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A Modified Fuzzy Support Vector Machine Classification-based Approach for Emotional Recognition Using Physiological Signals

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Abstract

Emotional state recognition has become an essential topic for human–robot interaction researches that diverted and covers a wide range of topics. By specifying emotional expressions, robots can identify the significant variables of human behavior and apply them to communicate in a very human-like fashion and develop interaction possibilities. The multimodality and spontaneity nature of human emotions make them hard to be recognized by robots. Each modality has its advantages and limitations, which, along with the unstructured behavior of spontaneous facial expressions, make several challenges for the proposed approaches in the literature. The most important of these approaches is based on a combination of explicit feature extraction methods and manual modality. This paper proposes a modified fuzzy support vector machine (FSVM) classification-based approach for emotional recognition using physiological signals. The main contribution of this study includes applying various data extraction indices and proper kernels for the FSVM classification method and evaluating the signal's richness in experimental tests. The developed emotional recognition method is also compared with conventional SVM and other existing state-of-the-art emotional recognition algorithms. The comparison results show an improved accuracy of the developed method over other approaches.

Keyword: Emotional Recognition, Physiological Signals, Support Vector Machine, Fuzzy Classification.

1. Introduction

Computers do not have emotional feelings, but if we would like to interact between computers and people with the possible naturality, the computer should consider human emotions. The affective computing field is a relatively young research base, where computer researchers have considered emotions for the past 20 years (Picard, R. W., 2010). People show their emotions by expressing their faces, tones, sounds, modes, movements, and physiological signals. Emotion recognition using electrophysiological signals is one of the branches of affective computing, and many researchers use bio signals to estimate people's affect. Physiological signals are helpful because, in the opposites to other signals, they are not controllable by humans, and they are strongly correlated to human emotions. People often express their emotions during interaction with computers, but computers do not recognize them. It's not necessary for the computer to always pay attention to emotions, but it can be advantageous in many areas: health care, games, and e-learning. Applications that make people feel more comfortable with human feelings are beneficial for aged people's medical applications (Rattanyu, K., Ohkura, M., & Mizukawa, M., 2010, October) and car drivers (Katsis, C. D., Katertsidis, N., Ganiatsas, G., & Fotiadis, D. I., 2008). Polyclinics also utilize emotional changes and are physiologically monitored, such as blood pressure, pressure, breath, and skin conduction (Liu, C., Conn, K., Sarkar, N., & Stone, W., 2008).

Recognizing human facial expressions and emotions has been applicable in different fields, from evolutionary Biology, biological psychology, and neuroscience to computer and cognitive science. This state is due to recognizing human facial expressions and emotions in communications, social relationships, and Interactions (Barros, P., Jirak, D., Weber, C., & Wermter, S., 2015). Studying sensation through physiological processing signals can provide clinical applications for the timely diagnosis and treatment of mental disorders. The primary purpose of this paper is to detect emotional states based on fuzzy classifications of physiological signals. Moreover, emotions in two dimensions of Arousal and Valence are examined using physiological signals.

a. Motivation

In this paper, sensory sensitivity in an automated system is increased by examining the brain's electrical activity and the environment in emotional state changes. Research sources have proven that the brain is the primary source of emotion (Hakamata, A., Ren, F., & Tsuchiya, S., 2008, October; Mi, L., Liu, X., Ren, F., & Araki, H., 2009). Electric brain activity can provide emotional information to the user without any intermediary (Mi, L., Liu, X., Ren, F., & Araki, H., 2009; Khosrowabadi, R., & bin Abdul Rahman, A. W., 2010, December), as well as environmental signals, including emotional information. Therefore, it can be inferred that their anxiety states include high and low arousal, and valence's emotional state also includes positive and negative valence. The condition of anxiety, including high and low arousal, and valence's mood, also includes positive and negative valence. For recorded physiological signals, a label is considered. In this case, emotional states are divided into both sides, and each class of emotion must be individually trained to classify the test signals with a high percentage of accuracy.

On the other hand, these signals can be classified according to the two -Valence Arousal dimensions; in this case, the signals are classified into four classes. In this paper, with the help of the fuzzy vector machine, brain signals that contain emotional information are categorized. Also, the classification accuracy should be significantly increased compared to conventional methods. The proposed method, fuzzing the data in the training phase and fuzzy the test data, reduces the effect of noise and data and increases the accuracy of classifying the physiological signals. As well as giving the value to each data to improve fuzzy classification, optimization methods can be used to select optimal parameters.

b. Literature review

Two major approaches are presented for emotion modeling: the discrete model, whose main problem is the limited selection and cultural dependence, labels the emotions, e.g., fear, sadness, and happiness. On the other hand, the continuous model employs continuous scales; for instance, the 2D model has valence and arousal axes, and the 3D model employs an additional dimension, usually called dominance.

In (Barros, P., Jirak, D., Weber, C., & Wermter, S., 2015), emotion recognition from physiological signals is performed; however, the employed dataset is straightforward, and only a limited number of recognition approaches are examined.

It has been shown that physiological signals in different emotional situations, such as fear, sadness, and happiness, affect heart rate, respiration changes, skin conductivity, and body temperature affected by emotional states (Kim, J., & André, E., 2008). Many studies have been conducted on the sensory recognition of physiological signals. Using the EEG terminal, Choppin designed a system for people with ALS that automatically recognizes their emotions and allows them to communicate with the outside environment and express feelings. Acquiring neural networks in this category for classifying emotions led to a 64% classification for three emotional classes (Lahane, P., & Sangaiah, A. K., 2015).

Some of the works of literature tried to extract only the intensity of the emotion from the EEG signal and the other physiologic signals. Different classifications have been used to classify EEG, environmental, and both signals, and the results have shown that the accuracy of the classification of emotions on EEG signals alone was approximately equal to the precision obtained from all physiological signals. Combining these signals' information increases the accuracy, using the audible stimulus to stimulate the emotions and the SVM for the EEG signal classification; the accuracy of 90% for the four senses of pleasure, anger, sadness, and joy has been achieved. However, using the IADS database for selecting the best drives and the linear binary method of Fisher Separator were used in classifying information, resulting in a gravity of 97.4% for the intensity of emotion and 94.9% for their nature (Chanel, G., Kronegg, J., Grandjean, D., & Pun, T., 2006, September). In the other studies, heart signals, skin temperature and direction, signals from the electrical activity of the muscles, blood volume pulses, and respiration rate have been considered. For example, In (Kim, K. H., Bang, S. W., & Kim, S. R., 2004) presents an independent user-friendly automated system by grading classifying three classes 78/8% by extracting and classifying heart rate and skin temperature information using the Yashtian vector machine classifier.

In (Haag, A., Goronzy, S., Schaich, P., & Williams, J., 2004, June) reviewed all of the physiological signals and used two separate neural network algorithms to find out the quantity (intensity) and quality (nature) of emotions. This method classified emotions with an accuracy of 6.96% and 89/93% in intensity and nature, respectively. Moreover, in (Khalili, Z., & Moradi, M. H., 2008, December) by using the images in the LAPS database and classification with the genetic algorithm to select the appropriate features, we reached an accuracy of the extraction of EEG and environmental signals in the page-nature severity of 66.66%. In (Koelstra, S., Muhl, C., et al., 2011), (Christy, T., Kuncheva, L. I., & Williams, K. W., 2012) using compound combinations, the Naïve Bayes classifier reached the classification accuracy of 62%, 57/6%, and 62.49% for intensity, nature, and interest, respectively. Also, the use of the vector class of the supporting vector has increased these accuracies to 63.99% (intensity) and 49.62% (nature). Several studies have been done to diagnose feelings. However, in the past, the focus has been on face and speech modalities, and less attention has been paid to physiological parameters. In (Rigas, G., Katsis, C. D., Ganiatsas, G., & Fotiadis, D. I., 2007, July), the features extracted from electrocardiogram and respiration signals for 9 subjects. Mentioned subjects were stimulated by viewing the images selected from 1APS, which were used by the K-NN and randomized strain for diagnosis of the feelings of happiness, hatred, and fear were 48%, 68%, and 69%, respectively. In (Mi, L., Liu, X., Ren, F., & Araki, H., 2009), electrocardiogram signals, electromyograms, electric conduction of the skin, and the fear of three subjects triggered by musical stimulation have been recorded. By extracting the attributes and applying the classifications for the four classes, the accuracy of 65% and the classification of the two classes of nature and excitement were 89% and 77%, respectively. In (Gouizi, K., Bereksi Reguig, F., & Maaoui, C., 2011), the features of the electromagnetic signals, respiration, electrical conductivity of the skin, skin temperature, pulsed blood volume, and heart rate were extracted to identify emotions. This research uses the supporting vector machine method for categorizing emotions into pleasure, sadness, fear, hatred, neutrality, and entertainment. In this study, the LAPS system was used to stimulate stimulation, and the accuracy of the diagnosis of various conditions in this experiment was 85%.

(Yin, Z., Zhao, M., Wang, Y., Yang, J., & Zhang, J., 2017) proposed a novel ensemble classifier with a multiple-fusion layer of stacked autoencoder for recognizing emotions, where the deep structure is identified using a physiological time series data-driven method. Each stacked autoencoder includes three hidden layers to filter the unwanted noisy data in the physiological features and leads to providing more stable feature representations. This approach uses an additional deep neural network model to reach the stacked autoencoder ensembles. The physiological features are clustered into subgroups based on different feature extraction methods, with each subset singly encoded by a stacked autoencoder. The reached stacked autoencoder initialization is merged based on the physiological modality to make six encodings, which are then fed to a three-layer, adjacent-graph-based network for feature combination.

The combined features are used to recognize binary arousal. Based on the evaluation results, compared with the well-established emotion classifier, the proposed method's mean classification rate and F-score improved by 5.26%. In (Hong, K., Liu, G., Chen, W., & Hong, S., 2018), a novel classification algorithm based on signal amplification and correlation analysis called Eulerian magnification-canonical correlation analysis is proposed. This method extends emotional and physical stress signals in different frequency ranges as a signal amplification approach. Then, the Sparse coding and canonical correlation analysis combine the original signal and its amplified features. In this approach, the extracted entropy features train the correlation weight between emotional and physical stress, which adjusts stress classifications. Based on the evaluation results, the proposed classification method reaches an accuracy rate of 90%. In (Zhang, B., Morère, Y., et al., 2017) proposed a novel method for the potential of stress recognition using data from heterogeneous sources.

