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New Approach of Estimating Sarcasm Based on the Percentage of Happiness of Facial Expression Using Fuzzy Inference System

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Abstract

The procedure of determining whether micro expressions are present is accorded a high priority in the majority of settings. This is due to the fact that despite the best attempts of the person, these expressions will always expose the genuine sentiments that are buried under the surface. The purpose of this study is to provide a novel approach to the problem of measuring sarcasm by using a fuzzy inference system. The method involves analysing a person's facial expressions to evaluate the degree to which they are taking pleasure in something. It is feasible to distinguish five separate areas of a person's face, and precise active distances may be determined from the outline points of each of these regions. This category includes the brows on both sides of the face, as well as the eyes and lips. In order to arrive at a representation of an individual's degree of happiness while working within the parameters of the fuzzy inference system that has been provided, membership functions are first applied to computed distances. After that, the findings from the membership functions are put to use in yet another membership function so that an estimate of the sarcasm percentage may be derived from them. The suggested method is validated by using photos of human faces taken from the SMIC, SAMM, and CAS(ME) 2 datasets, which are the industry standards. This helps to guarantee that the method is effective.

Introduction

From the early researches on facial expressions (FE) until the modern ones, all studies prove that the FE can be classified to seven emotions as mentioned in Figure (1). The process of facial expression recognition (FER) tries to detect these human emotions from the input face image. This process gets great attention because their significant applications in the daily life like (detecting any abnormal behaviors of the human, computer interfacing systems, autonomous driving, managing health systems, etc) (Yang et al., 2017). Even the happy emotion of FE reflects positive state for the person but it can hide negative states like stress or any unpleasant feelings (Lyubomirsky et al., 2005; North et al., 2011). Thus, the issue of detecting happy emotion is not enough, but the degree of happiness must be guessed.

The field of FER takes wide area of research for many years and most studies found in literature try to improve the findings of the early approaches in this topic. Some of these studies using different intelligent techniques deal with the universal facial emotions (UFE) (See for example: Cowen & Keltner, 2020; Sato et al., 2019; Gendron et al., 2018). In (Bennett, 2015), a classification method of classifying UFE has been developed using deep locality preserving CNN.

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This method is evaluated using the face images with various ages from RAF-DB dataset. The accuracy results of this method are less than 60% for disgust and fear while exceeds 70% for other emotions. Similar approach in (Jain et al., 2019) uses deep neural network model with a number of convolution layers to perform FER of only six FE. This approach is evaluated by the face images from two datasets (CK+ and JAFFE). The confusion matrix results of this method view better accuracy results (exceeds 80%) for all six emotions for both the datasets used. The previous approaches and other existing works (Dhall et al., 2014; Schmidhuber, 2015; Zhao et al., 2015; Boughrara et al., 2016; Yu & Zhang, 2015; Kim et al., 2016) uses different ways of CNN as the deep learning techniques for FER. These techniques give significant results especially for Emotion Recognition.

Figure 1. The universal FE of seven emotions (Bennett, 2015).

On the other hand, the early existing approaches of FER are based on extracting some FE features from the input face image and then using some these features to train an intelligent system to classify the facial emotions. Commonly, there are three types of features (appearance, geometric, and motion features). These features are computed for some local regions inside face image which are highly related to facial emotion changes because they reflect any individual expressions inside these regions based on the fact that the global and detail data are considered in these features (Mavadati et al., 2013; Kobayashi & Hara, 1997). In (Zhong et al., 2014), a multi task learning approach was proposed to detect the effective regions in the input face image called (key regions) and the powerful features are extracted from these regions using a sparse coding strategy.

Figure 2. Some Face Images with front View from FEI Dataset.

Finally, the SVM technique is used to predicate facial emotions. Also, multimodal FER algorithm was proposed in (Zhang et al., 2015). In this algorithm the texture and landmark features which are extracted from the input facial images are integrated together to accelerate FER performance. This FER method is evaluated using the face images from CKþ and NVIE databases. The simulation results view significant detection accuracy (exceeds 90%) for all UFE in comparison with other existing algorithm which are used the same two features.

Face Image Dataset

The FEI face database is a Brazilian face database that contains a set of face images taken between June 2005 and March 2006 at the Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. There are 14 images for each of 200 individuals, a total of 2800 images. All images are colorful and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees.

