Classifying Emotion based on Facial Expression Analysis using Gabor Filter: A Basis for Adaptive Effective Teaching Strategy

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Abstract. Emotion is equivalent to mood or state of human emotion that correlates with non-verbal behavior. Related literature shows that humans tend to give off a clue for a particular feeling through nonverbal cues such as facial expression. This study aims to analyze the emotion of students using Philippines-based corpus of a facial expression such as fear, disgust, surprised, sad, anger and neutral with 611 examples validated by psychology experts and results aggregates the final emotion, and it will be used to define the meaning of emotion and connect it with a teaching pedagogy to support decisions on teaching strategies. The experiments used feature extraction methods such as Haar-Cascade classifier for face detection; Gabor filter and eigenfaces API for features extraction; and support vector machine in training the model with 80.11% accuracy. The result was analyzed and correlated with the appropriate teaching pedagogies for educators and suggest that relevant interventions can be predicted based on emotions observed in a lecture setting or a class. Implementing the prototype in Java environment, it captured images in actual class to scale the actual performance rating and had an average accuracy of 60.83 %. It concludes that through aggregating the facial expressions of students in the class, an adaptive learning strategy can be developed and implemented in the classroom environment.

Keywords: emotions, facial expression, Gabor filter, adaptive learning, facial expression, emotion detection, teaching pedagogy

1 Introduction

Emotion elicits stimuli such as happy, fear, neutral, angry, disgust, sad, which provides the signal to individuals to make strategic actions and decision making [1]. Decision making is significant to the educational setting environment in terms of how they develop students' and teachers' self-regulation [2] thus improve academic achievement [3]. Emotion is now being observed and given so much attention [4] to transform

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learner's values and behavior [5], motivate learning [6] and creates different classroom contexts, [7].

Furthermore, emotion influenced individual intrapersonal, interpersonal and social, cultural and political dimensions [8] In fact teachers are encouraged to read the facial expression of students' in order to assess the level of understanding [9] educators are also help to strengthen knowledge acquisition through employing an engaging environments [10], consider emotion through integration of experience to the academic study [11] and [12] stated that it is vital to detect one's emotion before applying mitigation technique. On the other hand, emotion influence teachers' decisions about their delivery of instruction together with its content in facilitating learning [13] and it revealed that teachers understand the aims of education by giving importance on creating positive-student teachers relationship to support student development both academically and socially [14]. There are several studies conducted to observe the leaner's emotional behavior as the basis for employing interventions and teaching strategies. A study revealed that the active participation of students in the class connotes happiness which means that the students showed interest in their studies [15] A teaching strategy is to adapt either these two approaches by asking the students or proceed to the next level of discussion. With regards to student's avoidance of discussion and absence of engagement, it connotes the fear emotion [16], [10] The strategy is to employ group activities [17]. In a collaborative approach, students create a project in a group to elicit interactions among the members of the group [18], [19]. Application of real-world engagement and connection in concepts and experiences [20] encouragement of students to respond question and provides them investigative techniques that apply inquiry approach [21] [22] and recognizing prior knowledge, an integrative approach [23] and the application of inquiry or constructivist approach [24], These approaches are applied to elicit learning. According to UNESCO, an effective pedagogy holistically develops learners. However, it was found out that social and emotional pedagogy is not a core set of things that teachers know instead they perform within the rhythms of their work in terms of considering the student emotions and social positionalities through their planning instructional practices [25].

Through the advancement of technology, detection of emotion is one the emerging research field in affective computing. There are application and tools being using computer vision learning analytics and machine learning [26]. Several, studies conducted focusing on the emotion that implements different approaches and applied best-suited algorithms. Emotion analysis using feature dimensionality techniques, [27][28] Some of the studies are analyzing the sentiments of the customer [29], recognizing the malicious intention through gesture [30], detecting the stress level of a person [31] determining student emotion in computer programming activities [32] , assessing the emotion of participants interacting the computer interfaces activities [30], identifying the level of student engagement in Java Programming activity [33] and capturing emotion expressed in mobile phone and internet to activate and express emotion [34]. Majority of these studies are utilizing the Cohn Kanade and JAFEE databases. In this study, it attempted to build a Filipino-based facial expression corpus to localize the detection and recognition methods.

