



## A Comparative Analysis of Wavelet-Based FEMG Signal Denoising with Threshold Functions and Facial Expression Classification Using SVM and LSSVM

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### ABSTRACT

This work presents a technique for the analysis of facial electromyogram signal activities to classify five different facial expressions for computer-muscle interfacing applications. Facial electromyogram (FEMG) is a technique for recording the asynchronous activation of neuronal inside the face muscles with non-invasive electrodes. FEMG pattern recognition is a difficult task for the researcher, where classification accuracy is key concerns. Artifacts, such as eyeblink activity and electroencephalogram (EEG) signals interference, can corrupt these FEMG signals and directly affected the classification results. In this work, a robust wavelet-based thresholding technique, which comprised of a wavelet transform (WT) method and the statistical threshold, is proposed to remove the different artifacts from FEMG datasets and improve recognition accuracy rate. A set of five different raw FEMG data set was analyzed. Four wavelet basis functions, namely, haar, coif3, sym3, and bior4.4, were considered. The performance parameters (signal-to-artifact ratio (SAR) and normalized mean square error (NMSE)) were utilized to understand the effect of the proposed signal denoising protocol. After denoising, the effectiveness of different statically features has been extracted. Two pattern recognition algorithms support vector machine (SVM) and the least square support vector machine (LSSVM) are implemented to classify extracted features. The performance accuracy of SVM and LSSVM classifier was evaluated and compared to know which classifier is the best for facial expression classification. The results showed that: (i) the proposed technique for denoising, improves the performance parameter results; (ii) The proposed work gives the best 95.24% classification accuracy.

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### NOMENCLATURE

PT	Proposed threshold	Ci	DWT coefficients
WP, Q (t)	Mother wavelet	K	Length of FEMG signal
$\beta_i$	Statistical threshold	P	Scaling parameter
$\beta_{NEW}$	Proposed threshold	Q	Shifting parameter
SAR	Signal to artifact ratio	std	Standard deviation
NMSE	Normalized mean square	N	Number of wavelet coefficient at each level
WT	Wavelet Transform	Ti	Threshold improvement factor of PT
DWT	Discrete wavelet transform	$\alpha_i$	Universal Threshold
SVM	Support vector machine		
LSSVM	Least square support vector machine		

### 1. INTRODUCTION

Recently researchers and scientists giving the highest priorities for developing a methodology to interface

between electronics-mechanics with biology-medicine and try to improve the lifestyle. This study will help patients who are critically disabled and cannot even move their neck by inventing controlling devices, such as hands-free wheel-chairs. Since for designing such a system, strong human-computer interfaces have been needed [1]. Recognizing the facial expression through

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bioelectrical action and transform into control commands for the system have focused in this study.

FEMG is the accepted standard for measuring facial muscle activity [1-3]. However, FEMG signals are nonlinear and random, generated by the summation of action potentials from thousands of motor units [4]. Surface electrodes acquired the recruitment and firing frequency of action potential.

EMG signals are a noninvasive technique of understanding muscle activity [5]. Due to the nonlinear and random nature of FEMG signals, mathematical tools such as DFT and FFT are failed to provide specific information. For analysis of such a signal, DWT methods were introduced, which provide better time-frequency information [6]. The FEMG signal having amplitude range differs from 0 to 12mv and frequency range differs from 0 to 450Hz respectively.

Table 1 depicts the previous research work which were used FEMG signals to classify either facial expressions or emotions. In all the studies, the number of classes, channels, segmentation with feature extraction method, and classification results were shown. This paper proposed an EMG based technique for recognizing five different facial expressions by proposing the methodology that results in good recognition accuracy. A wavelet-based denoising protocol comprised with a statistical threshold proposed to clean the FEMGs and improve the signal to noise ratio. This study on FEMG signal analysis is carried out in different stages. (1) Proposing a FEMGs denoising

protocol, (2) Selecting the informative and discriminative FEMG features (3) Examining SVM and LSVM pattern recognition classifiers and identifying the best one.

## 2. SUBJECT AND EXPERIMENT SETUP

The ethical committee formed by the electrical department VJTI Institute Mumbai has approved the experimental work for FEMG signal recording.

