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Comparative Analysis of Facial Expression Recognition Using HMM and SVM

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Abstract:
In this paper, we compare and investigate facial expression recognition system (FERS) based on well-known features using Hidden Markov Model (HMM) and Support Vector Machine (SVM) and also with combination of HMM and SVM. In recent years, there has been increasing usage of deep learning techniques in FERS however which also suffers from the problem of generalization. In this aspect this paper systematically investigates the performance of FERS using conventional AI techniques. We exploit well-known features landmark and texture based LBP. We also propose logical partitioning of face and obtained encouraging results. We have tested on dataset CK+ and spontaneous own created dataset named 'OAK'. Experiments are conducted with different combinations of parameters to verify the efficiency of FER. This paper aims to compare the FERS performance using SVM and HMM. Results clearly reflect the efficiency of SVM with landmark feature.
Keywords: *Facial Expression Recognition, HMM, LBP, Landmarks, SVM*

I. Introduction

Facial expression is one of the effective ways to convey emotion and feeling. During social interaction, expression contributes nearly 55% of emotion [1]. Facial expression signals emotion, communicative intent, individual differences in personality, and psychiatric and medical status, and helps to regulate social interaction. Now a day's, facial expression recognition is important and challenging area in computer vision domain. The FER is getting attention due to its potential in area like robotics; one can build robots with social skills. e-Learning becomes efficient for understanding the frustration level of student. Patient pain level can be monitored in clinical setup. Truthfulness can be detected in police interrogation and job interviews. FER combined with different modalities like speech, gaze etc. can be useful in real time surveillance system. FER consists of steps which are face detection, feature selection, feature extraction and feature classification.

Figure 1: block diagram of FER

In this process, the images or videos are the input. They are loaded first and the first step is face detection. Feature extraction is next step which helps to acquire the prominent features. This stage of FER followed by classification and recognition approaches that surmise emotions or mental states based on the extracted FE features. The vast majority of techniques use a multi-class classification model where a set of emotions mental states are to be detected.

We compare well-known traditional approaches specifically HMM and SVM. We basically build facial expression recognition system based on landmark, texture features using SVM, HMM and also with the combination of these classifiers