Scale might vary about 10% and the original size of each image is 640x480 pixels. In this dataset, all faces are mainly represented by students and staff at FEI, between 19 and 40 years old with distinct appearance, hairstyle, and adorns. The number of male and female subjects is exactly the same and equal to 100. Also, the normal face image (without any Fes) is available for all person considered in this dataset. Figure 2 shows some examples of image variations from the FEI face database.

Methods

The happy facial emotion can be considered as a psychological emotion because it is strongly related to human actions such as physiological reaction and any FE (Hao et al., 2019).

As mentioned previously, the happiness feeling cannot be explained directly from the smiling face because some undefined expressions may be hidden behind it. Thus, a new approach of FER with two stages has been proposed in this paper to determine the degree of happiness and the credibility of it by estimating the percentage of sarcasm found the same face.

The main algorithm of the proposed approach is mentioned in Figure. The first five steps in the proposed algorithm can be represented as the preprocessing phase which is applied on the input face image to detect the effective regions inside the face area which are considered in the FER. The findings related to the standard regions in human face can be determined from the preprocessing steps. Only two regions (left/right eyes and mouth) are considered in the proposed approach to estimate percentage of happy and to aggregate the sarcasm percentage.

In the first region, four distances are obtained, two in each eye between the two points in the upper and the lower limits of eye, respectively. While, in the second region focused on mouth, eight distances are obtained between the five points in the upper and the lower limits of the outer boundaries of lips in the mouth. The other three distances in this region are determined between the same limits, but with the inner boundaries of lips.

All points in these two regions are mentioned in Figure 4, the points of first region are viewed with circular red marker, while the points of second region are viewed with plus blue marker. In this figure, there are two face images for the same person. The first image is in normal emotion and other in happy emotion which is collected from FEI dataset. The preprocessing steps in the proposed algorithm are applied on these two images separately.

The first step to determine happiness expression start from the finding distances which are obtained in the preprocessing steps. The mathematical difference of each distance in the normal face image and the corresponding distance in the emotion image is determined. The first effective criterion is average distance of eyes (ADE) which is obtained by the taking the average of the four differences in the left/right eyes. The average of both eyes is considered if there is any difference in the opening angle of left/right eyes. The second criterion is average distance of outer mouth (ADOM) which is obtained by the taking the average of the five differences in the upper/lower limits of the outer boundaries of lips. Similarly, the third criterion is average distance of inner mouth (ADIM) which is obtained by the taking the average of the three differences in the upper/lower limits of the inner boundaries of lips.