In this method, reaction time is used along with physiological signals to recognize different stress states. The experiments in this approach are designed with two different stressors: visual stressors and auditory stressors. During the experiments, the subjects perform reaction time tasks to achieve the data for an individual's stress. This approach records three physiological signals along with Electrodermal activity, Electrocardiography, Electromyography, and reaction times. In this method, the classifier for stress recognition is based on the Support Vector Machines given the physiological signals and reaction time. The evaluation results show the overall good recognition performance of the SVM classifier. Moreover, this paper proposes a novel strategy of recognition using decision fusion. The recognition is obtained by combining the classification results of physiological signals and reaction time with the voting approach, which improves recognition accuracy.

The recognition accuracy depends on the dataset utilized in the analyses. For example, some main affecting factors are the emotional mood of the subject before the experiment, uncertainties like personal judgment, environmental issues, and conditions in which the subjects have not participated in the experiments voluntarily.

c. Contributions of manuscript

The main contribution of this paper is to propose an emotional state recognition. The employed dataset contains 32 individuals having 40 physiological signals for each of them, all of which passes through a preprocessing stage. Four emotional states in the 2D plane of valence and arousal are considered, i.e., HV, HA, LV, and LA. Features in both time and frequency domains and chaotic theory are utilized here, including mean, variance, bandpass, energy, entropy, and fractal. It is worth noting that the energy and entropy features are calculated through the wavelet transform; the bandpass feature is also determined using the Fourier transform. Then, KPCA is used as a dimension reduction technique, whose outcome expedites the algorithm and improves the training performance and prediction accuracy.

Afterward, the classification is carried out by taking advantage of the FSVM method, i.e., having robustness against artifacts. Furthermore, several kernels of FSVM is explored to find the most suitable kernel, including linear, quadratic, polynomial, multilayer perceptron, and radial basis function. In addition, all parameters of KPCA and FSVM kernels are simultaneously optimized by genetic algorithm. Moreover, the correlation between all physiological signals and emotional dimensions (valence and arousal) is calculated to investigate whether appropriate electrodes are adopted for each feature.

d. Organization of manuscript

The rest of the paper is organized as follows. Section 2 describes the applied data in the analysis and the proposed clustering method. Section 3 is intended to introduce the proposed FSVM classification-based approach for emotional recognition using the physiological signals method. Accuracy results of the developed and state-of-the-art emotional recognition methods are provided in Section 4. and finally, in Section 5, conclusions and future work are provided.

2. The applied data in this research

The comprehensive database used in this paper is extracted from the provided datasets in (Mi, L., Liu, X., Ren, F., & Araki, H., 2009). This database contains EEG and peripheral signals collected from 32 participants between 19 and 37 with an average age of 26.9 through Audio-Visual Stimuli (lyric video). Half of the participants were women, and none had experienced nervous disorders or consumed alcohol drinking or drugs. They were not under any medication and had a normal or near-normal vision.

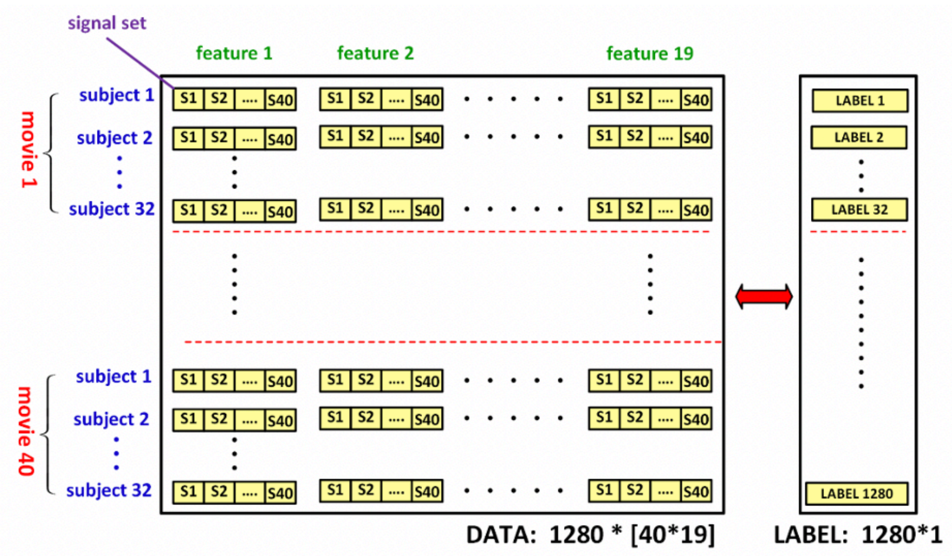


Fig. 1: Applied data and features in the proposed method

Signal recording was performed in two laboratories with controlled light (The first 22 people participated in a laboratory in Tonto city, and the rest participated in the laboratory in Geneva).

The stimuli used in this experiment were selected in several steps. First, among 120 initial stimuli, half were selected as semi-automatic, and the rest were selected as manually. After that, a one-minute highlight part was determined for each stimulus. Finally, 40 final stimuli were selected using a web-based cognitive testing experiment. Fig. 1 presents the applied data and features in the proposed method.

In this poll, each participant assigns the Arousal scoring parameters from 1 to 9 to a discrete scale after watching each video. Eventually, after distributing the results in two-dimensional space, 40 final videos be selected for participating in the experiment. Video has selected the videos with the highest scores and the least standard deviation to increase the power of emotion. 10 videos are selected among videos that are located in the corner of each quadrant because they are the most significant distance from the neutral state. Fig. 2 indicates the selected videos as stimuli.

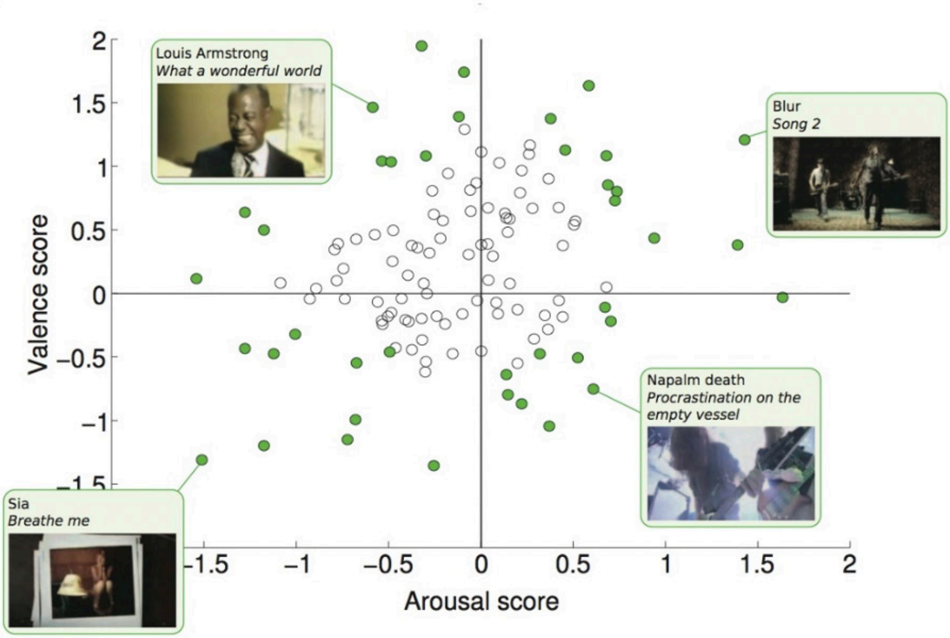


Fig. 2: Filled spots represent the selected music videos as stimuli (Katsis, C. D., Katertsidis, N., Ganiatsas, G., & Fotiadis, D. I., 2008)

The Valence-Arousal space can be divided into 4 quadrants: Low Arousal-Low Valence (LALV), High Arousal-Low Valence (HALV), Low Arousal-High Valence (LAHV), and High Arousal-High Valence (HAHV).

3. Proposed Method

This section introduces the proposed FSVM classification-based approach for emotional recognition using physiological signals.

3.1. Pattern recognition

Pattern recognition involves various steps, including preprocessing, feature extraction, selection, and classification (Hossain, M. S., & Muhammad, G., 2019). First of all, the collected information is recalled and then appropriately organized. In the next step, based on the EEG signals nature, the proper attributes are considered for the samples in which the system used in the classification is trained. Finally, the accuracy of the results and performance of the system is examined.

3.2. Data collecting and categorizing

In this section, raw data was collected from (Koelstra, S., Muhl, C., et al., 2011) (which includes receiving one hour of a physiological signal from the volunteer while watching the video). 63 seconds of compelling physiological EEG and peripheral signal data are processed and filtrated using the status signal. Finally, proper signals with their labels are extracted. Therefore, preprocessing is performed on the signals. In the end, organization data be usable. In other words, the outputs of 40 signals with a proper label for each participant. The block diagram in Fig. 3 shows the details of the different parts of this section.

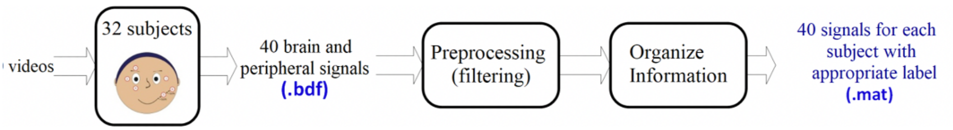


Fig. 3: Block Diagram of Calling and Organizing Information Section

3.3. Extraction of proper features

Choosing the appropriate feature is the most critical challenge in classifying physiological signals. Intuitively, the appropriate extracted features are those features that are as selective as possible to the signals. For this purpose, fractals, bandwidth, mean, variance, and violet are extracted properties where the block diagram is observable in Fig. 4.

