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***Research paper***

# Support Vector Machine Performance with Optimal Parameters Identification in Recognising Asphyxiated Infant Cry

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## Abstract

Detection of asphyxia in infant at an early stage is crucial to reduce the rate of infant morbidity. The information regarding asphyxia can be extracted from infant cry signals using support vector machine (SVM) combined with effective feature selection methods such as principal component analysis (PCA) or orthogonal least square (OLS). The performance of SVM in recognizing infant cry with asphyxia after undergone comprehensive identification of optimal parameters at the feature extraction and classification stages has not been reported. This paper describes the two stages of optimal parameter identification; at Mel-frequency Cepstral coefficient (MFCC) analysis stage, SVM with and without employing the PCA and OLS stages, and the performance of the SVM in recognizing infant cry with asphyxia resulted from all levels of optimal parameters identification. The SVM was first optimized after performing MFCC analysis to find the optimum parameters. Two types of kernels were used, the polynomial and RBF kernels. The subsequent SVM optimizations were conducted after PCA and OLS were employed. In the PCA, the significant features were selected using eigenvalue-one-criterion (EOC), cumulative percentage variance (CPV) and the Scree test (SCREE). The SVM performance was evaluated based on classification accuracy and computation time. The experimental results have shown that the optimized SVM was able to recognize the asphyxiated infant cry with an accuracy of 94.84% and computation time of 1.98s using PCA with EOC and RBF kernel.

***Keywords***: *Asphyxia; Infant cry; orthogonal least square; principal component analysis; support vector machine.*

## 1. Introduction

One of the major causes of infant morbidity is asphyxia which is considered as the respiratory failure. It occurs due to inadequate intake of oxygen [1]. Diagnosing asphyxia in infants at early birth is very important so that appropriate treatment can be given before serious complication arises. Without proper treatment, a condition called hypoxia may occur which can cause more complicated issues for example damage to infant's brain, organs, tissues or even fatality.

Asphyxia is associated with neurological dysfunction level which influences the sound of the cry produced by the infants [1]. The cry signals of asphyxiated infants have distinct patterns compared to that of healthy infants [2-3]. Computer-Based analysis can be used to distinguish between the healthy and asphyxiated infant cries [2-3].

In the conventional Computer-Based analysis, the cry signals will go through pre-processing to remove interferences before going through the feature extraction stage where the features of the signals are extracted. The suitable method for analyzing infant cry is Mel-frequency Cepstral coefficient (MFCC) due to its ability in recognizing and differentiating speech patterns [4-6]. The drawback of this method is that high dimensional feature is produced, which contain redundant and less significant information. An additional stage called feature selection has to be employed before the classification process to select significant features. Features resulted from extraction process have a large dimension, thus needs to be removed. The feature selection process will help to reduce the dimension of the signals, increase the accuracy of the classifier and reduce the computation time. Various feature selection techniques have been used by researchers to select features from infant cries such as principal component analysis (PCA), fuzzy relational product (FRP) and statistical method [7-10]. There is no report describes the use of Orthogonal Least Square (OLS) to select infant cry features. Based on our previous studies, OLS is capable of selecting significant features from MFCC [4, 11, 12]. However, the studies only used a small number of samples and reported the preliminary results.

In this work, OLS and PCA are used to select useful information and remove the redundant features. PCA is selected based on its excellent performance in the study of infant cry recognition and gait analysis [13, 14]. PCA has not been applied to both normal and asphyxiated cry. Furthermore, three types of PCA selections criteria known as eigenvalue-one-criterion (EOC), cumulative percentage variance (CPV) and Scree test (SCREE) have not been investigated yet in the previous study. Support vector machine (SVM) is a suitable classifier to distinguish the infant cry with asphyxia since it has good generalization ability and resistant to the over-fitting problem than other classifiers [15-18]. However, to achieve high accuracy, optimization of SVM has to be carried out.

This paper describes the performance of optimized Support Vector machine in recognizing asphyxiated infant cry. Two levels of optimal parameters identification were conducted; the first level is at the feature extraction stage and the second level is at the SVM

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classification with and without employing feature selection methods. The optimum parameters and method are selected based on the highest classification accuracy and lowest computation time.