In this study, the myon made aktos-mini EMG acquisition device depicts in Figure 1 used for FEMG signal recording. The electrodes were cleaned with alcohol, and then a gel is used to increase the conductivity of the electrode. After that, two pairs of non-invasive electrodes are attached to the specified participant's face in the bipolar configuration as shown in Figure 1(a). The recorded signal sampled at 1KHz sampling frequency. FEMG data were collected from thirty physically fit subjects, including sixteen males and fourteen females in the age group of 18-40. The five facial expressions considered in this work are smiling, closing both eyes, opening the mouth saying 'a', raising the eyebrows and keeping the face in a neutral state. Participants were asked to perform each expression for two seconds of time duration. Each expression can be performed twice by each participant with ten seconds rest between them. Hence for each expression, four (2×2) seconds are informative information recorded

**TABLE 1.** Literature review in the area of FEMG Analysis

Classes	Channels	Segmentation (msec)	Features	Classifier	Accuracy (%)	Ref.
5	3	-	-	Thresholding	-	[7]
5	3	200	MAV	SVM	89.7	[8]
3	4	10	MRMS	LS	100	[9]
6	8	-	AV	Gaussian	92.00	[10]
5	1	400	RMS,FMDZC, MAV	BP, ANN	98.7	[11]
4	-	-	VAR	MLP,KNN	61.0,60.7	[12]
5	1	200	FMD,SC,WL,FMN	SVM	93.75	[13]
4	-	-	Wavelet	SVM	-	[14]
5	2	256	RMS	FCM	90.80	[15]
8	3	200	RMS	FCM, SVM	80.40,91.80	[16]
10	3	256	RMS	FCM	90.4	[17]
5	1	200	8 time domain features	SVM	93.50	[18]
4	-	-	Wavelet coefficients	LSSVM	91.6	[19]
10	3	256	WL, RMS, MAV	FCM	21.5-90.8	[20]
10	3	256	RMS, MAV	LSSVM	19.7-97.1	[21]
2	3	100	MAV	BPANN	80.-90.	[22]

through, data acquisition device. For five different, expressions each of 8000 sample's datasets (2 [no. of channels] × 4 seconds [informative signal] × 1000 [sampling frequency]) are collected from each subject. The band-stop filter with 50 Hz frequency is applied to remove the effect of line frequency noise.

### 3. WAVELET TRANSFORM AND WAVELET BASIS FUNCTION

Wavelet Transform (WT) converts the time-domain FEMG signal into its set of basis functions known as wavelets [23, 24]. These wavelet functions are achieved by doing dilation and shifting of the mother wavelet shown in Equation (1) [25].

$$\omega_{p,Q}(t) = w\left(\frac{t-Q}{P}\right) \tag{1}$$

In Equation (1), P indicates a scaling parameter whereas Q shifting parameter [25]. The FEMG datasets, decomposed into multi-level wavelet coefficients in order to get precise information where artifacts are available. Figure 2 shows the DWT decomposition structure.

WT of the FEMG datasets provides the multi-level coefficients which show the correlation between FEMG datasets with wavelet basis functions. Figure 3 depicts some WT basis functions implemented in this study. These wavelet functions resemble the characteristic of eye blinks activity, EEG artifacts, and perform well [26]. The selection of efficient wavelet basis function is considered as a dominant parameter in wavelet denoising for the FEMG signal. For non-stationary signals, biorthogonal is best for decomposing the signal.

In this work, we have implemented and compared symlet3, haar, coif3, and biorthogonal 4.4 wavelets basis function. Figure 3 depicts wavelet basis functions implemented in this work for artifact removal from FEMG data.

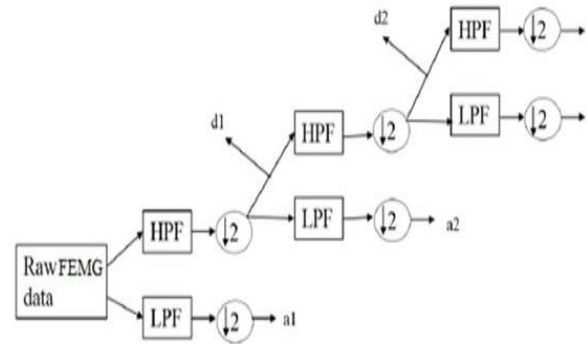


Figure 2. A DWT decomposition structure

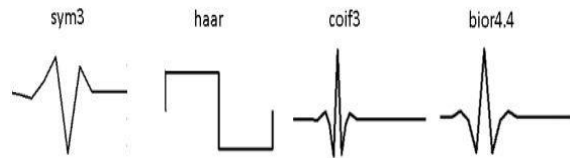


Figure 3. Wavelet basis functions applied for artifact removal from FEMG data

### 4. PROPOSED METHODOLOGY FOR FEMG SIGNAL DENOISING

The universal threshold (UT) was first suggested by Kumar et al. [26]. Threshold values are determined by the following relation:

$$\beta_i = \alpha_i \sqrt{2 \log K} \tag{2}$$

Here K represents the length of the raw FEMG signal,  $\alpha_i$ , mean absolute deviation, and  $\beta_i$  is the threshold at *i*th decomposition level.

Statistical threshold (ST) was recommended by Krishnaveni et al. [27], which practically depends on the statistics of the signal. The effective threshold value  $\beta_i$  is determined by the following equation:

$$\beta_i = 1.5 * \text{std}(C_i) \tag{3}$$

where  $C_i$  represents the DWT coefficients at the *i*th level and factor 1.5 is the approximate value of Gaussian noise.

The proposed threshold (PT) presented in this work depends on the statistics of the FEMG signal characteristic. The PT is adaptive to distinct sub-band by analyzing the wavelet coefficients. Mathematically, PT derived by the superposition of the universal threshold and the statistical threshold. The thresholds values of  $\beta_{NEW}$  determined by the following equation:

$$\beta_{NEW} = T_i * \text{std}(C_i) \tag{4}$$

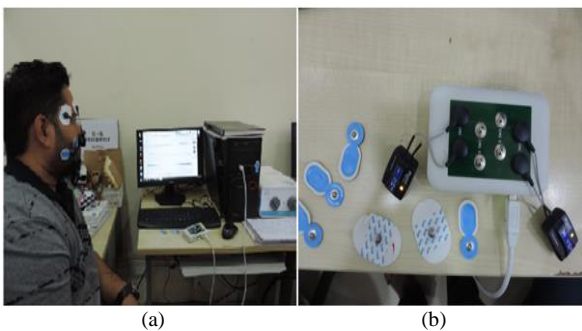


Figure 1. (a) Setup for FEMG Signal Recording, (b) Wireless Data acquisition System

$$T_i = \frac{(\alpha_i - U_i)}{e^{(\alpha_i + U_i)}} \tag{5}$$

Std(C<sub>i</sub>) represents the standard deviation of wavelet coefficients at the i<sup>th</sup> level. Where T<sub>i</sub> is the threshold improvement factor, and α<sub>i</sub> indicates the universal threshold function

$$U_i = \frac{\sum_i |C_i|}{N} \tag{6}$$

where N represents the number of wavelet coefficients at each level. Hard thresholding sets any coefficient greater than the threshold value to zero [28]. In this paper, hard thresholding was implemented, which removes wavelet coefficients (artifacts) if the wavelet coefficient is greater than the PT value. Figure 4 depicts the general steps of the proposed methodology for denoising of FEMG signal.

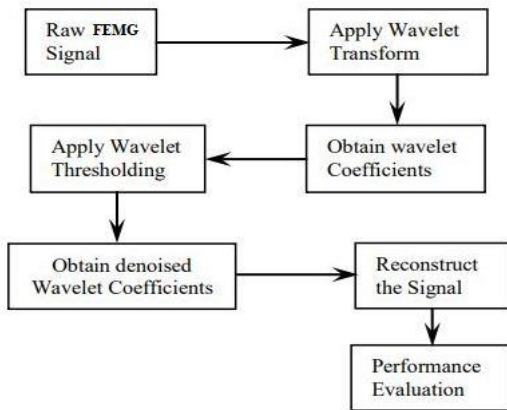
**4. 1. Performance Parameters**

The performance of the proposed threshold is based on the two statistical performance parameters. The performance parameters are SAR and NMSE, observed in this work. SAR is a technique to estimate the amount of artifact removal in a FEMG signal after processing with the proposed algorithm [29]. If F is the FEMG signal with artifact and F̂ is the corrected signal obtained after processing then

$$SAR = 10 \log \left( \frac{std(F)}{std(F - \hat{F})} \right) \tag{7}$$

NMSE define the difference between F1(j) (signal without artifact) and F2(j) ( signal with artifacts) [11]. NMSE is computed in dB using the given equation.