II. Related Work

Local binary pattern (LBP) and landmark are the popular techniques to extract the features from the facial region. LBP works best for extracting the textural information of face. Earlier LBP is used for classification of texture but now days it is widely adopted method for facial expression classification. The main characteristic LBP provide is the less complexity in computation and robustness to the change in illumination [2]. In [3] LBP is used with Gabor filter [4] and used with combined novel facial feature representation approach [1]. Authors have first applied Gabor filters on the input image and then local binary pattern is extracted from the Gabor magnitude picture. Multimodality learning with combination of texture and landmark modality has been proposed by Zhang et.al in [5]. Perveen and et al. proposed the method to retrieve the bounding boxes that helps to compute the facial characteristic points (FCP) in [6]. S. He, S. Wang and Y. Lv. in [7] conducted the experiment of facial expression by capturing the landmark points. Initially, they have normalized the sequence according to the pupil coordinates. Later point distance variation is selected as feature to train the Hidden Markov Model (HMM) for the classification of the expressions. In [8] Yang Zhang have presented 3D action unit intensity estimation and facial emotion recognition in which support vector machine and feed forward neural network is employed for classification purpose. Feature selection was carried by minimal redundancy maximal relevance (mrMR) to extract most relevant feature. The research work provides in [7] deals with the head movements.23 key points were labeled manually from apex to onset frame. Point distance and point displacement [9] are used as the feature set. Hidden Markov model is employed as the classifier. The modification in facial recognition system with the modified boosting algorithm for dimensionality reduction in feature set by B. Yao, H. Ai, Y. Ijiri and S. Lao[10]. Local binary pattern has been used with Gabor filter for gender recognition in research work of the Chen et al. [11]. Ghimire, D [12] was extracted the landmark points of facial representation and conducted the classification using the multiple adaboost. The classification of seven expression (happy, surprise, sad, disgust, angry, fear and contempt) using techniques local binary pattern and also used edge detectors (sobel and canny) for feature extraction and classification purpose they have used multi-class SVM and adaptive multiclass SVM in [13]. Shan et al. [14] have conducted the study on LBP and boosted LBP features for facial recognition and their study showed that boosted LBP is more effective for feature representation. Chowdhary et al. [15] proposed facial recognition system using 2D fisher linear discriminant (FLD) for feature extraction and employed multi-class SVM for classification purpose. The face expression is recognized by applying Gabor filter on the whole face and on the certain action unit in [16]. After extracting the feature normalization is performed and classification is done with naïve Bayesian classifier. . L. Happy and A. Routray have proposed the facial recognition method by combining the appearance-based feature extracted from local binary pattern and shape descriptor by extraction pyramid of histogram of gradients in [17]. Feature dimensionality is reduced with the linear discriminant analysis method, for classification SVM is employed. For classification, authors in [18] have proposed the system that is based on Eigen face. In order to extract the facial region, hue and saturation values are used. Eigen ace is extracted and Euclidian distance is calculated from the mean Eigen face to classify the emotion in one of the emotion category. Zhang et al. [19] have presented the method which is the combination of local binary pattern and local fisher discriminant which is named as 'LFDA'. They have extracted LBP feature and then low dimensionality discriminating features are retrieved for improving the recognition of the expressions. SVM classifier is used for classification purpose. Feature extraction on key areas is done in [20], where authors have extracted the local binary pattern from the key portion as well as from whole facial region for e.g. Nose, eyes ears etc. Both the local and global features are concatenated to form feature vector. SVM and neural network are used for recognizing the emotions. The large set of geometric curve which are calculated and Euclidian distance function is applied on the facial surface, together combined to classify the gender in [21]. In [22] kim et al. have proposed a system a emotion recognition system using 2-D discrete cosine transform feature vector. Embedded hidden Markov model is employed for classification. Evaluation showed the improvements of 7.9%. To deal with the illumination problem, M. S. Kaushik and A. B. Kandali in [23] have implemented histogram of gradient (HOG) along with local binary pattern. In 2018 N. Özbey in[24] has extracted the local binary pattern around the landmark using the active shape model. Ding et al.in [25]have proposed the double local binary pattern (DLBP) for the detection of the peak expressions. Taylor based feature are extracted based on LBP and Taylor expansion. Effect of Multiview orientation and multi-resolution is investigated in [26] by extracting the local binary pattern from the sub-block of the facial image. Most convolutional neural network architecture have achieved significant results. Alexnet [27] is based on basic CNN in which max pooling is applied on convolved features. Relu (rectified linear unit) is the activation function applied on the layered stack.

In general, various approaches have shown significant improvement and advancements in FERS. However, with the various features and classifier FER accuracy fluctuates which itself is obvious.

III. Proposed System

Overview

In this paper, we propose three different approaches using different feature extraction techniques and classifiers, which are explained in section. 3.2 And section 3.3. Overview of the proposed system is shown in fig 2.

