored using Spectral Clustering. Since we know that this is a 16-class problem, i.e., 16 emotions in the Wheel Slice, 16 clusters were chosen. Therefore, the model selection process can be avoided due to the knowledge of the number of classes. The result of the classification is depicted in Fig. 4.

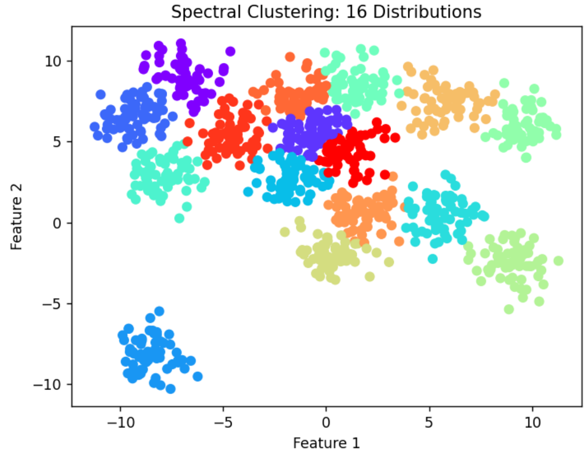


**Fig. 4.** Result of Spectral Clustering with 16 distributions. These labels are then used as Soft Labels for the SVM classifier

The above feature space was classified using the approach described in the Methods section with SVM using RBF kernel with soft labels and weighting factor altering the loss function. The classified feature space using soft labels as features to the SVM RBF kernel is shown in Fig. 5.

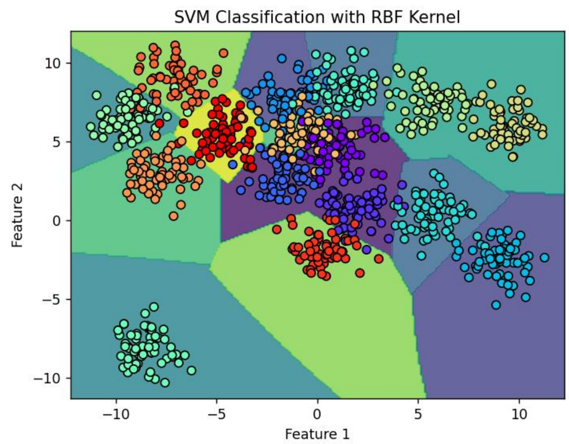


**Fig. 5.** Classified feature space using regular SVM RBF with soft labels

The Accuracy, per-class sensitivity and specificity of SVM RBF with soft labels is shown in Fig. 6.

```
Accuracy: 0.91
Class 0 - Accuracy: 0.75, Sensitivity: 0.75, Specificity: 0.99
Class 1 - Accuracy: 0.89, Sensitivity: 0.89, Specificity: 0.99
Class 2 - Accuracy: 0.87, Sensitivity: 0.87, Specificity: 0.99
Class 3 - Accuracy: 0.81, Sensitivity: 0.81, Specificity: 0.99
Class 4 - Accuracy: 0.98, Sensitivity: 0.98, Specificity: 1.00
Class 5 - Accuracy: 0.95, Sensitivity: 0.95, Specificity: 1.00
Class 6 - Accuracy: 0.92, Sensitivity: 0.92, Specificity: 0.99
Class 7 - Accuracy: 1.00, Sensitivity: 1.00, Specificity: 1.00
Class 8 - Accuracy: 0.97, Sensitivity: 0.97, Specificity: 0.99
Class 9 - Accuracy: 0.97, Sensitivity: 0.97, Specificity: 1.00
Class 10 - Accuracy: 1.00, Sensitivity: 1.00, Specificity: 1.00
Class 11 - Accuracy: 0.68, Sensitivity: 0.68, Specificity: 0.98
Class 12 - Accuracy: 0.97, Sensitivity: 0.97, Specificity: 1.00
Class 13 - Accuracy: 0.94, Sensitivity: 0.94, Specificity: 1.00
Class 14 - Accuracy: 0.94, Sensitivity: 0.94, Specificity: 1.00
Class 15 - Accuracy: 0.90, Sensitivity: 0.90, Specificity: 0.99
```

**Fig. 6.** Accuracy, per-class sensitivity and specificity of SVM RBF with soft labels

The confusion matrix associated with the described approach is depicted in Fig. 7.