3.4. Classification by FSVM

Since the EEG signal processing in this article has a long length, many channels are used to record it. The criterion of classification selection is the low volume of required computations. The speed of SVM training is higher than the other classifications, and with the best feature space size, it has the best performance compared to other classifications.

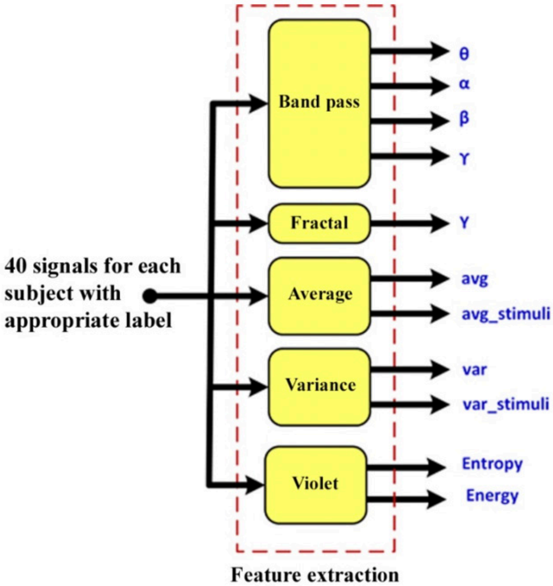


Fig. 4: Feature extraction block diagram

First, consider the formulation of soft-margin vector machines as follows:

$$y_i(w^T x_i + b) \geq 1 - \xi_i$$
$$\xi_i \geq 0 \qquad i = 1, \dots, N \tag{1}$$

Where x_i, y_i and $\zeta_i$are input vector, labels, and slack variable, respectively. Moreover, the initial programming problem is converted as follows:

$$Minimize\ \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{N}\xi_i$$
$$subject\ to\ y_i(W^T X_i + b) \geq 1 - \xi_i \tag{2}$$
$$\xi_i \geq 0 \qquad i = 1, \dots, N$$

In eq. (2), C, is a free parameter (defined by the user) and specifies the effectiveness of slack variables in determining the margin. The geometric concept of a vector machine with a soft margin is shown in Fig. 5.

$$W^t X + b = 0$$
$$W^t X + b = C$$
$$W^t X + b = -C$$

By using Lagrange multipliers and simplification, the following equation obtains:

$$L(\alpha) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \vec{x}_i^T \vec{x}_j \tag{3}$$

$$\sum_{i=1}^{N}\alpha_i y_i = 0,\ \ \alpha_i \geq 0, i = 1, \dots, N \tag{4}$$

Lagrange multipliers are replaced in the following equation to calculate W and b.

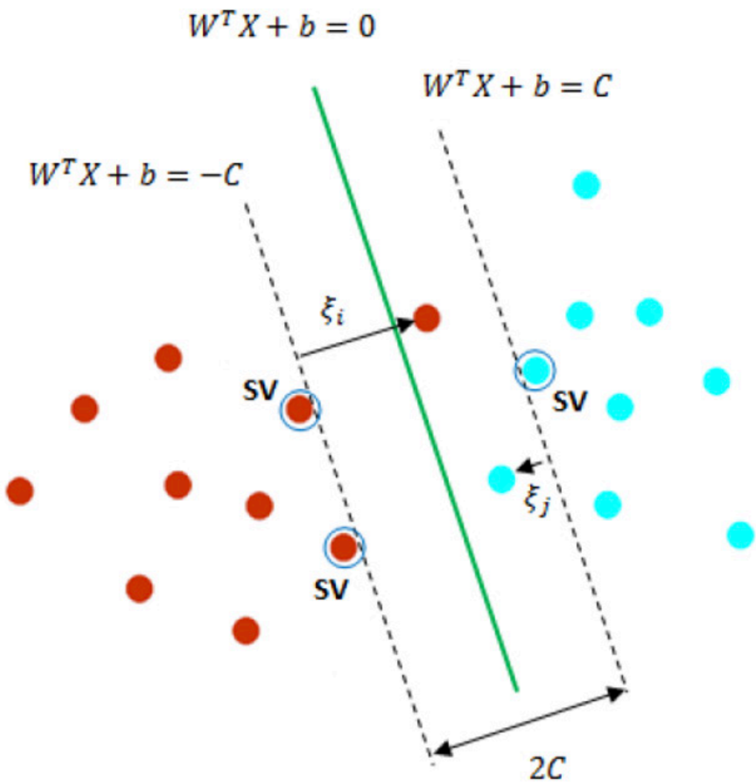


Fig. 5: Effect of slack variable in SVM performance (Barros, P., Jirak, D., Weber, C., & Wermter, S., 2015)

$$w = \sum \alpha_i y_i x_i$$

$$b = y_k(1 - \zeta_k) - w^T x_k, \qquad k = argmax(a_i) \tag{5}$$

The final SVM hyperplane can be obtained by applying these parameters in the central equation of the separator hyperplane.

If the problem data, in addition, are not linearly separatable, they also have a sophisticated distribution, and the SVM with a soft margin not be responsive. The mapping method can be used in a higher-dimensional space to solve this problem. For this purpose, the proper strategy is to use the kernel trick (Hakamata, A., Ren, F., & Tsuchiya, S., 2008, October).

In this regard, consider the relation (0.3) in the feature space as follows.

Therefore consider (3) in the following feature space:

$$L(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \varphi(X_i)^T \varphi(X_j)$$

$$\textstyle\sum_{i=1}^{N} \alpha_i y_i = 0, \qquad \alpha_i \geq 0, \qquad i = 1, \ \dots, N \quad (6)$$

In this equation φ is the mapping function. If we have:

$$K(X_i, X_j) = \varphi(X_i)^T \varphi(X_j) \tag{7}$$

Then eq. (7) can be rewritten as follows:

$$L(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(X_i, X_j)$$

$$\sum_{i=1}^{N} \alpha_i y_i = 0, \quad \alpha_i \geq 0, \quad i = 1, \ \dots, N \tag{8}$$

In eq. (8), the function $K(.)$ is called the kernel function. Furthermore, if the internal multiplication of input data vectors can be modeled with a kernel function, it is no longer necessary to know or obtain the mapping function. This state the kernel trick.

Some of the most usable standard kernel functions are:

As stated in the previous section, fuzzy membership variables are also free parameters of FSVM, which should be considered appropriate values. For this purpose, a lower bound must be determined for membership values, indicating the sample's lowest value. After that, the main characteristic of the dataset is determined, which describes the importance of samples. In the end, the relationship between the primary dataset and fuzzy membership values should be well defined; this relationship can be described and applied as a mathematical equation.

The proper choice of fuzzy membership functions in the given problem is significant in designing the FSVM classifier. The rule to assign appropriate membership values to each data depends on the importance of the data to their classes. In this work, to the training set efficiently, first, the raining set was divided into two sets: the positive training and the negat. The density $\rho(x_i)$ of the x_i points was defined as the number of data points in its neighborhood. We have:

$$\rho(x_i) = N(x) = N(\{x | \|x - x_i\| \leq T\}) \tag{9}$$

This state refers to the Euclidean distance and the cardinality of the x_i set. T is the threshold of the distance between two classes (S^+, S^-). Therefore, the positive density $\rho^+(x_i)$ and the negative density $\rho^-(x_i)$ are stated as follows respectively:

$$\rho^+(x_i) = \begin{cases} N(\{x | \|x - x_i\| \leq r.d, x \in S^+\}) \ \forall x_i \in S^+ \\ N(\{x | \|x - x_i\| \leq r.d, x \in S^-\}) \ \forall x_i \in S^- \end{cases}$$

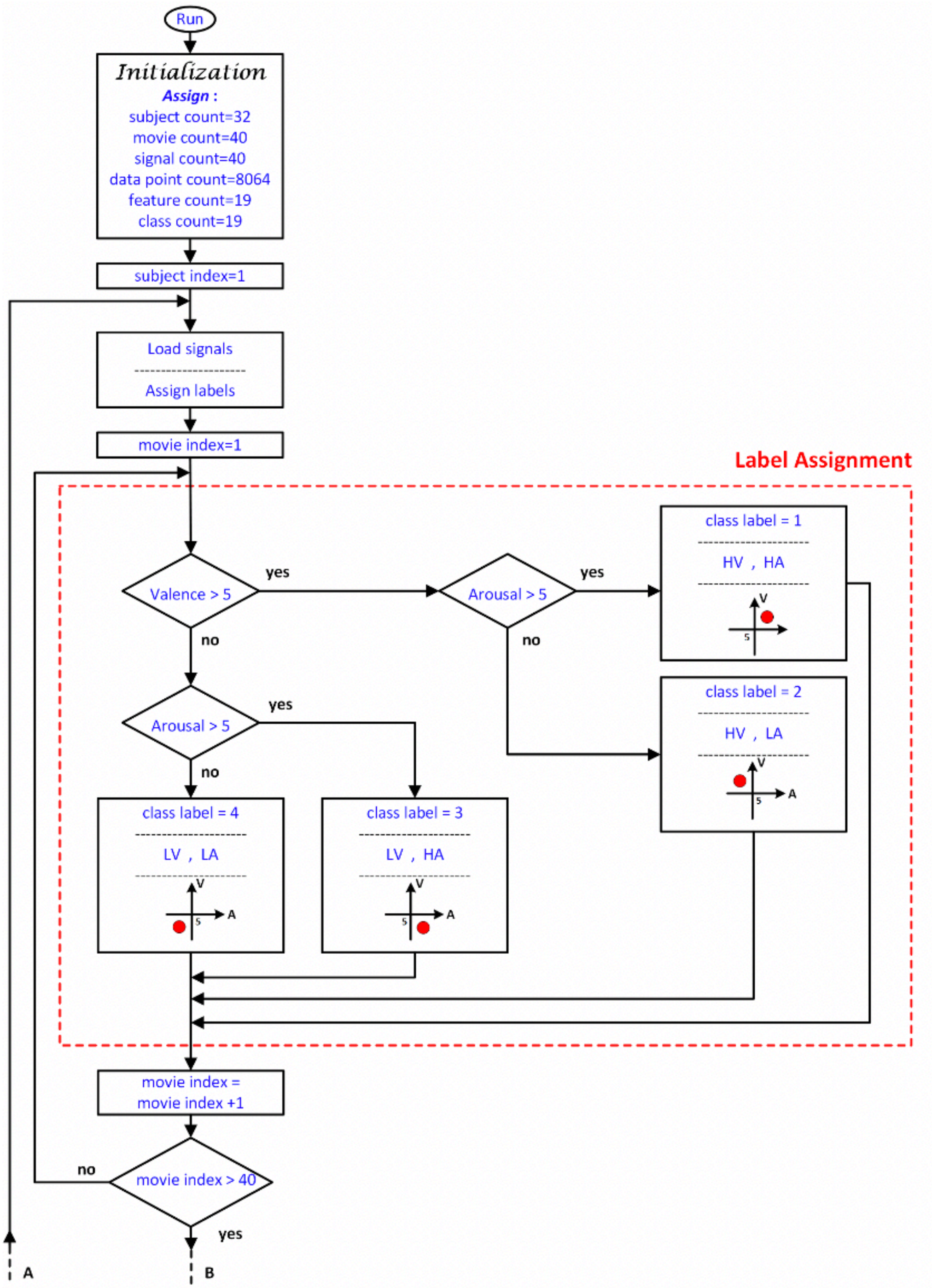
$$\rho^-(x_i) = \begin{cases} N(\{x | \|x - x_i\| \leq r.d, x \in S^-\}) \ \forall x_i \in S^+ \\ N(\{x | \|x - x_i\| \leq r.d, x \in S^+\}) \ \forall x_i \in S^- \end{cases} \tag{10}$$

