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Compound Facial Emotion Recognition based on Facial Action Coding System and SHAP Values

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Abstract

Human facial emotion recognition is a difficult task in computer-human interaction. Facial emotion recognition is required in many applications like medical, security, video games, e-physiotherapy, and counselling. Literature has many studies that have focused only on 6 basic emotions but advanced studies suggest human emotions are not limited to these 6 basic emotions. A human face can exhibit many other emotions, which are generated by combining the two basic emotions, these derived emotions are known as compound emotions. Recognition of compound emotions is also a very important task; hence this study proposes the use of the Facial Action Coding System (FACS) to identify 12 compound emotions. The authors identified and derived the intensities of 17 AUs with Openface library. Finally, two machine learning classifiers SVM (Support Vector Machine) and KNN (K-nearest neighbour) were implemented to identify 12 compound emotions, and results were compared. The experimental results show that the SVM classifier outperformed with an emotion recognition rate of 98.31% while the recognition rate of K-NN was 93.66%. The authors also implemented SHAP values to observe the AUs association with each compound emotion.

1. Introduction

The human face is considered to be the mirror of emotions. Human face and facial expressions are the most powerful way to convey an emotional state (Ekman and Rosenberg). The movement of facial features shown on the human face is known as facial expression, these facial expressions are used to define human emotions (Swaminathan, Vadivel, and Arock). Most of the previous studies of facial expression recognition and emotion detection were focused only on 7 basic emotions (Happy, sad, anger, disgust, fear, surprise, and neutral). However, apart from these 7 basic emotions, recent studies have defined 21 other compound emotions (Du, Tao, and Martinez). Compound emotions can be generated by combining any 2 basic emotions, for example, happy and surprised emotions can be combined to generate a happily surprised compound emotion. The images of 12 compound emotions identified in this research are shown in figure1 (Du, Tao, and Martinez). Facial action coding system analysis (FACS) depicts that the production of these 12 compound emotions is different from basic emotions but can be generated using basic emotions. The famous psychologists Ekman and

Friesen (Ekman and Friesen) proposed the FACS in 1978, after studying the anatomy of the face and the classification of facial expressions. Since then, FACS is a leading standard in understanding facial behavioral research. The use of FACS is not limited to behavioral science research but it is widely applied in computer analysis of the face (Ekman and Rosenberg). FACS helps in identifying and scoring the Action Units (AUs), these AUs exhibit the muscular activity that produces momentary changes in the facial appearance.

FIGURE 1. Images of 12 Compound Emotions

Facial action coding system analysis (FACS) depicts that the production of these 12 compound emotions is different from basic emotions but can be generated using basic emotions. The famous psychologists Ekman and Friesen (Ekman and Friesen) proposed the FACS in 1978, after studying the anatomy of the face and the classification of facial expressions. Since then, FACS is a leading standard in understanding facial behavioral research. The use of FACS is not limited to behavioral science research but it is widely applied in computer analysis of the face (Ekman and Rosenberg). FACS helps in identifying and scoring the Action Units (AUs), these AUs exhibit the muscular activity that produces momentary changes in the facial appearance. FACS divides the human face into 46 AUs, each AU is represented by a name and a number, for example, AU4 is Brow Lowerer. Individual AUs could be unable to express distinct semantic facial expressions, but the combination of them does. This method has served as a crucial psychological foundation in the field of facial expression recognition (FER) (Tan et al.). This research suggests a technique to recognise 12 novel compound emotions based on facial action unit detection in order to better comprehend human emotions. Further, SHAP values were also used to show the contribution of AUs in defining a compound emotion.

