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FACIAL EMOTIONS RECOGNITION SYSTEM FOR TESTED IMAGES BY USING NAIVE BAYES CLASSIFICATION

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Abstract

Facial Expression Recognition (FER) has challenging task in computer vision. These expressions are very important carriers for human to convey emotions in communication. Here we present basic expressions like angry, fear, neutral, sadness, surprise and disgust. One of the non-verbal communication method by which one understands the mood of a person is the expression of face. Colored image or an image in a video sequence is the input of the processing system. Different classifications and algorithms are available for FER, of which different classifications gives different accuracies. The existing SVM and Naïve Bayes classification is proposed to classify the facial expressions and the accuracy of detecting the emotion is calculated.

I. Introduction

Faces play a crucial role in FER. Interaction with others humans possess and express various emotions. Emotions are mainly reflected through facial

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expressions but they are also reflected through body gestures, voice, and skin. We, humans obviously know the emotion of a person to whom we interact. But computers do not possess any emotions and they also couldn't understand the user's emotion. So computers are "Emotionally Challenged". Here we propose Naive Bayes classification method for recognizing emotions in human faces very effectively. Naive Bayes classifiers are collection of algorithms based on probability theory.

II. Features For Emotions Recognition

To describe the physical phenomenon, extracting the best features is the foremost thing in facial expression identification system. Before the recognition of any facial expressions, categorizing the ocular message disclose by human facial expression is the primary which is to be achieved. There are 6 basic universal emotions that are directly related to facial expressions. The emotions correspond to Happiness, Anger, Fear, Sadness, Neutral, and Surprise. A facial feature in a face includes eyes, nose and mouth. The lengths and widths of facial features are extracted and the measurement ratios are calculated which are further used for classifying an emotion.

III. Brief Discussion of Various Classifications

There are many classification techniques some of the image classification techniques are as follows

A. Bayesian Classification. Naive Bayes classifiers are a collection of classification algorithms based on Bayes' theorem. This is not a single algorithm but collection of algorithms.

B. Support vector machines (SVM). These are data points and are very much closed to hyper plane and influence the position and orientation of the hyper plane.

C. Genetic Algorithm. Genetic algorithm is used to exploit the temporal correlation in the subsequent frames of a video sequence, i.e.

i. Initialization of the parent population

ii. Selection of fit individuals

iii. Cross over and mutation.

iv. Termination.

IV. Existing Method

The existing classification technique is support vector machine (SVM). The process of SVM is as follows:

i. Image-Based Classification: In this method optimize classification of images. Here images can be divided into sub images for segmentation.

ii. Support vector machines in nutshell: In training stage the received data as input in machine learning algorithms. i.e. $S = ((x_1, y_1), \ldots, (x_i, y_i))$, $y_i \in \{-1, 1\}$ where x_i is the inout data and y_i is class label.

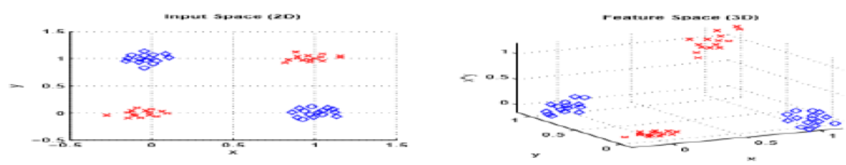


Figure 1. The two bit parity problem.

Nonlinear function of the form: $f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b\right)$

Table 1. The Kernel Formula Functions.

Kernel	Formula
Linear	$x * z$
Polynomial	$(\gamma x * z + c)^{\text{degree}}$
Radial basis function	$\exp\ (-\gamma \mid x - z \mid^2)$
Sigmoid	$\tanh\ (\gamma x * z + c)$

Figure 2. Test image 1 to SVM.

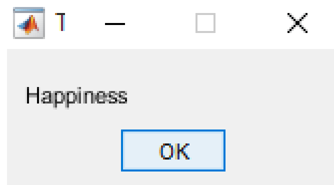


Figure 3. Results of Test image 1 to SVM.