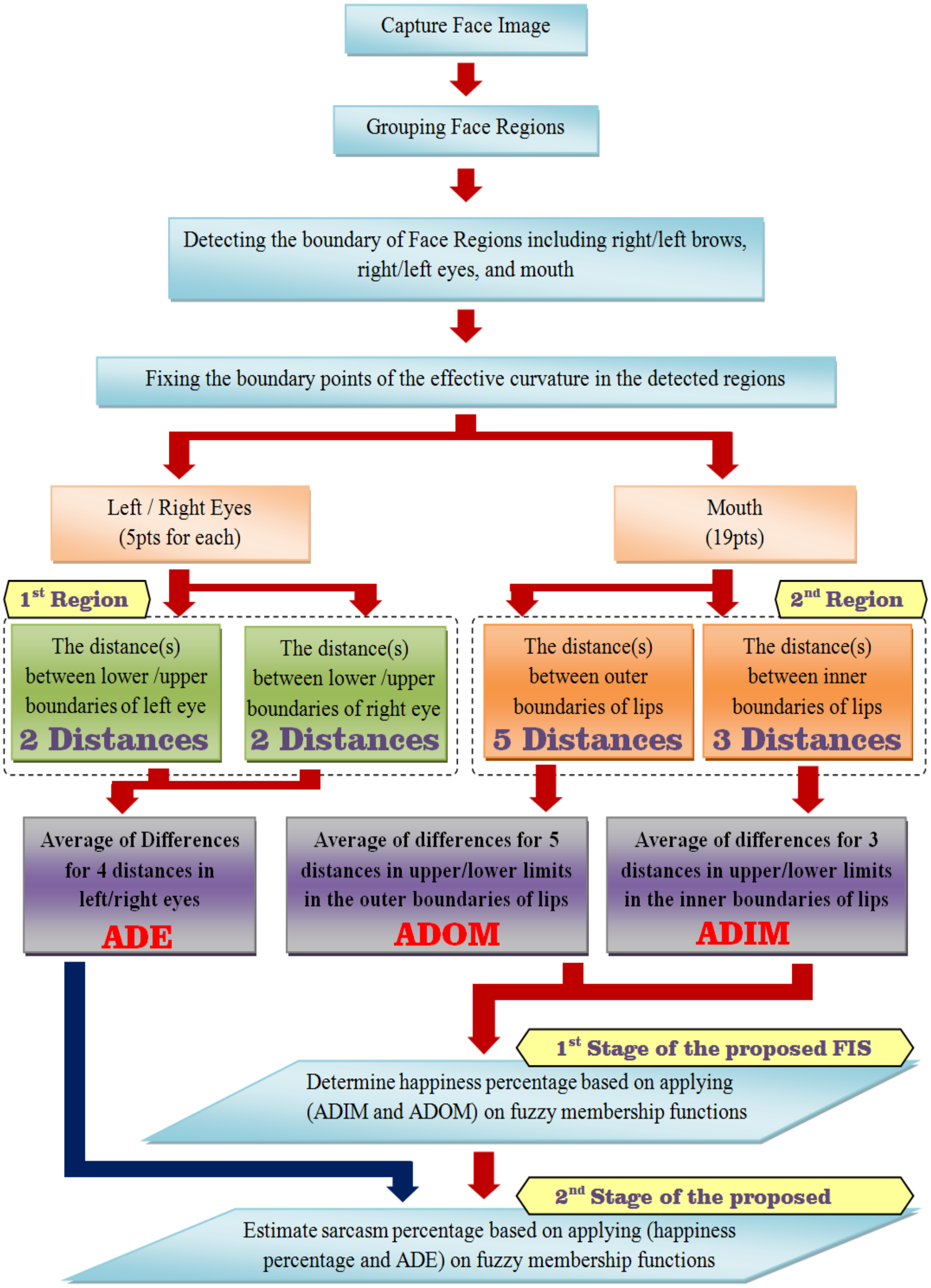

Figure 3. The Main Algorithm of the Proposed Approach.

The ADIM and ADOM criteria are considered to determine the percentage of happiness according the equation defined in (1).

$$Happiness\ (\%) = (10 + ADOM) * 2 + (3 + ADIM) * 1.75 \qquad (1)$$

The suggested happiness percentage equation is a summation of two parts. The first part (10+ADOM) *2 assumed to score 65% as a maximum value, while the second part (3+ADIM)*1.75 assumed to score 35% as a maximum value. The selection of the displacement values 10 and 3are performed to normalize the ADOM and ADIM values to match the required threshold maximum percentage limits of both parts 5 and 35, respectively. While, the selection of weighted values 2 and 1.5 are performed to fix the maximum limits in the first and the second parts as 65% and 35%, respectively. It is important to know that the overall maximum and minimum values of the ADOM and ADIM criteria for all the candidates in the FEI dataset take the significant impact to set the displacement values in the happiness equation. While the distribution of 65% and 35% for the weighted values in the same equation are considered mainly to increase the effect of the outer boundaries less than twice from the inner boundaries. This assumption based on the fact that most happy emotion on the face leads to significant change in the outer boundaries of the lips but with less degree in the inner boundaries.