2. Related Work

A study (Zhu, Li, and Wu) is applied to identify 7 basic expressions on the Yale dataset and 8 expressions on the JAFFE dataset by implementing Equable Principal Component Analysis which is a depiction of emotional features and Linear Regression Classification (LRC). The approach of PCA proposed for mining the facial feature has a significant capacity for enhancing the accuracy and generalisation performance of the feature vector. The LRC method's classifier is particularly efficient in the recognition of the other expressions. The accuracy was 89.1% and 91.1% on the Yale and JAFFE database. Another work employed a cascade regression tree to extract facial features from the CK+ dataset, authors compared the results using logistic regression, SVM, and, NN, to present a Facial Emotion Recognition (FER) system to identify six facial emotions. (Bilkhu, S. Gupta, and Srivastava). Another study used both kernel-based PCA and PCA methods on 3D face images to identify 4 facial expressions. On the Imperial College London dataset, the K-NN classifier is used to identify facial expressions; kernel PCA surpassed PCA with 77.29% accuracy whereas PCA only managed 52.69% (Peter, Minoi, and Hipiny). A combination of Local Tetra Pattern and Local Directional Number Pattern was implemented to identify 3 expressions (disgust, smile, sad, and surprise) on JAFFE dataset with an accuracy rate of 90%. The association between the indicated pixel and its neighbours is encrypted using the suggested approach. For numerous patterns coding from the texture of a face, LDPN implements stable directional information against noise over intensity. The local texture's spatial frame is described by the LTrP method using the centre pixel direction. According to the pixel direction, determined by the vertical and horizontal derivatives, the LTrP technique encrypts the image (Emmanuel and Revina). Using orthogonal planes and low-dimensional feature space, the extraction of a pyramid depiction of uniform Temporal Local Binary Pattern (PTLBPu2) was suggested in (Abdallah, Guermazi, and Hammami) as a dynamic technique based on facial features extraction from expressions using videos. The most discriminating sub-regions are then chosen using the suggested procedure. By using the PCA approach, the feature space that is focused on low-dimensional feature space is

reduced. SVM classifier and the C4.5 algorithm are used to classify face expressions. The popular facial expression databases MMI and CK+ were used for the experiments. The experimental finding demonstrates that in an uncontrolled situation, 92% of recognitions were accurate. Another work in FER used the Histogram of Oriented Gradients (HOG) for feature extraction and the Viola-Jones algorithm for face detection. To reduce dimensionality and extract the most

recognition rate of 93.53% with the SVM, 82.97% with the MLP, and 79.97% with K-NN classifier (Dino and Abdulrazzaq). In the reference (Tarnowski et al.) 7 basic emotions were analyzed Coefficients describing elements of facial expression were used as features. K-NN and MLP neural networks were applied with 96% and 90% accuracies respectively. A summary of related work is given in table 2.

3. Proposed Methodology

Datasets: The Extended Cohn-Kanade (CK+) dataset is employed in this research, CK+ is widely used for classifying facial expressions under laboratory control, it contains 593 video clips from 123 unique subjects who are between the ages of 18 and 50, as well as representing different genders and ethnicities. A change in facial expression from neutral to a definite peak expression is represented in each video. It was shot at 30 frames per second. Anger, disdain, disgust, fear, happiness, sorrow,and surprise are the seven expression classes that have been assigned to 327 of these clips. To discover the relation between the AUs and emotions, we use a portion (500 sequences) of the CK+ collection that has been classified for AU and emotion. We use the leftover databases CK+ (pictures not used for learning) and real-world videos to validate the performance. For this work, we collected videos from 11 subjects. The videos were gathered to track an experiment that categorizes a subject's emotions.

Action Unit Extraction

By evaluating facial expressions with FACS, authors used Openface library to classify the analyzed AUs; Openface detects the faces in a rectangle-shaped space, and as a result, noise such as background colour is present when faces are recognized (Baltrusaitis et al.). With the help of dlib, 68 different facial landmarks can be located. This will allow the removal of any noise from a facial image. OpenFace is an open-source library, which incorporates facial landmark identification, emotion recognition, head posture, and eye gaze estimation, it pre-processes SAMM Long Videos (C. H. Yap, Kendrick, and M. H. Yap). In this work, authors solely pay attention to face alignment and AU detection. It uses an affine transformation. Dlib's face landmark detector picks up the facial landmarks. (Baltrusaitis et al.). Landmarks of currently identified faces are compared with a neutral appearance using a similarity transform. Deep networks are used by OpenFace's Convolutional Experts Constrained Local Model (CE-CLM) to identify and track facial landmark characteristics (T. Pravin et al.). From the original version of the deep network, which had 180,000 parameters, to roughly 90,000 parameters. With little accuracy loss, this lessens the complexity of the model and speeds it up by 1.5 times. Additionally, CE-CLM employs 11 initialization hypotheses at various orientations, which results in a 4-fold gain in performance. Additionally, it makes use of sparse response maps, which increases model performance by 1.5 times compared to the reference frame and eliminates changes brought on by scaling (V. S. R. T. Pravin and Thiruppathi). The final output is 112 by 112 pixels in size and has an interpupillary distance of 45 pixels. The complete framework of Openface is shown in figure 2.