Where d is the distance between the centers of two classes (S^+, S^-) and r is a predetermined coefficient related to the threshold T in eq (1). It indicates the data's attitude $x_i$toward its class in the training set. Principally, both (S^+, S^-)have a small value from outliers, and the standard data point, without any noise, S has a considerable and S perim small value. Therefore, the assigned membership value of the data point x_i can be determined by the following membership function:

$$S_i = \frac{\rho^+(x_i)}{\rho^+(x_i) + \rho^-(x_i)} . \frac{\rho^+(x_i)}{\rho^+{}_{max}} \tag{11}$$

Where $\rho^+{}_{max}$is the highest value $\rho^+(x_i)$for all training data points?

Figs 6-9 shows the loading data and features extraction workflows, the Main algorithm (K-Flod and FSVM classification), FSVM training, and test functions, respectively.


Run
Initialization
Assign :
subject count=32
movie count=40
signal count=40
data point count=8064
feature count=19
class count=19
subject index=1
Load signals
Assign labels
movie index=1
Label Assignment
Valence > 5
yes
no
Arousal > 5
yes
no
class label = 1
HV , HA
class label = 2
HV , LA
Arousal > 5
yes
no
class label = 4
LV , LA
class label = 3
LV , HA
V
A
5
movie index =
movie index +1
movie index > 40
no
yes
A
B

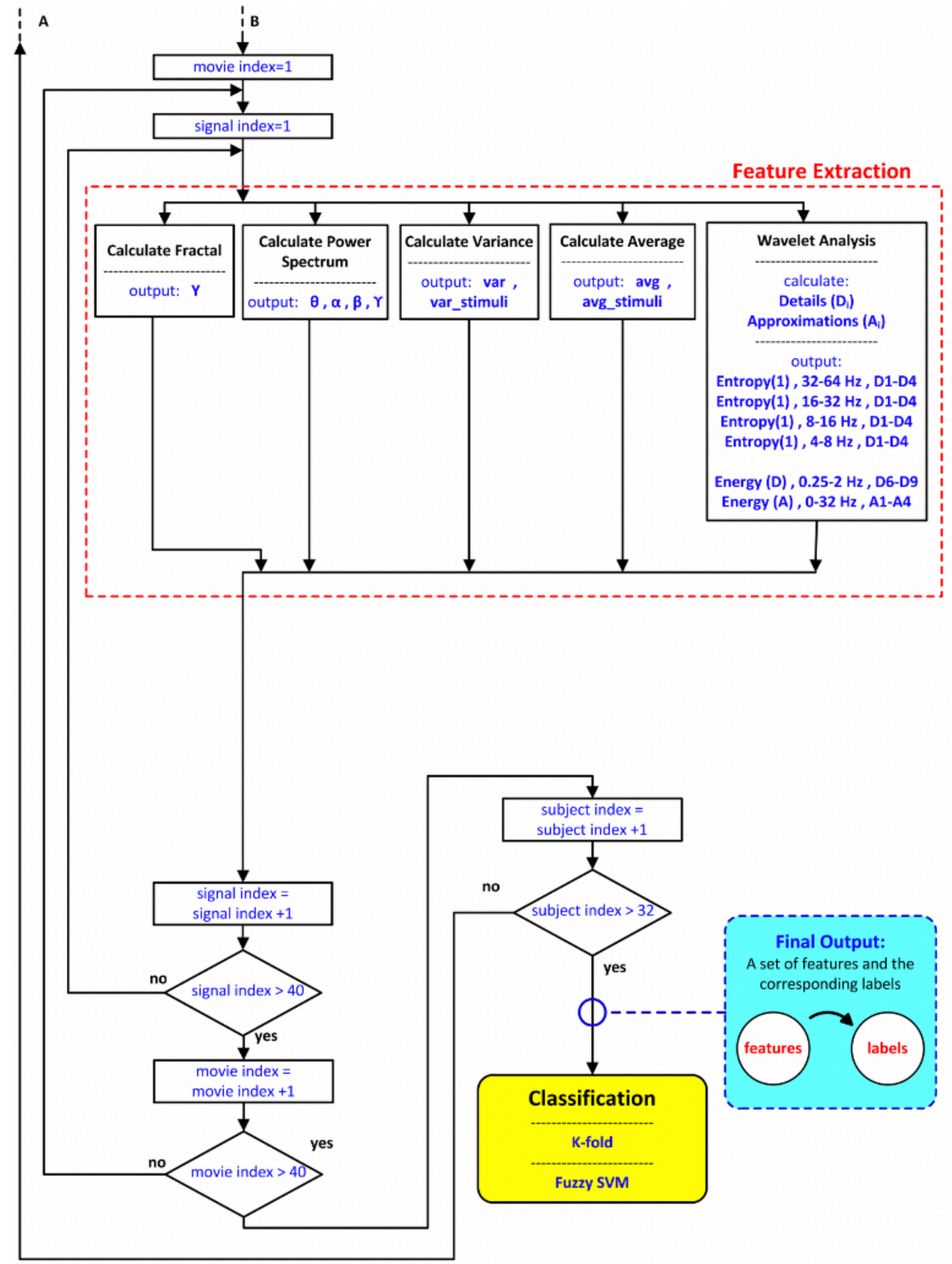
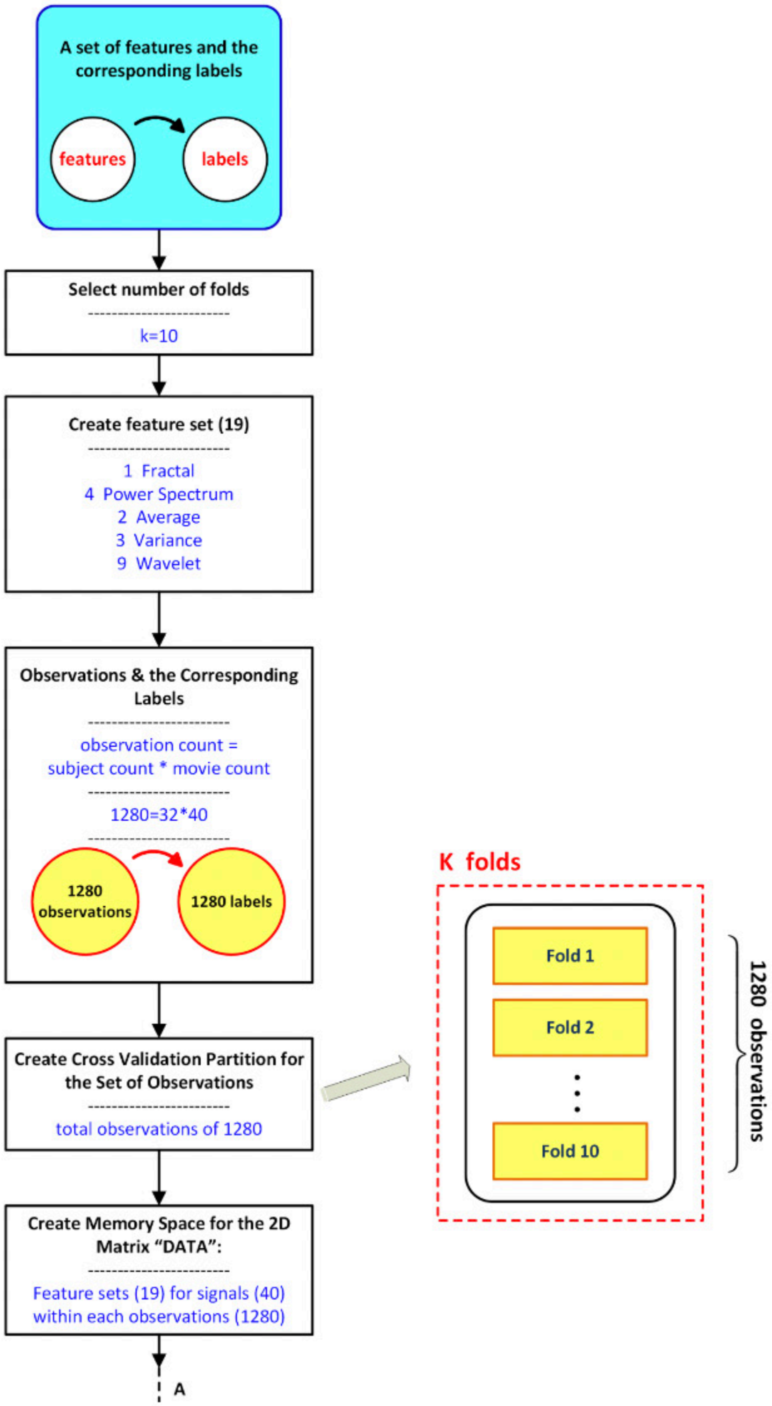
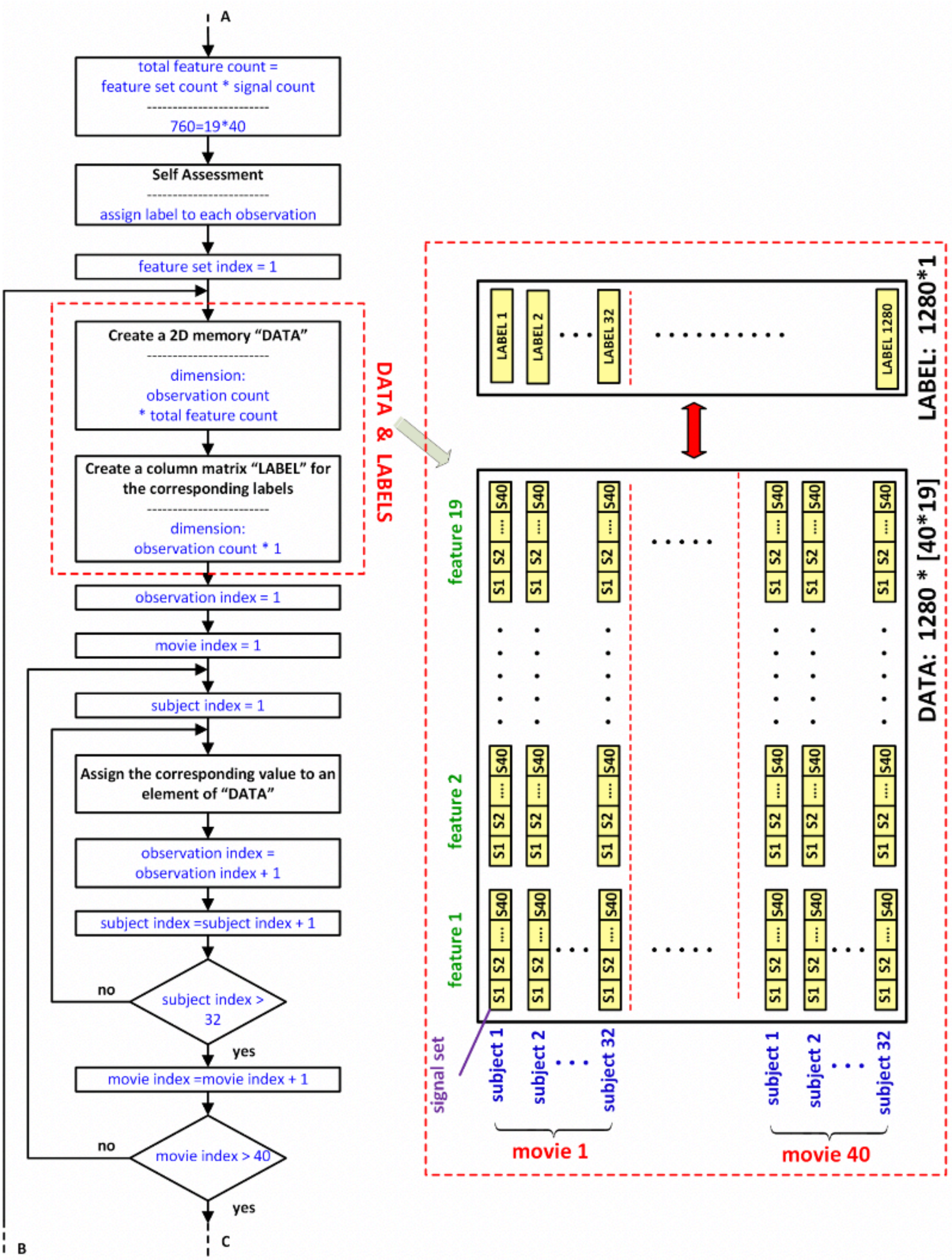


