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A predictive model to find out students facial emotion using Convolutional Neural Network

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ABSTRACT

Emotion Recognition, also known as Facial Expression Recognition, is a valuable way to enhance the capabilities of current Human-Computer Interaction Technology. In this paper, we use the AdaBoost algorithm to determine class function parameters and then use a Fuzzy Conclusion System to develop a facial expression recognition system by first detecting the face from the background, rooting intriguing features from it, and finally classifying the face into one of five feelings: happy, horselaugh, sad, nausea, and neutral. With our outfit, we were able to achieve a success rate of 92.42 percent, which is really encouraging. All of the faces should have correct picture brightness and be in near-anterior exposures. The Indian Face Database was used.which was erected in 2002 by a group of IIT Kanpur scholars, for training purpose.

Keywords: Facial expression, Emotion recognition, Expression Recognition, Fuzzy Inference System, AdaBoost.

Introduction:

Mortal Facial expression recognition is a relatively new field in which researchers are experimenting. If properly implemented, it has the potential to enhance the Human Computer Interface to a whole new level by expanding commerce beyond textbooks, clicks, and touches. It may be used for everything from games to online agencies. The three main parts of the technique are face recognition from an image/videotape stream, facial point point birth, and finally interpreting those features to determine emotion. We discuss all three steps in our work, with a focus on the last stage, inferring sentiments from uprooted data. The goal of this research is to define five basic emotions: neutral, happy, laughing, sad, and nauseous.We utilised the Haar cascade training, which was first proposed by Viola-Jones [1], for face identification since it is a very popular, efficient, and rapid way of detecting faces. A mixture of Edge and Skin Detectors is used to retrieve feature points. We used fuzzy logic to evaluate emotions from characteristics, taking into account [2]'s suggestions. All of the faces are believed to be approximately frontal. For training purposes, we used the Indian Face Database [3]. The following are the sections of the paper: The approach for Face Detection is described in Section 2, the Feature Point Extraction Method is described in Section 3, and the last stage of the process is described in Section 4: inferring human emotions from the data. Finally, we end our discussion with experimental results.

II. Face Detection

This is the first stage, in which the human face is recognised and separated from the rest of the backdrop in a given image. To detect faces, we employed Viola-Jones' Haar classifiers, which produce a boosted rejection cascade [1]. Due to its high computation speed and accuracy, this is now the most well-known approach for detecting faces. In a nutshell, this approach starts by transforming a pixel picture to an integral image by adding the pixel intensities to the left and above each pixel and assigning an integer value to that pixel. Following that, multiple rectangular sections of increasing widths known as detection windows are moved across the input picture one by one, computing the Haar-like characteristic of that subsection of the image.

The difference between the pixel values of consecutive thickish sections at a designated point in a discovery window is calculated via a Haar-suchlike point. This distinction is frequently used to categorise print subsections. For example, in a mortal face collection, it's typical to see that the area around the eyes is darker than the area around the cheeks in all faces. As a result, a brace of two contiguous blocks over the eye and the impertinence area serves as a haar point for face detection.

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Because such a Haar-like feature is merely a weak classifier, the Adaboost learning algorithm is employed, resulting in the organisation of these weak haar-like features into a classifier cascade, resulting in a strong classifier. [1] The outcome of applying this procedure to a test image is shown in Figure 1. The green rectangle denotes the classifier's detection of the face.

III. Feature Point Extraction

In this part, we portray our proposed framework to dissect understudies' looks utilizing a Convolutional Neural Network (CNN) engineering. To start with, the framework distinguishes the face from the input picture and these recognized countenances are trimmed and standardized to a size of 48×48. Then, at that point, these face pictures are utilized as a contribution to CNN. At last, the result is the look acknowledgment results (outrage, joy, misery, repugnance, shock, or impartial). Figure 1 presents the construction of our proposed approach. Figure 2 depicts the 21 features of this study that we deem 'interesting.' We utilise them to determine the width of the eye, the height of the brows, and other extracted feature values.

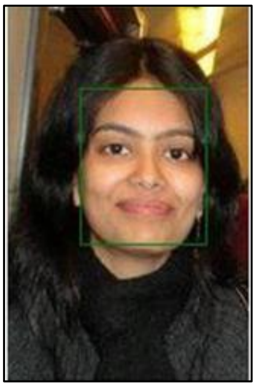

Figure 1: In the test image, a face was detected. The face boundary, as recognised by the Viola-jones Method, is shown in green.

$$CrEyeMap\ 1\ 3[\ Cb^{2}\ (255\ Cr^{2}\ )\ Cb\ Cr\ ]$$

Figure 2: An intriguing feature point on a face from the Indian Face Database.

