Journal of Theoretical and Applied Information Technology
15th December 2021. Vol.99. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TWO FACIAL EMOTION DETECTION BASED ON NAIVE BAYESIAN CLASSIFIER

URIEL ALAN FLORES-JUAREZ[1], JESÚS ANTONIO ÁLVAREZ-CEDILLO[1], TEODORO ÁLVAREZ-SÁNCHEZ[2]

[1]Instituto Politécnico Nacional, UPIICSA, Av. Te 950, México City, México

[2]Instituto Politécnico Nacional, CITEDI, Instituto Politécnico Nacional 1310, Tijuana, BC, México

E-mail: [1]ufloresj1900@alumno.ipn.mx, [1]jaalvarez@ipn.mx, [2]talvarezs@ipn.mx

ABSTRACT

Emotion is an affective state of a subjective reaction in an environment accompanied by physiological and endronic changes in human beings; this happens suddenly and abruptly in the form of a crisis. In the article, Bayes' theorem's implementation was developed that allows classifying two facial emotions of the human being. Our central premise is based on realizing a Bayesian model to generate a supervised learning model, which uses the analysis of data collected to create an emotions classifier. The Naive Bayes classifier training model results provide a functional form of probability to capture joint statistics of local appearance and position on the object whose one-to-one match result is slightly higher than 56%. This value is less than the method used by Schneiderman and Kanade. Concluding that the proposed algorithm is better than those analyzed because several external variables such as lighting, pose, and detection of characteristics can change the performance in terms of precision.

Keywords: *Emotional computing, Naive Bayesian Classifier, Emotions, a system for predicting joy and sadness*

1. INTRODUCTION

A current problem, referring to the investigation of human behaviour is the emotions, compared to the traditional conception between emotion and intellect, the most recent theories indicate the influence of emotions in the mechanisms of rational thought.

An emotion is an affective state that generates a subjective reaction to the environment that is accompanied by organic, physiological and endocrine changes of natural origin, influenced by experience.

Emotions have an adaptive function of the body to its surroundings; this occurs suddenly and abruptly, in the form of a crisis.

In the human being, the experience of emotion generally involves a set of cognitions, attitudes and beliefs about the world, which the human being uses to assess a specific situation and how said the situation is perceived.

Emotions have been considered unimportant, and the most rational part of the human being has always been given more relevance. However, emotions, being affective states, indicate individual internal states, motivations, desires, needs and even goals.

A classic problem related to emotions is to determine from the emotion what will be the future behaviour of the individual.

There are six essential categories of emotions.

• FEAR: Anticipation of a threat or danger that produces anxiety, uncertainty, insecurity.

• SURPRISE: shock, amazement, bewilderment. It is very transitory. It can give a cognitive approximation to know what happens.

• AVERSION: Disgust, disgust, we tend to move away from the object that produces aversion.

• ANGER: Anger, anger, resentment, fury, irritability.

• JOY: Fun, euphoria, gratification, content, gives a feeling of well-being, security.

• SADNESS: Grief, loneliness, pessimism.

If the end is the adaptability of emotions, we would have different functions:

• FEAR: Search for protection.

• SURPRISE: Helps to guide the human being in the face of the new situation.

• AVERSION: Produces rejection of the approaching phenomenon.

• IRA: Induce towards destruction.

• JOY: It leads to reproduction (we want to reproduce that event that makes us feel good).

• SADNESS: Motivates towards a new personal reintegration.

The humans have forty-two different faces. Depending on the emotion this movie, and with this, it is possible express one an emotion. There are different smiles, which express different degrees of happiness. The different facial expressions are international; within different cultures, there is a similar language.

Emotions have particular behavioural components, which are the way they are displayed externally. They are an axis of measurement that can be controlled, based on the family and cultural learning of each group:

• Facial expressions.

• Actions and gestures.

• Distance between people.

• Non-linguistic components of verbal expre-ssion (non-verbal communication).

Other components of emotions are physiological and involuntary, the same for all:

• Tremor

• Blush

• Sweating

• Heavy breathing

• Pupillary dilation

• Increased heart rate

These components are what is at the base of the polygraph or the "lie detector". It is assumed that when a person lies, they feel or cannot control their physiological changes, although there are people who with training can control it.