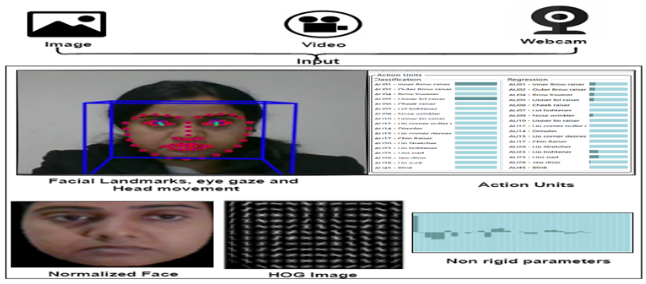

FIGURE 2. Framework of Openface 2.0

While the occurrence of 18 AU is reported as a binary value (0 absent, 1 present), AUs intensity levels are categorized in 6 levels; AU not present-O, Mild-A, Slight-B, Moderate-C, Severe-D, and Extremely severe-E. Further, intensities of 17 AUs were presented as a regression output from 0 to 100. We simply concentrated on the presence of 17 AUs for the construction of our model (excluding AU45).

TABLE 1. **Summarized Related Work**

Authors	#Emotions Identified	Dataset	Accuracy	Classifier	Drawback
Emmanuel and Revina (2015)	4	JAFEE	90%	SVM	Identified emotions are less and less accuracy
Zhu et al., (2016) (Zhu, Li, and Wu)	7	Yale and JAFFE	91.1%	LRC	pollution problem in face recognition
Tarnowski et al., (2017) (Tarnowski et al.)	7	KDEF	96% 90%	KNN MLP	No compound emotions were analyzed
Abdallah et al., (2018) (Abdallah, Guermazi, and Hammami)	6	CK+	92%	SVM	No compound emotions were analyzed
Bikhu et al., (2019) (Bilkhu, S. Gupta, and Srivastava)	6	CK+	89%	SVM	Less effective recognition performance
Hivi and Maiwan (2019) (Dino and Abdulrazzaq)	7	CK+	93.33% 82.57% 79.97%	SVM NN KNN	No compound emotions were analyzed
Peter et al., (2019) (Peter, Minoi, and Hipiny)	4	Imperial College London	77.29%	KNN	Identified emotions are less and less accuracy

Frames with intensity levels of at least 2 were designated as positive examples, whereas the remaining frames were designated as negative examples.

Classifiers

Two machine learning algorithms K-NN and SVM were employed to handle this multi-class classification problem. These machine-learning models are very efficient and require a small dataset. The K-nearest neighbour classifier finds the pattern space for the k-training tuples that seem to be the closest to the unknown tuple. The unknown tuple's k "nearest neighbours" are the k training tuples.

A machine learning model is used by SVM, a classification and regression prediction tool, to enhance predicted accuracy while automatically avoiding over-fitting to the data. Researchers have employed a variety of techniques to address the issue of multiclass categorization, including one vs. one and one vs. The Multiclass Support Vector Machine, which is an extension of the linear Support Vector Machine, and is implemented based on the one-to-rest or OVA classification.