Figure 4. Results of SVM for test image 1.

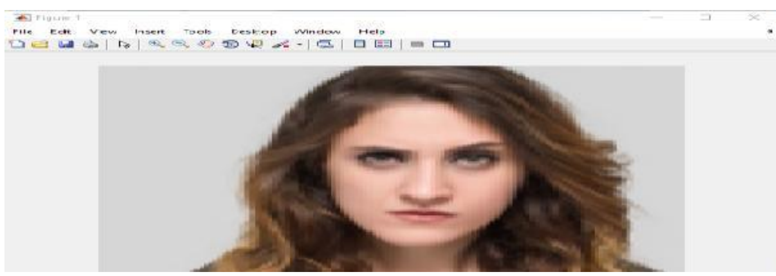


Figure 5. Test image 2 to SVM.

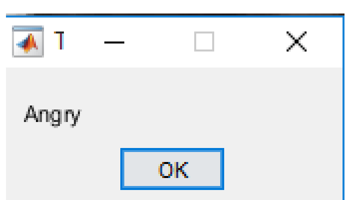


Figure 6. Results of Test image 2 to SVM.

The proposed classification technique is naive bayes classifier it is based on probability theory *A*. Naive Bayes Classifier: Hypothetically probability conditional model is $p(c \mid F_1, \ldots, F_n)$ here C is the dependent class variable. F_1 through F_n are feature variables. By applying bayes theorem can be written as

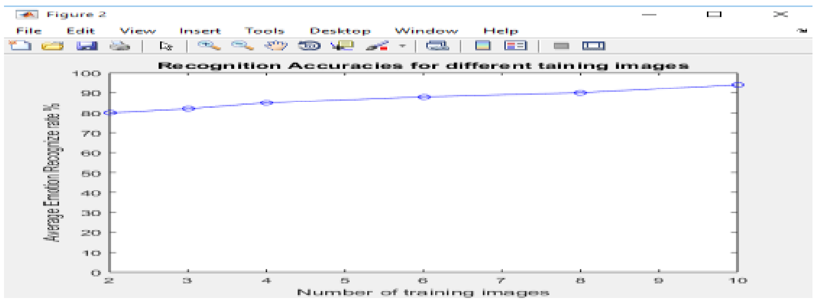


Figure 7. Result of SVM for test image 2.

IV. Proposed Classification

$$p(c \mid F_1, \ldots, F_n) = \frac{p(c)\, p(F_1, \ldots, F_n \mid C)}{p\, F_1, \ldots, F_n}.$$

Another form of equation can be written as $\text{posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$ present the naive contingent independent presumptions become possibly the most important factor: $p(F_i \mid C, F_j) = p(F_i \mid C)$. Here $i \neq j$, $p(C, F_1, \ldots, F_n) = \frac{1}{z} P(C) \prod_{i=1}^{n} p(F_i \mid C) Z$ is scaling factor depends on $F_1, \ldots, F_n$.

B. Parameter estimation $p(x = v \mid c) = \frac{1}{2\pi\sigma_c^2} e^{-\frac{(v-\mu_c)^2}{2\sigma_c^2}}$ another normal strategy for taking care of nonstop qualities is to utilize binning to discretise the qualities. As a rule, the circulation strategy is a superior decision if there is a limited quantity of preparing information, or if the exact conveyance of the information is known. The discretization strategy will in general improve if there is a lot of preparing information since it dispersion of the information. Hence credulous bayes ordinarily utilized.

C. Training: Example training set below. Values correspond to measurement ratios of respective features.

Table 2. Measurement ratios for Facial Features.

Name	Eye1	Eye2	Nose	Mouth	Emotion
A	0.12033	0.14583	0.25117	0.10977	Happy
B	0.14309	0.17083	0.26526	0.10308	Happy
C	0.2567	0.25397	0.41991	0.22936	Angry
D	0.27203	0.27381	0.4026	0.18349	Angry

Table 3. Mean and Variance Values of Eye 1 and Eye 2 Features for Happy and Angry Emotions Emotion.

