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Recognition of emotions by analyzing facial expressions from user experience evaluation videos

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Abstract - New technologies grow every day, some examples are robots, augmented reality technology, algorithms and machine-to-machine communications that facilitate the development of various activities. In this sense, the evaluation of the user experience (UX) must also adapt to these advances, a relevant source of information in the UX process is the affective computation by means of facial expression analysis techniques that the user presents during the interaction with a software product, for this reason, this article presents an emotion recognition system through the analysis of facial expressions using a Vector Support Machine (SVM) classification algorithm. Characteristic points of the face were extracted using a pre-trained model which locates 68 points (x, y) and places them on the face, of which only 17 points were used to calculate geometric distances between certain muscles of the face, which allows identify emotions, the classification algorithm was trained with own dataset. The tests were with the CK+ dataset used in the literature, tests were also carried out with videos. The results obtained were 84.52% accurate, in the recognition of three emotions: happiness, anger, surprise and neutral.

Index Terms - classifier, Emotions, artificial vision, Facial Action Code System, facial recognition

ANTECEDENTS, MOTIVATION Y OBJECTIVE

A. Antecedents

As mentioned in [1] the key challenges in facial expression recognition include an optimal pre-processing, feature extraction or selection, and classification, particularly in conditions of variability of input data, view or head pose, ambient disorder and lighting, and multiple sources of facial variability.

In the context of recognition and classification of emotions and cognitive states using machine learning and deep learning algorithms, a systematic review of the literature was carried out, in which the works [1] - [19] were analyzed. In [14] it is explained that the exploration for the automatic detection of gestures of the hands on the face, movements of head and eyes are fundamental for the recognition of emotions and cognitive states in conjunction with facial expressions. In addition, the implementation of different learning algorithms allows obtaining favorable results, but still with the opportunity for improvement. The state of the art is divided into two sections: 1) Face and facial expression detection and 2) Emotion recognition.

In the first section, papers [10], [11] and [19] were analyzed, which provided relevant ideas for the localization and pre-processing of the face based on the quality of the databases, feature extractors and pattern classifiers. In the second section of the analysis of the state of the art, the works of [1] - [19] were studied, where their main objective was to perform the recognition of emotions using preprocessing techniques and Machine Learning and Deep Learning algorithms. These works served as the basis for the construction of the emotion classification system that is the objective of this research. Works such as [2] and [4] report having implemented neural network architectures and despite having good results, the computational cost is high, so for this research it was decided to use classical supervised learning machine algorithms, such as that of [5]; besides considering the works of [6] and [7] which use of geometric techniques for the recognition of emotions with good results.

B. Motivation

The list of new technologies grows every day. Robots, increased reality, algorithms, and machine-to-machine communications help people with a wide variety of tasks. They can facilitate individuals' life and improve their personal and work relationships. Just as digital products (software) have evolved, the way they are evaluated must be adapted to these new changes too, such as the evaluation of user's experience of digital products (software), currently more reliable methods have been sought to obtain information on the impact that a digital product causes in a user when they use it, some techniques use physiological data such as EEG, ECG, GSR and biometric signals such as eye tracking that provide relevant information during the user's experience evaluation process (UX) having more precise information than in the tools used in a conventional UX evaluation (see Fig. 1). On the other hand, to increase the precision in the recognition of emotions and emotional states, artificial vision techniques can be applied to analyze the user's facial expressions during interaction with software, since they reveal emotional and cognitive complex states which are expressed by users unconsciously and can provide valuable and important information to a UX evaluator.

