FILIPINO BASED FACIAL EMOTION FEATURES DATASETS USING HAAR-CASCADE CLASSIFIER AND FISHERFACES LINEAR DISCRIMINANT ANALYSIS ALGORITHM

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ABSTRACT

Emotion detection is one of emerging topics in the field of research. In fact, various studies conducted utilized the available datasets – applying different methodologies and implementing the best suited algorithms to improve the classification performance and increase the recognition rate. This study aims to apply the Filipino-based facial emotion features through the revalidation of the available features in Visage Cloud API. It served as a basis in determining how the emotion differs from the expert's validation and testing through the WEKA tool. The validation mainly checked the classification accuracy performance of the Fisher Faces Linear Discriminant Analysis used in this study. In result, the study marked a classification accuracy of 90.66% based on the API outcomes with 150 instances and 83.61 % classification rate for 609 features – it clearly outperformed the results acquired in the existing studies. Furthermore, the prototype model was built using Phyton and tested on 10 subjects with two groups of training datasets validated by the API of 150 features. The used datasets also adopted the validation of the experts with 609 facial features and a recognition rate of 22.98 % and 54.2 % respectively.

KEYWORDS – Emotion, Facial expression, Filipino based features

INTRODUCTION

Emotion is embedded in humans that is responsible on how they react and respond to certain scenarios based on their facial expressions as these are one of the key elements to better interpret one's emotion. It provides information about their mental status, and even the physical state of the person. Furthermore, emotion is greatly being assessed through communication. Based on studies conducted there were only about 7% to 38% rate in terms of interpreting the information contributed in verbal forms while in the non-verbal form, it recorded a rate of 55% – pertaining towards the emotional or facial expressions. [2][3] The keen observation of the non-verbal information implied by a person greatly helps in identifying the genuine individual perception. With the continuous evolution of automated technology and computer-human interaction, emotion and facial recognition emerged. It bears a process where the computer systems try to understand the human emotions. The said recognition area is undeniably considered as an innovative trend and one of the huge topics being discussed in the field of computer vision. Emotion recognition using computer vision has numerous and real-life systems like virtual reality, video-conferencing, lie detection, anti-social intentions, and many other. [4] Most of these application and studies used validated databases such as Jaffe, CK (Cohn Kanade) [5]. However, even though there are already existing databases to look at, the method of recognizing emotions through facial features is still complicated due to the proper feature extraction needed which also requires varied steps. [6] There are also different methods and algorithms that one may consider for it already proved its effectiveness on diverse and available datasets. Likewise, the existing types of recognition can also be utilized in a wide innovative range, for it can make emotion recognition more useful in gathering genuine and unconscious feedbacks by just detecting an individual's facial expressions that suggest efficient and reliable data.