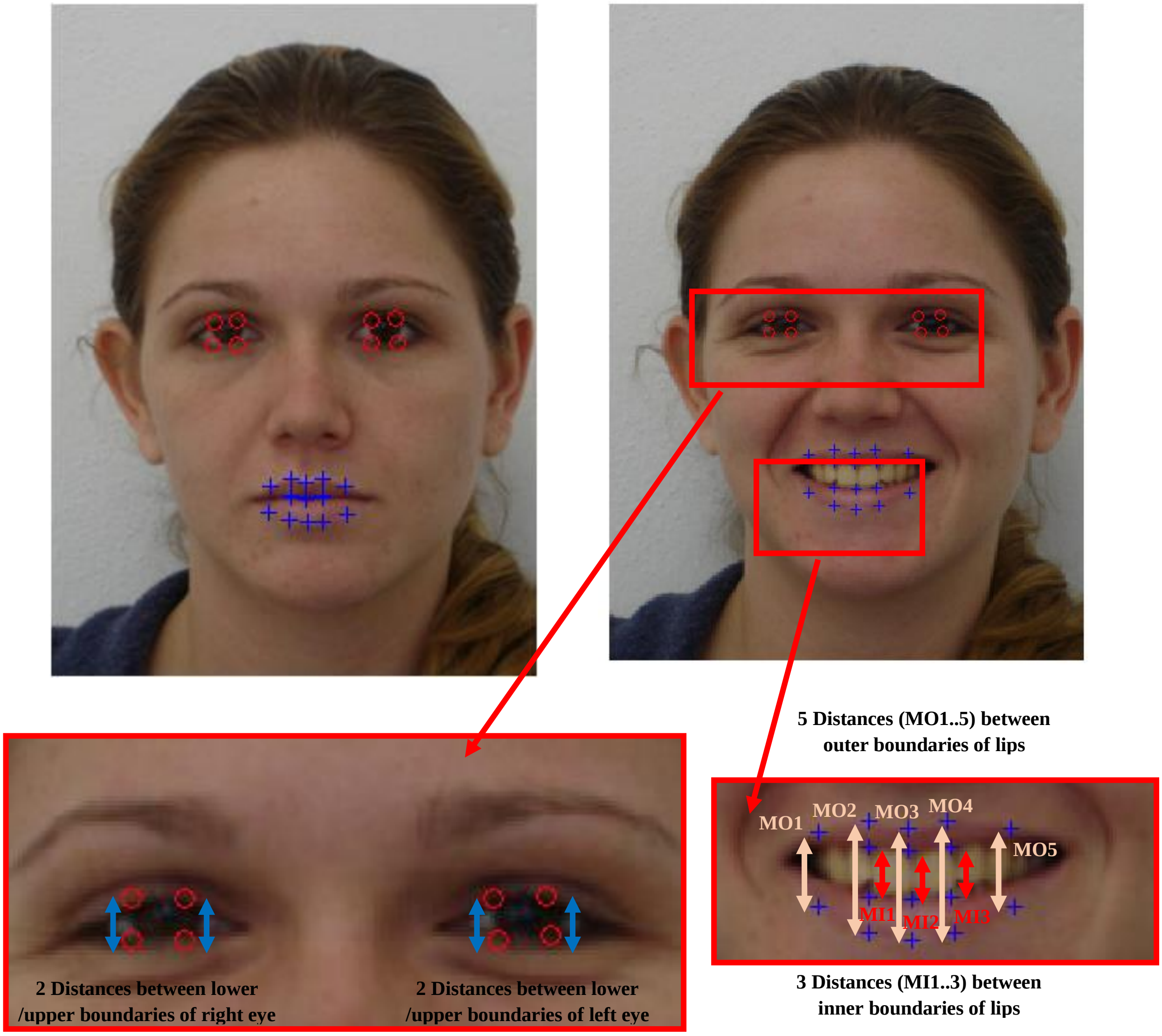

Figure 4. The detected points of the two effective regions in the face (left/right eyes, and mouth).

The happiness percentage and the first criterion ADE are used to estimate the percentage of sarcasm according the equation defined in (2).

$$Sarcasm\ (\%) = (6.6 + ADE) * 5 + (100 - Happiness\%) * 0.8 \qquad (2)$$

In the same manner of happiness percentage, the suggested sarcasm percentage equation has two parts. The first part is related to the ADE criterion and takes the largest computed value in the final estimation percentage of sarcasm. The various forms of eye movement like winking, rolling, and squinting were considered by many well studies in literature (Attardo et al., 2003; Haiman, 1998; Hancock, 2004). While, the second part of happiness percentage takes lower effect on the final estimation percentage of sarcasm. For example if the determined happiness percentage is 70%, the resulted value which is used in this equation is 24% only.

The most credible condition of a happy face, which has been confirmed by a doctor (Bassam Aysar Dheyaa) and psychologist (Madhea Nsaif Raheem), is the appearance of a smile and clearly through the movement of the mouth and the widening of the space between the lips, which in turn will lead to pressure on the muscles of the gland. This pressure will result in similar pressure on the eye muscles, causing them to close more.