Furthermore, to test the efficiency and effectiveness of the experiment by applying the best-suited algorithms to achieve higher accuracy to be implemented in the prototype model. The model can be useful for educators to assess the emotion of the students in a classroom setting environment. Moreover, this study provides discovery to analyze further the first build datasets based on Filipino features. Initial experiments were conducted on the previous paper from the average accuracy result from the still images [35]. The objectives of this paper include a) to build and analyze the Filipino based facial features using OpenCV with Haar Cascade Classifier for detection, Gabor Filter, and Eigenfaces API for features extraction, Support Vector Machine for classification and Euclidean distance for recognition b) to formulate teaching pedagogy based on the types of emotion c) to develop a prototype model that will be able to classify the emotion, aggregated the detected emotion which processed different type of formats and finally d) to test the recognition accuracy of the prototype model.

2 Methodology

This study applied an experimental approach where facial expression emotion of the subject is captured in supervised learning, utilization of the best suited algorithms for face detection, features extraction and face recognition and classification of facial features, the formulation of proposed teaching pedagogy based on the aggregated emotion and the testing of the developed prototype model which are able to accommodate different of formats such as still images, real-time video and video file for processing the images.

2.1 Building the training dataset

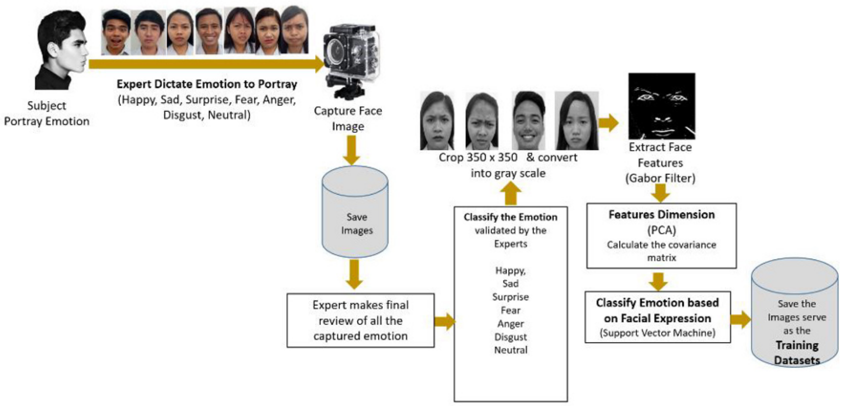

Fig. 1. Annotation of Emotions from Images by Psychologist

Fig. 1, the study built the training datasets with the assistance of the experts in validating and verifying the portrayed facial expressions of the subjects. The validation applied two approaches, first is to instruct the topic by providing a sample image on how to describe the required emotion. However, among the emotions, specifically "fear" emotion was the difficult emotion to be portrayed, it needs assistance for the experts to institute a scenario or provide a role play for the subject act the required emotion. All l images were reviewed again by the experts after taking the images to ensure the accuracy of the portrayed emotion. Their total images are total of 611 images composed of 281 images of female and 331 images of male subjects ages from 18 to 20 years old portraying the emotions on " Happy," "Fear," "Neutral," " Sad," "Surprised," "Disgust" and "Anger." This presentation of images is not balanced due to the elimination of incorrect emotion portrayed from 1024 images down to 611. To determine the accuracy, the images are fed into Weka tool to balance the features and utilize Rapid Miner tool to check the classification accuracy.

Table 1. Filipino based Facial Features Datasets

Emotion	Female	Male	Total
Happy	44	60	104
Fear	30	31	61
Neutral	44	54	98
Sad	37	43	80
Surprised	43	46	89
Disgust	42	43	85
Anger	41	53	94
Total	**281**	**331**	**611**

Table 1 shows the number of emotions portrayed by the subjects ages 18 to 20 years old. These images are not balanced due to the elimination of incorrect emotion portrayed from 1024 images down to 611. These images are fed into Weka tool to balance the features which will be used to check the classification accuracy using Rapid Miner tool.