Different researchers nowadays seek to detect emotions to improve the experience of people when interacting with a computer application. In 1997, in the book Affective Computing, its author (Rosalind Picard), created the term Affective Computing, where she argues the need to take into account emotional factors in software design.

Affective Computing is currently an emerging research area whose objective is focused on the development of devices and systems that are capable of recognizing, interpreting, processing and simulating human emotions to improve the interaction between the user and any computer system or robot.

These effective systems should:

1. Capture and recognize the emotional states of the user through measurements on signals generated in the face, voice, body.

2. Process that information to classify, manage, and learn through algorithms that are responsible for collecting and comparing large amounts of information.

3. Generate responses and corresponding emotions, expressed through different channels of colour or sounds.

Devices for detecting emotions have evolved significantly, allowing computer systems to recognize the emotional state of a user. Through cameras, it is possible to capture observable properties of emotions, such as skin colour, body movements, gestures, or even the detection of facial expressions based on the analysis of muscle movements or characteristic points of the face.

Special devices, such as eye-trackers, allow obtaining information on the dilation and monitoring of the pupils. The microphones allow capturing the language and the variations in intonation, tone or volume of the voice.

Obtaining information that is difficult to observe, using sensors that record physiological measurements such as respiration, pulse, galvanic resistance of the skin, body temperature or through electrodes that detect brain activity.

In general, it is possible to use informal probabilities to express information or uncertainty for a phenomenon that has unknown quantities. The use of probabilities to interpret the information allows the use of formality in the analysis of the information.

From the mathematical point of view, it can be shown that with the Calculus of Probabilities, a set of rational beliefs can be estimated numerically and demonstrate that there is a direct relationship between probability and information.

The application of Bayes theory naturally allows beliefs to be updated when new information appears. This inductive learning process through Bayes theory is the basis of Bayesian Inference.

Bayesian methods provide the basis for determining the estimators which fit the parameters that have better statistical properties.

The correct application of this theory allows:

1. Obtain a simple description of the observed data;

2. Estimation of missing data and

3. Have information to estimate future predictions

The Bayesian methodology is made up of three fundamental steps:

1. Specify a probability model that includes some prior knowledge (a priori) about the parameters of the given model.

2. Update the knowledge about the unknown parameters, conditioning this probability model to the observed data.

3. Evaluate the fit of the model to the data and the sensitivity of the conclusions.

The fundamental difference between classical (frequentist) and Bayesian statistics is in the representation of the concept of probability.

For classical statistics, it is an objective concept, found in nature, while for Bayesian statistics, it is found in the observer, which makes it focus on a subjective concept.

Classical statistics is only taken as a source of information for the samples obtained, assuming, for mathematical developments, that an infinite size could be taken for a sample hypothetically. In the Bayesian case, in addition to the sample, it is also essential to determine the previous or external information that is possessed about the phenomena that are being modelled.

The main objective of the naive Bayesian classifier is to transform the information in order to obtain a prediction [1],[2],[3]. About the implementation of Bayes' theorem, it is possible to identify several areas of opportunity.

In particular, in the area of emotions [4], there is a significant potential whereby delimiting the correct characteristics, probabilistic information is transformed into an admissible prediction [5].

It is necessary to highlight the relevance of the application of Bayes' theorem to the detection of emotions, given that at present the amount of information that is generated daily on the Internet is overwhelming, various tools are needed in order to process said information using supervised and deep learning techniques, as well as emphasize the mathematical basis of these techniques [6].

It is possible to produce a mathematical model, that is, a classifier, that generates an approximation in the detection of two emotions, precisely the emotions of joy and sadness. One of the most critical components in this work is to delimit the quantifiable characteristics because they will be the source of information that feeds the naive Bayesian classifier, resulting in a model that can identify between the emotions of joy and sadness based on a mathematical calculation.

The facial characteristics with the most significant presence of each emotion are delimited, the distance between nose-eyebrow, nose-eyelid, and finally, the distance from the nose to the lower lip. With the data collected, the calculation is carried out in order to obtain a reliable approximation when distinguishing between the emotions of joy and sadness.