The displacement and the weighing values of this part are designed to generate a smaller percentage when the eyes are more closed and the angle of the mouth opening or the movement of the lips is clear. And vice versa, the determined sarcasm percentage is increased gradually as the eye opening expands, even with a large smile on the face.

Proposed FIS of Estimating Happiness and Sarcasm Percentage

Fuzzy inference is the process of designating a structural mapping to generate an output from a given input based on fuzzy logic rules. Then, this mapping performs a basis from which decisions can be made, or patterns discerned (Sumathi & Paneerselvam, 2010). Recently, the FISs are the significant tools to solve engineering problems according their unique facilities to determine complex phenomena. Also, this mapping is a nonlinear system and the main path starting from inputs to output is characterized in conditional form using set of "IF-THEN" logical rules.

Typically, there are three main units (fuzzification unit, inference engine, and defuzzification unit) in each fuzzy logic based system as mentioned in Figure 5.

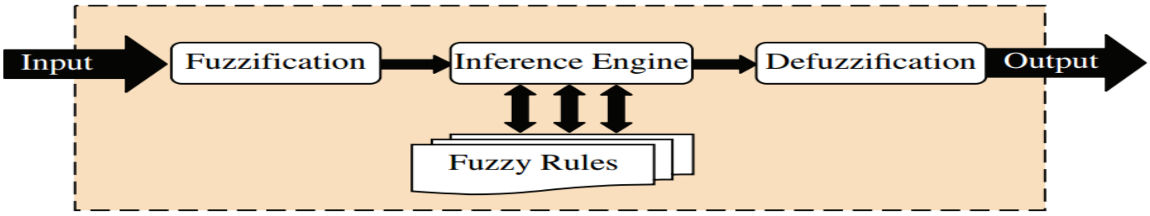

Figure 5. Typical FIS Model (Salih et al., 2014).

A new design of FIS approach has been proposed in this study to aggregate happiness and sarcasm class. In the proposed FIS that builds using Mamdani method, there are two input membership functions (MFs) which are determined mathematically using (1) and (2), respectively. According the definition in (1), the first MF that is related to the happiness percentage is determined using ADIM and ADOM in the form of sub input MFs. While, the sub input MFs in the second MF that is related to the sarcasm percentage represent ADE and happiness percentage.

As mentioned in Figure 5, the defuzzification process is the final step in each FIS, which is implemented by aggregating the obtained value for all output MFs. The classification of happiness and sarcasm into multi categories represents the defuzzification process in the proposed FIS using the fuzzy rules defined in (3) and (4), respectively. The centroid method is considered for defuzzification process because it computes all defuzzified values at a significant fast rate and high precision of accuracy (Sumathi & Paneerselvam, 2010).

$$F_1(x) = \begin{cases} Simmple\ Smile, & if\ x \leq 25\% \\ Medium\ Smile, & if\ 25\% < x \leq 60\% \\ Clear\ smile, & if\ 60\% < x \leq 85\% \\ Very\ High\ Smile, & if\ 85\% < x \end{cases} \quad (3)$$

Where:

x: is the happiness percentage obtained by (1).

$F_1(x)$: is the computed class of happiness.

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$$F_2(x) = \begin{cases} No\ Sarcasm, & if\ x \leq 35 \\ Normal\ Smile, & if\ 35\% < x \leq 75\% \\ Heavy\ Sarcasm, & if\ 75\% < x \end{cases} \quad (4)$$

Where:

x: is the sarcasm percentage obtained by (2).