2.2 Processing the images

Fig. 2, the prototype model was developed in JAVA and utilized an OpenCV for face image detection. The model detects multiple face images using Haar Cascade Classifier. Once detected, the images were zoomed using Bicular interpolation and Replication algorithm. Then, these images would then, be cropped and converted into grayscale for the extraction of the features using Gabor Filter and Principal Component Analysis to optimize the search space. The facial features are classified using Support Vector Machine. For recognition purpose, the new input image will be compared to the training datasets using Euclidean distance finding its closest image vector. All detected emotions are aggregated every 20 seconds. The result of the aggregated would be then the basis for determining the recommended teaching strategies according to conditions set in this study focusing the negative emotions composed of "Anger," "Disgust," "Sad," "Fear" and "Surprise." If one of these emotions marked the highest percentage, and if all these emotions are equal in percentage, then the prototype will aggregate as the basis for teaching strategies recommendation. Moreover, the prototype model is capable of processed features extraction by producing a pixel value of the image and generate a histogram. Also, the model allows uploading of video file format limited to 500m only, enable the teacher to set up a class schedule and generate PDF file report indicating the number of faces detected, teaching strategies recommendation and the histogram of detected emotion.

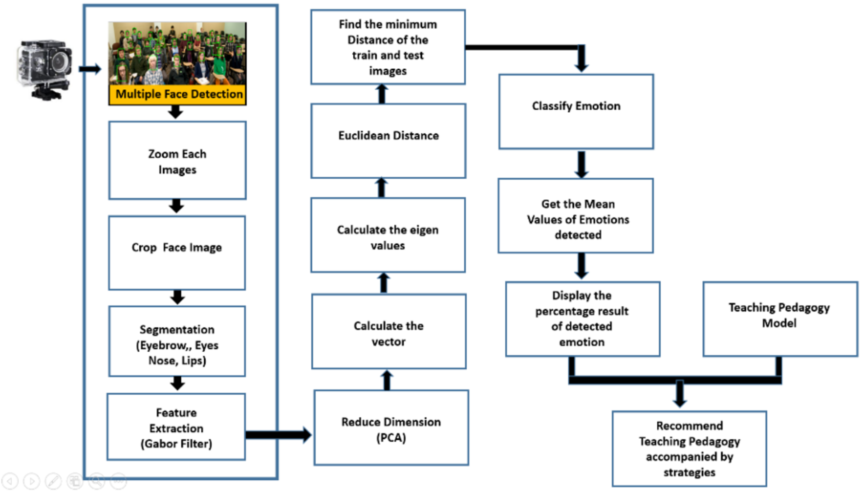

Fig. 2. Conceptual Framework

2.3 Formulation of the Teaching Pedagogy Matrix

The survey was facilitated where the respondents were asked to rank the teaching strategies according to each emotion. The survey questionnaire was formulated from various sources and validated by experts. The questionnaire was composed of two parts: (1) the profile of the respondents and the teaching pedagogies/approaches identified such as Constructivism, Integrative, Reflective, Inquiry-Based, and Collaborative. The survey questionnaires were answered by 15 educators with master's and Doctorate in Education. The respondents ranked the five teaching pedagogy approaches by writing 1 is the best, and 5 is the least teaching pedagogy to be applied for a particular emotion. The data was tabulated based on the weighted mean and the frequency count. The result was ranked. Accordingly, the lowest number of count means represent the priority pedagogy for a certain emotion. The matrix was based on the pedagogy approaches which is equally distributed by 20% and with regards to the color-coding assignment of each pedagogy was based from sources where Orange color refers to Collaborative, Green color refers to Constructivism, Yellow color refers to Inquiry-based, Gray color refers to Integrative and Blue refers to Reflective.

3 Results and Discussion

Table 2. the Filipino based facial features were analyzed using different types of classification algorithms which among the algorithms provide higher accuracy as the basis for the implementation in the prototype model. Based on the results, the Support Vector Machine outperformed other algorithms specifically, the algorithm marked excellent performance on emotion such as " Disgust", "Fear" and "Happy" while the "Neutral and Sad " marked little difference in percentage because of the similarity in some facial features of the subject except for the lip area where the subject is advised to make pouty lips . It is same with the "Anger" and "Surprise" emotion were the features are difficult to distinguish because there are some facial features looked like Anger even it is not, particularly in the eyebrow and eye part.