Fig. 6: The flowchart of Loading data and feature extraction in the proposed method


A set of features and the corresponding labels
features
labels
Select number of folds
k=10
Create feature set (19)
1 Fractal
4 Power Spectrum
2 Average
3 Variance
9 Wavelet
Observations & the Corresponding Labels
observation count = subject count * movie count
1280=32*40
1280 observations
1280 labels
Create Cross Validation Partition for the Set of Observations
total observations of 1280
Create Memory Space for the 2D Matrix "DATA":
Feature sets (19) for signals (40) within each observations (1280)
A
K folds
Fold 1
Fold 2
Fold 10
1280 observations


A
total feature count =
feature set count * signal count
760=19*40
Self Assessment
assign label to each observation
feature set index = 1
Create a 2D memory "DATA"
dimension:
observation count
* total feature count
Create a column matrix "LABEL" for
the corresponding labels
dimension:
observation count * 1
observation index = 1
movie index = 1
subject index = 1
Assign the corresponding value to an
element of "DATA"
observation index =
observation index + 1
subject index =subject index + 1
subject index >
32
no
yes
movie index =movie index + 1
movie index > 40
no
yes
B
C
DATA & LABELS
LABEL 1
LABEL 2
LABEL 32
LABEL 1280
LABEL: 1280*1
feature 1
feature 2
feature 19
S1
S2
S40
signal set
subject 1
subject 2
subject 32
movie 1
movie 40
DATA: 1280 * [40*19]