2. THE NAIVE BAYES METHOD

To implement a supervised Bayesian classification given by an object described by a set of attributes or characteristics [7], $X_1, X_2, \ldots, X_n$, to one of m possible classes, C1, C2, …, Cm, such that the probability of the class given the attributes is maximized:

$$Arg_C[Max\ P(C|X_1, X_2 \ldots X_n)] \quad (1)$$

If the set of attributes is expressed as: $X = \{X_1, X_2, \ldots, X_n\}$, equation (1) can be written as Argc [Max P (C | X)]. The formulation of the Bayesian classifier [8], based on the use of Bayes rule to calculate the posterior probability of the data class of the features.

$$P(C|X_1, X_2 \ldots X_n) = P(C)P(X_1, X_2 \ldots . X_n|C)/ P(X_1, X_2 \ldots X_n) \quad (2)$$

One-way summary of the formula (2) is:

$$P(C|X) = P(C)P(X|C)/P(X) \quad (3)$$

The denominator, P (X), does not change in the classes so that it can be considered as a constant.

Journal of Theoretical and Applied Information Technology
15th December 2021. Vol.99. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A classifier that learns from a set of data requires estimating probabilities, a priori and likelihood, from the data, known as the parameters of the classifier.

Likewise, the application of this classifier greatly facilitates learning by assuming the independence of the defined characteristics of each class [9]. Consequently, a useful model for decision making is obtained [10].

2.1 PARAMETERS

The results are closely related to the specification of the parameters; for this particular case, the parameters are linked to facial emotions [11], focusing on joy and sadness, which are described later.

In the learning process, the characteristics are used in order to determine a set of suitable parameters [12], to generate the model that allows to correctly predict each emotion, due to this the naive Bayesian classifier is one of the oldest workhorses used in machine learning [13].

2.1.1 Joy

Understanding human emotions are one of the skills necessary for a computer to interact wisely with a human [14]. Joy occurs when our mood is one of optimism, success, and excitement, as shown in Figure 1 self-esteem, confidence, and well-being.

Physiologically, because of this, it increases the heart rate, blood pressure, and activity in the hypothalamus, it facilitates empathy, as it is a very contagious emotion, especially if it reaches the level of laughter; and communication with others, for provoking a greater availability to social interactions.

It is an ally of creativity, learning and memory, making us more receptive to stimuli.

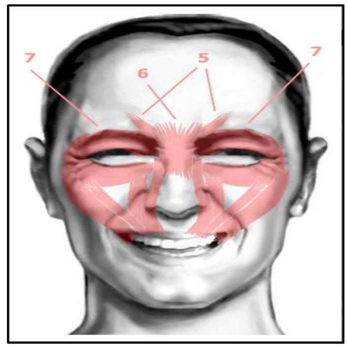

Figure 1. Joy. Source: ResearchGate Sindy Vargas

When we express joy, the corners of the lips are pulled back and up simultaneously, and it is according to the degree of expression that the teeth will be exposed or it will remain as a simple smile.

Facial expressions are the most expressive way in which humans display their emotions [15]. For this reason, the emphasis was placed on the characteristics of joy, the cheeks, as a consequence, rise in the same way, while the nasolabial fold goes down from the nose to the corner of the lips. In the eye area, inevitable wrinkles appear on the lower eyelid and in the outer corner of the eye, towards the scalp.

2.1.2 Sadness

This emotion in the literature has captured the interest of researchers, some researchers that involve various fields [16].

The physiological reaction that causes sadness is crying, which helps to release internal tension and anguish. It usually appears in situations of disappointment, anxiety, which cause both losses of control and headaches, reluctance or apathy. An example is shown in figure 2.

As in the laughter that causes joy, in crying, as a reaction to sadness, we also have specific levels. At a low level, they cry softly, but with constant tears, being typical for external stimuli to the individual. At a high level, breathing is short, and tears are abundant, caused by emotionally intense events.

When we express sadness, muscularly the inner angles of the eyes rise, and the skin of the eyebrows forms a triangle.

Contrary to the smile that causes joy, when we are sad the corner of the lips slopes downwards, which can very commonly cause small lip tremors. The head usually tilts down, lowering the gaze in turn.