$$NMSE = 20 \log E \left\{ \frac{\sum [F1(j) - F2(j)]^2}{\sum [F1(j)]^2} \right\} \tag{8}$$



**Figure 4.** Block diagram of the proposed methodology for FEMG signal denoising

**5. FEATURE EXTRACTION**

Analysis of large numbers of FEMG data is a difficult task for researchers and dimension reduction is a necessary step for further analysis. Feature extraction performs a key role by converting huge datasets into the précised meaning. There are various techniques with numerous complexity in time and frequency domain, which shows different FEMG characteristics [5]. For feature extraction, we implemented a WT method that generates wavelet coefficients [29-36]. An active part of FEMG data containing 8000 samples with a sampling frequency of 1000Hz. The FEMG data then decomposed into 3 levels of decomposition using on wavelet family ‘db4’. The frequency bands for decomposed wavelet coefficients are 0 - 120 Hz. Out of every decomposed frequency sub-band, we extracted six different features using wavelet coefficients. According to literature, very rare studies analyzed and compared FEMG frequency domain features [30]. The perfect evaluation and analysis are required to discover the most discriminative FEMGs feature by selecting a range of classifiers. In this paper, the performance accuracy of six widely used frequency domain FEMG features is determined. The wavelet domain extracted features are mean, variance, covariance, standard deviation, energy, and RMS.

**6. CLASSIFICATION**

For recognition of different facial expressions, extracted features must be classified into accurate classes. The selected classifier must be fast and efficient enough to meet the proper requirement. Here, two pattern recognition algorithms are implemented on extracted features to classify the FEMG datasets. The selection of classifiers will be based on several criteria, such as high-performance accuracy based on literature, processing time, etc. Frequency-domain features can be given to classifiers that classify facial expression. The implemented classifiers were grouped into different kernel machine method. The optimum model of the classifier can be designed by examining a wide range of kernel values in order to find the best performance of the classifier. For this purpose, a 70-30 cross-validation scheme is used to test the parameters and evaluate the classifier performance. In this work, SVM [13, 33] and LSSVM [31] are utilized.

SVM is a nonparametric classifier, and it targets to determine discriminant hyperplanes that differentiate the data into various groups [30]. A multiclass SVM with a polynomial kernel function was implemented. The Polynomial kernel is given good accuracy compared to other nonlinear kernels. The mathematical equation of the polynomial kernel given as follows:

$$f(y_i, y_j) = (y_i * y_j + 1)^c \tag{9}$$

where  $c$  represents the degree of the polynomial. The recognition accuracy depends on the degree of the polynomial ( $c$ ). For FEMG datasets (nonlinear), poly-order should be more than one.

LSSVM is the advanced version/model of SVM classifiers, and it improves the process during the testing and training phase [31]. In this technique, equality constraints were implemented to find the solution to the optimal problem by dealing with a set of equations instead of the quadratic optimization problems [20]. The LSSVM methodology was implemented in this paper formed by the Gaussian kernel function. The Gaussian kernel  $GK(K_a, K_b)$  defined as follows:

$$GK(k_a, k_b) = \exp\left\{-\frac{\|k_a - k_b\|}{2\sigma^2}\right\}; a, b = 1, 2, \dots, N \tag{10}$$

Here  $\sigma$  shows the width of the Gaussian kernel [37, 38].

### 7. RESULTS ANALYSIS AND DISCUSSION

Let  $Y[n]$  is the recorded FEMG signal (with artifacts) and  $Y_{tr}[n]$  is the true FEMG signal (artifact-free). The objective of the wavelet-based proposed thresholding algorithm in this work is to estimate  $Y_{tr}[n]$  by efficiently removing artifacts from  $Y[n]$ . The proposed algorithm for denoising of FEMG signals as follows:

- Wavelet transforms with different wavelet basis function, decompose the actual FEMG signal  $Y[n]$  into wavelet coefficients  $W_i^n = [W_i^1, W_i^2, \dots, W_i^n]$  at each scale  $i$ .
- Wavelet coefficients  $W_i^n$  at each scale  $i$ , was thresholded, by applying appropriate thresholding function shown in Equation 5. The thresholded wavelet coefficients  $T_i^n = [T_i^1, T_i^2, T_i^3, \dots, T_i^n]$  are the estimate of the coefficient values of  $Y_{tr}[n]$ .
- Denoised (reconstructed) signal was obtained by applying the inverse wavelet transform on the thresholded wavelet coefficients  $T_i^n$ .