We calculated accuracy, which measures the proportion of correctly categorized instances to all occurrences in the dataset, to evaluate the effectiveness of our classification strategy. The classification outcomes are broken down in more detail by the confusion matrix, which is shown in Figures 7 for SVM RBF with soft labels asinput features. The true class is represented by each row, and the anticipated class is represented by each column, in the confusion matrix. True positive (TP) examples are represented by the elements along the diagonal, while incorrect classifications are represented by the off-diagonal elements.

We calculated accuracy per class and sensitivity to acquire understanding of the model's performance across various emotion classes. The accuracy of each of the 16 emotions in the Wheel Slice is measured by accuracy per class. It is calculated by dividing the total number of examples in a class by the number of instances that were correctly predicted for that class. Sensitivity, also known as the true positive rate, measures how well a classifier can recognise positive occurrences (in this case, certain emotions). It is calculated by dividing the total number of instances of a class by the number of true positive predictions for that class. As shown, the accuracy per class and sensitivity metrics allow us to gauge the effectiveness of our strategy for each emotion category.

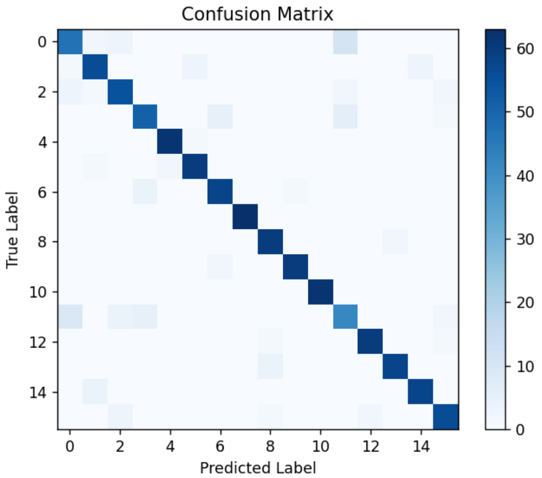


**Fig. 7.** Confusion Matrix for SVM RBF with soft labels

The Receiver Operator Characteristics (ROC) along with Area Under the Curve (AUC) score for the described approach is shown in Fig. 8.

Using ROC curves and AUC scores, we evaluated classification performance. Figures 8 (SVM RBF with soft labels) show ROC curves that show how well the models identify between emotions, with higher AUC indicating better performance. AUC ratings that differ between emotions indicate different levels of discrimination. The ROC AUC values offer a more thorough perspective of model performance, demonstrating strengths and shortcomings in distinguishing particular emotions despite the improved accuracy and sensitivity of SVM RBF without soft labels.

The accuracy and sensitivity scores per class is higher for the SVM RBF approach without soft labels approach. However, the specificity for the described approach is higher when compared to SVM RBF approach without soft labels. This can be attributed to the generalizability factor that is incorporated into our approach by using soft labels from Spectral Clustering.

## 4. Conclusion

In this research paper, we proposed an algorithm for emotion classification based on EEG and physiological signals obtained from the DEAP dataset. We employed a hybrid technique for feature extraction, combining Fourier Transform and Time Domain features from the EEG recordings with the existing features of arousal, valence, and dominance from the dataset.