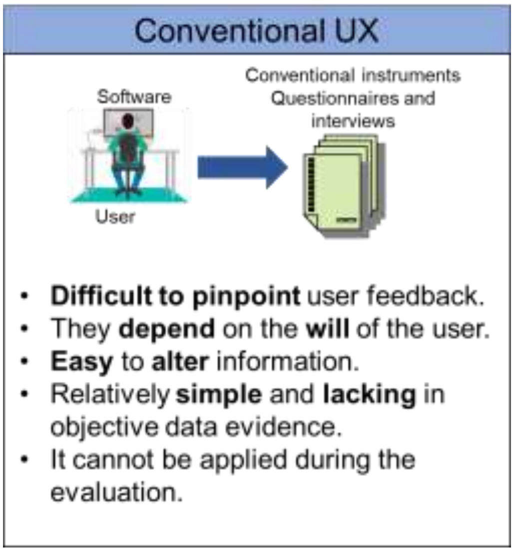

Fig. 1 Tools used in a conventional UX evaluation

Techniques and algorithms able to identify emotions and cognitive states through facial expression recognition systems are proposed in the literature, which vary in their precision's level. The difference in the accuracy they present is due to factors that prevent a good identification of the characteristics of the face, such as: occlusion, noise, brightness of the image, posture or the orientation of the face, etc. Another factor that influences the recognition of emotions are the image repositories that are used for classified algorithms learning since they are generally acquired in controlled environments, different from those used in real systems. And if a high level of precision is desired, for example, with deep learning architectures, it implies having a high computational cost for the amount of images to be trained and have an optimal efficiency.

Depending on the availability of data, the papers published in [1] - [19] are usually classified into two categories. The first category is the appearance-based method that uses texture mode and explores expression's differences in pixels' space. Considering the image of the complete facial texture as the expressive characteristic, some works map the high-dimensional vector in the low-dimensional subspace applying a dimensionality reduction algorithm, such as the main component analysis (PCA) [9] and [11]. Some other researchers select some representative facial areas as objects of analysis and propose many local's feature extraction's methods to calculate descriptors for these areas. Methods include Haar Cascades [19], Edge Extraction Filter (EEF) [4] and Histogram of Oriented Gradients (HOG) [9]. Although the appearance-based method can capture detailed and subtle information of facial expression, the features are highly sensitive to luminance, head posture variation, and occlusion. The second category can be considered as a geometric-based method. This method generally needs to mark a facial feature point whose corresponding movements can help to capture expressive features such as those used in [5], [6] and [7].

Therefore, the objective of this work is to present the results of a system that performs the recognition of three emotions through facial expression analysis, implementing a machine learning classification algorithm, by extracting characteristics with a geometric-based method, to be used in a user´s experience (UX) evaluation process in order to obtain information on user's emotional impact regarding the use of the user's interface (UI) digital product (software) and to serve the evaluators of the UX to identify positive or negative aspects related to the UI. To validate the results of this research, the performance of the algorithm was verified using the classical recognition metrics and seeking that the computational cost is not high.

C. Objective.

Develop and evaluate an algorithm to detect of three basic emotions, through the analysis of facial expressions in videos of users who participate in the evaluation process of digital products user's experience.

METHOD

The human face is considered the main visual system to show emotions, as well as being the most important and complex part of non-verbal communication. Mental states are thoughts and ideas that accompany the mood. They are divided into two categories: cognitive states and affective states [27]. A cognitive state is a neuropsychological condition that a subject present during the performance of one or more cognitive tasks, which contemplate the necessary processes for calculation, concentration and memory, while affective states are understood as the neuropsychological condition that a subject present. Affective states are classified into emotions and feelings [27], a categorization of mental states according to neuroscience can be seen in (Fig. 1).

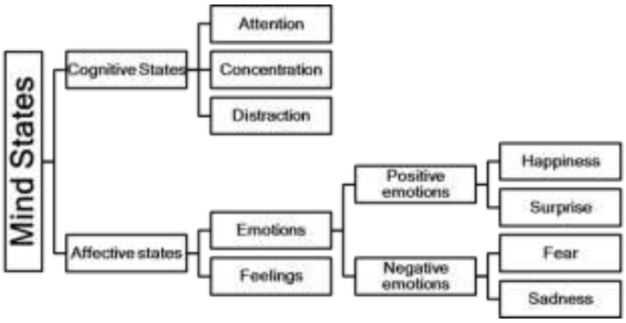

Fig. 2. Classification of emotions [27]