Table 2. Classification Result based on Various Algorithms

EMOTION	SVM	Decision Tree	KNN	Naïve Bayes	Neural Networks	AVERAGE Accuracy
Anger	78.43%	70.59%	77.45%	82.18%	83.33%	78.39%
Disgust	100%	17.65%	85.29%	90.20%	47.06%	68.04%
Fear	100%	0%	72.55%	100%	62.75%	67.06%
Happy	100%	57.84%	91.18%	94.57%	92.16%	87.15%
Neutral	47.06%	1.96%	40.22%	62%	12.75%	32.79%
Sad	58.82%	0%	49.02%	79%	17.65%	40.89%
Surprise	76.47%	8.82%	95.10%	83.24%	78.43%	64.42%
ACCURACY	**80.11%**	**22.41%**	**72.97%**	**80.07%**	**56.31%**	

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Table 3. Prototype Model Recognition Result in Different Formats

Format	Detected Images	Percentage
Still Images	24/35	68.57%
Uploaded Video File	3/5	60%
Real-Time Video	7/13	53.84%
Average		**60.83%**

Table 3. showed the results of the three (3) different formats applied in the experiment focusing the frontal view. And to, re-assure the accuracy of the prototype since it will not produce 100% accuracy due to the limitation of the datasets, the experts checked the performance of the proto-type In the first experiment using still images there were about 11 out of 35 or 31.42 % emotions are detected incorrectly composed of 1 image for "Anger" emotion, 2 images for "Happy" emotion, 4 images for "Neutral" emotion , 2 images for "Disgust" emotion and 2 images for "Sad" emotion. This is due to resolution and distance issues. Some of the face images processed in the prototype model are too near; thus, it looks big-ger than the other images. In the experiment no. 2 using an uploaded video file format captured in a 16-megapixel resolution from cellular phone camera there are two subjects that are not into frontal view which greatly affect the result of the recognition. And for the third experiment, the real-time video format was used where the prototype is installed with a native built-in camera of a laptop. There were about 48 images captured; however, only 13 images are in frontal view 7 of which are correctly detected and labeled accordingly. The results are affected due to some issue on distance and blurry images.

Table 3. Emotion Classification Result based on Actual Classroom Environment

Emotion	Class1 (Earth Science)	Class 2 (Stat & Probability)	Class 3 (Physics)	Class 4 (Programming Class)
Anger	2/18 or 11%	3/42 or 7%	2/26 or 8%	4/30 or 13%
Disgust		2/42 or 55%		3/30 or 10%
Fear				2/30 or 7%
Happy		1/42 or 2%	1/26 or 4%	
Neutral	8/18 or 44%	5/42 or 12%	7/26 or 27%	4/30 or 13%
Sad	8/18 or 44%	26/42 or 62%	13/26 or 50%	5/30 or 17%
Surprise		5/42 or 12%	3/26 or 12%	8/30 or 27%
PEDAGOGY	INTEGRATIVE	REFLECTIVE	INTEGRATIVE	CONSTRUCTIVISM

Table 4. shows the result of classified emotion per class. The class provides exercises dealing with problem-solving activities. Based on the observation of the researcher and the teacher, the students, therefore, find difficulty in solving the provided activity. With the used of the prototype model, the prototype resulted a "Sad" emotion marked the highest percentage in three (3) classes for Earth Sciences, Stat & Probability, and Physics while in programming it generates an emotion "Surprise." This result validates the initial assessment of the teachers and the sentiments of the students as well because most of the students got the lower score in this experiment activity

