

Efficient Fr a Geometrical-Model-Based Face Segmentation and Identification in Terms of Identification the Face

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Abstract:

A useful geometrical face model and an efficient facial feature detection approach are proposed. Since human faces are constructed in the same geometrical configuration, the proposed approach can accurately detect facial features, especially the eyes, even when the images have complex backgrounds. Experimental results demonstrate that the proposed approach can efficiently detect human facial features and satisfactorily deal with the problems caused by bad lighting condition, skew face orientation, and even facial expression.

Keywords: Geometrical face model Facial feature detection Face recognition Image processing.

1. INTRODUCTION

Over the past decade, technology and affective computing have grown to be extremely important and play a significant role for understanding the human behaviour. The field of emotion recognition is now an area of study that is rapidly growing to support applications such as monitoring of patient's interactions as well as feedback in E-Learning as well as contests, psychology and entertainment industry. Recent years have seen researchers have made significant contributions to advancements in the field of affective computing. Emotion is a heightened, subjective, and fluctuating state of mind that indicates the worth of stimuli, whether positively or negatively. The physical basis of human emotions must be investigated. The same process is triggered in robots, since robots are expected within their environment and be able to interact with humans on the emotional level. Particularly social learning, gestures, natural expression of language emotional recognition, the synthesis of interactions between partners are all key aspects. A system that can recognize and understanding emotions through FR as part of the Human-Computer Interaction (HCI) method could facilitate interaction with users. It should be capable of "perceive, interpret, express and regulate emotions".

While recognizing facial expressions is an easy task for most people, it's an extremely challenging job for computers. One reason could be because it's been discovered that the differences between images representing the same concepts are usually greater than the differences in facial expressions resulting from the changing of lighting and directions. These variations are further exacerbated by other factors like gender, occlusion, and even the ethnicity of origin. The varying appearances can make it difficult to pinpoint facial areas and to extract fundamental facial expression characteristics. In non-restricted environments the variations can be more difficult to predict than in controlled conditions.

II Related Work

To speed up the learning process and speed up learning, the normalization layers within the network built in LRN (local response normalization) (LRN) are changed to normalization layers for batch training [30]. A batch normalization layer is an integral component of the model and is responsible for normalization of each mini batch. This allows the network to be trained at greater rate of learning that otherwise is difficult and unstable when using regular LRN layers. The use of batch normalization was proven to provide the same high-quality performance but using 14 times fewer training repetitions. It is a great way to improve the performance of your custom CNN. The overview of the architecture of the proposed custom CNN is shown in Figure 1. Subsequently, the layers, size of kernels, number of kernels, and strides for each layer used in custom CNN architecture, all in all the custom CNN contains seven convolution layers as well as 6 batch normalization layers that are in between each layer of convolution. Between each convolution layers, a maximum layer of pooling is included to limit the size of the input is used to create subsequent layers. The activation function used in the system uses a rectified linear unit (ReLU). Many dropout layers are integrated into the ReLU to prevent overfitting. To show the fact that this specific CNN is more effective in its parameters than other CNN that are utilized to create the customized CNN layout are calculated. This article provides in-depth information on ways to estimate the amount of the output features of each layer, as well as methods to estimate the quantity of parameters related to convolution layers and fully connected layers within the CNN.

III Methodologies

The main purpose of this research is to investigate face expression recognition algorithms. limited and unconstrained environments. Despite efforts by researchers for several decades, this issue remains unsolved. To reach the desired objective, the goals of this study can be broken down into three distinct parts, each of that are each pursued independently. The first objective is to explore new methods to extract features. Due to the wide range of distinctions between classes as well as the similarities between classes, efficient feature extraction is essential to recognize facial expressions. The features extracted should be able to be able to represent various facial expressions and in a way that is not affected by age, gender or gender, nor appearance. It is also beneficial to use features that are resistant to Occlusions and localization errors. The third goal is research of the use of combination and feature selection methods to recognize facial expressions. It is widely accepted the fact that recognition of facial expressions could be enhanced by the combination of several characteristics. But, there is usually no clear way to choose and blend different types of features.