A. Units of Action.

Each observable facial movement is called an Action Unit (AU) in this way the composition of the expression of an emotion can be divided into one or several AU for the different representations of one or several emotions. The most effective way to be able to measure emotions in the human face is by means of some facial action coding system with which the movement of certain regions of the face can be related to some identifier (unit of action) and that the algorithms can learn from it. The facial action coding system is established as a standard for the measurement of facial expressions, the psychologist Paul Ekman and Wallace V. Friesen adopted a taxonomy of human facial movements for their appearance on the face called Facial Action Coding System (FACS) [24] based on a system originally developed by a Swedish anatomist named Carl-Herman Hjortsjö. It is a common standard for systematically categorizing physical expression of emotions and it has been useful for psychologists and animators.

B. *Facial points of reference*.

The description of the face is a very important phase for the algorithm's development. In this case, it is done by detecting facial points of reference or key points of reference on the face. This task is complemented with information such as facial alignment, head posture estimate, face swapping, flicker detection, drowsiness detection, facial expression detection (emotions), etc. In the context of facial points of reference, it is necessary to detect important facial structures on the face using shape prediction methods. The detection of facial points of reference is carried out in two stages: 1) Localization of the face in the image and 2) detection of key facial structures on the face such as nose, jaw, eyes, eyebrows and mouth.

C. Proposed Solution.

For the development of the algorithm, the solution scheme shown in (Fig. 2) was proposed, it consists of 10 stages, the first five is the method for the extraction of characteristics based on the calculation of geometric distances and the other five stages correspond to the training, validation and testing of the classifier. Each of the proposed stages is described below.


Fig. 3 Scheme of the emotion classification system.

D. Images

In this first stage, an analysis of the state of art was carried out to select the most widely used public repositories of images. Cohn-Kanade extended (CK +) [21] was selected, in addition to this repository, an own data set was created to strengthen the training of the algorithm used. Table I shows the characteristics of the selected data sets.

Table I. Repositories for training and testing the algorithms.

BD	**Number**	**Emotions**	**images by class**
Ck+	432 Frontal Gray Scale	Happiness, Anger, Surprise, Neutral	108
OWN	432 Frontal RGB	Happiness, Anger, Surprise, Neutral	108

According to what has been reported, the lighting variation in the images of the selected sets is minimal since they were taken in controlled environments; that is, in a well-lit area. Examples of each data set are displayed in (Fig. 4 and 5).

Fig. 4 Faces with the emotions of Happiness, Anger, Surprise and Neutral respectively from the data set CK + [21].

Fig. 5 Faces with the emotions of Happiness, Anger, Surprise and Neutral respectively from the OWN data set.

Each set of images was divided into folders with a numerical label from 0 to 3 that corresponds to the 4 emotions that are intended to be recognized with the classifier 0 = Joy, 1 = Anger, 2 = Surprise and 3 = Neutral.

E. *Face Detection and identification of facial points***.**

The facial expression detection system begins with the localization of the face in an image to extract the features or facial traits that are required to be able to recognize emotions. For face detection, images are resized to 280x280 pixels and transformed to gray levels. Since the description of the face is carried out through geometric distances between some points of the components of the face, the color information is eliminated. Subsequently, the face is in the image using the previously trained facial points of reference's detector, which is included in the Dlib library [22]. This library was presented in [23] where it estimates the location of 68 points that they assign to facial structures on the face.

In this work the description of the face is made through geometric distances of certain muscle movements specified by Ekman [24] according to each expression. To carry out this process, the coordinates of facial features are taken in this way: [starting point, ending point]. That is, for the detector to make the prediction of the points, the grayscale images are passed as an input parameter, in it, the face is located obtaining the predictor points on a face that is presenting a facial expression as in the (Fig. 6).

Fig. 6. The 68 facial landmarks positioned on the face that present the emotion of happiness.