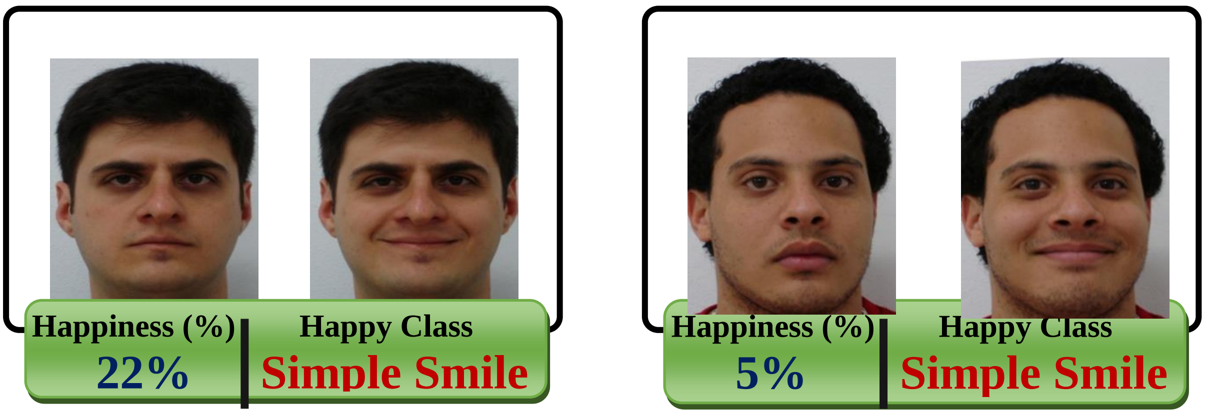
$F_2(x)$: is the estimated class of sarcasm.

Simulation Results

The analytic performance of the proposed approach for determining happiness percentage and estimating sarcasm percentage is validated by 100 face images from FEI dataset. These face images are annotated manually including happiness and sarcasm percentages by expert Psychologists. On the other hand, the happiness and sarcasm percentages are annotated automatically using the proposed approach of FE. The determined happiness percentages of automatic annotation for all validated records match the corresponding manual annotations with 91%. Also, the face images in each of the four categories (Simple Smile, Medium smile, Clear Smile, and Very High Smile) shown in Figure 6 which are classified by the proposed approach FE match completely the basic meaning of each category according the difference in mouth movement including its outer and inner boundaries between the raw and FE image.

In the same way, the previous matching percentages are recomputed for sarcasm. The first matching percentage between the manual and automatic annotation scores 94%. While, the concept of computing a second matching percentage is totally different from a happiness one. This concept relates to the effect of mouth movement as a result of a smile on the movement of the gland muscles, which causes the eye opening to close more and more. The degree to which this relationship between mouth movement and eye opening is achieved will lead to an estimate of the level of sarcasm as mentioned in the last paragraph in section 3. The face images in each of the three categories (No Sarcasm, Normal smile, and Heavy Sarcasm) shown in Figure 7 which are classified by the proposed approach FE match completely the basic meaning of each category according the relation between the movement of mouth and opening angle of eyes.

The high precision of matching percentages in both scenarios of computing happiness and sarcasm percentage proves the capability of the proposed approach of FE to perform accurate results of happiness and sarcasm percentages.