The performance of the proposed threshold was measured by SAR and NMSE. The methodology that gives the maximum value of SAR and the minimum value of NMSE is more acceptable. Table 2 compares the SAR values on FEMG signals using different threshold and different wavelet basis functions. From Table 2, it is noted that SAR values are maximum when DWT + PT combination is used with all four types of wavelet basis function, indicating DWT + PT effectively reduces the artifacts, while DWT + ST and DWT + UT is conservative. Table 3 compares the NMSE values on FEMG signals using different thresholds and different wavelet basic functions. Based

on Table 3, DWT + PT again performs well. The lower value of NMSE shows the best performance. NMSE values are minimum when PT is applied with DWT and a combination of all four basis functions. The proposed algorithm is tested for FEMG signals with artifacts. The sample for an eight-second epoch is shown in Figure 5, along with the reconstructed FEMG signal obtained after PT.

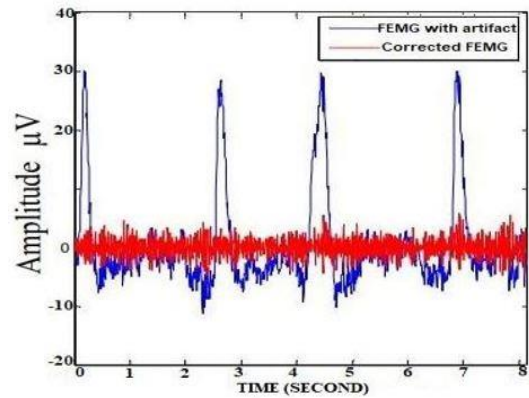
Classification accuracy is the most important parameter to estimate the system performance. The classification accuracy of classifiers is better by applying denoised features, obtain after PT rather than the raw ones. The LSSVM classifier gives the best classification results, which is 95.24%, followed by SVM (91%), respectively. Table 4 depicts the facial expression classification confusion matrix for the LSSVM model. Table 5 depicts the facial expression classification confusion matrix for the SVM Model. The results show that all five facial expressions (five classes) recognized with high accuracy. For comparison of SVM

**TABLE 2.** SAR on FEMG signals with different threshold and wavelet basis function

Thresh.	sym3	Haar	Coif3	Bior4.4
DWT+UT	1.28±0.63	1.13±0.49	1.31±0.63	1.3 ± 0.62
DWT + ST	1.91±0.85	1.88±0.75	1.9±0.82	1.88±0.73
<b>DWT + PT</b>	<b>2.53±0.96</b>	<b>2.98±0.79</b>	<b>2.30±0.85</b>	<b>2.28± 0.85</b>

**TABLE 3.** NMSE on FEMG signals with different threshold and wavelet basis function

Thresh.	sym3	Haar	Coif3	Bior4.4
DWT+ UT	-5.21±2.7	-4.8±1.90	-5.23±2.7	-5.29±2.35
DWT + ST	-7.97±2.1	-5.9±2.55	-7.5±3.3	-7.32±3.15
<b>DWT + PT</b>	<b>-8.82±3.7</b>	<b>-8.57±2.6</b>	<b>-8.74±3.2</b>	<b>-8.87±3.22</b>



**Figure 5.** FEMG with an artifact and corrected FEMG signal using PT

**TABLE 4.** The facial expression classification confusion matrix for the test set using the LSSVM

Facial Expression	Class 1	Class 2	Class 3	Class 4	Class 5
Class 1	98.8	1.2	0	0	0
Class 2	4.7	90.5	1.2	1.2	2.4
Class 3	0	2.4	89.3	0	8.3
Class 4	0	0	0	100	0
Class 5	0	0	2.4	0	97.6
<b>Average(%): 95.24</b>					

**TABLE 5.** The facial expression classification confusion matrix for the test set using the SVM Model

Facial Expression	Class 1	Class 2	Class 3	Class 4	Class 5
Class 1	90	0	4	6	0
Class 2	3	95	0	0	2
Class 3	4	0	92	4	0
Class 4	5	0	6	81	8
Class 5	0	3	0	0	97
<b>Average(%): 91.0</b>					

**TABLE 6.** The classification accuracy obtained from different classifiers

Sr. No.	Classifier	Classification Accuracy (%)	
		RAW FEMG	Denoised FEMG (After Proposed Threshold)
1	LSSVM	87.3	95.24
2	SVM	86.9	91
3	KNN	85.1	90.1
4	ANN	83.6	89.3
5	LDA	80.5	85.14

with LSSVM, we implemented the same training and test set for the SVM and LSSVM based on recognition model. The results show that the performance of the SVM model was lower than that of the LSSVM model. Table 6 compares the classification accuracy of different classifiers for raw and denoised FEMG signal.