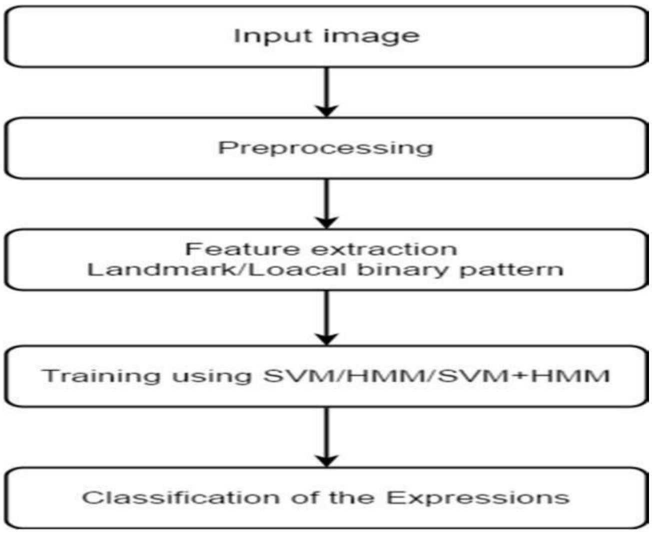

Figure 2: flow chart of proposed system

Input image is first fed to the system. Conversion of RGB image to gray scale is performed in order to reduce the dimension which eventually reduces the complexity. We extract two different features namely: landmark and local binary pattern. After the extraction of these features, feature set is fed into the classifier HMM, SVM and combination of two classifiers. We classify basically six different expressions namely 'Happy', 'Sad', 'Surprise', 'Fear', 'Angry' and 'Disgust'. Proposed systems are tested on the frontal faces as well as multi-view images. Feature extraction and classification are elaborated further in the next sections.

Feature Extraction Techniques

This section briefly explains different feature extraction techniques.

Landmark

Facial landmarks are a set of salient points, generally located on the corners, tips or mid points of the facial segments. Landmark points are called anchor points or key points. Landmark points explain the geometry of the face. Geometric features [28] describe the faces through distances and shapes. 68 key points are located and their differences with the mean distance are calculated. First, facial image is preprocessed in order to deal with illumination problem. Histogram equalization is applied on the image to improve the contrast and handle the illumination problem. Later using the shape predictor, we extract the 68 landmark points from the face. These points are found on the edge of lips, eyebrows and on the contour of the lips. The coordinate of 68 points in image are obtained.

$$I = \{(x0, y0), (x1, y1) (x67, y67)\} \quad (1)$$

(x29, y29) mean coordinates are considered as the centroid in both the axis. This point is located at the center of the nose. Later, mean distance is a calculated between each point value and centroid point value.

$$Ix= xmean-xm \qquad \text{where } 0 < = m < =0 \quad (2)$$

$$Iy= xmean-xn \qquad \text{where } 0 < = n< =0 \quad (3)$$

Ix and Iy are the list containing the differences with mean point. To deal with head movement, we calculate the angle between the line which passes to the mean point and vertical axis which eventually handle the spontaneity.

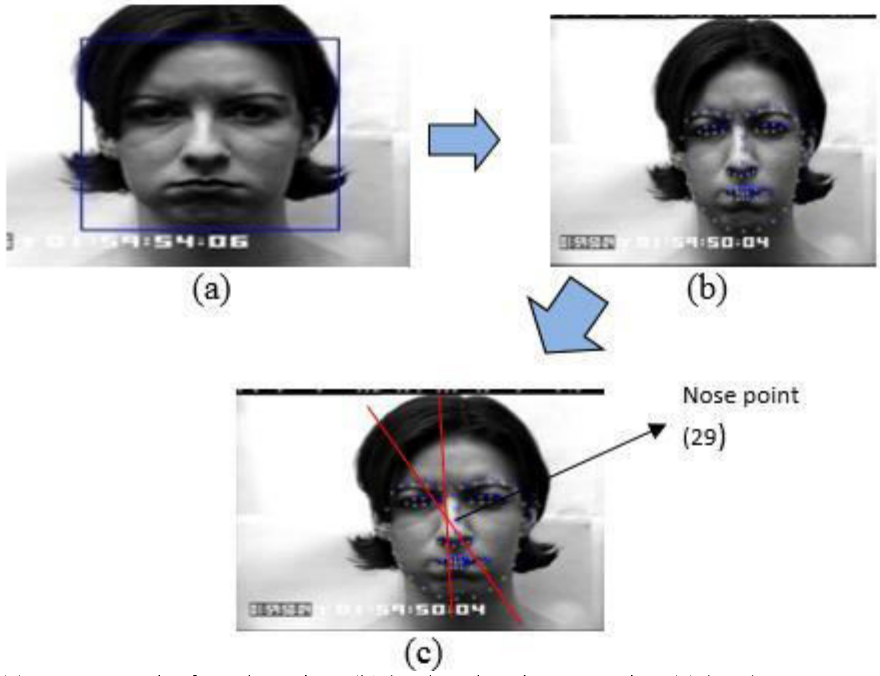

Figure 3: (a) represents the face detection, (b) landmark point extraction (c) head movement calculation

Local Binary Pattern

Local Binary Pattern (LBP) is a simple but very efficient feature extraction method of texture information. Textural related features are extracted from pixel value, which are further capable of capturing the subtleness and detail of the facial expression. We also propose the method of logical partitioning of image before applying the local binary pattern. More elongation of the mouth and the highly opened eyes are results of surprise expression. We partition images into three segments. The empirical finding indicates that each partition has feature which are slightly discriminating than the other segments. In LBP method, pixel values in neighborhood are obtained by the thresholding of the center pixel. Later, we obtain LBP histogram.