Fig. 3. Prototype Model Capture

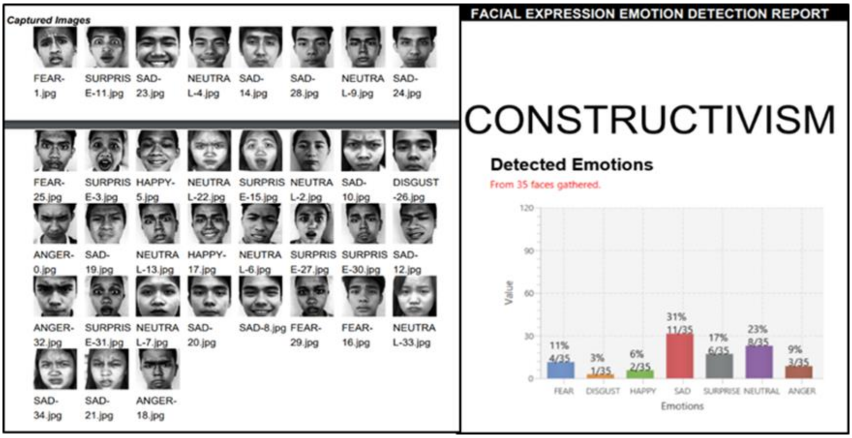

Fig. 4. Prototype Model Capture

In Fig. 4 and 5, the developed prototype model provides a panel to view the captured video, it also provides label " the continuous quality improvement (CQI)" result, the histogram of the detected emotion, the number of faces detected and generation of PDF report which contains the class information, the histogram of detected emotions and the teaching strategies recommendation. Moreover, the prototype can re-simulate the captured video. This prototype can be helpful for educators to visually view the student emotion and utilize the detected emotion report for further assessment or may address some issues and concerns.

4 Conclusion and Recommendations

Based on the result, it indeed provides good results even though the images are captured in various formats which marked an average result of 60.83 % and recorded 80.11% for classification accuracy utilizing the new build Filipino features. The build features are then recommended for utilization. Furthermore, the study can be useful for educational institutions to assess the emotional state of the students that will possibly affect students learning performance. This prototype model can be a great of help for the educators to manage the class more productively and effectively. To achieve the efficiency of the recognition and to strengthen appropriate teaching strategies recommendation applicable based on emotion. This study would like to recommend the following. Educators should develop an empirical study to identify what appropriate teaching strategies of an emotion which is suitable and applicable based on the topics and activities conducted. Utilize state-of-the-art resources for better detection and recognition. Consider algorithms which provide great performance in image processing. Consider building datasets in different angles, distance, and lighting concerns to increase the accuracy. Utilization resources that could provide a high-end camera for better detection and recognition. Apply other algorithms that will more improve the recognition accuracy and can efficiently optimize the image processing. Consider building datasets in different angles, distance, and lighting concerns to increase the accuracy.

References

1. Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. Annual review of psychology, 66, 799-823.
2. Pekrun, R., & Goetz, T. (2002). Positive emotions in education. Beyond coping: Meeting goals, visions, and challenges. E. Frydenberg.
3. Rienties, B., & Rivers, B. A. (2014). Measuring and understanding learner emotions: Evidence and prospects. Learning Analytics Review, 1, 1-28.
4. Pitt, A. J., & Brushwood Rose, C. (2007). The significance of emotions in teaching and learning: On making emotional significance. International journal of leadership in education, 10(4), 327-337.
5. Türkkahraman, M. (2012). The role of education in societal development. Journal of educational and instructional studies in the world, 2(4).
6. Demetriou, H., Wilson, E., & Winterbottom, M. (2009). The role of emotion in teaching: are their differences between male and female newly qualified teachers' approaches to teaching?. Educational studies, 35(4), 449-473.
7. Meyer, D. K., & Turner, J. C. (2002). Discovering emotion in classroom motivation research. Educational psychologist, 37(2), 107-114.
8. Fried, L., Mansfield, C., & Dobozy, E. (2015). Teacher emotion research: Introducing a conceptual model to guide future research.
9. Mangurian, L. P. (2007). Learning, Emotion, and their Application for Teaching. In ACRL Thirteenth National Conference (pp. 1-10).
10. Shuck, B., Albornoz, C., & Winberg, M. (2013). Emotions and their effect on adult learning: A constructivist perspective.