## 2. Research Method

The process of recognizing the infant cry with asphyxia includes preprocessing, feature extraction, feature selections and finally classification. In this study, the normal and asphyxiated infant cry signals were obtained from the University of Milano–Bicocca [19]. The features of the cry signals were extracted using MFCC and the significant features were selected using PCA and OLS. To obtain optimum results, the identification of optimal parameter was carried out at the feature extraction and classification stages. The pre-processing stage was performed to normalize and pre-emphasize the signal. Here, the amplitude of the cry signals was normalized in the range of +1 to -1, each signal was sampled at eight kHz and the energy of the signal was increased to ease the extraction process. After pre-emphasizing, the signals were divided into one second which resulted in 316 segments of normal cries and 284 of asphyxiated cries.

### 2.1 Identification of Mel-frequency Cepstral Coefficient Optimal Feature

In the feature extraction stage, MFCC was used and the signals were passed through five stages. The first stage was frame blocking, followed by windowing and fast Fourier transform (FFT) computation. Then, Mel-frequency wrapping and the Discrete Cosine Transform (DCT) computation were carried out as shown in Fig. 1.

The signal was first divided into equal frames and followed by the multiplication of each frame with a Hamming window with a width of 25ms and an overlapped of 50% between successive frames to minimize signal discontinuities. Fast Fourier transform was computed and the resultant spectrum was passed through triangular filter banks to produce Mel-spectrum. Equation (1) was used to map the acoustic frequency to a 'perceptual frequency' [20]. To generate the corresponding coefficients, DCT was then computed using Equation (2). This process converts the Mel-spectrum into a time domain coefficient [20-22]. Here, the optimal number of filter bank was obtained by varying the number of filter banks in the range of 20 to 30. From the number of filter bank variations, ten to twenty coefficients were produced which formed 121 feature sets. To select the optimum number of the filter bank, classification using SVM was carried out as described in Section 2.2.

$$mel = 2595\log_{10}(1+ freq/700) \tag{1}$$

$$\tilde{C_n} = \sum_{k=1}^{K}(\log \tilde{S_k})[(\pi n(k-1/2))/K] \tag{2}$$

where S is the log energy output of kth filter and n=1,2…M

The decision function can be expressed as:

$$y(x) = sign\left[\sum_{i=1}^{N} y_i \alpha_i K(x_i, x_j) + b\right] \tag{3}$$

where N is the total support vector number, $\alpha_i$ is a Lagrangian multiplier, $x_i$ is a component vector of $x$ and $y_i$ is the label associated with $x_i$; +1 or -1, $x_j$ is support vector and $K(x_i, x_j)$ is the kernel function.

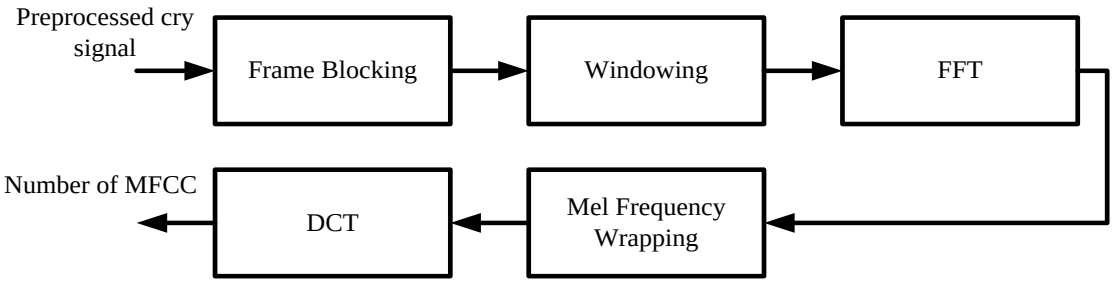



**Fig. 1:** Process of producing MFCC

### 2.2 Identification of SVM Optimal Model

It has been reported that SVM is a good classifier in classifying cases in geoscience and remote sensing [23] and biomedical areas such as alertness from EEG [24], cancer [25-29], heart disease [30, 31], image processing [32-34], chemistry area [35] and speaker identification [36-38]. In the classification using SVM, a hyperplane is used to distinguish between two cases. Thus, it is important to construct an optimal separating hyperplane. Optimal hyperplane is achieved when there is a large distance between hyperplane and data point, which can be accomplished by selecting appropriate regularization parameter (*C*) and kernel function [39, 40]. The data can be linearly separated if they are transformed into high dimensional space using a kernel function. Based on the value of *C*, the hyperplane is created into these transformed data. Overfitting or underfitting of data may occur if the value of *C* is large or small respectively.