Figure 2. Sadness. Source: ResearchGate Sindy Vargas

The implementation of these emotions is based on a fundamental approach of emotions [17], [18].

3. RELATED WORKS

According to the research carried out by A. Calvillo [2], the Naive Bayes algorithm contributed to finding the business objectives of his research on student dropout, through data mining, generation of a model with the which managed to classify this type of student [19].

The Naive Bayes algorithm has been used in the analysis of human resource management trends [20], for the semantic analysis for the classification of texts thanks to its useful properties for supervised learning [21]. This analysis consisted of a classificatory model that included two classes of words, the first belongs to the frequency in scientific texts and the second class belongs to the frequency in the company's reports.

Lastly, information analysis is essential for decision-making [22], [23], according to Tume Ayala, having a business intelligence tool is a pillar for decision-making; Using algorithms of decision trees, Naive Bayes, association rules, it is possible to rank and discern the information with added value [24], [25], which will later be used by the organization to make correct decisions.

Facial expressions generate important clues about emotions. In the literature, different researchers have developed different methods to classify the affective states of the human being [20], [21], [22], [23].

These methods use local spatial position or the displacement of some specific points, and some use entire regions of the face [26], [27], [28].

Some of these research works are unimodal, that is, using only the recognition of facial expressions, others try to use more than one type of input, such as speech processing, body movement, hand gestures.

Castellano [29] created a system for the recognition of bimodal emotions, based on both facial expression recognition analysis and voice timbre, the strengths and limitations of the unimodal and multimodal systems were analyzed, and the two approaches were discussed.

Other researchers developed a system based on facial expressions, using facial markers, and Principal Component Analysis to reduce the number of features per image. Mouth area markers are not considered, as these could confuse the classifier by causing the expression to be classified as happiness while the person is speaking [20], [21].

Bruce et. AL in 1986 [30], shows different approaches of the analysis of facial expression is performed statistically using the extremes of an expression, which requires finding clues in the wrinkles, positions and shapes of the face to help infer the emotional state of a person, without success. In the second approach, the analysis is oriented gestures, for which successive images are extracted to detect facial expression, which is analyzed to find variations, and in this way, they are assigned to previously defined emotional states.

4. DEVELOPMENT

According to the theory of the Bayesian classifier, the parameters with which the calculation will be made have been determined. Three measurements will be made on the face with the two emotions to be classified; the first measurement will be Nose-Eyebrow, the second measurement will be Nose-Eyelid and finally Nose-Lower lip.

Journal of Theoretical and Applied Information Technology
15th December 2021. Vol.99. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

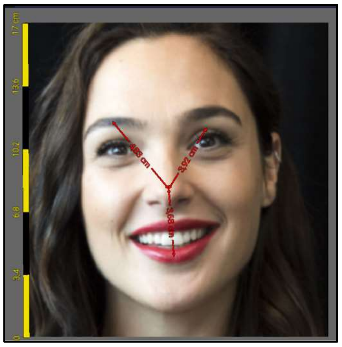

Figure 3. Facial measurements of joy. Source: Image captured from the Internet

Figure 4. Facial measurements of joy Source: Image captured from the Internet

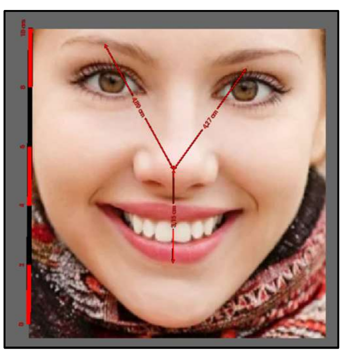

Figure 5. Facial measurements of joy Source: Image captured from the Internet

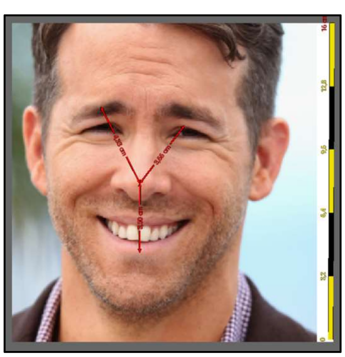

Figure 6. Facial measurements of joy Source: Image captured from the Internet

Figure 7. Facial measurements of joy Source: Image captured from the Internet

Figure 8. Facial measurements of sadness Source: Image captured from the Internet