Emotion	Eye 1(μ)	Eye 1 (σ_c^2)	Eye 2(μ)	Eye 2 (σ_c^2)
Happy	0.13171	0.00012	0.15833	0.00015
Angry	0.264365	0.00005	0.26389	0.00009

Table 4. Mean and Variance Values nose and Mouth Features for Happy and Angry Emotions.

Emotion	Nose (μ)	Nose (σ_c^2)	Mouth(μ)	Mouth (σ_c^2)
Happy	0.258215	0.00004	0.106425	0.00001
Angry	0.411255	0.00007	0.206425	0.00052

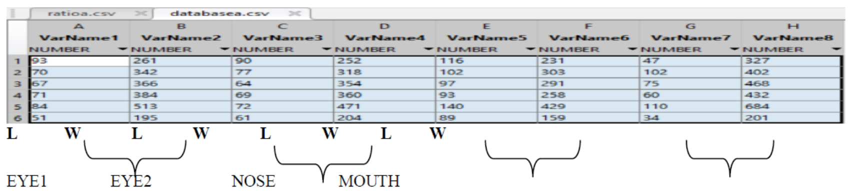
D. Experimental setup: Data is split into 2 sets i.e.

i. Training set: Parameters estimation is done only by using training set.

ii. Test set: By using the test set, classification is performed. In summary, it can be described as

E. Tested results: Input to the naïve bayes classifier is shown in figure 1

Figure 8. Input to Naviebayes classifer.



ratioa.csv | databasea.csv

	A VarName1 NUMBER	B VarName2 NUMBER	C VarName3 NUMBER	D VarName4 NUMBER	E VarName5 NUMBER	F VarName6 NUMBER	G VarName7 NUMBER	H VarName8 NUMBER
1	93	261	90	252	116	231	47	327
2	70	342	77	318	102	303	102	402
3	67	366	64	354	97	291	75	468
4	71	384	69	360	93	258	60	432
5	84	513	72	471	140	429	110	684
6	51	195	61	204	89	159	34	201

Figure 5.5. Lengths and widths for calculating measurement ratios of facial features.

A VarName1 NUMBER	B VarName2 NUMBER	C VarName3 NUMBER	D VarName4 NUMBER
0.35632	0.35714	0.50216	0.14373
0.2682	0.30556	0.44156	0.31193
0.2567	0.25397	0.41991	0.22936
0.27203	0.27381	0.4026	0.18349
0.32184	0.28571	0.60606	0.33639
0.1954	0.24206	0.38528	0.10398

Figure 9. Measurement ratios of facial features.

6. Testing: Naive Bayes classifier applied on the trained dataset and test image the below table 5.4 shows the sample data for testing emotion four features.

Table 5. Sample data for Testing.

Emotion	Eye1	Eye2	Nose	Mouth
Sample	0.12033	0.25397	0.26526	0.18349

Naive bayes follows posterior probability and the result angry is as shown in Figure 5.4.

Figure 10. Result picture it shows angry emotion.

Accuracy Calculation: The formula for calculation of accuracy is as follows i.e.

$$\text{Accuracy} = \frac{(\text{tested images} - \text{failed images}) \times 100}{\text{tested images}} \%.$$

For SVM the Tested images = 68, Failed images = 11 and accuracy is 83.82%. For naive bayes classifier the Tested images = 68, Failed images = 07 and accuracy is 89.70%.

V. Conclusions

In this paper we presented both SVM and Naive Bayes classifier and this is a method of recognizing emotions by using facial expressions. We successfully used SVM and Naive Bayes classifier to detect facial expressions or emotion. Naïve Bayes classifier uses posterior probability which is the key. When compared to SVM the accuracy of detecting the emotions in Naive Bayes classification has increased from 83.82% to 89.70%. The Accuracy of the Naïve Bayes classifier is calculated. For future work, by taking large datasets the accuracy can be improved. To further improve the success rate or accuracy of recognition system following methods have to be used i.e. Advanced pre-processing methods and Hybrid Algorithms.

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