The kernel function can be expressed as:

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \tag{4}$$

The common kernels used are polynomial and radial basis function (RBF) which can be expressed using (5) and (6) respectively.

$$K(x_i, x_j) = (x_i \bullet x_j)^d \tag{5}$$

$$K(x_i, x_j) = \exp\left(\gamma \left\| x_i - x_j \right\|^2\right) \tag{6}$$

Where $d$ is polynomial order and $\gamma$ is the kernel width.

To obtain the optimal feature set, the 121 feature sets extracted from the MFCC analysis were passed through SVM with different kernels; polynomial and RBF kernels. To obtain an optimal model of SVM with the polynomial kernel, $C$ was varied from 0.000001 to 0.01 and $d$ was varied from two to four. For SVM with RBF kernel, $C$ and $\gamma$ were varied from 0.01 to 100 and 0.001 to 0.05 respectively. The range of $C$, $d$, and $\gamma$ was selected according to the previous studies and several experiments. Here, the training and test datasets were separated using 10-cross validation.

### 2.3 Identification Of SVM Optimal Model After Applying PCA

PCA with three algorithms; EOC, CPV, and SCREE was performed on the optimized feature set to select the significant features. PCA involves a mathematical procedure that transforms redundancy variables into employment variables called principal components. The most important process offered by this analysis is the elimination of unwanted components and retainment of information. EOC retains components that have eigenvalue equal or greater than one. The eigenvalue is greater than one means that the component has less variance. In CPV, components are retained if the components have the cumulative percent of the variance accounted for at least 70% (and sometimes 80%) [41]. SCREE is a technique where a graph is used to display the eigenvalue and preserves the components that have the large distance from each other. It is a common practice that the SCREE is supplemented with other techniques such as EOC and CPV [42]. After performing PCA on the extracted features, optimization of SVM was carried out by varying the $C$ and $d$ values for polynomial kernel, and $C$ and $\gamma$ for RBF kernel as described in Section 2.2. This approach is called PCA-SVM.

### 2.4 Identification Of SVM Optimal Model After Applying OLS

OLS is another method used in this study to select the significant features from the optimized features obtained from the MFCC analysis. It is an algorithm used to determine the significant terms in a linear regression model [43, 44]. It has the capability to reduce MFCC features. It operates by estimating the contributions of each lagged feature to the reduction in error, or error reduction ratio (ERR) and calculates the percentage reduction made by each feature with respect to the output mean squared error (MSE). Then the lagged features are ranked according to its contribution in reducing error in the model [45, 46]. The significance values of MFC coefficients were ranked based on the value of ERR. The higher the ERR value, the more significant the MFCC is. After applying OLS on the optimized features, the SVM optimization was performed using the same technique and setting as described in Section 2.2. This method is called OLS-SVM.

## 3. Results and Analysis

### 3.1 Optimum MFCC Feature Set and Parameter

The effect of varying the number of coefficient and filter bank on the classification accuracy of SVM with the polynomial kernel ($C$ = 0.0001 and $d$ = 2) is shown in Fig. 2. Obviously, feature sets generated from ten coefficients produces the highest classification accuracy (94.17%) and feature sets generated from 20 coefficients gives the worst classification accuracy. The results show that a small number of coefficients is sufficient to classify the infant cry accurately. The same observation is obtained for the SVM with RBF kernel. The highest classification accuracy (93.84%) is obtained when ten coefficients with 22 and 25 filter banks are used. Therefore, feature set generated from ten coefficients and 22 filter banks is chosen as the best set since it offers the highest classification accuracy for both SVM with polynomial and RBF kernels.