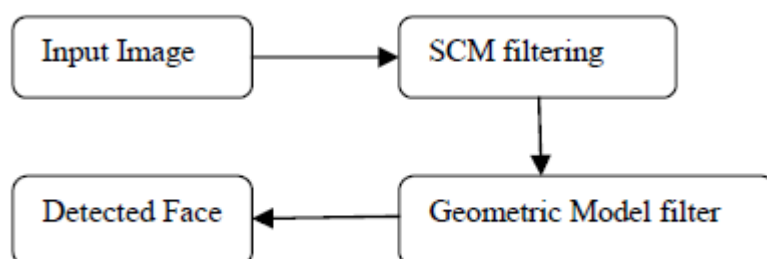


Fig 1: Proposed Face Detection Block Diagram

IV PROPOSED WORK

Gabor Filter:

Gabor filters form the sets of wavelets. Each wavelet has the same frequency and direction and expanding the signal by using these sets of wavelets provides the localized frequency descriptor as well as capture features of the signal. One of the Gabor filter's specializations is that the size of frequency, illumination, and orientations can be controlled to suit various applications in which the object of interest can appear at different sizes or pose Gabor filters using multiple scales or multi-orientation can be the best appropriate for feature extraction.

Local Binary Pattern (LBP):

The LBP calculates the brightness ratio between each pixel of the image as well as its local neighborhood. Binary sequences are coded to form the locally specific binary pattern. Then, it applies a multi-region histogram for an image description feature. image. The last stage in the system for facial recognition is classification which is achieved either through recognition attempts or through interpretative.

Geometric Based Face Detection:

PCA model of the facial structure to detect faces automatically. This method increases the face detection rate and reduces the search area. Skin Color Modeling (SCM) is among the most effective methods for detecting faces in images or video. But selecting features is essential for greater performance of template matching with regard to detection rates and time. This paper outlines an effective feature extraction and selection method which is based upon the geometric structure of the face's border and the interior. To depict the structure of the face Principal Component Analysis (PCA) and edge detection using canny methods are employed. The combination with PCA geometric models and the SCM method could provide greater face detection accuracy, and increase the complexity of processing. Both models can filter images using pixels to determine the area of the face. Both are very quick and efficient when it comes to large images databases. The system proposed uses skin color models to reduce the search area. The orientation-invariant threshold is that is based on geometric models enhances the efficiency of the system. In order to ensure templates, correspond the feature extract and selectivity, by combining a new method of combining geometric filters and SCM filter is described.

Fiducial Points

To establish the foundation of our geometrical approach, we employed the fiducial point set. In our experiments, we examined 37 of these points. Certain of them are detected automatically, while the rest are manually extracted. We are working towards automated point detection. The approach used to facial key point extraction is described in [66]. After the detection of the points, their coordinates could be corrected by an operator (manually) to enhance their position. The coordinates of the points could be stored along with the image in databases. A sample of the investigated face key points

Feature Choosing

Geometric characteristics can be displayed through perimeters, segments and the areas of certain figures derived from the detected points. We looked at different subsets the features in search of the most robust ones, but because of the large number of them, we are unable to report about the most robust results of our search at this time. So, in order to show our findings in comparison with the results of other recognition tests, we examined the feature set that is described in [77]. It consists of 15 segments that connect the points as well as the mean values of 15 symmetrical segment pair. The feature set explored isn't the greatest one; the particulars of its analysis are provided.

The Feature Set Optimization

Once an appropriate feature set is discovered, it is able to be improved using the presenting method. How do you choose the ideal subset of features? The goal was to identify the feature space with largest distances between clusters, and the smallest distances between the patterns of a cluster. In our study, all the database images from the same individual were viewed to be one single cluster.

FR Based on The Features

The values of the feature are saved along with the person's identification photographs in the database. If the image is normalized based on the scale, rotation and intensity levels, fiducial points are identified and the value that represent the characteristic are calculated. The database images are patterns within the features space. To determine the most similar to the image that we tested, we must evaluate the Euclidean distances between it and all other images.