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To compute the retrieved characteristics, we utilise the following 7 equations, as proposed by [3]:

A. Width of the Eye

$$we=((x_{11} - x_{10})+(x_5 - x_6))\sim 2$$

B. Height of eyebrows 1:

$$he1 = ((y_{15} - y_4) + (y_{15} - y_2)) \sim 2$$

C. Height of eyebrows 2:

$$he2 = ((y_{15} - y_3) + (y_{15} - y_1)) \sim 2$$

D. Width of Mouth

$$wm = x_{19} \sim x_{18}$$

E. Openness of Mouth

$$om = y_{21} - y_{20}$$

***F*. Nose Tip-lip corners**

$$nl = ((y_{18} - y_{15})+(y_{19} - y_{15}))-2$$

G. EYE Check Distance:

$$ec = ((y_{16} - y_9)+(y_{17} - y_{14}))\sim 2$$

To improve the accuracy of our feature values, we combine Edge Detection and Skin Detection Algorithms. [2] For example, while calculating eye opening, we first identify the eye by converting the picture from RGB to YCbCr colour space. Then, based on the notion that high- Cb and low-Cr values may be found around the eyes, we create a chrominance eye map. This map may be written as follows:

Next, we create a new eye map using the luminance component, taking use of the fact that eyeballs have both dark and bright pixels in the luminance component and highlighting these contrasting locations with grayscale operators. This map may be written as follows:

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LEyeMap Dilate Y x y Erosion Y x y

where Y(x, y) denotes the image of the face.

An AND operator is now used to integrate both eye maps. To brighten both eyes and reduce other face characteristics, the generated eye map is dilated and normalised. The position of the ocular area is monitored using a threshold that is appropriate for the situation. Once the eye region has been identified, a template matching technique is used to it in order to determine which window contains the eye. For template matching, we employ the correlation coefficient [2]. The window has been slid open. Gradually over the eye areas, until the window with the greatest correlation coefficient is selected. To detect the eye centre, eyelids, and right and left edge points of the eye, the Canny Edge Detector method is now employed in conjunction with a skin detection technique. Other feature points on the face are calculated using similar methods. Figure 3 depicts the typical method of recognising the feature-containing region and subsequently extracting the important feature points.

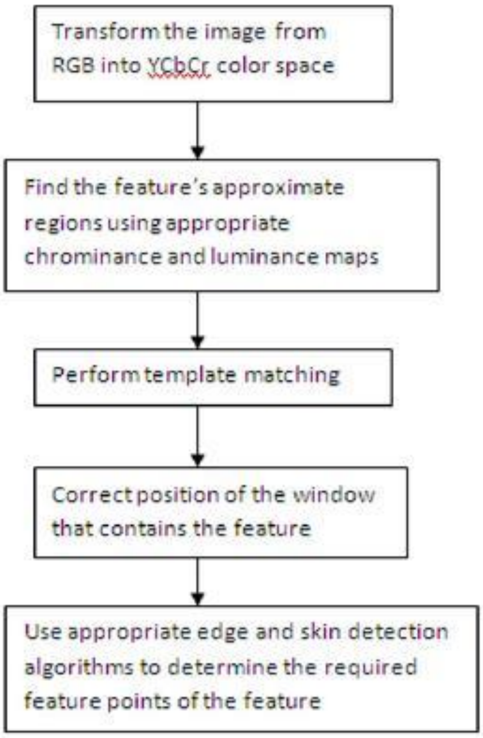

Figure 3. A generic approach for recognising a feature-rich region and extracting the needed feature points.

IV. Facial Expression Recognition

We establish our fuzzy set as a collection of 5 values for each extracted feature: Very Large, Large, Medium, Small, and Very Small. If we have a neutral face image, we may compare the extracted features' values to the values acquired by the former for a more accurate result. The difference between the 7 feature values produced by the two photos is fuzzified in this example. All feature values are normalised to a range of [0, 1], and Gaussian membership functions are used to classify them as well as the classifier's efforts The parameters of the class functions are found using the AdaBoost system. We create weak classifiers manually to categorise colourful elements of sensations based on the rule matrix in Table 1 and observation. For the distribution, the AdaBoost Algorithm is also employed to provide strong classifier parameter values. In terms of delicacy and computing speed, this method is advantageous.

It's worth noting that if we had a neutral face image on hand, we'd get different results than if we didn't. Both of them are determined using the training photo database. When defuzzifying, we use the fuzzy rules generated from the rule matrix in Table 1 to establish the degree of class of each data point with respect to the appropriate emotion.

	WE	HE1	HE2	WM	OM	NL	EC
Happiness	M	M	M	VL	S	S	S
Laughter	M	M	M	M	VL	L	VS
Sad	S	M	L	M	VS	M	M
Disgust	M	VS	S	M	S	S	S
Neutral	M	M	M	M	M	M	M

VS:Very Small, S: Small, M:medium,L: large, VL: Very Large

Table1: Rule Matrix for Fuzzy Inference System Classifier

The emotion which has the highest number of features belonging to it is recognized as the resulting emotion. In case of a tie, the one having the highest summed up probability of belongingness of the features is selected.

V. Result and Conclusion

In terms of calculation time and real-time accuracy, the Fuzzy Inference System for identifying emotion is an efficient method. Our Fuzzy Classifier's identification rates for diverse emotions are shown in Table 2. A recognition rate of 92.42 percent appears to be extremely impressive. However, it should be emphasised that if additional emotions were identified, this proportion would almost certainly decrease, though not much. Figure 4 depicts an emotion that has been accurately identified.

Emotion	Recognition Rate (in %)
Happy	93.6
Laughter	96.2
Sad	94
Disgust	89.7
Neutral	88.6
Average Recognition Rate	92.42

Table 2: Recognition rates of different emotions by the Fuzzy Classifier

Fig.4: Detected emotion = Happy

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