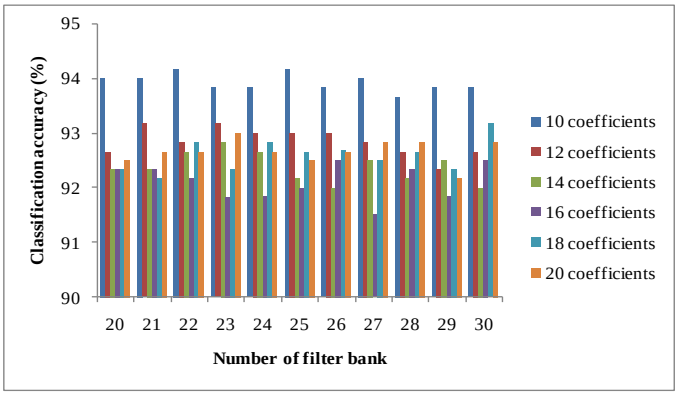



**Fig. 2:** Classification accuracy of SVM with the polynomial kernel for various coefficients and filter bank numbers

### 3.2 Performance of SVM in Classifying Features Selected By PCA

The CPV has retained 54 principal components since their cumulative percentage of variance is above 80% as shown in Table 1 and reduced the dimension of the input feature from [1240 x 600] to [54 x 600]. Unlike CPV, EOC only retains 23 PCs (see Fig. 3) as they have eigenvalue greater than one but reduces more the original dimension than CPV which is to [23 x 600]. The red line indicates an eigenvalue = 1. The Scree test preserves only three principal components due to the large gap between the elements and decreases the dimension of input feature from [1240 x 600] to [3 x 600].

**Table 1:** Percentage of cumulative variance for a sample of principal components for SVM with RBF kernel

| Principal Component (PC) | Cumulative variance (%) | Principal Component (PC) | Cumulative variance (%) |
|---|---|---|---|
| 17 | 62.795 | 42 | 76.895 |
| 18 | 63.810 | 43 | 77.195 |
| 19 | 64.767 | 44 | 77.492 |
| 20 | 65.674 | 45 | 77.783 |
| 21 | 66.517 | 46 | 78.054 |
| 22 | 67.295 | 47 | 78.318 |
| 23 | 68.043 | 48 | 78.572 |
| 24 | 68.736 | 49 | 78.823 |
| 25 | 69.375 | 50 | 79.072 |
| 26 | 69.975 | 51 | 79.314 |
| 27 | 70.560 | 52 | 79.550 |
| 28 | 71.119 | 53 | 79.781 |
| 29 | 71.665 | 54 | 80.007 |

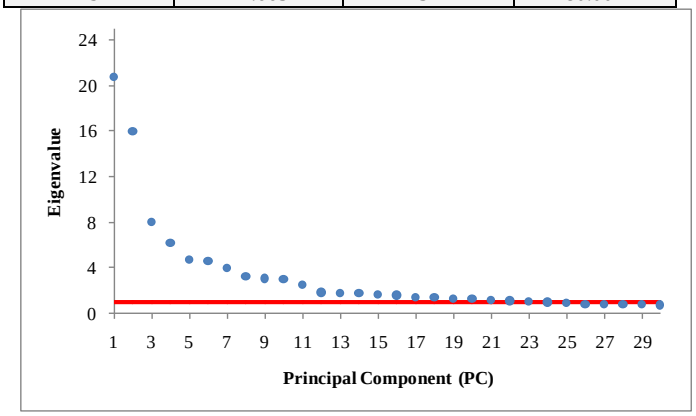



**Fig. 3:** Eigenvalue for the first 30 principal components obtained using EOC selection method for SVM

When SVM with the polynomial kernel is optimized on PCA selected features by varying $C$, a small increment is found in the classification accuracy as shown in Fig. 4. Here, the $d$ is fixed at three. Note that the classification accuracy slowly increases when $C$ is more than 0.0001 for SCREE algorithm. Using EOC and

CPV, the classification accuracy decreases initially and then saturates. As shown in the figure, the highest classification accuracy (94.18%) is obtained with EOC selection algorithm when $C$= 0.00001.