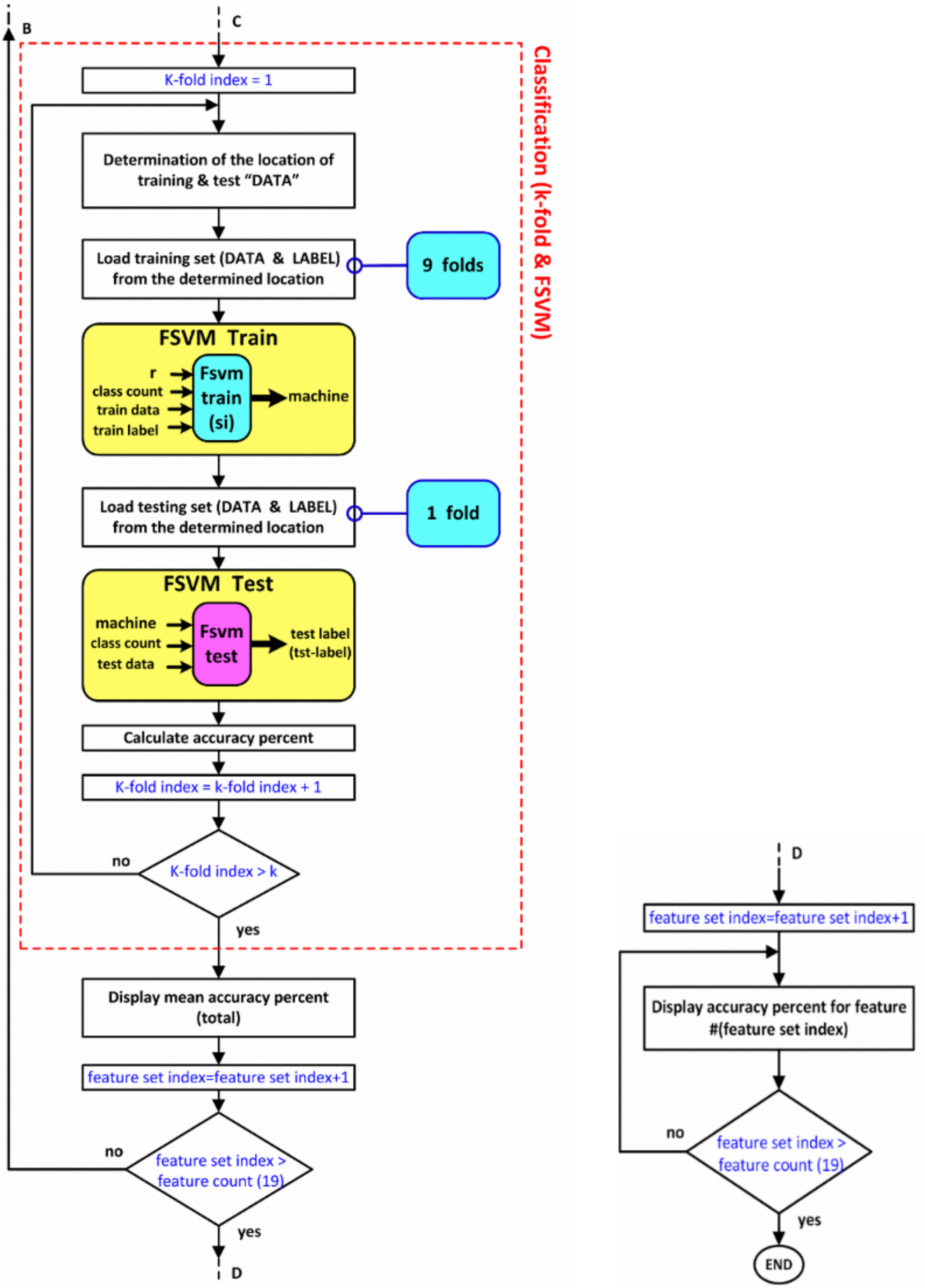


Fig. 7: The flowchart of the Main algorithm of the proposed approach

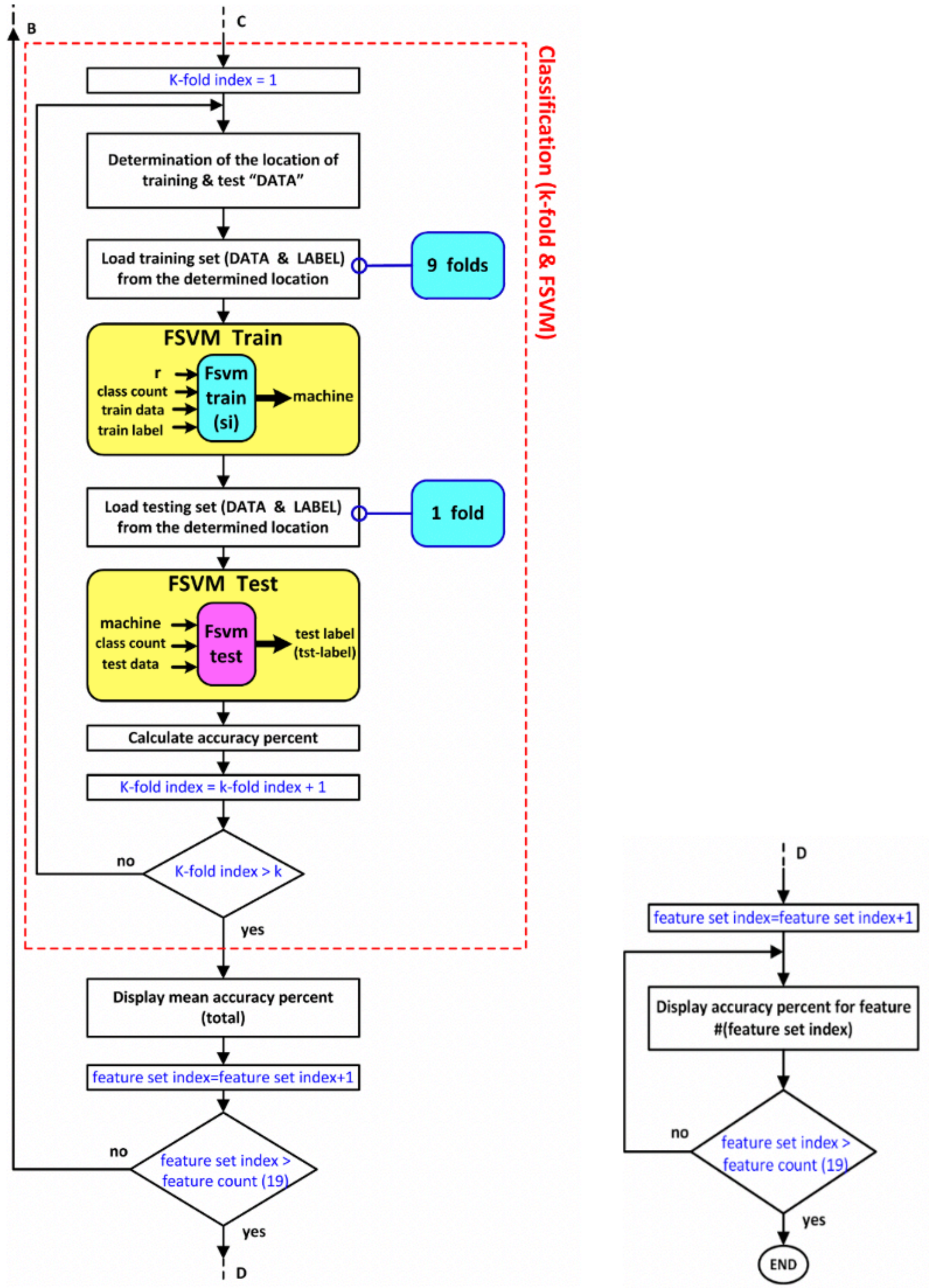
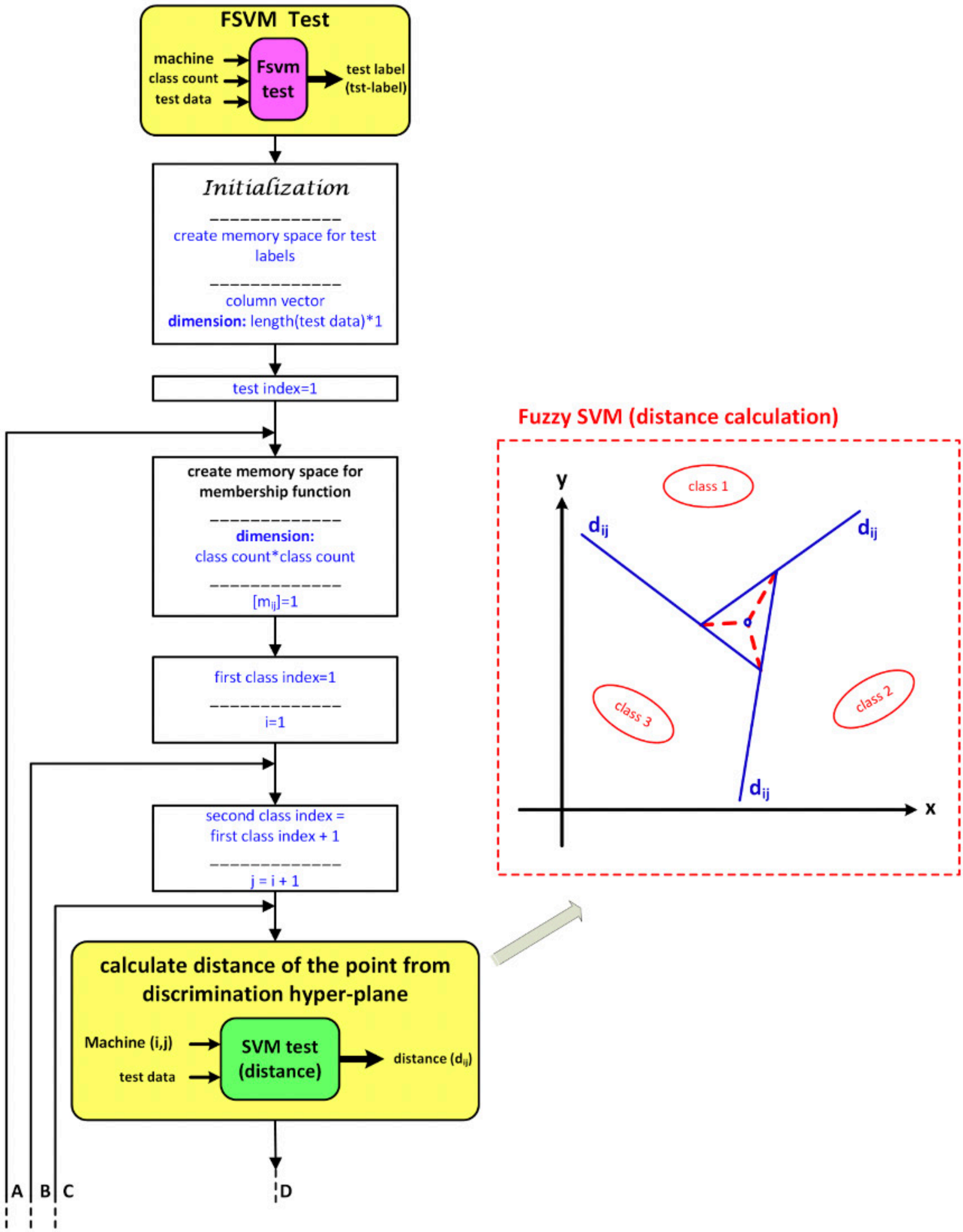
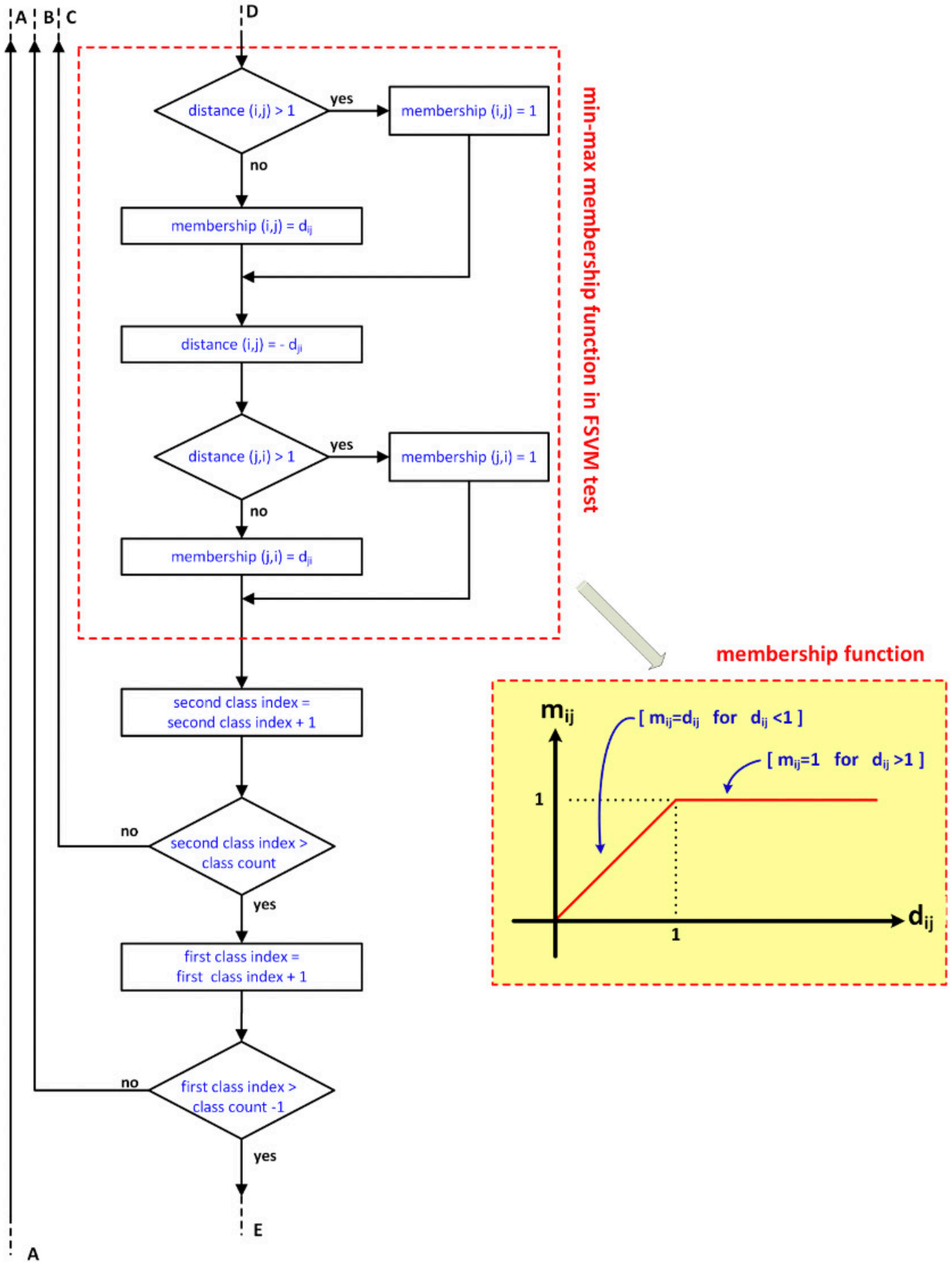