F. Selection of important characteristic points.

Of the 68 points proposed in [22], only those that serve as a basis for calculating the necessary distances to identify emotions and subsequently save those distances in a CSV file are considered, in order to obtain the distances of the opening of the eyes, new points were created by adding 4 points to the mask assigning them a number, remaining as follows: the points [69,70] for the opening of the right eye and [71,72] for the opening of the left eye. The 17 selected points are the following:

Left eye: points [45, 71,72]
Mouth: points [60, 64, 62, 66, 48, 54]
Left eyebrow: points [22, 25]
Nose: points [27]
Right eyebrow: points [18,21]
Right eye: points [36, 69,70]

The selected points on the face can be visualized in (Fig. 7) and the distances considered for the description of the facial expression present on the face in (Fig. 8).

Fig. 7 The 17 facial points of reference positioned on the face of one of the people from the CK + Database [21] expression of anger.

1.- Upper_Eyelid_Elevator_Length_of_Right_Eye	[69,70]
2.- Left_Eye_Upper_Eyelid_Elevator_Length	[71,72]
3.- Length_of_the_right_commissure_of_the_Elevator_of_the_right_inner_eyebrow	[18,89]
4.- Length_of_the_left_commissure_of_the_Elevator_of_the_right_inner_eyebrow	[21,69]
5.- Length_of_the_left_commissure_of_the_Elevator_of_the_left_interior_eyebrow	[25,71]
6.- Length_of_the_right_commissure_of_the_Elevator_of_the_left_interior_eyebrow	[22,71]
7.- Length_of_right_commissure_of_Elevator_of_the_inner_eyebrow_commissure_right_right_eye	[18,36]
8.- Length_of_the_left_commissure_of_the_Elevator_of_the_inner_eyebrow_left_commissure_of_the_left_eye	[25,45]
9.- Length_of_the_right_commissure_of_the_left_eyebrow_at_the_beginning_of_the_septum	[22,27]
10.-Length_of_the_left_commissure_of_the_right_eyebrow_at_the_beginning_of_the_septum	[21,27]
11.-Length_of_the_right_raised_cheeks	[36,48]
12.-Length_of_the_left_raised_cheeks	[45,54]
13.-Length_of_the_left_and_right_inner_corner_of_the_mouth	[60,64]
14.-Length_of_the_lower_and_upper_inner_lip_of_the_mouth	[62,66]

Fig. 8 Combination of facial points that are taken as characteristics to train the classification algorithm.

G. Calculation of the Euclidean's distance.

Once the AUs have been identified, the distance between these points is calculated using the Euclidean's distance equation as indicated in formula 1, obtaining 14 combinations of points, which interfere in each of the Units of Action of each emotion to be recognized, determined by the psychologist Paul Ekman, in his Coding System of Facial Action [24].

$$d_{e(p_1,\ p_2)} = \sqrt{(x_2-x_1)^2 + (y_2-y_1)^2} \qquad (1)$$

Where d_e(P1, P2) is the distance that aims to be calculated from a characteristic point of the face to another characteristic point of the face; for example, to calculate the length of the upper and lower eyelid of the left eye, the distance between point 71 and 72 has to be calculated as seen in (Fig. 9).

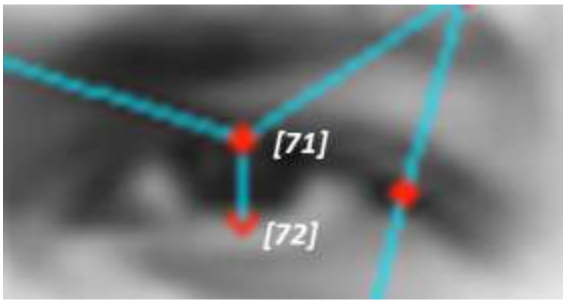

Fig. 9. Point 71 and 72 of the left eye.

H. Store the information in a CSV.

Once the calculation of the distances between the points has been carried out, they are collected in a vector which is stored in a CSV file with which the classification algorithm will be trained later. The data set contains 14 combinations of points that will be the characteristics and a column called class that is the label of the emotion that corresponds to each image, (Fig. 8) shows these 14 characteristics.