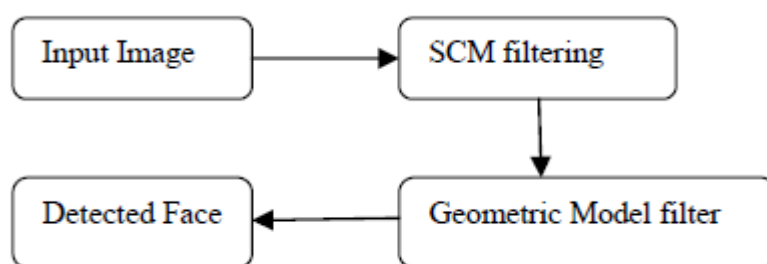


Fig 2: Proposed Face Detection Block Diagram

The model we proposed was trained with the expressions included simultaneously. We employ an online augmentation technique that includes horizontal flipping as well as random shifting to improve the quality of images from training sets. The output size of each convolutional layer could be described as follows:

$$N = \frac{I - F + 2P}{S} + 1,$$

in which K represents the dimensions of output for the layer, i.e. there are K types of outcomes. S is the probability of a result. is the probability of obtaining the outcome i.e $I = 1, 2, \dots K$. and Softmax loss that is utilized for update and gradient calculation is calculated using the following formula.

$$L = - \sum_{i=1}^K y_i \log S_i,$$

$$\frac{\partial L}{\partial z_k} = \frac{\partial L}{\partial S_i} \frac{\partial S_i}{\partial z_k},$$

$$\frac{\partial L}{\partial S_i} = \sum_{i=1}^K \left(-\frac{y_i}{S_i} \right),$$

$$\frac{\partial S_i}{\partial z_k} = \begin{cases} \frac{e^{z_i} \sum_{k=1}^K e^{z_k} - e^{z_i} e^{z_k}}{\left(\sum_{k=1}^K e^{z_k} \right)^2} = S_i (1 - S_k), & i = k; \\ \frac{e^{z_i} \cdot e^{z_k}}{\left(\sum_{k=1}^K e^{z_k} \right)^2} = -S_i S_k, & i \neq k, \end{cases}$$

$$\frac{\partial L}{\partial z_k} = \frac{\partial L}{\partial S_i} \frac{\partial S_i}{\partial z_k} = - \sum_{i=1}^K \frac{y_i}{S_i} \cdot \frac{\partial S_i}{\partial z_k}$$

$$= -S_k (1 - S_k) \cdot \frac{y_k}{S_k} + \sum_{i \neq k}^K \left(-\frac{y_i}{S_i} \right) \cdot (-S_i S_k)$$

where L represents the loss function, and the variable y_i represents the label that's value can be either 0 or 1 according to whether the output is in line with the real value.

V. Experimental Results:

Dataset Description

The Extended Cohn-Kanade (CK+) database [41] was utilized to assist in facial expression recognition. It includes six classes of facial expression (anger fear anger, displeasure with anger, joy, sadness and surprise). The database is comprised of 593 photographs of the 123 subjects. The sequences of photographs vary in between seven and sixty frames (i.e. seven to sixty frames) and also include the beginning (which is also known as face expression that is neutral) until the top in facial expression. The images from neutral to display that was to be used were digitally converted to 640 x 480 and arrays of 7 to 60 frames. The 593 images have an emotional category. They are the only images that adhere to the standard definition. In the research we conducted there were 315 successive sequences of data which are selected from the database to carry out basic facial recognition. The most commonly used method to checking the generalization efficacy that a classifier can achieve is to use the cross-validation method K-fold. Five-fold cross-validation was employed to maximize the use of the data available, and also to achieve an average accuracy in the results of classification.

Algorithm 1: Histogram Segmentation Algorithm

Data: $W = [w_1, \dots, w_c]$: histogram input

d : minimum depth of segment

r : minimum width of segment

Result: The largest segment in given histogram W

$egde_{begin} = false$

for $i = 1$ **to** c **do**

$$\hat{w}_i = \prod_{k=-r}^{-1} \delta(w_{i+k} - e_{i+k}^1) \prod_{k=1}^r u(w_{i+k} - e_{i+k}^1) - \prod_{k=-r}^{-1} u(w_{i+k} - e_{i+k}^2) \prod_{k=1}^r \delta(w_{i+k} - e_{i+k}^2)$$

where

$$e_i^1 = \begin{cases} 0 & , -r \leq i \leq -1 \\ d & , 0 \leq i \leq r \end{cases}, e_i^2 = \begin{cases} d & , -r \leq i \leq -1 \\ 0 & , 0 \leq i \leq r \end{cases}$$

if $\hat{w}_i = 1$ **and** $egde_{begin} = false$ **then**

$temp = i$

$egde_{begin} = true$

endif

if $\hat{w}_i = -1$ **and** $egde_{begin} = true$ **then**

$(temp, i)$ is new segment.