LITERATURE REVIEW

The advances in deep learning have brought speed, efficiency, and accuracy for algorithms to obtain the necessary abilities to perform methods in areas of computing, analysis, and detection of people's emotions through photographs [2] by considering their facial expressions through the aid of different algorithms. [9] Various proposed algorithms have already been proved as effective in the field of facial recognition [12] including the prevalent techniques and methodologies being employed for detecting face – a process that is also anchored to the different databases which set distinction between original and saved images. [13] Nevertheless, as proven in the existing studies, the facial and emotion recognition process is very complicated and thus, it also encounters different challenges that greatly motivated the researchers to seek for improvement through experimentations and cross validations. One of the methods being used in conducting the experiments is the Principal Component Analysis (PCA) where features are extracted using the JAFEE database. The recorded accuracy rate of emotion recognition utilizing the JAFEE database with the leave-one-out strategy is 95.71%; and a rate of 94.13% by using the cross-validation strategy – having seven (7) varied emotions by means of 2D-LDA and SVM. [15] Additionally, a study using CNN datasets with five experiments got an increment rate of 0.2737% founding on the facial temperature of the participants. [14] The combination of PCS, LDA, and ICA findings' issue pointed out that the noise and occlusion in scaling differs from image to image, and video stream movements of the observed faces. The noise issues were also affected by poses and angles of the faces particularly, the frontal and non-frontal views – therefore, making the PCA method essential in obtaining the best-suited variables to be used in differentiating each emotion. [15] The use of Cohn Kanade database on the other hand, promotes the evaluation and development of an algorithm that allows automatic detection of the facial expressions. [16] The utilization of Indian Face datasets together with the use of OpenCV 2.4.2 implementation in the Haar Cascade Classifier acquired a 100% while the AND Caltech database with frontal face images as subjects marked 93.24% accuracy in detection provided with complex backgrounds. [17] The studies are also using the LDA technique for features extraction, and Fisher faces for real time facial expression testing [8] and with the intervention of Extended Cohn-Kanade datasets, it managed to have an accuracy rate of 56%. Notably, this method also got 90% in terms of recognition – leaving out the "disgust" emotion for the system is unable to detect it. [9] The widely used datasets lead the researchers to come-up with a Filipino-based facial feature datasets to provide a new insight and discover the unique features of a Filipino – to identify how it differs from the available datasets and to address the recommendation of the previous studies relating towards the re-validation of the Filipino-based features using Visage Cloud API. The researchers also employed a different algorithm in order to check its classification performance and recognition.

Research Objectives

- To build and utilize the Filipino-based facial features.
- To revalidate the facial expression using Facial Emotion API.
- To apply Haar-Cascade Classifier to detect face images; Fisher Faces Linear Discriminant for facial features classification.
- To build a prototype model that will detect the emotions through facial expressions.

Theoretical Framework

Fisher faces LDA Algorithm is a technique being used to maximize the separation between classes [8], [11] using Linear Discriminant Analysis. It is effective in terms of light condition and angle variation since there is no need for it to estimate the face surface under normal and light source director, no need to capture in different lighting condition, and does not accurate positions which means that the algorithm is flexible to handle different lighting conditions and angle variations. The difference and uniqueness of this algorithm addressed the issues in computing the discriminant vectors without the covariance matrix [10].

The Visage Cloud API is an in-cloud REST API that can be applied to different areas in implementing security like face detection, recognition, and classification of new data. The study used the API to determine the classification of the emotions implied in the captured images that are found in the Filipino-Based Facial Feature Database (FIL Database).

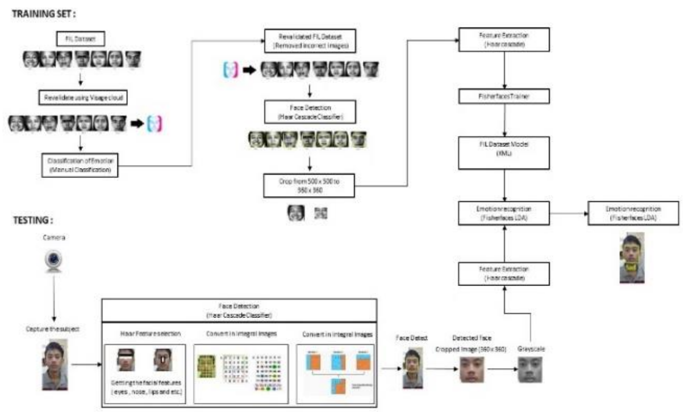

Figure 1. Model of the study

The Figure shows the conceptual framework of the study in which the model built the training dataset – composing of 609 original images and 150 re-validated images. The said images were then used for classification and testing the accuracy of the prototype based on actual application. Specifically, the model could detect face images using Haar-Cascade Classifier then it would be processed from its RGB to Grayscale then cropped to 300x300. After that, the cropped images would be then processed by applying the Fisher Liner Discriminant Analysis for feature extraction. The extracted images represent the weight vector of an image to be compared to the training datasets to detect the emotion.