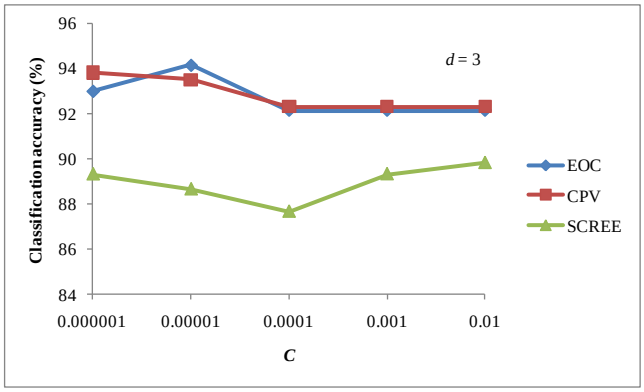



**Fig. 4:** Effect of varying $C$ on the classification accuracy of PCA-SVM with the polynomial kernel using EOC, CPV, and SCREE

Comparison of the classification accuracy of SVM with polynomial kernel combined with EOC, CPV, and SCREE selection algorithm when $d$ is varied and $C$ is fixed at 0.00001 is shown in Fig. 5. For SVM with the polynomial kernel, the optimal $d$ is three since it produces the highest classification accuracy (94.18%). This optimal value is obtained when EOC selection algorithm is employed.

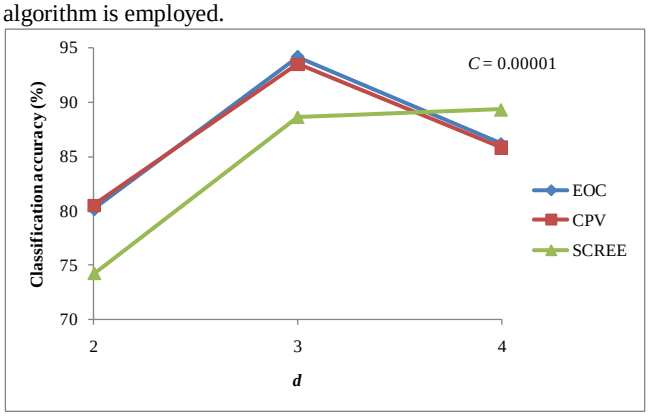



**Fig. 5:** Classification accuracy of PCA-SVM with the polynomial kernel when d is varied and C is set to 0.00001 using EOC, CPV, and SCREE

For the SVM with RBF kernel, it is found that EOC algorithm produces the highest classification accuracy when $C$ = 1 and the rate of increment in classification accuracy is affected by the input feature vector dimension. It is observed that when $\gamma$ increases, the classification accuracy reduces for EOC, CPV, and SCREE. The highest classification accuracy (94.84%) is obtained at $\gamma$ equals to 0.025 when the EOC selection is employed. The worst classification accuracy is found when SCREE is used.

### 3.3 Performance of SVM in Classifying Features Selected By OLS

Table 2 shows the ten coefficients ranked by the OLS algorithm. The top of the list is the coefficient with the highest ERR whereas the bottom of the list is the coefficient with the least ERR. From Table 2, the fourth, first, third, seventh, fifth and tenth coefficients contain significant information.

**Table 2:** Ranking of coefficients using OLS

| Coefficient Number | ERR | Ranking |
|---|---|---|
| 4 | 0.178 | 1 |
| 1 | 0.161 | 2 |
| 3 | 0.155 | 3 |
| 7 | 0.020 | 4 |
| 5 | 0.020 | 5 |
| 10 | 0.011 | 6 |
| 6 | 0.011 | 7 |
| 2 | 0.009 | 8 |
| 8 | 0.007 | 9 |
| 9 | 0.005 | 10 |

The effect of varying the number of coefficients on classification accuracy of the SVM with the polynomial kernel using optimal values of $C$ (0.0001) and $d$ (2) is shown in Fig. 6. Note that the highest classification accuracy is 93.34% when eight coefficients are used.

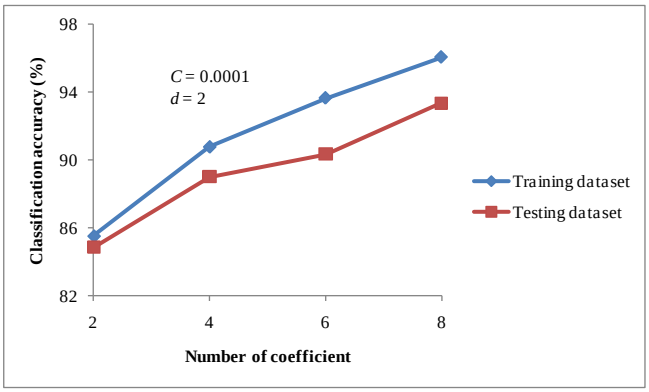



**Fig. 6:** Classification accuracies of OLS-SVM with the polynomial kernel for various coefficient numbers

For SVM with RBF kernel, it is observed that using the optimal values of $C$ (1) and $\gamma$ (0.007), the highest classification accuracy for both the training and testing datasets are 93.34% and 94.74% respectively when eight coefficients are used.