Original Image Segmented Image LBP Image

Figure 4: LBP image representation

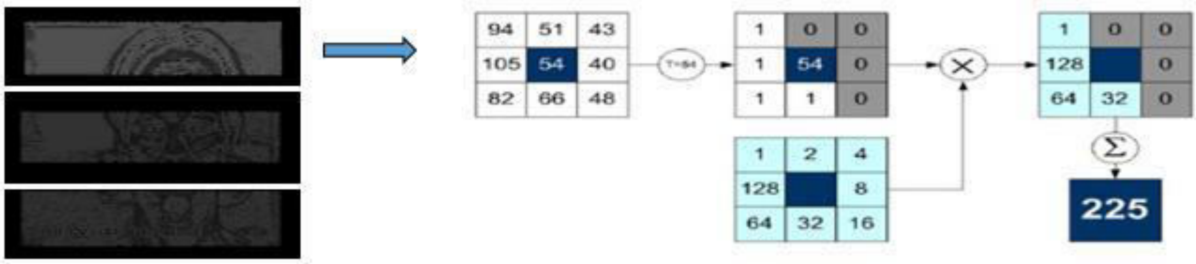

Figure 5: Calculation of LBP image

After calculating the LBP feature, histogram of LBP image is computed as follows in equation (5)
After partitioning the image into three sections, we perform LBP operator over the each section of image. These sections (segments) are relevant because only appropriate portion of face is used for emotion classification and it limits the searches which can improve the speed and performance of facial expression recognition.

Classification

The proposed system is evaluated using the frontal images of CK+ and multiview images of our own created dataset named "OAK". This system uses hidden markov model(HMM), support vector machine (SVM) and hierarchical SVM-HMM classifier.

Hidden markov model is supervised learning technique. It is a stochastic process based on probability. Hidden markov model is not only used in the expression recognition but has wide application in finance market, weather prediction, biometric for gene sequences etc. hidden markov model is based on markov chain. Its states are not visible, but visible on the output of the states. When all the probability distribution of the output of each state is known, next state is predicted through the current states. [6]. Support vector machine (SVM) [4] is used for classifying the expression classes. SVM uses nonlinear classification which maps the feature vector to higher dimensional plane and separates the two classes by a linear decision boundary. However, SVM is a two-class classification technique. There are six emotions namely: 'happy', 'sad', 'surprise', 'fear', 'angry' and ' disgust' have been classified using HMM. However due to closeness among few expressions happy, sad, surprise, fear, angry, disgust. It is observed that accuracy declines due to falling into near similar expressions. We have grouped similar expressions in one expression group. For understanding the feature behavior of each expression group we created three emotion groups consisting two expressions each. These emotion groups are detrimental, unfavorable and delightful. Detrimental emotions are expressed using fearful and angry facial expression; delightful emotion is expressed with joy and surprise expression while unfavorable emotions are showing some sadness or being disgust.