Fig. 8: The flowchart of the FSVM training function


FSVM Test
machine
class count
test data
Fsvm test
test label (tst-label)
Initialization
create memory space for test labels
column vector
dimension: length(test data)*1
test index=1
create memory space for membership function
dimension:
class count*class count
[m_ij]=1
first class index=1
i=1
second class index = first class index + 1
j = i + 1
calculate distance of the point from discrimination hyper-plane
Machine (i,j)
test data
SVM test (distance)
distance (d_ij)
A
B
C
D
Fuzzy SVM (distance calculation)
y
x
class 1
class 2
class 3
d_ij
d_ij
d_ij


A
B
C
D
distance (i,j) > 1
yes
no
membership (i,j) = 1
membership (i,j) = d_{ij}
distance (i,j) = - d_{ji}
distance (j,i) > 1
yes
no
membership (j,i) = 1
membership (j,i) = d_{ji}
min-max membership function in FSVM test
second class index =
second class index + 1
second class index >
class count
no
yes
first class index =
first class index + 1
first class index >
class count -1
no
yes
E
A
membership function
m_{ij}
[m_{ij}=d_{ij} for d_{ij} <1]
[m_{ij}=1 for d_{ij} >1]
1
1
d_{ij}

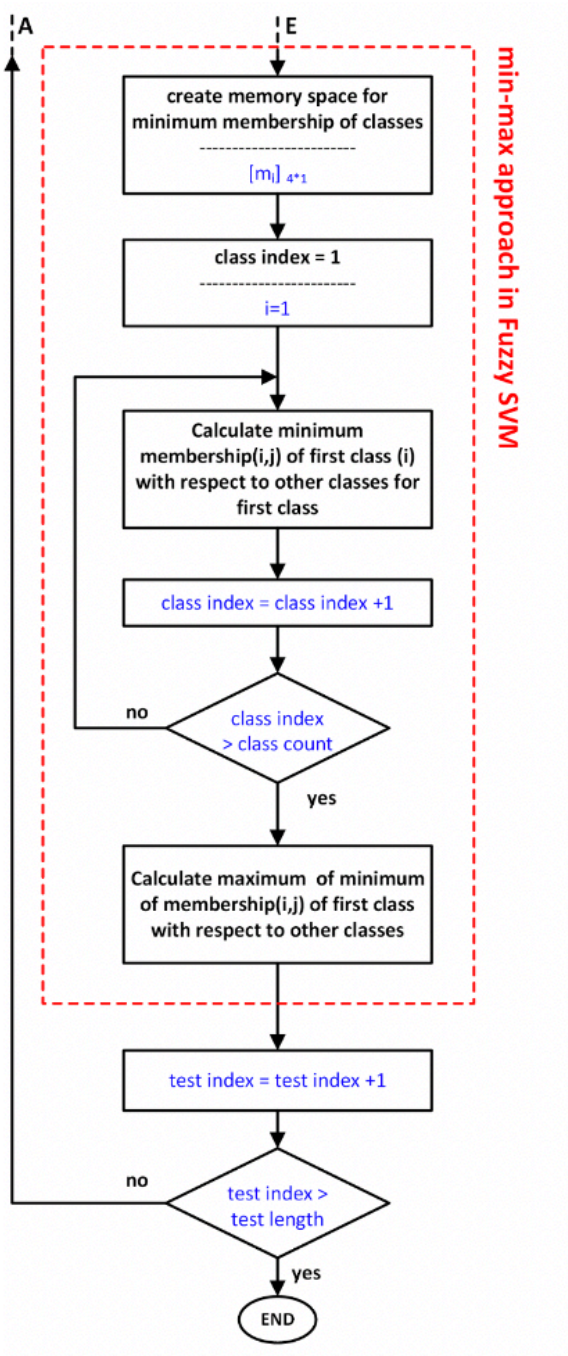


Fig. 9: The flowchart of the FSVM testing function

4. Case study

In this section, the result of the FSVM classification is presented. Due to different parameters regulations, they are carefully evaluated, and the results of FSVM classification are compared with the conventional SVM.

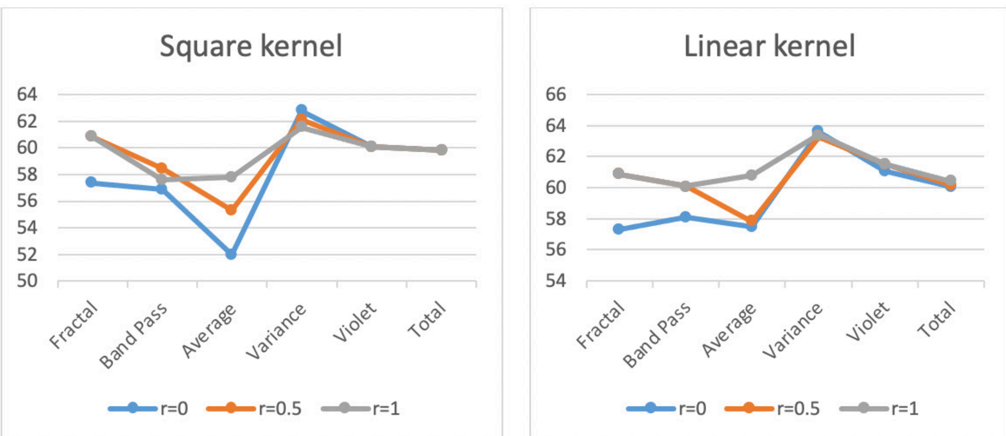
$$E = \frac{1}{K}\sum_{i=1}^{k} E_i \tag{12}$$

Note: The k-Fold method was used to confirm the results. This method divides the data into several parts. The method is to first all data is divided into k equal (or approximately equal) parts. Then, the classification of k times is performed so that one of the sections is considered the test group in each repetition, and the rest of the k-1 group is used as training data for classifying the learning process. In this method, practically, after classifying the training, it is asked to predict the accuracy of the category of the test sample, then the classification error is calculated for each sample, and finally, using the averaging of eq. (29) is measured with the total error of classification.

4.1 Effect of R parameters on the accuracy

As mentioned in the previous section, in FSVM, by defining a membership function for each data point on the soft margin of SVM, the membership value called (S_i) is allocated. Regarding the value of S_i more valuable data for SVM, the data is considered more valuable for SVM. Therefore, SVM converted to FSVM with data fuzzification. The Considered membership function is determined based on the data distance to the center of the class so that d is the distance between classes, T is considered the neighborhood radius from data, and $r = T/d$ is a factor of neighborhood radius. This factor has a value between 0 and 1, so that fuzzy properties are lost by approaching 0 and becoming a simple SVM and vice versa.

In fig. 10 correctness percentage of FSVM is evaluated for each kernel and based on the variation of r for all features. In the linear kernel curve, the best correctness percentage is obtained for $r = 1$. Therefore, this value for the r parameter is used as follows.



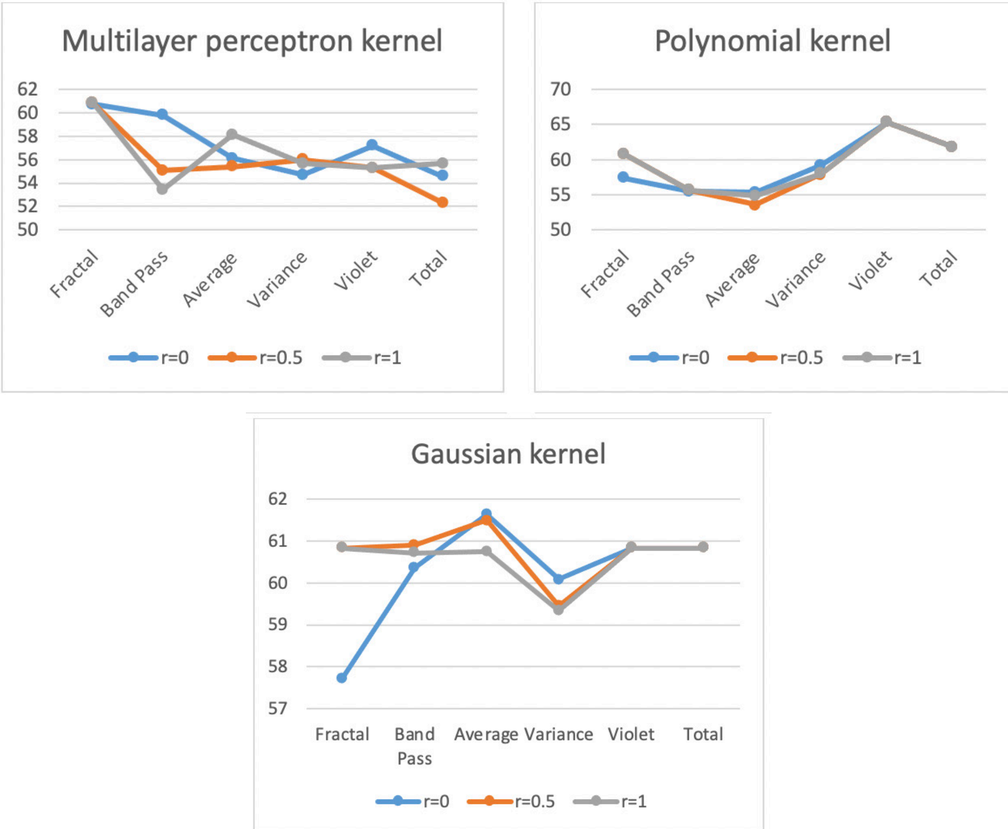


Fig. 10: The percentage accuracy of different r ranges for different types of kernels

4.2. The effect of free-parameter C changes on the percentage of accuracy

In eq. (15) parameter C has the role of the regulation parameter. Whatever parameter is more significant, the border of the cloud is narrower, and the number of unclassified points is lowered. This section discusses the effect of this parameter classification on the FSVM classification's accuracy rate. As shown in the following graphs, bandwidth, average, variance, and wavelet features show an average correctness percentage for FSVM with r=1 and $C \in [10\ 100]$. Variation of parameter C for each feature has a different effect on the accuracy rate of their results. In fig. 11, the wavelet feature has the highest accuracy rate at the change of parameter C in a range of 30 to 80. With some accuracy in the graphs, it can be concluded that the wavelet curve has the highest accuracy percentage.