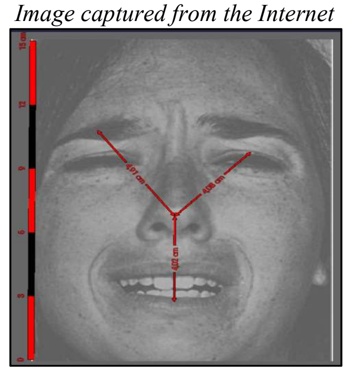

Figure 9. Facial measurements of sadness Source: Image captured from the Internet

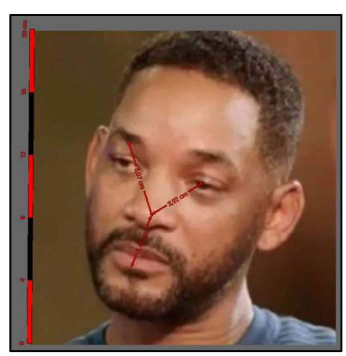

Figure 10. Facial measurements of sadness Source: Image captured from the Internet

Figure 11. Facial measurements of sadness Source: Image captured from the Internet

When obtaining the measurements of the parameters determined for the classifier, said information was collected in the Table 1. Data from 10 samples have been collected, each with three different parameters that will be used in the Bayesian classifier to generate an approximation and reveal whether the emotion in the test is Joy or Sadness.

To perform the calculations, a Gaussian distribution was used to obtain the necessary data, which are the mean and variance for each data set used for this classifier.

Table 1: Facial measurements corresponding to the emotions Joy and Sadness. Source: self-made.

Emotion	Nose-Ceja	Nose-Eyelid	Nose-Lip Lower
Joy	*4.83*	*3.92*	*3.68*
Joy	*5.64*	*4.38*	*4.35*
Joy	*4.33*	*3.66*	*3.5*
Joy	*4.89*	*4.27*	*3.15*
Joy	*4.52*	*3.78*	*3.26*
Sadness	*5.07*	*3.92*	*3.47*
Sadness	*4.91*	*4.08*	*4.02*
Sadness	*4.78*	*4.64*	*3.64*
Sadness	*4.09*	*3.91*	*2.38*
Sadness	*4.69*	*4.06*	*2.66*

Table 2: Values used for training. Source: self-made.

	Eyebrow		Nose-nose nose-lip Eyelid		Lower	
Emotion	Media	Variance	Media	Variance	Media	Variance
Joy	4,842	0.25127	4,002	0.096920	3,588	0.22407
Sadness	4.708	0.139819	4.122	0.089919	3,234	0.47428

For this training, the distribution of the variables to determine the correct emotion is equally probable.

P (A) = 0.5

P (T) = 0.5

At the end of the training with the collected information, different samples of these emotions can be evaluated, which will be evaluated in the system.

5.1 Test Data

The test values used in the tests are those shown in table 3.

Table 3. Values used for testing.

Emotion	Nose-Eyebrow	Nose-Eyelid	Nose-Lower Lip
?	4.12	3.68	2.98

These values were processed using the following steps:

1. Calculate the posterior probability of the data

$$p(N - C|joy = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}$$

2. Get the product of the data.

$$posteriori(Sad) = \frac{P(T)\, p(NC|T)\, p(NP|T)\, p(NLI|T)}{Evidence}$$

$$posteriori(joy) = \frac{P(A)\, p(NC|A)\, p(NP|A)\, p(NLI|A)}{Evidence}$$

Step 1

P (A) = 0.5

P (NC | A) = 0.02558

P (NP | A) = 0.01650

P (NLI | A) = 0.04484

Step 2

Post (A) = product = 0.0000094628

Step 1

P (T) = 0.5

P (NC | T) = 0.00041

Journal of Theoretical and Applied Information Technology
15th December 2021. Vol.99. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

P (NP | T) = 2.51328-05

P (NLI | T) = 0.72877

Step 2

Post (T) = product =0.00000000375

With a posteriori results of each option, we can see that the highest belongs to the emotion of Joy, it is assumed as the correct classification.