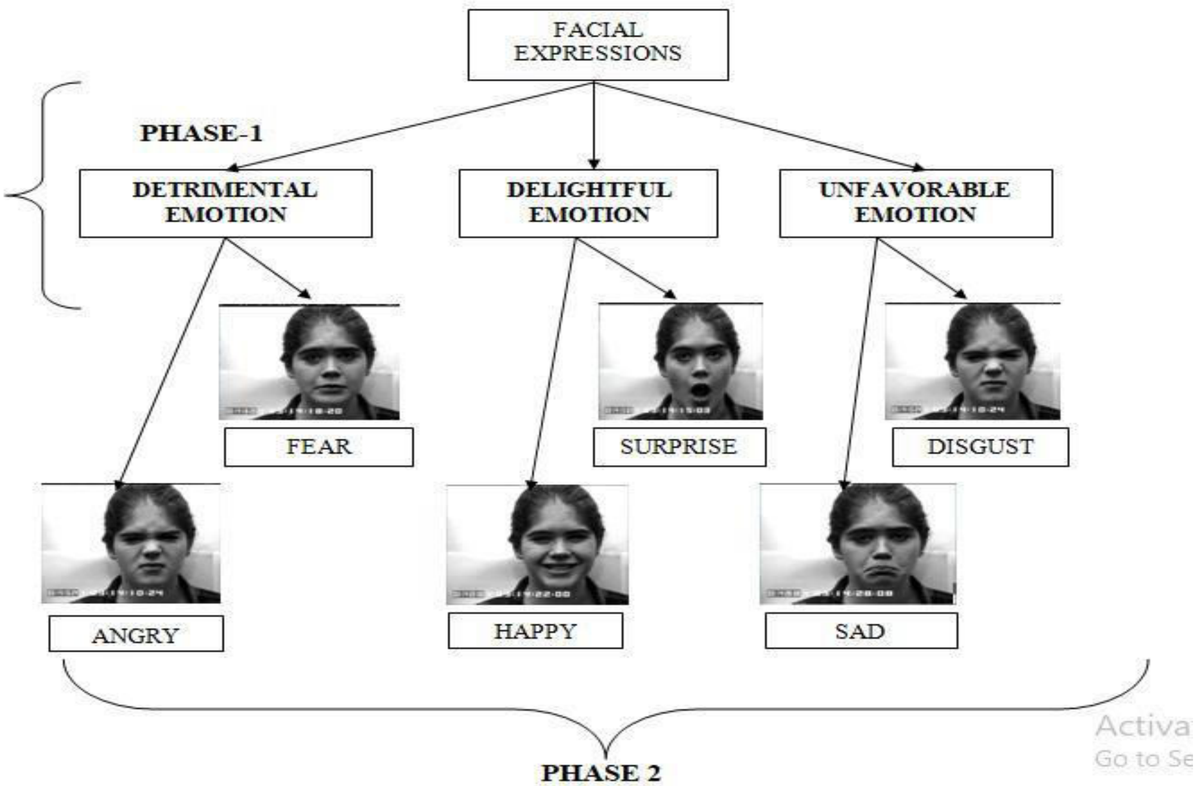

Figure 6: hierarchical classification representation

In the hierarchical classification, first phase performs the classification of emotion using the support vector machine. Further classification of individual expressions is done in phase 2 using HMM. We have conducted our experiment on CK+ dataset and OAK datasets.

Experiments and Performance analysis

The proposed system is evaluated by frontal images of Cohn and Kanade Extended Dataset (CK+) [29] and own created dataset OAK which is created in indoor environmental condition. irst, we describe dataset which are used in experiments and later we discuss the analysis of the results based on the features and classifiers .

Dataset

CK+ dataset is designed by Kanade [5] which is developed for automatic facial analysis. In this dataset there are 527 sequences from 123 subjects whose ages range from 18 to 50. This dataset consist of posed and non-posed expression concurrently. Each sequence expression begins with a neutral expression and proceeds to a peak expression. This experimental facial expression images has 490* 640 resolution. The second dataset OAK has 720*576 resolution This dataset consider 6 subjects with 593 sequential images of each subjects. For training and testing we consider six basic expressions (angry, disgust, fear, happy, sad, surprise) for both the datasets.

IV. Results and discussions

In this section, we analyze the performance of developed FER based on earlier described features using the HMM, SVM and using both. We conduct experiments with variations of SVM kernels on both the datasets.

FER based on Landmark

Classification accuracy of FER based on landmark using HMM with the provision of 3 groups (“Detrimental”,”Unfavorable”, ”Delightful”) is depicted in Table I, for both the datasets while performance of FER using SVM for 3 groups is depicted in Table II.