$egde_{begin} = false$

endif

end

Geometric Feature-Based Facial Expression Recognition:

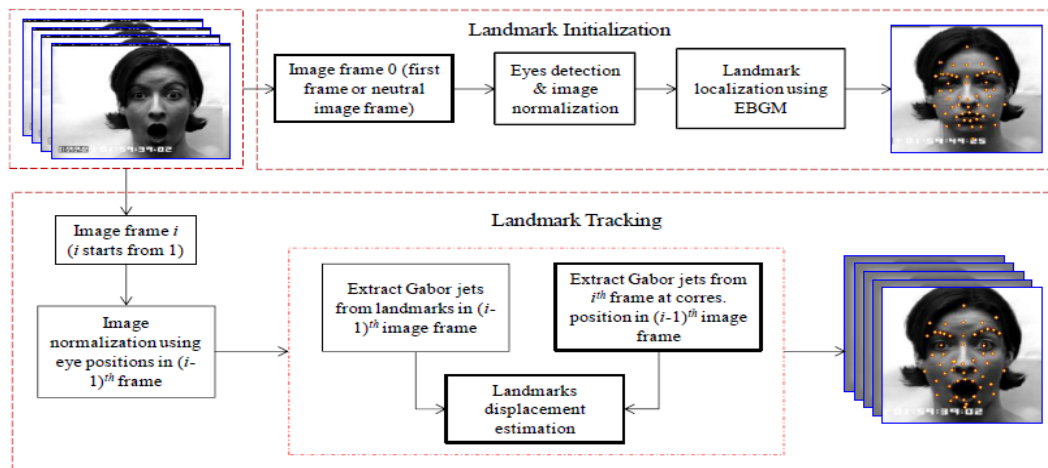


Fig 3. Block diagrams of the overall landmark tracking and initialization process.



Figure 4 : Examples of the results of tracking facial landmarks.

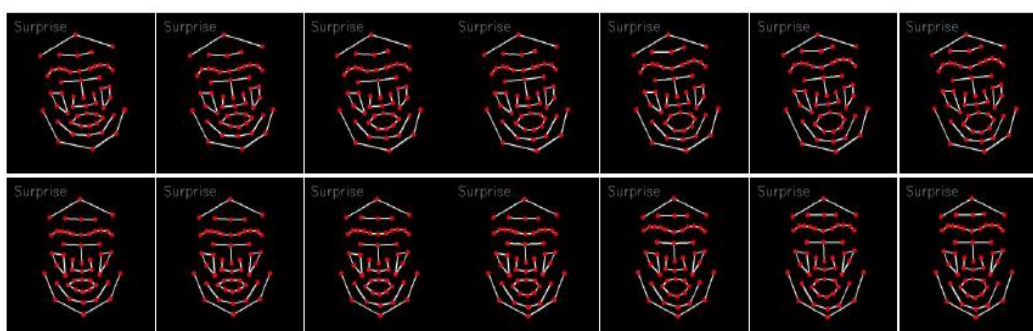


Fig 5: Examples of marker tracking sequences that are prior to (First row) and the following (Second row) normalization.

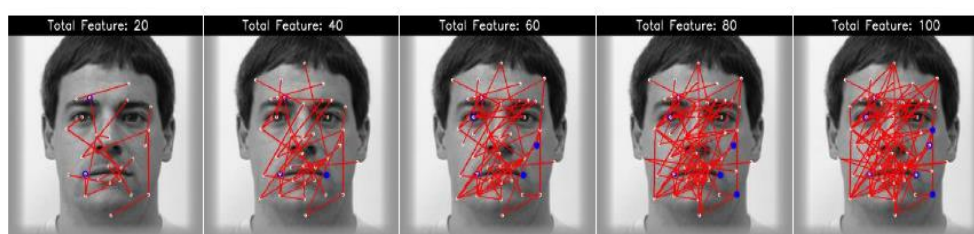


Figure 6: The first few (20 40, 40, 40 60 and 100) options are chosen with multi-class AdaBoost.