4. Results

Coded in Python 3, this experiment was trained and modeled using a Windows 10 setup with an Intel Core i5-8250U processor clocked at 2.30 GHz and 16 GB of RAM. Utilizing Python 3 and the sklearn package, SVM and K-NN classifiers were used. The 10-fold Cross-validation approach is employed in the experiment to evaluate the model. To prevent any over-fitting issues, K-fold cross-validation is used. There is not much of a difference between the test accuracies using 5 cross-validation and 10 cross-validation due to the small size of the dataset. As seen in table 2, although authors tested several values of k, there was no significant variation. In general, 10-fold cross-validation provides the highest level of accuracy.

TABLE 2. **K Fold Cross Validation**

#	K-fold CV	Test accuracy (SVM)
1	K=3	96.47
2	K=5	97.03
3	K=7	97.80
4	K=10	98.31

The dataset is partitioned into ten subsets with a ten-cross validation. Nine subsets were used for training and one for testing, computing the average of the output outcomes over the ten evaluations (Priya et al. P. Gupta, Maji, and Mehra Lawrence, Campbell, and Skuse). As a result of giving a model the chance to train on various train-test splits, it is typically the preferable strategy. Results for both the classifier are shown in table 3 and table 4. The true negative rate which is also known as specificity is the highest (1) in happily surprised and sadly surprised emotions using SVM, and also in fearfully disgusted and sadly fearful emotions using K-NN. The lowest value of specificity (0.89) is in sadly disgusted emotion using K-NN. Another attribute sensitivity means the true positive rate of the measured emotion. Its peak value (1) is in fearfully angry emotion for the SVM and for the emotion of fearfully surprised for K-NN. Sensitivity lowest value (0.86) is in disgustedly surprised emotion for the K-NN. The value of False Positive (FP) i.e., incorrectly classified values is (0) when specificity is 1. Finally, the F-Measure is the harmonic mean of sensitivity and precision. The F-Measure maximum value (0.99) is in fearfully surprised emotion for the SVM. The overall classification accuracy is 98.31% using the SVM and 93.66% using K-NN. Table 5 represents the comparison of the proposed model with state-of-art in terms of accuracy.

AUs Observed in Each Basic and Compound Emotion

A model is trained using a dataset in machine learning techniques, and the model then makes predictions. However, it is impossible to anticipate how crucial certain AUs will be in making predictions (P. Gupta, Maji, and Mehra Lawrence, Campbell, and Skuse Nadeeshani, Jayaweera, and Samarasinghe). Its complex to interpret a model's working based on the predicted outcomes, hence SHAP value method can be implemented which can show the contribution of each AU to the target emotion. As shown in figure 3: AU importance plot for happily surprised emotion AU1, AU2, AU5, AU12, AU25, AU26 are the most important AUs in predicting happily surprised emotion. Similarly, contribution of AU4, AU6, AU9, AU10, and AU17 was observed in predicting sadly disgusted emotion as shown in figure 4. Table 6 represents the summary of AUs Association with each Compound Emotion.