Table I: Classification accuracy of FERS based on Landmark using SVM and HMM for 3 emotions

Dataset	SVM			HMM	
	Kernel	Regularization parameter (C- Gamma)	Accuracy (%)	No. of HMM component	Accuracy (%)
CK+	Linear	10	47.22	2	40
		100	47.22		
		1000	50.00		
	RBF	10 - 0.00001	67.00		
		1000 -10	69.00	3	43.33
		1000 - 0.00001	75.00		
	Poly (degree-3)	1000 - 10	75.00		
	Linear	10	80.00	2	50
		100	81.66		

OAK		1000	76.66		
	RBF	10 - 0.00001	53.00		
		100 - 0.00001	61.00	3	57
		1000 - 0.00001	75.00		
	Poly (Degree-2)	1000 - 0.00001	55.00		
	Poly (Degree-3)	1000 -10	85.00		

Number of components mentioned in Table I refers to the number of states in HMM. It is generally observed that increasing in number of states can provide the better understanding and prediction of any system state in HMM with 3 number of components. We achieve 57% accuracy and then onwards it declines for classification of 3 groups. SVM offers variety of kernels besides linear shown in above table. Even with various combination of regularization parameter (C) and gamma. Regularization parameter(C) controls the tradeoff between the achieving a low training error and a low testing error that is the ability to generalize your classifier to unseen data. Gamma parameter defines how far the influence of a single training example reaches, with low values meaning ‘far’ and high values meaning ‘close’. The Gamma parameter can be seen as the inverse of the radius of influence of samples selected by the model as support vectors. C and gamma value affects the classification accuracy.

Table II: Classification accuracy of FERS based on Landmark using hierarchical classification

Dataset	Number of HMM components	Accuracy (%)
CK+	3	50
	4	53
	5	56
	6	58.33
OAK	2	53.33
	3	66.66

Table III: Classification accuracy of FERS based on Landmark using SVM for 6 expressions

Dataset	Kernel	Regularization Parameter (C)	Gamma	Degree	Accuracy(%)

CK+	Linear	10			79.12
		100			86.80
		1000			91.66
	RBF	1000	1		43.22
		1000	0.01		58.94
		1000	0.0001		76.12
		1000	0.00001		94.60
	Poly	1000	10	2	93.17
		1000	10	3	94.11
		1000	10	4	87.74
OAK	Linear	1000			96.77
	RBF	1000	10		98.94
	Poly	1000	10	3	99.98

Table II and III depicts the classification accuracy of FER based on landmark using hierarchical and SVM classification for six expressions. It becomes evident from both the tables that SVM is quite superior to hierarchical classification (SVM+HMM).

FER based on Local Binary pattern (LBP)

This section demonstrates the results obtained with local binary pattern feature using SVM , HMM and both for 6 expressions as well as 3 groups.

Table IV: Classification accuracy of FERS based on LBP with logical partitioning using HMM for 3 emotions

Dataset	SVM			HMM	
	Kernel	Regularization Parameter (C-Gamma)	Accuracy (%)	No. of components	Accuracy (%)
	Linear	10	44	3	42.5
		100	63.88		

CK+		1000	55	4	50
	RBF	1000 - 1	87		
		1000 - 10	91	5	53
	Poly (Degree-3)	1000 - 10	98		
OAK	Linear	10	56.66	3	58
		100	76.66		
		1000	85	4	63
	RbF	1000 - 0.00001	55		
		1000 - 10	85	5	63
	Poly (Degree-3)	1000 - 10	96		

Table V: Classification accuracy of FERS based on LBP with logical partitioning using hierarchical classification (SVM+HMM) for 6 expressions

Dataset	Number of HMM component	Accuracy (%)
CK+	2	60
	3	70
	4	75
	5	76.66
OAK	2	50
	3	73.33
	4	53.33

Table IV and V reflects the recognition accuracy achieved of FER system using LBP feature with logical partitioning for classifying 3 group using SVM and HMM classifiers. SVM outperforms by achieving the 85% and 96% accuracy in CK+ and OAK datasets.