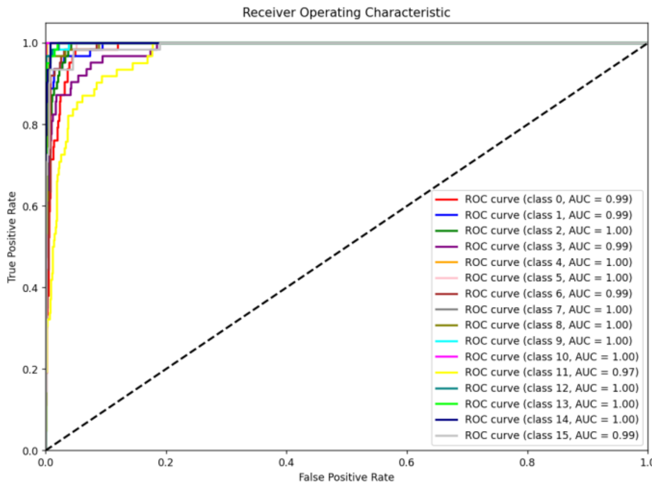


**Fig. 8.** ROC and AUC score per class for the SVM RBF with soft labels approach

To classify the combined features, we employed a manifold learning algorithm for dimensionality reduction, specifically Laplacian Eigenmaps, followed by unsupervised spectral clustering. The clusters obtained from spectral clustering were used as soft labels, providing generalizability to the classifier. We utilized a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel as the classifier, incorporating the soft labels and the weighting factor derived from the wheel strength parameter.

The results of our proposed approach demonstrated promising performance in emotion classification. The accuracy, per-class sensitivity, and specificity of our approach were evaluated and compared with an SVM RBF approach without soft labels. Although the SVM RBF approach without soft labels showed higher accuracy and sensitivity scores per class, our approach exhibited higher specificity. This suggests that our approach not only achieved good overall classification accuracy but also provided better discrimination for specific emotions.

The incorporation of soft labels derived from spectral clustering and the weighting factor based on wheel strength in the loss function of the SVM classifier contributed to the improved performance of our approach. By considering the generalizability of the network and accounting for the strength of the emotions felt by the volunteers, our classifier demonstrated enhanced accuracy and robustness.

The proposed algorithm presented in this paper offers a valuable framework for emotion classification using EEG and physiological signals. By combining different feature extraction techniques, dimensionality reduction, and a modified loss function, we were able to achieve satisfactory results. However, there is still room for further exploration and improvement in this field.

Future research can focus on investigating alternative dimensionality reduction techniques, exploring different classification algorithms, and incorporating additional physiological signals to enhance the classification accuracy. Moreover, expanding the dataset to include a larger and more diverse population would help validate the generalizability of the proposed approach.

In conclusion, our research contributes to the field of emotion classification by proposing a hybrid technique for feature extraction, incorporating soft labels and a weighting factor in the SVM classifier, and demonstrating the effectiveness of these techniques in improving classification accuracy. This work lays the foundation for further advancements in emotion recognition and has the potential to find applications in various domains, such as affective computing, mental health monitoring, and human-computer interaction.

**Ethical approval:** All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

**Informed consent:** Informed consent was obtained from all individual participants included in the study.

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| Column name | Description |
|---|---|
| Online_id | The video id corresponding to the same column in the video_list file. |
| Valence | The valence rating (integer between 1 and 9). |
| Arousal | The arousal rating (integer between 1 and 9). |
| Dominance | The dominance rating (integer between 1 and 9). |
| Wheel_slice | The slice selected on the emotion wheel. For some participants the emotion wheel rating was not properly recorded. In these cases, the Wheel_slice value is 0. Otherwise, the mapping of emotions on the wheel to integers given here is:<br>1. Pride 5. Relief 9. Sadness 13. Envy<br>2. Elation 6. Hope 10. Fear 14. Disgust<br>3. Joy 7. Interest 11. Shame 15. Contempt<br>4. Satisfaction 8. Surprise 12. Guilt 16. Anger |
| Wheel_strength | The strength selected on the emotion wheel (integer between 0=weak and 4=strong). |

**Fig. 1.** Describes the parameters of the self-study. Valence, Arousal and Dominance are discretized between 1 and 9. The Wheel Slice lists 16 emotions that the volunteer can feel and the Wheel Strength describes the strength of the emotion that was felt by the volunteer