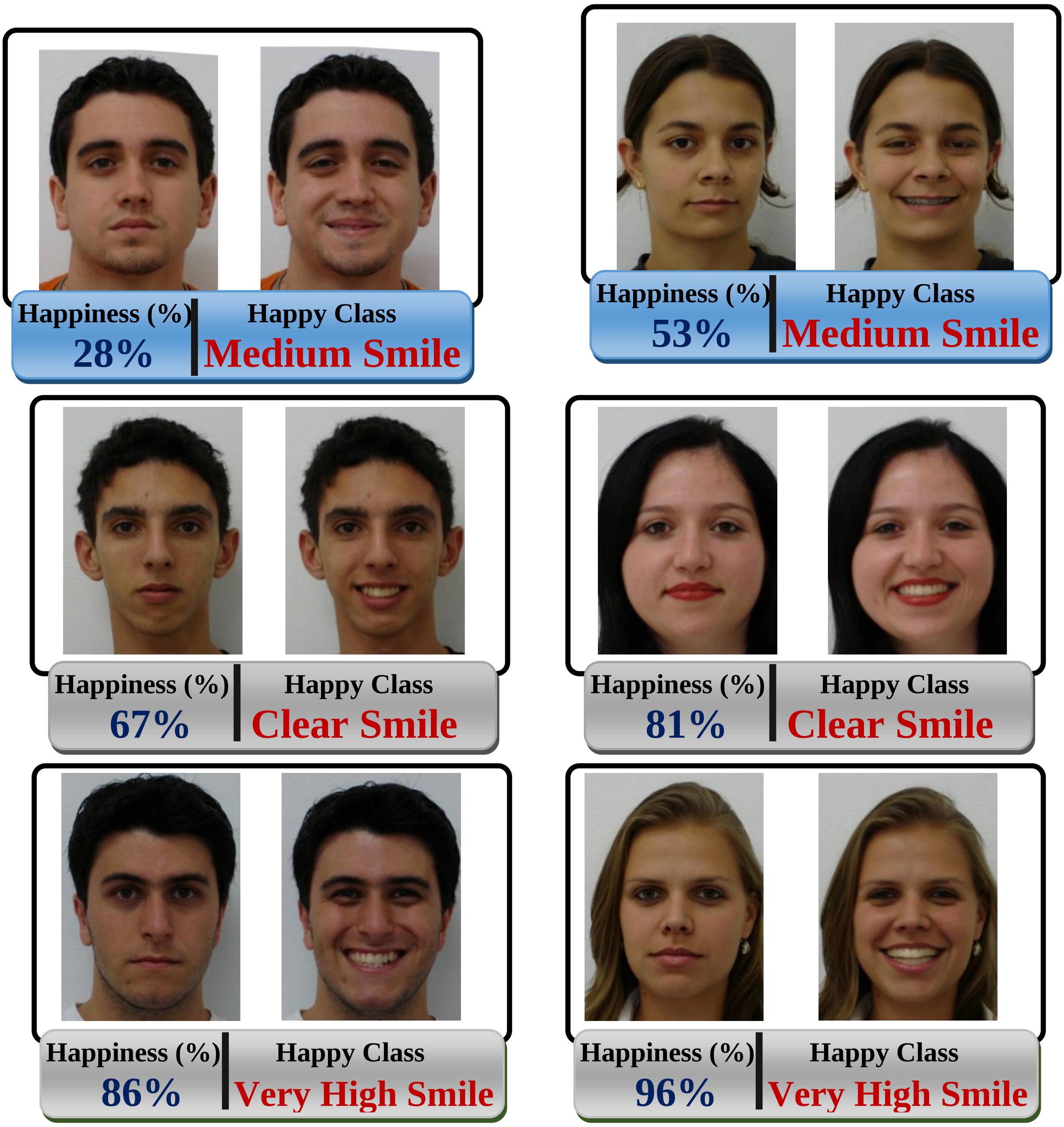
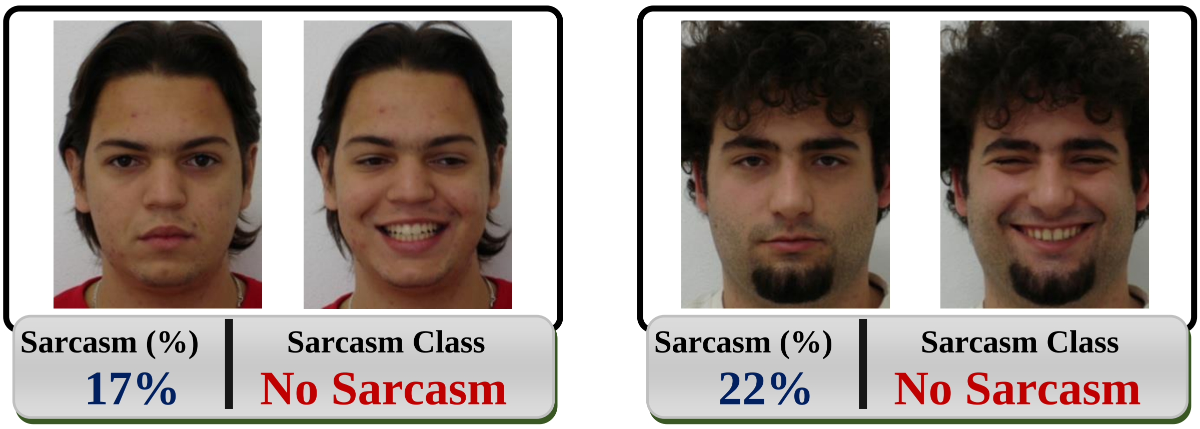