### 3.4 Overall Performance of SVM in Classifying Significant Features

Using polynomial kernel, the same optimal $C$; 0.0001 and $d$; 2 are obtained for SVM and OLS-SVM. While for PCA-SVM, different optimal $C$ and $d$ are found, which are 0.00001 and 3 respectively. The classification accuracy in Fig. 6 shows that PCA-SVM (EOC) is the most accurate method (94.17%) followed by OLS-SVM (with eight coefficients) (92.67%). The classification accuracy obtained from SVM (92.51%) is comparable to OLS-SVM since the difference between their classification accuracies is about 0.17%.

Using RBF kernel, the optimal $C$ is one for SVM, PCA-SVM, and OLS-SVM. The optimal values of $\gamma$ are 0.009 found for SVM, 0.0025 for PCA-SVM and 0.007 for OLS-SVM. The highest classification accuracy is 94.84% when PCA-SVM with EOC is used. The SVM provides 93.84% accuracy whereas OLS-SVM with eight coefficients produces 93.34%. These results indicate that the classification accuracy is influenced by the feature selection algorithms since the lowest number of support vector yields the highest classification accuracy.

Table 3 shows the computation time of SVM, PCA-SVM, OLS-SVM with polynomial and RBF kernels in classifying infant cry patterns. Clearly, PCA-SVM with both kernels takes the shortest time to classify the infant cries. OLS-SVM also saves computation time. It can be concluded that by combining feature selection algorithms with SVM affects the classification performance and computation time as well.

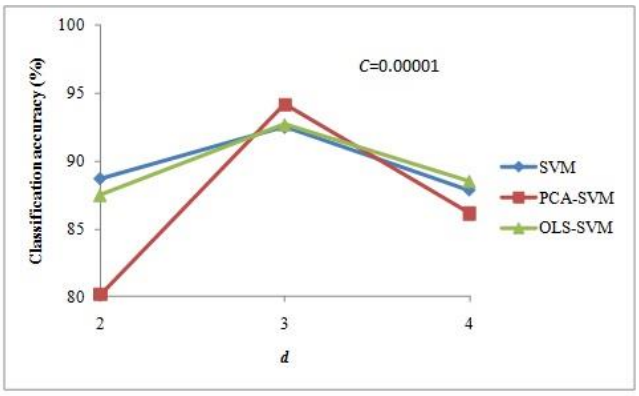



**Fig. 6:** Variation in classification accuracy with *d* using SVM, PCA-SVM and OLS-SVM with polynomial kernel (testing dataset)

**Table 3:** Computation Time of SVM, PCA-SVM, and OLS-SVM with Polynomial Kernel

| Methods | Computation Time (s) Polynomial Kernel | Computation Time (s) RBF Kernel |
|---|---|---|
| SVM | 60.84 | 62.88 |
| PCA-SVM | 1.87 | 1.98 |
| OLS-SVM | 45.08 | 36.89 |

## 4. Conclusion

The optimal parameters identification of MFCC and SVM with and without applying feature selection methods has been carried out successfully. Using the optimum parameters, the performance of SVM, PCA-SVM, and OLS-SVM in classifying asphyxiated infant cries was investigated. Two types of kernels; RBF and polynomial kernels were employed in the classification process.
Without feature selection method, SVM managed to classify the infant cry with asphyxia with an accuracy of 93.84% using RBF kernel and 92.51% using polynomial kernel. The optimal feature set was produced from ten coefficients with 22 filter banks. Using PCA as the feature selection method, PCA-SVM produced the highest classification accuracy. With EOC as the PCA criteria, for RBF kernel, the classification accuracy is 94.84% whereas, for the polynomial kernel, it is 94.17%. OLS-SVM produces the lowest classification accuracy compared to SVM and PCA-SVM, which is 93.34 when RBF kernel was employed and 92.67% for the polynomial kernel. Results from this study also shown that the computation time can be shortened by employing OLS and PCA and the best SVM kernel for classifying asphyxiated infant cry is RBF kernel.

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