The blue dots represent the feature vector drawn from landmark tracking data and changes with time. A red line that connects two landmarks shows how the features vector was drawn from landmark tracking results, as it changed in shape in time.

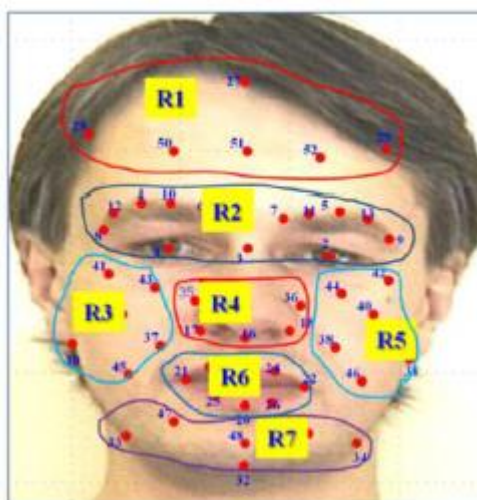


Fig 7: Grouping landmarks into various areas based on facial geometries.

Expression	Face Regions (Single/Pair) with the Most Discriminative Landmarks
Anger	R1-R2, R2, R2-R3, R5-R7, R6, R6-R7
Disgust	R1-R2, R2, R2-R3, R5, R5-R6, R5-R7
Fear	R1-R2, R2, R3-R6, R5-R6, R2-R7, R4-R7, R6-R7
Happiness	R1-R2, R2, R2-R4, R2-R6, R3-R6, R4-R6
Sadness	R2-R3, R2, R3-R7, R5-R6, R6, R5-R7, R6-R7
Surprise	R1-R3, R2, R2-R3, R2-R7, R2-R5, R7

Fig 8: Emotions from the faces

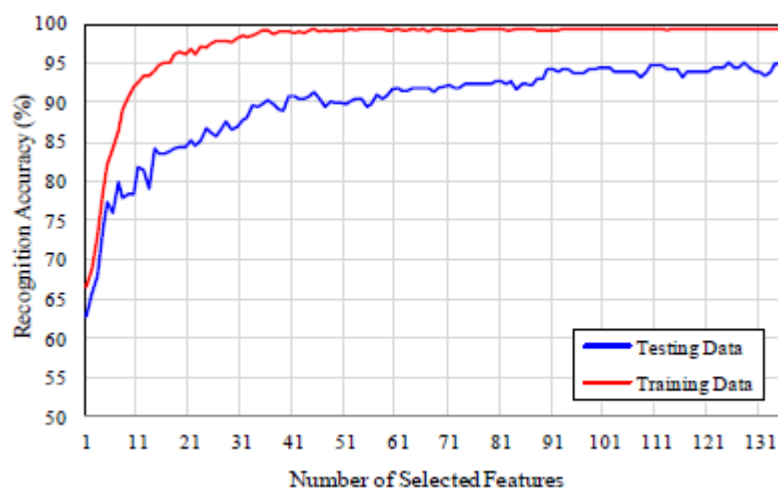


Fig 9 Accuracy of recognition under various quantities of AdaBoost chosen features.

	Anger	Disgust	Fear	Happiness	Sadness	Surprise
Anger	90	5	0	0	5	0
Disgust	0	95	0	5	0	0
Fear	0	0	84	12	0	4
Happiness	0	0	3.08	96.92	0	0
Sadness	6.67	0	3.33	0	90	0
Surprise	0	0	0	1.25	0	98.75

Table 1 : Confusion matrix to aid facial expression recognition in percentages employing Multi-class AdaBoost using 75 features vectors.

Based on 52 results from landmark tracking there are 1 378 feature vectors that can be employed, But only a small percentage can recognize the essential facial features. The highest accuracy in classification at 95.17 percent is achievable by using the minimum of 100 and the 125 features vectors. The confusion matrix utilized to recognize facial expressions uses the multi-class AdaBoost that includes features vectors that are 75 and along with 125 feature vectors, and 125 feature vectors. Certain expressions of fear and joy can be misinterpreted to mean the same. The distinction between fear and happiness did not work since both expressions are based on the similar facial expressions. The sad and angry facial expressions can be difficult to differentiate from human behaviour. Expressions of facial anger the emotion of anger were believed to represent expressions of happiness.