5. RESULTS

When analyzing the results, it can be assumed that the result with the highest value, the highest probability, is the Posteriori (A) corresponding to the correct classification. According to figure 12. The results of the training model are correct; they match the correct dimensions and emotion.

Figure 12. Facial measurements of joy in the test image. Source: self-made

Even with a relatively small sample, the results obtained have acceptable certainty. By increasing the number of samples, the certainty will increase.

In the literature, Schneiderman and Kanade described a naive Bayes classifier to estimate the joint probability of local appearance and position of facial patterns [31].

Operations are focused on local appearance because the intensity patterns around the eyes are much more distinctive than the pattern around the cheeks.

Our Naive Bayes classifier provides a functional form of posterior probability to capture joint statistics of local appearance and position on the object.

Figure 13 shows an implementation, where the maximum precision is located in range one, which is a one to one match result, it is slightly higher than 56%. This value is lower than the methods used by Schneiderman and Kanade [31], due to:

- Type of lighting
- The different orientations of the head

Twenty-five samples of faces were used, of different people of different traits, and showing a different overall brightness.

Based on the results, it was observed that the difference in lighting affects the overall performance.

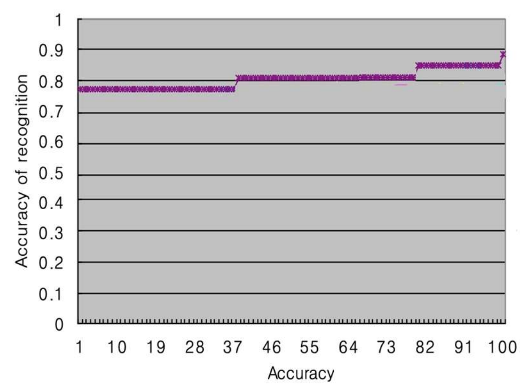

Figure 13. Cumulative match characteristic chart at 85% accuracy. Source: self-made

The Figure 14 show the Cumulative match characteristic chart at 85% accuracy.

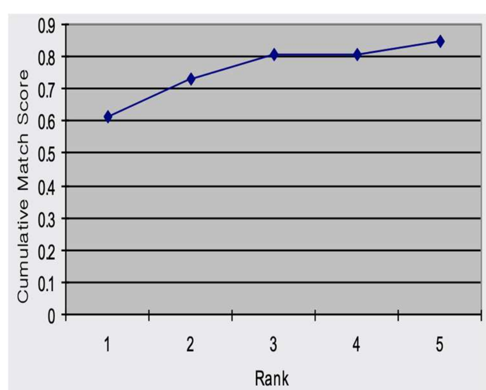

Figure 14. Proposed Accuracy. Source: self-made

6. CONCLUSIONS

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The implementation of Bayes' theorem generated a classifier that allows other learning scenarios. The methodology consisted of classifying relatively subjective aspects determining the subjective parameters of the expressions of emotions: sadness, joy, surprise, in which numerical data are obtained.

The data entered for the subjective parameters are defined; without knowing the emotion that the system provides us, it will give us an approximation of the emotion that can be, with sufficient certainty.

The proposed algorithm has improved the literature researched and compared with the results due to various external variables such as lighting, pose, and detection of features that can change performance in precision.

With the implementation and knowledge acquired, in the detection and recognition of faces, for future research, a new interface is proposed that can quickly test the performance of the algorithms, thus increasing the accuracy rates and having a more robust classifier to solve these problems.

ACKNOWLEDGMENTS

We appreciate the facilities granted to carry out this work to the Instituto Politécnico Nacional through the Secretariat of Research and Postgraduate with the SIP 20210388, and SIP 20210841. To the Interdisciplinary Unit of Engineering and Social and Administrative Sciences, Center for Technological Innovation and Development in Computing and Digital Technology Research and Development Center. Likewise, to the Program of Stimulus to the Performance of the Researchers (EDI) and to the Program of Stimulus COFAA.

REFERENCES

[1] M. Beltran, Bayesian networks applied to credit scoring problems, A practical application, Cuadernos de Economía, Vol. 37, 2019.