I. Train the classifier.

According to the study of the state of the art, an algorithm for classification was selected, which is one of the algorithms that have been used in the recognition of emotions with geometric basis [5], [6] and [7]. The algorithm is called Support Vector Machine SVM [25], it is a classification and regression algorithm developed in the 90s, within the area of computational science. Although initially developed as a binary classification method, its application has been extended to multiple classification and regression problems. SVMs have turned out to be one of the best classifiers for a wide range of situations, so that it is considered one of the benchmarks in the field of statistical learning and machine learning.

To start training the classification algorithm, we proceeded separating the own data set combined with the FER2013 data set [26], for each class 108 images were taken, to avoid an imbalance of classes in the Dataset, later they were established the optimal hyperparameters with which they allowed to obtain a precision in recognition of 84.52%. The training and experimentation of two more algorithms, RandomForest and KNN, were also carried out. They were trained with the same data set as the first algorithm and the optimal hyperparameters were chosen for each one, section 5 shows the obtained results for each algorithm. The algorithms were developed with the Python programming language, using the Sklearn libraries for the classifier, Matplotlib for generating the graphs, Pandas for managing the dataset and Numpy for arrays and vectors.

J. Evaluation with test data.

After learning, the algorithm was evaluated, in this test the CK + data set was considered. From this dataset, 20% of the data was taken to test the classifier algorithm.

RESULTS, DISCUSSIONS AND CONCLUSIONS

This section presents the results obtained from each classifier algorithm, see Table II and the comparison with other similar works, see Table III.

*A. **Metrics.***

The metrics that were evaluated in this experiment were precision, Recall and F1-Score. Tables II to IV show the results of the metrics, obtained for each emotion for each evaluated algorithm, and Table V shows the percentage of precision of each algorithm.

Table II Support Vector Machine Algorithm Metrics.

Emotions	Precision	Recall	F1-Score
Happiness	0.96	0.92	0.94
Anger	0.71	0.62	0.67
Surprise	0.91	1.00	0.95
Neutral	0.76	0.79	0.78

Table III Random Forest Algorithm Metrics.

Emotions	Precision	Recall	F1-Score
Happiness	1.00	0.88	0.93
Anger	0.57	0.75	0.65
Surprise	0.97	0.95	0.97
Neutral	1.00	0.74	0.72

Table IV KNN Algorithm Metrics.

Emotions	Precision	Recall	F1-Score
Happiness	1.00	0.96	0.98
Anger	0.80	0.50	0.62
Surprise	1.00	0.90	0.95
Neutral	0.67	0.92	0.77

Table V Accuracy of each Algorithm.

Algorithms	Accuracy
Support Vector Machine	84.52 %
Random Forest	82.14 %
K-Nearest Neighbors	84.52 %

Table VI Comparison of the classification of emotions with a geometric basis and the one proposed.

Author	Algorithm	Accuracy	Facial Points
[6]	FCM	93.67 %	44
[5]	Multilayer Perceptron	88.03 %	68
	Support Vector Machine	38.46%	68
Selected	Support Vector Machine	84.52%	17

As it can be seen in the charts, good results were obtained with the three algorithms, but although good results were obtained in the Accuracy in the metrics, the best classification algorithm of the four emotions can be identified, of the three, the one with the best results in the metrics was the classifier with Vector Support Machine performing a good recognition in each given emotion. The development of the system was carried out using the OpenCV library, Dlib, Sklearn, Numpy and Pandas with the Python programming language.

B. Video tests.

Tests were carried out with the video processing, implementing the Vector Support Machine algorithm, which gave the best result in the previous tests, obtaining a good percentage of recognition for each emotion, the classification results in a video with the percentage of recognition's probability of each emotion.

Fig. 10. Shows the video results obtained for the happiness emotion. The graph indicates the percentage of recognition.

Fig. 10. Emotion of Happiness and its Units of Action.

Fig. 11. Shows the video results obtained for the emotion of Anger, the graph indicates the percentage of recognition.

Fig. 11. Anger Emotion and its Units of Action.

Fig. 12. Shows the video results obtained for the surprise's emotion, the graph indicates the percentage of recognition.

Fig. 12. Surprise Emotion and its Units of Action.

Fig. 13. Shows the video results obtained for the Neutral emotion, the graph indicates the percentage of recognition.