Figure 6. The Determined Happiness Percentage and Four Categories of Happy Class



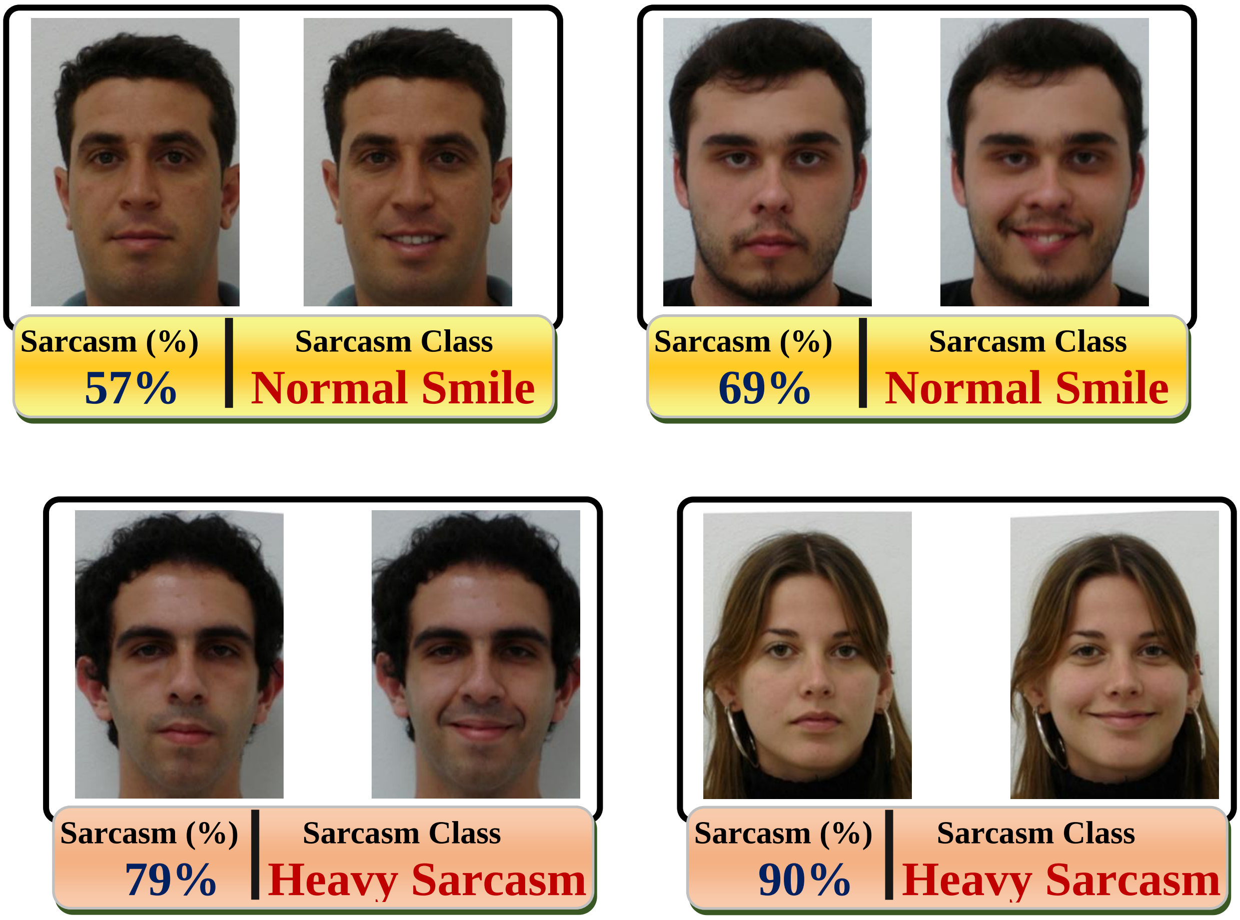


Figure 7. The Estimated Sarcasm Percentage and Three Categories of Sarcasm Class

Conclusion

In this study, a new smart approach using smart fuzzy technique to determine the happiness percentage and estimating sarcasm percentage has been proposed. Based on well-known exiting work on FE found in literature, the idea of estimating sarcasm percentage from face image and based on difference of Fes in face image is novel. The proposed approach address the problem of the fake smile expression by estimating sarcasm degree is not based on the joy that appears on the face through the movement of the mouth only, but rather on the effect of joy on the movement of the gland muscles and thus the effect on the degree of contraction of the eyes. The significant simulation results recorded in this research with respect to the manual annotation open the way to implement additional work about sarcasm based on other FE.

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