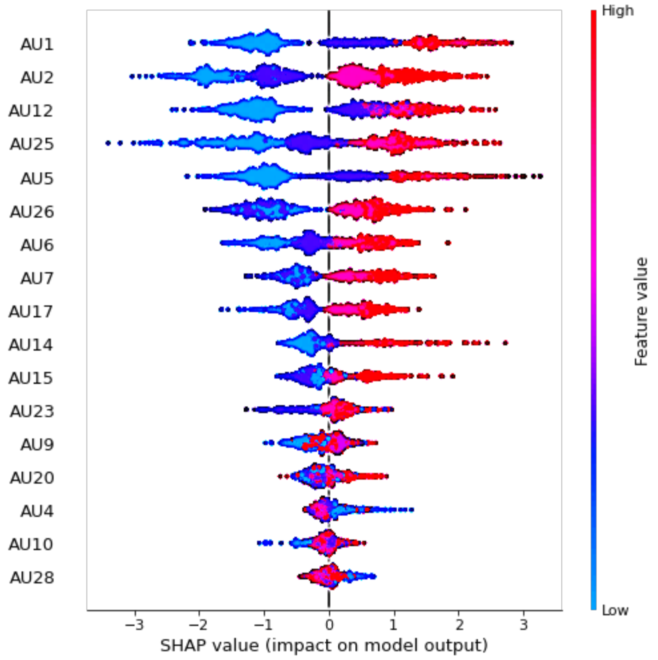

FIGURE 3. **SHAP AUs Importance Plot for HappilySurprised Emotion**

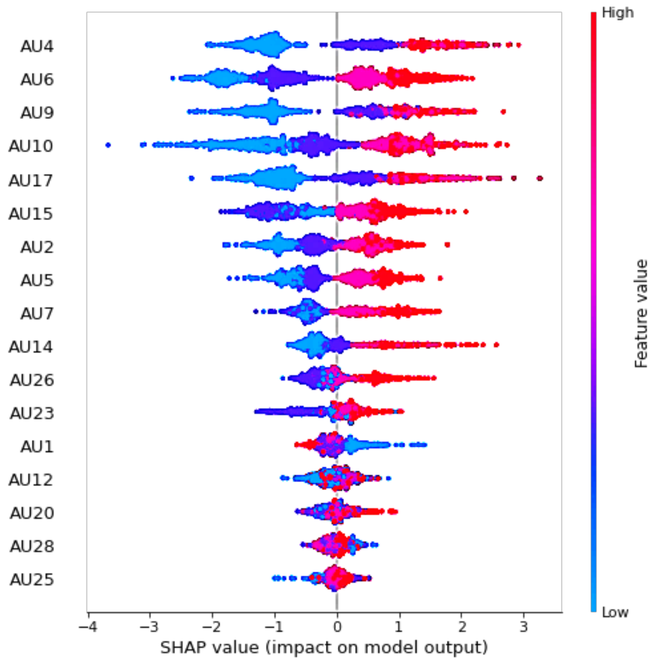

FIGURE 4. **SHAP AUs Importance Plot for Sadly Disgusted Emotion**

5. Conclusion

Compound emotions, which are generated by combining two or more fundamental emotion categories, such as happily surprised, happily disgusted, and sadly surprised were presented in the current study as an essential type of emotion category. Six fundamental and twelve more complex facial manifestations of emotion made up 18 categories of emotion. Last but not least, this identification of Face Action Units and their intensity was used to reasonably map them to the associated basic and compound facial emotions. The technique described in this research

TABLE 3. Results with SVM

Combined Emotion	Specificity	Sensitivity	FP rate	Precision	F-measure
SVM Accuracy = 98.31					
Happily surprised	1.00	0.99	0.00	1.0	0.97
Happily disgusted	0.99	0.93	0.01	0.98	0.96
Fearfully surprised	0.99	0.94	0.01	0.98	0.99
Fearfully disgusted	0.98	0.97	0.02	0.97	0.95
Fearfully angry	0.99	1.0	0.01	0.99	0.95
Sadly surprised	1.00	0.92	0.00	1.0	0.91
Sadly fearful	0.97	0.94	0.03	0.96	0.93
Sadly disgusted	0.98	0.98	0.02	0.98	0.95
Sadly angry	0.98	0.89	0.02	0.97	0.91
Disgustedly surprised	0.99	0.94	0.01	0.98	0.95
Angrily surprised	0.97	0.98	0.03	0.97	0.94
Angrily disgusted	0.99	0.98	0.01	0.98	0.92

TABLE 4. Results with K-NN

K-NN Accuracy=93.66 Combined Emotion	Specificity	Sensitivity	FP rate	Precision	F-measure
Happily surprised	0.91	0.92	0.09	1.0	0.98
Happily disgusted	0.99	0.98	0.01	0.98	0.94
Fearfully surprised	0.99	1.0	0.01	0.99	0.97
Fearfully disgusted	1.0	0.99	0.0	1.0	0.98
Fearfully angry	0.98	0.98	0.02	0.98	0.93
Sadly surprised	0.99	0.99	0.01	0.99	0.91
Sadly fearful	1.0	0.99	0.0	1.0	0.84
Sadly disgusted	0.89	0.90	0.11	0.89	0.85
Sadly angry	0.90	0.92	0.10	0.90	0.89
Disgustedly surprised	0.93	0.86	0.07	0.92	0.80
Angrily surprised	0.91	0.91	0.09	0.91	0.89
Angrily disgusted	0.94	0.94	0.06	0.94	0.93