11. Felten, P., Gilchrist, L. Z., & Darby, A. (2006). Emotion and Learning: Feeling Our Way toward a New Theory of Reflection in Service-Learning. Michigan Journal of Community Service Learning, 12(2), 38-46.
12. Tabbasum, H, Emaduddin, S, M., Awan Agsa & Ullah, R. (2019). Multi-Class Emotion Detection using Textual Analysis. The International Journal of Emotional Education. Vol 9, Number 1 pp. 85-98
13. McCaughtry, N. (2004). The emotional dimensions of a teacher's pedagogical content knowledge: Influences on content, curriculum, and pedagogy. Journal of Teaching in Physical Education, 23(1), 30-47.
14. Reeves, J., & Le Mare, L. (2017). Supporting Teachers in Relational Pedagogy and Social Emotional Education: A Qualitative Exploration. International Journal of Emotional Education, 9(1), 85-98.
15. Kimura, Y. (2010). Expressing emotions in teaching: Inducement, suppression, and disclosure as a caring profession. Educational Studies in Japan, 5, 63-78.
16. Essel, G., & Owusu, P. (2017). Causes of students' stress, its effects on their academic success, and stress management by students. Seinäjoki University of Applied Sciences, West Finland.
17. Marshall, E., Mann. V., & Wilson, D., (2016). Maths anxiety: A collaboration. HEA STEM conference, Nottingham
18. Reed, Z, A., (2014). Collaborative Learning in the Classroom. Center for Faculty Excellence, United States Military Academy, West Point, New York
19. Roselli, N. D. (2016). Collaborative Learning: Theoretical Foundations and Applicable Strategies to University. Journal of Educational Psychology-Propósitos y Representaciones, 4(1), 251-280.
20. Villanueva, M. G. F. (2010). Integrated teaching strategies model for improved scientific literacy in second-language learners (Doctoral dissertation).
21. Adams, P., & Findlay, C. (2015). Transforming Pedagogy and Practice Through Inquiry-Based Curricula: A Study of High School Social Studies. One World (04750209), 3(2).
22. Preston, L., Harvie, K., & Wallace, H. (2015). Inquiry-Based Learning in Teacher Education: A Primary Humanities Example. Australian Journal of Teacher Education, 40(12), n12.
23. Akpan, J. P., & Beard, L. A. (2016). Using Constructivist Teaching Strategies to Enhance Academic Outcomes of Students with Special Needs. Universal Journal of Educational Research, 4(2), 392-398.
24. Guthrie, K. L & McCracken, H., (2010). Reflective Pedagogy: Making Meaning in Experiential Based Online Courses. The Journal of Educators Online, Volume 7, Number 2,
25. Ferry, M., McCaughtry, N., & Kulinna, P. H. (2011). Social and emotional pedagogy: Rhythm and junctures. Journal of Teaching in Physical Education, 30(1), 13-30.
26. Bosch, N., D'Mello, S., & Mills, C. (2013, July). What emotions do novices experience during their first computer programming learning session?. In International Conference on Artificial Intelligence in Education (pp. 11-20). Springer, Berlin, Heidelberg.
27. Sarmiento, A. L., Aviñante, R. R., Liwanag, J. L., & Dadiz, B. G. (2018, June). Dimension Reduction Techniques Analysis on Image Processing for Facial Emotion Recognition. In Proceedings of the 2018 International Conference on Control and Computer Vision (pp. 23-27). ACM.
28. Prospero, M. R., Lagamayo, E. B., Tumulak, A. C. L., Santos, A. B. G., & Dadiz, B. G. (2018, June). Skybiometry and AffectNet on Facial Emotion Recognition Using Supervised Machine Learning Algorithms. In Proceedings of the 2018 International Conference on Control and Computer Vision (pp. 18-22). ACM.

29. Cambria, E. (2016). Affective computing and sentiment analysis. IEEE Intelligent Systems, 31(2), 102-107.
30. Greene, S., Thapliyal, H., & Caban-Holt, A. (2016). A survey of affective computing for stress detection: Evaluating technologies in stress detection for better health. IEEE Consumer Electronics Magazine, 5(4), 44-56.
31. Choi, J., Lee, S., Lee, C., & Yi, J. (2001). A real-time face recognition system using multiple mean faces and dual mode fisherfaces. In ISIE 2001. 2001 IEEE International Symposium on Industrial Electronics Proceedings (Cat. No. 01TH8570) (Vol. 3, pp. 1686-1689). IEEE.
32. D'Mello, S., & Calvo, R. A. (2013, April). Beyond the basic emotions: what should affective computing compute?. In CHI'13 Extended Abstracts on Human Factors in Computing Systems (pp. 2287-2294). ACM.
33. Ramos, A. Flor, J. & Casabuena , M., (2017). Face Expression Emotion Detection using Eigenfaces, Fisherfaces & Local Binary Histogram Algorithm towards Predictive Analysis of Students Emotion in Programming. 8th Euro Conference on Big Data and Applications, Gwangeong Korea
34. Serrano-Puche, J. (2015). Emotions and digital technologies: Mapping the field of research in media studies.
35. Ramos A. L. A. and Dadiz B. G., (2018). A Facial Expression Emotion Detection using Gabor Filter and Principal Component Analysis to identify Teaching Pedagogy. 1-6. 10.1109/HNICEM.2018.8666274.