	Anger	Disgust	Fear	Happiness	Sadness	Surprise
Anger	95	5	0	0	0	0
Disgust	0	95	1.67	3.33	0	0
Fear	0	0	92	8	0	0
Happiness	0	0	3.08	96.92	0	0
Sadness	6.67	0	0	0	93.33	0
Surprise	0	0	0	1.25	0	98.75

Table 2: Confusion matrix for facial expression recognition in percentages, using multi-class AdaBoost with 125 feature vectors.

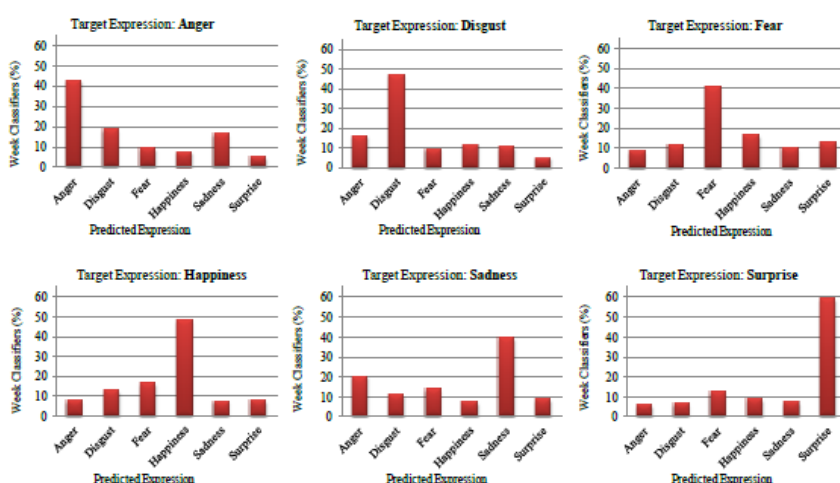


Fig 10: Average score of confusion for week classifiers as a percentage, to recognize every facial expression class.

Table 3 Several existing gender recognition methods and their accuracy

Feature	Dataset	No. of Sample	Accuracy
Neural Network	Personal	90	92.90%
Boosted LBP	LFW	7443	96.81%
Haar Features	Web Images	3500	83.00%
NABP	LFW	13000	93.74%
Fisher Vector encoding	LFW	13233	94.50%
Color	FERET	1762	98.90%
MSLBP	FERET	1762	94.29%

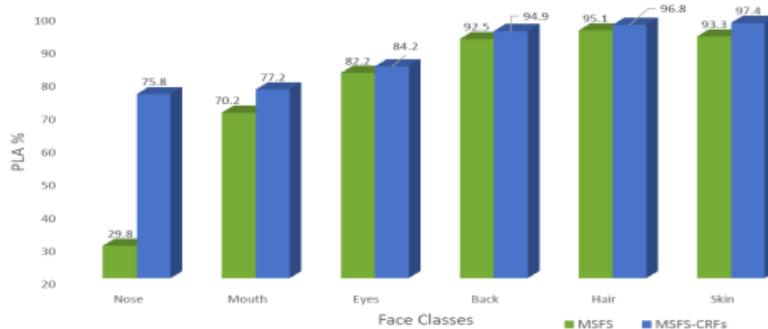


Figure 11: Performance comparison.