Table VI: Classification accuracy of FERS based on Landmark using SVM for 6 expressions

Dataset	Kernel	Regularization parameter (C)	gamma	degree	Accuracy (%)
CK+	Linear	1000			25.88
		10000			54.41
		100000			67.64
	RBF	1000	10		71.56
		1000	100		86.74
		1000	1000		81.86
	poly	1000	10	2	71.43
		1000	10	3	77.45
		1000	10	4	78.43
		1000	100	4	78.43
OAK	Linear	1000			96.66
	RBF	1000	1		98
		1000	10		100
	Poly	1000	10	3	100

Recognition accuracy for classification of six expression is depicted in the table V and VI. Our system using both the classifier, SVM and HMM in hierarchical order have attained accuracy of 76.66% and 73.33% in CK+ and OAK respectively. Classification with SVM classifier in degree 3 of polynomial kernel has achieved 86.74% and 100 % accuracy with LBP feature for CK+ and OAK dataset respectively.

Comparative Performance Analysis

We have thoroughly analyzed the performance of FER based on very essential and well known features using SVM and HMM and combination of both. Table I to VIII shows the accuracy of various proposed approaches. Initially, we formed three groups to boost the classification accuracy. Which has eventually obtained moderate accuracy with landmark feature of nearly 75% using SVM. System developed using SVM in first phase (classification in 3 groups) and HMM in second phase (group classification in individual expression) merely succeed to achieve 58% and 66% of accuracy on CK+ and OAK dataset respectively. It is clearly reflected from table IV that SVM outperform over all earlier proposed techniques with very high accuracy of 94.6% and 99.9% on CK+ and oak dataset respectively.

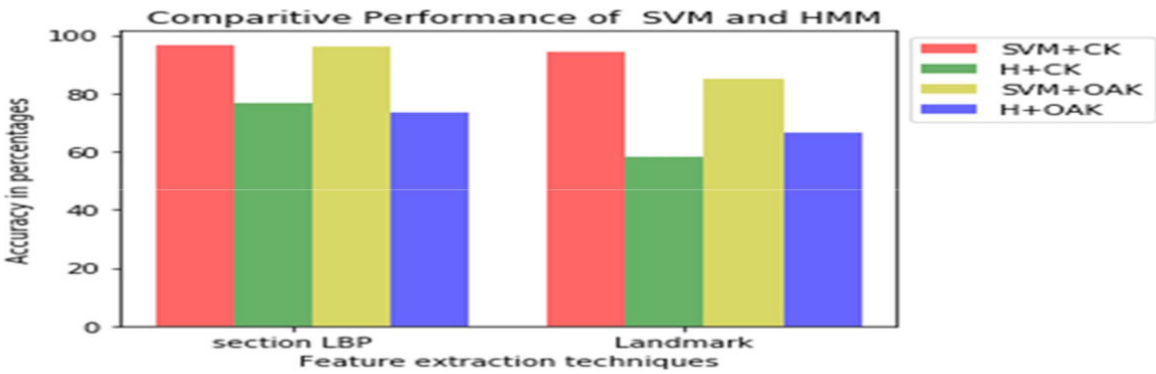

Figure 7: graph representation of classifier performances

In overall, it is observed that use of LBP feature with logical partitioning is found efficient for the classification of expression into 3 groups. Efficiency reaches nearly 98% on CK+ and 96% on the OAK dataset. Figure 7 clearly shows that SVM outperforms the HMM and combination of classifiers (HMM+SVM) with landmark and section LBP features.

V. Conclusion

In this paper, we have conducted systematic investigation of the FERS using the classifier SVM and HMM. We have conducted our experiments using two features, landmark and local binary pattern and understood the behavior of both classifier and its combination by varying the parameters. We have tested our proposed system with well-known dataset CK+ and own created dataset named OAK. Empirical results shows that the SVM is found more robust and efficient with the use of landmark feature than HMM. In spite of increase in usage of deep learning techniques, obtained results clearly indicate the huge relevance of SVM for such classification problems. Deep learning techniques demand complex architecture massive training datasets and better support from hardware like GPU and also still lacks in generalization. Hence, SVM producing quite good and comparable results can be definitely favored over deep learning techniques because of its simplicity and no need of any extra hardware setup.

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