Fig. 13. Video sequence detecting Neutral emotion.

It is worth mentioning that when the emotion is presented in a more pronounced or marked way, the classifier reaches the following percentage for each emotion, see Table VII.

Table VII Precision of recognition of emotions in video.

Emotions	Precision
Happiness	95.43 %
Anger	98.6 %
Surprise	91.46 %
Neutral	88.00 %

CONCLUSION.

In this work the development of an algorithm for the recognition of emotions was presented, through of the analysis of facial expressions taking some reference points of the face. The system was evaluated with two sets of images. The system performs well. However, there is still work to improve the precision of recognition, which is 84.52%, to improve these results, work can be done with improving the images' processing, applying lighting and contrast filters, performing an alignment of the face, obtaining images with greater clarity and that faces have more pronounced the expressions for each emotion and increase the number of images for each class. As future work, the classifier will be implemented in platform of user experience evaluation called UXLab in order to identify mental states in users who participate in the process of evaluating the user's experience of digital products..

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REFERENCES

[1] Sunitha A, P. Ajay Kumar Reddy, S.Nanda Kishore, G.N Kodanda Ramaiah (2017), Recognition of Facial Emotions Based on Sparse Coding. Journal of Engineering Research and Application, ISSN: 2248-9622.

[2] Nwosu, L, Wang, H., Lu, J, Unwala,I, Yang, Zhang, T.(2017, Septiembre). deep convolutional neural network for facial expression recognition using facial parts. DOI 10.1109/DASC-PICom-DataCom-CyberSciTec.2017.213

[3] Krestinskaya, et al. (2017, septiembre 13-16). Conferencia Internacional sobre Avances en Informática, Comunicaciones e Informática (ICACCI) Udupi, India, Facial Emotion Recognition using Min-Max Similarity Classifier. IEEE. 10.1109/ ICACCI.2017.8125932

[4] Liu Xiao, Lee Kiju. (2018, August 15-17). IEEE Games, Entertainment, Media Conference (GEM), Galway, Irlanda, Optimized Facial Emotion Recognition Technique for Assessing User Experience.IEEE, 10.1109 / GEM.2018.8516518

[5] M. Alvarez V, et al. (2018, August 22-24). Conferencia Internacional sobre Investigación en Inteligencia y Computación en Ingeniería (RICE), San Salvador, El Salvador, Facial Emotion Recognition: A Comparison of Different Landmark-Based Classifiers. IEEE. 10.1109 / ARROZ.2018.8509048

[6] Dewi, Y.L, Widyanio, M., Basaruddin, T. (2018). Geometric facial components feature extraction for facial expression recognition.

[7] Mangal, Divya., Prajwala.(2018, Abril 3-5). International Conference on Communication and Signal Processing, Facial expression recognition by calculating euclidian distance for Eigenfaces using pca.

[8] Kartali, et al. (2018, November 20-21).14th Symposium on Neural Network and Aplication (NEUREL), Belgrade, serbia real-time algorithms for facial emotion recognition: a comparison of different approaches.IEEE.