TABLE 5. The Comparison of the Accuracy of the Proposed Model with State-of-Art

Literature	Dataset	Classifier	Accuracy
Abdallah et al., (2018) (Abdallah, Guermazi, and Hammami)	CK+	SVM	92%
Hivi and Maiwan., (2019) (Dino and Abdulrazzaq)	CK+	SVM NN KNN	93.33% 82.57% 79.97%
Nadeeshani et al., (Nadeeshani, Jayaweera, and Samarasinghe)	CK+, KDEF	KNN CNN	80% 86.66%
Lawrence et al., (Lawrence, Campbell, and Skuse)	CK, JAFFE, PSL	SVM KNN	65.35% 70.87%
Proposed model	CK+	KNN SVM	93.66% 98.31%

can recognize all 18 facial expressions. The classifiers are trained and tested with 10-fold validation. Facial expressions, SVM, and K-NN classification were all done using the three classifiers. The experiment's findings demonstrate that SVM is a superior classifier, with a 98.31% correct classification

TABLE 6. Summary of AUs Association with each Compound Emotion

Combined Emotion	AUs observed	Description
Happy	6, 12, 25	Cheek raiser, Lip corner puller, Lips part
Sad	1, 4, 15, 17	Inner brow raiser, Brow lowerer, Lip corner depressor, Chin raiser
Fearful	1, 4, 20, 25	Inner brow raiser, Brow lowerer, Lip Stretcher, Lips part
Angry	4, 7, 17	Brow lowerer, Lid tightener, Chin raiser
Surprised	1, 2, 5, 25, 26	Inner brow raiser, Outer brow raiser, Upper Lid Raiser, Lips part, Jaw drop
Disgusted	4, 9, 10, 17	Brow lowerer, Nose wrinkle, Upper lip raiser, Chin raiser
Happily surprised	1, 2, 5, 12, 25, 26	Inner brow raiser, Outer brow raiser, Upper Lid raiser, Lip corner puller, Lips part, Jaw drop
Happily disgusted	6, 9, 10, 12, 25	Cheek raiser, Nose wrinkle, Upper lip raiser, Lip corner puller, Lips part
Fearfully surprised	1, 2, 5, 20, 25	Inner brow raiser, Outer brow raiser, Upper Lid Raiser, Lip Stretcher, Lips part
Fearfully disgusted	1, 4, 9, 10,20, 25	Inner brow raiser, Brow lowerer, Nose wrinkle, Upper lip raiser, Lip Stretcher, Lips part
Fearfully angry	4, 5, 7, 20, 25	Brow lowerer, Upper Lid Raiser, Lid tightener, Lip Stretcher, Lips part
Sadly surprised	1, 4, 25, 26	Inner brow raiser, Brow lowerer, Lips part, Jaw drop
Sadly fearful	1, 4, 20, 25	Inner brow raiser, Brow lowerer, Lip Stretcher, Jaw drop
Sadly disgusted	4, 6, 9, 10, 17	Brow lowerer, Cheek raiser, Nose wrinkle, Upper lip raiser, Chin raiser
Sadly angry	4, 7, 15, 17	Brow lowerer, Lid tightener, Lip corner depressor, Chin raiser
Disgustedly surprised	1, 2, 5, 10, 17	Inner brow raiser, Outer brow raiser, Upper Lid Raiser, Upper lip raiser, Chin raiser
Angrily surprised	4, 7, 25, 26	Brow lowerer, Lid tightener, Lips part, Jaw drop
Angrily disgusted	4, 7, 10,17	Brow lowerer, Lid tightener, Upper lip raiser, Upper lip raiser

rate. Further, the SHAP value method was used to identify major contributing Action Units for each of the 18 emotions. To improve accuracy, we can test the suggested strategy with various machine learning algorithms in the future using our unique dataset that we are currently building.

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