METHODOLOGY

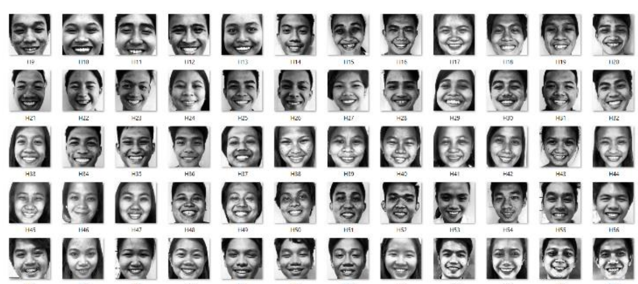

Figure 2: Training Datasets

Building the training datasets: The study built the dataset images which were participated by students ranging from 18-20 years of age with the help of experts to assist the subjects in portraying the required emotions such happy, sad, fear, neutral, anger, disgust, and surprised. The subjects agreed to the approval for the purpose of this study. The face images of the subject were captured using 16-megapixel camera in one (1) meter distance in frontal view. Furthermore, the study validated the 609 images through the help of psychologists by conducting two review techniques such as the correction of the subjects in portraying the emotion. The second review focused on checking of the still images by zooming in the images for clearer visibility of the significant features. On the other hand, these 609 images were processed with the help of Visage API as recommended by the previous studies. The API provided information of the emotion based from the face region of interest.

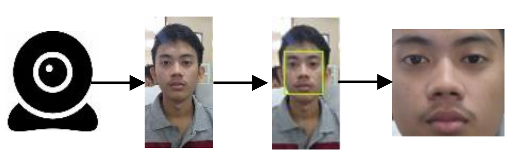

Figure 2. Face Detection & Resizing

The study used the Haar-Cascade Classifier for face detection particularly the most important part of the face image which comprises the nose, eyes, and lips of the subjects. The green box indicator served as the indication that the face was detected. The detected image would be converted into grayscale and cropped to 360 x 360. The algorithm used in this study marked a good performance and recorded high accuracy rates regardless of a simple or complex background in the images. [11]

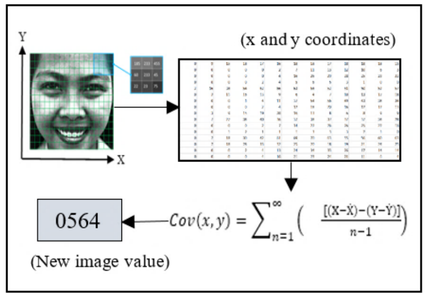

Figure 3. Extraction

The facial features were extracted using the Fisherfaces Linear Discriminant Analysis where the image was computed based on the x and y coordinates of each image. The said coordinates were computed to calculate the covariance matrix in reducing the dimension of the images. Each image was represented in a vector $\{x_1,x_2,x_3.....x_n\}$. This would be classified based on the category of the emotion$\{C_1,C_2,C_3.....C_n\}$. Each class of the emotion would be computed based on the mean value.Then, the over-all total mean of the entire class of emotion would be collected. In getting the new value of the image, the mean value of each class emotion would be used to subtract the weight value of the image class in that category (x_n) which would be the new value of the image (x_{nmt}).

$$S_n = x_{nm}x_{nmt} + x_{nm}x_{nmt}.....$$ eq.(1)

Lastly, to generate the scatter matrix of the seven (7) emotions by computing the total number of each class consisted of 94 for anger, 85 disgust, 61 fear, 96 neutral, 104 happy, 80 sad, 89 surprise.

$$Sb = 94(c_{1m} - m)(c_{1m} - m) + 85(c_{2m} - m)(c_{2m} - m).....$$ eq.(2)

and within class scatter matrix which is the summation of all scatter matrices as S_w.

$$S_w = S_1 + S_2 + S_3 + S_4 + S_5 + S_6 + S_7$$ eq.(3)

Building the Prototype Model: The prototype was built using an i5 core processing in Windows Operating System. The solution formulated was written in Python with integration to the Haar-Cascade Classifier which detected at least three (3) face subjects captured using an android smartphone attached to the application created by the researchers to capture the face images and Fisher faces LDA for recognition.