[9] Rabhi Yassine, et al. (2018, March 21-24). 4a Conferencia internacional sobre tecnologías avanzadas para el procesamiento de señales e imágenes (ATSIP), Susa, Túnez, A Real-time Emotion Recognition System for disabled persons.IEEE. 10.1109 / ATSIP.2018.8364339
[10] Cadena Moreano, J.A, La Serna Palomino, N., Llano Casa, A, C. (2019, September). A Facial recognition technique using SVM: A comparative analysis. e-ISSN: 1390-6542 / p-ISSN: 1390-9363.
[11] Sawhney Shreyak, et al. (2019, January 10-11). IX Conferencia Internacional sobre Cloud Computing, Data Science & Engineering (Confluence), Noida, India, India Real-Time Smart Attendance System using Face Recognition Techniques.IEEE. 10.1109/ CONFLUENCE.2019.8776934
[12] Lacort, J. (21 agosto 2017). Las claves de los sistemas de reconocimiento facial: ¿cuál es su verdadero nivel de seguridad? Recuperado el 2 de junio del 2020 de https://www.xataka.com/seguridad/las-claves-de-los-sistemas-de-reconocimiento-facial-cual-es-su-verdadero-nivel-de-seguri
[13] Hussain, J., Ali Khan, W., Hur, T., Bilal, H., Bang, J., Hassan, A. . . . Lee, S. (2018, Mayo 18). A Multimodal Deep Log-Based User Experience (UX) Platform for UX Evaluation. Sensors, 18(5). doi:10.3390/s18051622.
[14] Behera Ardhendu, et al (2020, abril), International Journal of Artificial Intelligence in Education. Associating Facial Expressions and Upper-Body Gestures with Learning Tasks for Enhancing Intelligent Tutoring Systems, https://doi.org/10.1007/s40593-020-00195-2
[15] Jain Udit, et al. (2018, mayo), 2do Congreso Internacional de Tendencias en Electrónica e Informática (ICOEI). Tirunelveli, India. Analysis of Face Detection and Recognition Algorithms using Viola Jones Algorithm with PCA and LDA. 10.1109 / ICOEI.2018.8553811
[16] Sharma S., et al. (2016, mayo 25-27). Conferencia Internacional sobre Tecnologías Avanzadas de Computación y Control de Comunicaciones (ICACCCT). Ramanathapuram, India, FAREC - CNN Based Efficient Face Recognition Technique using Dlib. IEEE. 10.1109 / ICACCCT.2016.7831628
[17] James Garrett, Jesse (2011) The Elements of User Experience: User-Centered Design for the Web and Beyond, Second Edition, ISBN 13: 978-0-321-68368-7
[18] Michael J. Lyons, Shigeru Akamatsu, Miyuki Kamachi, Jiro Gyoba. Coding Facial Expressions with Gabor Wavelets, 3rd IEEE International Conference on Automatic Face and Gesture Recognition, pp. 200-205 (1998). http://doi.org/10.1109/AFGR.1998.670949 Open access content available at: https://zenodo.org/record/3430156
[19] Yang, D, Alsadoon, A., P.W.C, Prasad, Singh, A, K, Elchouemi, A. (2017, Dic), International Conference on Smart Computing and Communications. Kurukshetra, India. An Emotion Recognition Model Based on Facial Recognition in Virtual Learning Environment Networks. https://doi.org/10.1016/j.procs.2017.12.003
[20] Valderrama Cárdenas, W. (2019). Reconocimiento automático del rostro para verificación de identidad para evaluación en línea (tesis de maestría). Morelos, México: CENIDET.
[21] Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., & Matthews, I. (2010). The Extended Cohn-Kanade Dataset (CK+): A complete expression dataset for action unit and emotion-specified expression. Proceedings of the Third International Workshop on CVPR for Human Communicative BehaviorAnalysis (CVPR4HB 2010), San Francisco, USA, 94-101.
[22] King, “dlib C++ Library,” 2015. [Online]. Available: Www.Dlib.Net.
[23] Kazemi, V, Sullivan, J. (23-28 June 2014). IEEE Conference on Computer Vision and Pattern Recognition. Columbus, OH, USA. One millisecond face alignment with an ensemble of regression trees. IEEE. 10.1109/CVPR.2014.241
[24] P.E Group "FACS Archives - Paul Ekman Group, LLC.," 2016 [Online]. Available: http://www.paulekman.com/product-category/facs/
[25] Joaquín A.R. (2021) Máquinas de Vector Soporte (SVM) con Python available under a Attribution 4.0 International (CC BY 4.0) at https://www.cienciadedatos.net/documentos/py24-svm-python.html
[26] Sambare, M. (2020, Julio 19). FER-2013 Learn facial expressions from an image. Version 1. https://www.kaggle.com/msambare/fer2013/metadata
[27] Jeovanny Soriano Terrazas (2018). Metodología para caracterizar e inducir estados mentales a través de realidad virtual inmersiva e interfaz cerebro computadora (Tesis de maestría). CENIDET, Morelos, México