## 8. CONCLUSION

An effective study based on FEMG signal analysis is presented here in order to provide the best performance to classify five different facial expressions. In this work, FEMG data acquired from myon made wireless data

acquisition device has been presented as a representative of the FEMG signal contaminated with artifacts to compare several wavelet-based techniques. The most common artifact in the FEMG signal is due to the effect of EEG interference and eye blink activity. A robust technique is proposed for FEMG signal denoising, including DWT with proposed thresholding (PT), and results show that the proposed method denoise the FEMG signal effectively and enhances the performance of the classifier. Based on the SAR results depicted in Table 2, DWT with PT using haar wavelet is to be more useful than other combinations. Based on analysis and results, DWT with PT using all WT basis functions have also performed satisfactorily for removing different artifacts while preserving original signals.

After denoising of FEMG data, features can be extracted using the WT method with the db8 family. Among all six features, RMS and energy is the most informative feature. Inspection on two classifiers SVM and LSSVM reveals that the LSSVM model has better capability to classify features giving 95.24% classification accuracy. Our study shows the proposed signal denoising protocol can improve the system performance. This presented work also helps to set up a systematic connection between the face muscle and machine. This interface can be applied for designing real real-time processing controlling devices like assistive wheelchairs.

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### Persian Abstract

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#### چکیده

این کار یک تکنیک برای تجزیه و تحلیل فعالیت های سیگنال الکترومیوگرام صورت برای طبقه بندی پنج حالت مختلف صورت برای برنامه های کاربردی واسط رایانه-عضله ارائه می دهد. الکترومیوگرام صورت (FEMG) روشی برای ضبط فعال سازی ناهمزمان نورو در عضلات صورت با الکترودهای غیر تهاجمی است. شناخت الگوی FEMG برای محقق کاری دشوار است، که در آن دقت طبقه بندی نگرانی های کلیدی است. مصنوعات، از قبیل فعالیت چشم بند و تداخل سیگنال های الکتروانسفالوگرام (EEG)، می توانند این سیگنال های FEMG را خراب کرده و به طور مستقیم بر نتایج طبقه بندی تأثیر بگذارند. در این کار، یک تکنیک آستانه محور مبتنی بر موجک، که از یک روش تبدیل موجک (WT) و آستانه آماری تشکیل شده است، برای حذف آثار باستانی مختلف از مجموعه داده های FEMG و بهبود میزان دقت تشخیص استفاده شده است. مجموعه ای از پنج مجموعه داده مختلف FEMG خام مورد تجزیه و تحلیل قرار گرفت. چهار تابع پایه موجک، یعنی `haar`، `coif3`، `Sym3` و `bior4.4` در نظر گرفته شد. از پارامترهای عملکرد (نسبت سیگنال به مصنوع (SAR) و میانگین خطای مربع عادی (NMSE) برای درک تأثیر پروتکل دیوایزینگ سیگنال پیشنهادی استفاده شده است. پس از `denoising`، اثربخشی ویژگی های مختلف استاتیک استخراج شده است. دستگاه بردار پشتیبانی الگوریتم ها (SVM) و ماشین بردار کمترین مربع پشتیبانی (LSSVM) برای طبقه بندی ویژگی های استخراج شده اجرا می شوند. علت عملکرد SVM و طبقه بندی کننده LSSVM مورد بررسی قرار گرفت و مقایسه شد تا بدانیم کدام طبقه بندی بهترین برای طبقه بندی بیان صورت است. نتایج نشان داد که: (۱) روش ارائه شده برای نانوایی کردن، پارامتر عملکرد را بهبود می بخشد؛ (ب) کار ارائه شده بهترین دقت طبقه بندی را نشان می دهد.

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