Metrics of Evaluation: To evaluate the classification accuracy of the training datasets of 609 and 150 images, the WEKA tool was used. For testing the recognition of the built prototype, 10 subjects were requested to portray the emotion using the accuracy formula, A = (P/N) x 100 where P stands for the number of detected emotions and N represents the number of testing images.

$$Accuracy = \frac{No.\ Of\ detected\ emotions}{No.\ Of\ testing\ images}$$

RESULTS AND DISCUSSION

Table 1: Number of validated images

Emotion	Original Images	Revalidated Images	Variance
Surprise	89	14	75
Sad	80	14	66
Happy	104	2	102
Neutral	96	61	35
Fear	61	8	53
Disgust	85	3	85
Anger	94	58	36
Total	609	157	451

Table 1 shows the two sets of training datasets composed of 609 and 157 images. In the original images with a total of 609 items, the “happy” emotion got the highest number for it was easy for the subject to portray this emotion and also influenced by the fact the Filipinos are known as a happy people. However, the “fear” emotion got the lowest number for the subjects, based on observation and assistance provided by the experts, they find difficulty to project the said emotion – the subjects needed motivation and acting talent to properly portray it. On the other hand, the original images were re-processed to address the recommendation of the previous studies in revalidation of the images using the Visage Clould API. In result the “Neutral” emotion marked the highest score and the lowest were the “happy” and “disgust” emotion. This implied that the validation made by the experts using their eyes as a way of assessing the emotion was quite different against the results of Visage API that were calculated according to the significant features of the face images based on its x and y coordinates region of interest.

Table 2. Comparative results of the revalidated and original images in classification accuracy.

Stratified cross-validation	Revalidated	Original
Correctly Classified Instances	136(90.6667 %)	511(83.908 %)
Incorrectly Classified Instances	14(9.3333 %)	98(16.092 %)
Kappa statistic	0.8833	0.8123
Mean absolute error	0.0373	0.046
Root mean squared error	0.1932	0.2144
Relative absolute error	11.6599 %	18.7735 %
Root relative squared error	48.275 %	61.2749 %
Total Number of Instances	150	609

The study fed the 609 images and 157 images to WEKA tool to test the classification accuracy. However, in the 157 images, the resampling method was used with 30 instances which represented the 150 images resulted to decreased in percentage. In particular, “Anger” emotion significantly decreased to 38%; “Neutral” decreased to 40.7% while the “Sad” and “Surprised” increased by 46.7%; and “Fear” increased to 26.7%. In result of this, the 150 images marked a classification accuracy of 83.09% and for the 609 images it recorded a classification accuracy of 90.66% using the applied eight (8)-fold cross validation using the Linear Discriminant Analysis.

Table 3. Testing the Recognition Accuracy using the Prototype Model

Recognition accuracy		
EMOTION	Re-validated	Original
SAD	0%	100%
HAPPY	0%	100%
NEUTRAL	100%	50%
DISGUST	0%	0%
ANGER	40%	40%
FEAR	0%	0%
SURPRISE	0%	100%
Total	22.98%	55.71%

Table shows the two datasets used in the study in checking the recognition accuracy using the built prototype model. In result, the 150 images noted a recognition rate of 22.98% while the 609 images marked a score of 55.71%. This confirmed that the algorithm used in this study outperformed the result of the previous study – utilizing the Filipino-based features datasets.

CONCLUSIONS AND RECOMMENDATIONS

The application of the Fisherfaces LDA algorithm in this study outperformed the previous results in using the Filipino-based feature datasets. The re-validation as recommended in the previous studies, is not applicable to be used as the training datasets due to the significant decrease of the number of images' representation. Consequently, it is recommended in this study to retain the 609 images as the training datasets to be used for further researches. The study recommends the following measures to be considered:

- Add more datasets in different angle variations and ethnicity to increase the accuracy.
- Utilize the Filipino-based feature datasets and apply other algorithms and approaches.

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