[2] A. Calvillo, A Bayesian classifier to search and classify research, DYNA New Technologies 2, Vol. 1, 2015.

[3] B. Oviedo, New simple Bayesian classifier for the analysis of educational data, Quevedo State University, 2019.

[4] G. Castellano, Emotion recognition through multiple modalities: face, body gesture, speech, LNSCS, 2008.

[5] Z. Hammal, Facial expression Classification: An approach based on the fusion of facial deformation using the transferable belief model. International Journal of Approximate Reasoning, Vol. 46, 2007.

[6] N. Friedman, Bayesian Network Classifiers, Machine learning, Vol. 29, 1997.

[7] L. Sucar, Bayesian Classifiers: from Data to Concepts, National Institute of Astrophysics, Optics and Electronics Tonantzintla, Puebla, México, 2009.

[8] Q. Bai, A Bayesian framework for online classifier ensemble, International Conference on Machine Learning, 2014.

[9] I Rish. An empirical study of the naïve Bayes classifier. IJCAI, 2001.

[10] N. Ye, Naïve Bayes Classifier, CRC Press, 2020.

[11] M. Mesa. The face, mirror of the soul, illustrating emotions, typology 4, 2015.

[12] D. Berrar, Bayes' Theorem and Naïve Bayes Classifier, Encyclopedia of Bioinformatic and Computational Biology, 2019.

[13] T. Calders. Three naïve Bayes approaches for discrimination-free classification. Data Mining and Knowledge Discovery, 2010.

[14] I. Cohen. Learning Bayesian network classifiers for facial expression recognition using both labeled and unlabeled data. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2003.

[15] N. Seben. Facial expression recognition fr-om video sequences: temporal and static modelling. Vol. 91, 2003.

[16] J. Zhang. Emotions recognition using multi modal data and machine learning techniques: A tutorial and review. Information Fusion, Vol. 59, 2020.

[17] P. Ekman. Are there basic emotions? Psy-chological Review, Vol. 99, 1192.

[18] M. Kowalska. Basic Emotions, Springer International Publishing, 2017.

[19] Z. Torres, C., Arce Ramos, C., & Lam Moraga, J. Study of variables that influence

the dropout rate of first-year university students, using data mining. Amazon Science (Iquitos), 2016. https://doi.org/10.22386/ca.v6i1.110

[20] T. Quirós, FJ analysis of trends in human resource management from an academic and business perspective. Sevilla University, 2015.

[21] G. Gautam. Sentiment analysis of Twitter data using machine learning approaches and semantic analysis. International Conference on Contemporary Computing, 2014.

[22] T. Ayala, VR, Development of business intelligence to analyze financial companies: Municipal Savings Banks. In the National University of Piura, 2014.

[23] D. Xhemali. Naive Bayes vs Decision Trees vs Neuronal Networks in the classification of training web pages. International Journal of Computer Science. Vol. 4, 2009.

[24] H. Zang. Naïve Bayes text Classifier. International Conference on Granular Computing, 2007.

[25] A. Wibawa. Naïve Bayes Classifier for Journal Quartile Classification, Vol. 91, 2019.

[26] Laptev, I., & Lindeberg, T. Local descriptors for spatio-temporal recognition. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),2006. https://doi.org/10.1007/11676959_8

[27] Hsu, R. L., Abdel-Mottaleb, M., & Jain, A. K. Face detection in color images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002. https://doi.org/10.1109/34.1000242

[28] Goffaux, V., & Rossion, B. (2006). Faces are "spatial" - Holistic face perception is supported by low spatial frequencies. Journal of Experimental Psychology: Human Perception and Performance. https://doi.org/10.1037/00961523.32.4.1023

[29] Castellano, G., Kessous, L., & Caridakis, G. (2008). Emotion recognition through multiple modalities: Face, body gesture, speech. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). https://doi.org/10.1007/978-3-540-85099-1_8

[30] Bruce, V., & Young, A. (1986). Urderstanding face recognition. British Journal of Psychology. https://doi.org/10.1111/j.2044295.1986.tb02199.x

[31] H. Schneiderman and T. Kanade, "Probabilistic Modeling of Local Appearance and Spatial Relationships for Object Recognition, Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 45-51, 1998.