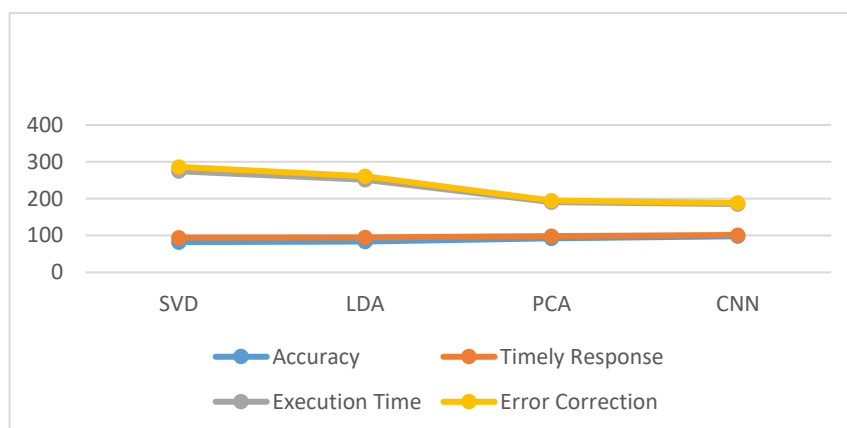


Fig 12: Comparison of the algorithms for geometric FR using data sets

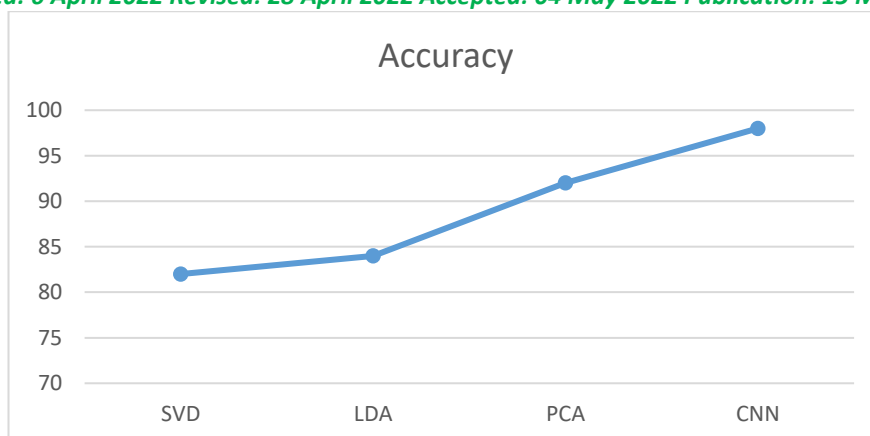


Fig 13: Accuracy Comparison of the algorithms for geometric FR using data sets

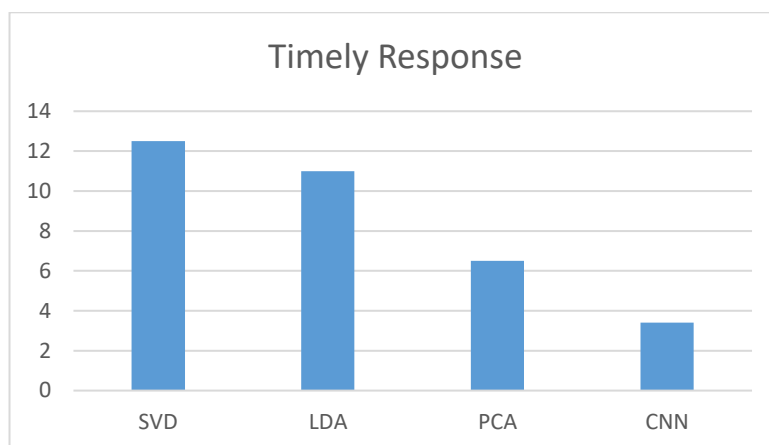


Fig 14: Timely response of the algorithms for geometric FR using data sets

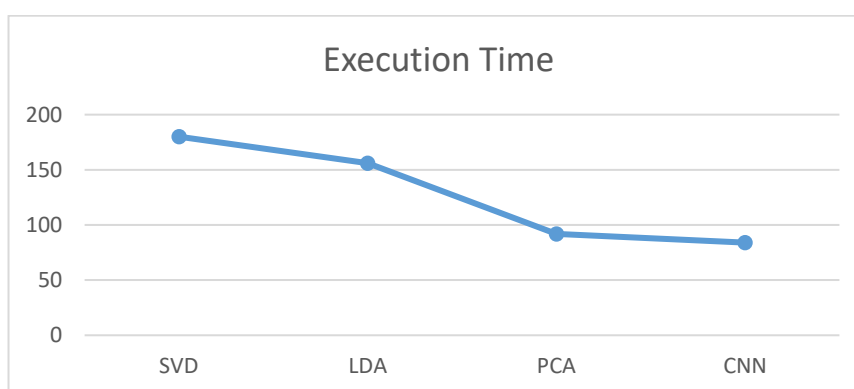


Fig 15: Timely response of the algorithms for geometric FR using data sets

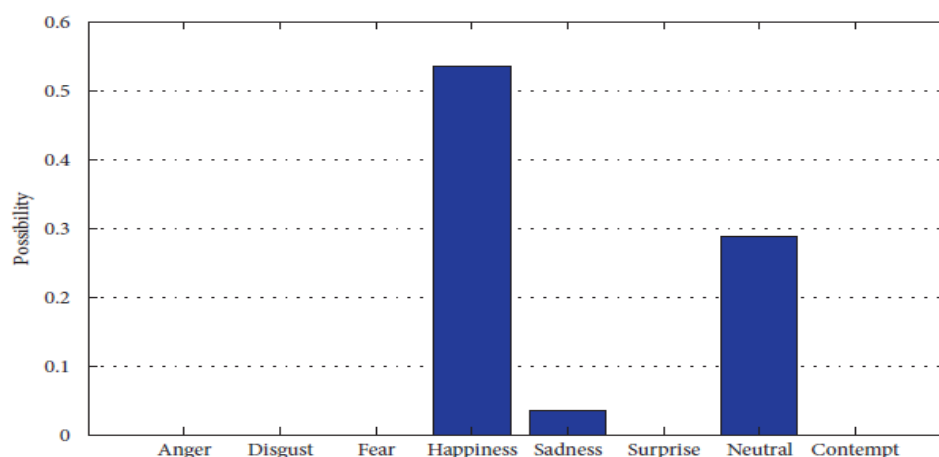


Fig 16: Timely response of the algorithms for geometric FR using data sets

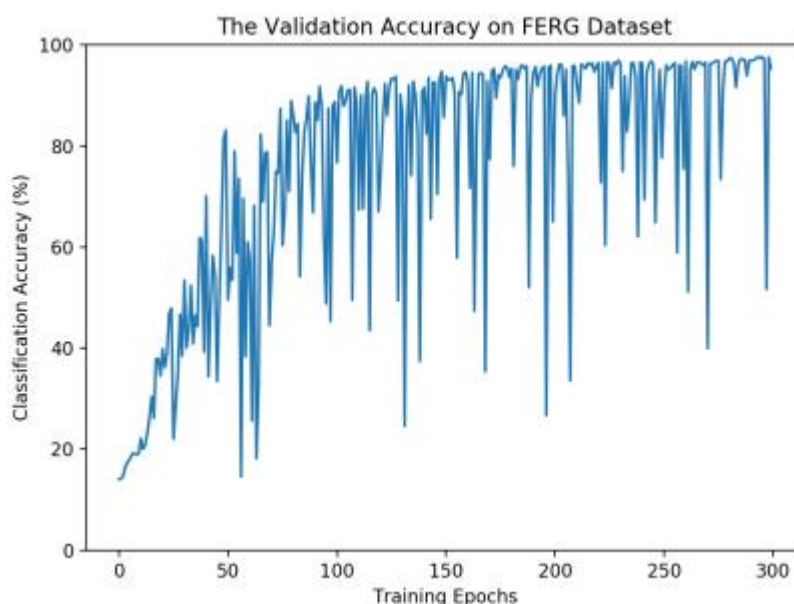


Fig 17: Timely response of the algorithms for geometric FR using data sets

VI. CONCLUSION

Different algorithms and methods are being studied for improving the precision of recognition facial expressions using images. A variety of approaches have been suggested to recognize facial expressions of the subjects. Most of the methods use the laboratory-controlled facial expression datasets, which have controlled conditions. Lighting is consistent and the images feature an entire frontal. The laboratory-controlled images have no occlusions in most of the cases. Therefore, facial detection as well as feature extraction become easier as part of the facial recognition. Thus, facial recognition in these datasets becomes more simple than real-time facial expression databases. In the case of these datasets the images are downloaded from the internet, as well as from real-world photos. This means that they face issues with lighting conditions, heads, different resolutions of the images, and various occlusions, such as glasses, hairs, etc. The main goal of this thesis is to design efficient models to recognize facial expressions using deep learning techniques in order to increase the accuracy of recognition for lower resolution images of the real-

time facial expression data that recognize seven basic facial expressions, including happiness, disgust, shock, angry, sad, fear, and neutral. In this research we have proposed three methods for recognizing facial expressions by using advanced techniques for deep learning.

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