4.3. Comparing the results of SVM and FSVM classifications in physiological signals

Various methods were investigated for extracting the characteristics of physiological signals. A category of features is extracted in the time domain, including average and variance, and the second category of these characteristics are frequency and time-frequency, such as Fourier and Violet, respectively. The final category of nonlin-

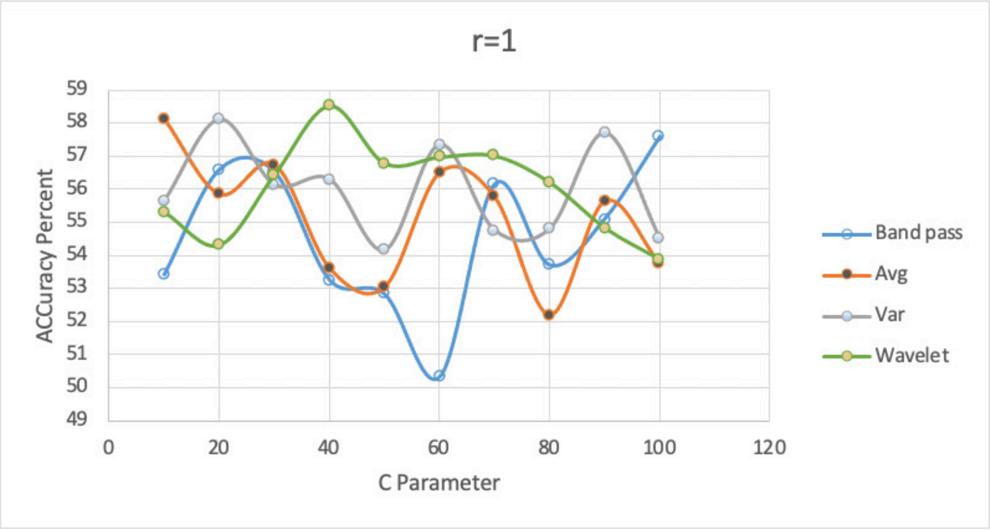


Fig.11: Comparison of correctness percentage in FSVM classifier by change of parameter C for MLP kernel and r=1

ear features includes the fractal dimension of physiological signals. As described in the previous section, FSVM is used for categorization. This paper uses a linear FSVM and nonlinear FSVM containing square, polynomials, multi-perceptron, and Gaussian kernels.

Table 1 shows the results for the correctness of each kernel related to classifying SVM and arousal index. The fractal feature obtains the best classification correctness percentage among the extracted features. As shown in Table 1, the multi-perceptron kernel has the highest accuracy percentage among the various kernels for the Arousal attribute. Alpha, Gamma, and Theta features are summarized in bandwidth feature space. According to the result of table 1, by considering the multi-perceptron kernel as the best responsive kernel in SVM, the Gamma feature has the best accuracy rate among the frequency space features. Moreover, energy and entropy features have better accuracy than multi-perceptron kernels.

Table 1: The mean of correctness (and standard deviation) of physiological signals classification for Arousal with SVM classification.

	Fractal	Theta	Alpha	Beta	Gamma	Passageway	Average	Variance	entropy	Energy	Violet	Total
Linear	59.7 (8.5)	47.8 (3.0)	46.9 (2.5)	47.3 (3.0)	48.5 (2.8)	49.4 (3.7)	51.1 (4.2)	45 (4.3)	43.4 (3.1)	51.8 (3.9)	44.9 (3)	46.4 (3.1)

Square	59.7 (8.5)	47.1 (3.1)	45.2 (1.9)	48.4 (4.3)	50.8 (3.4)	50.2 (3.4)	56.2 (4)	49.1 (5.9)	48.8 (4.2)	52.9 (4.3)	46.8 (3.4)	48.5 (4.1)
Polyno-mial	59.7 (8.5)	50.4 (4.3)	52.2 (2.3)	50 (3.0)	51.8 (5)	51.4 (4.5)	52.2 (2.6)	46.9 (2.4)	47.1 (4.2)	52.6 (4.8)	44.5 (3.7)	45.4 (4.6)
Multi-layer Percep-tron	61.6 (7.7)	60.7 (8.3)	59.9 (3.1)	45.4 (3.0)	49.6 (5.8)	54.1 (7.6)	60.9 (7.9)	45.5 (2.8)	60.7 (4.6)	45.5 (3.5)	53.7 (7.4)	51.4 (7.3)
Gauss-ian (RBF)	59.4 (8.5)	50.3 (5.2)	50.5 (3.6)	48.6 (3.8)	48.9 (5.1)	48.1 (4.2)	45.85 (3.7)	46.6 (3.3)	45.6 (3.2)	45.6 (3.2)	45.6 (3.2)	45.6 (3.2)

In table 2, the result of the FSVM classification for is given for all kernels and all types of features. According to these results, the wavelet feature in the polynomial kernel has the highest accuracy rate (65.32%). Moreover, the entropy feature in the linear kernel has the highest accuracy rate. Regarding the frequency space feature, the linear kernel has better results than the other kernels.

Table 2: The mean of the correctness (and variance) of physiological signals classification for arousal with the FSVM classification.

	Fractal	Theta	Alpha	Beta	Gamma	Passageway	Average	Variance	entropy	Energy	Violet	Total
Linear	60.83 (10.58)	60.71 (9.33)	61.25 (7.52)	60.68 (6.13)	60.52 (8.68)	60.09 (14.16)	60.87 (15.97)	63.41 (10.09)	64.67 (13.97)	61.06 (16.27)	61.51 (6.8)	60.42 (7.24)
Square	60.83 (10.58)	60.6 (9.65)	59.47 (7.62)	57.82 (4.48)	59.56 (12.04)	57.59 (14.75)	57.82 (27.54)	61.51 (31.08)	59.91 (19.04)	55.77 (19.09)	60.11 (12.1)	59.8 (17.46)
Poly-nomial	60.83 (10.58)	60.62 (14.07)	57.61 (4.61)	59.05 (8.33)	58.35 (15.19)	55.61 (16.41)	54.9 (15.7)	58.03 (21.84)	63.05 (13.56)	57.76 (19.4)	65.32 (29.16)	61.87 (18.45)
Multi-layer Per-cep-tron	60.83 (10.58)	57.97 (33.47)	53.37 (30.89)	57.06 (16.79)	58.45 (30.93)	53.42 (12.26)	58.12 (26.55)	55.66 (27.83)	53.22 (18.6)	53.12 (14.07)	55.31 (32.58)	55.65 (19.42)
Gauss-ian (RBF)	60.83 (10.58)	59.91 (10.74)	59.14 (9.33)	62.1	63.11 (33.25)	60.71 (17.25)	60.74 (10.04)	59.33 (5.28)	60.83 (10.58)	60.83 (10.58)	60.83 (10.58)	60.83 (10.58)

Table 3 indicates the result of the correctness percentage for each kernel related to SVM classification for the valence index. According to table 3, among the extracted features, the fractal feature indicates the highest accuracy rate for all kernels except multi-perceptron, while the Beta feature of the multi-perceptron kernel has an accuracy rate of %59.02. The Beta kernel has the highest accuracy rate among other features in a frequency domain feature with a multi-perceptron kernel. In the time-frequency domain, the energy feature with a polynomial kernel had the highest accuracy rate compared with the entropy feature.

By comparing various kernels, it is observed that the polynomial kernel has a better response concerning the average accuracy percentage, and the rate of dispersion is lower (standard deviation).

Table 4 summarizes the results of FSVM r=1 for all kernels and features. The entropy feature in linear kernel dedicated the highest accuracy rate (%66.31).

Table 3: The mean of correctness (and variance) of physiological signal classification for Valence with SVM class

	Fractal	Theta	Alpha	Beta	Gamma	Passageway	Average	Variance	entropy	Energy	Violet	Total
Linear	59.23 (30)	52.5 (23)	53 (28)	53 (31)	51.3 (21)	51.7 (28)	48.5 (7)	52.2 (32)	46.6 (37)	49.8 (15)	47.5 (13)	46.1 (12)
Square	59.2 (30)	54.12 (22)	54.1 (39)	53 (28)	53.9 (31)	49.2 (8)	51.1 (4)	51.1 (28)	49.3 (18)	53.3 (18)	48.2 (21)	47.3 (7.6)
Polynomial	59.2348 (30.08)	52.2 (11.5)	52.2 (21)	51 (15)	52.15 (20.2)	55.7 (31.9)	53.9 (14)	50.43 (22)	44.8 (16.7)	55.09 (24.3)	50.52 (30.5)	50.8 15.3
Multi-layer Perceptron	56.2 (45)	52.8 (34.6)	50.7 (22)	59.02 (13)	52.08 (47)	57.9 (47)	48.2 (30)	51.3 (30)	47.8 13.4	52.9 (33)	47.8 (12)	46.9 (5.9)
Gaussian (RBF)	58.9 (35)	52 (6.1)	54.6 (24)	51.9 (19)	49.8 (10)	51.5 (33)	49.9 (12)	49 (18)	48.3 (13)	48.4 (14)	48.4 (14)	48.4 (14)

Table 4: The mean of the correctness (and standard deviation) of physiological signals classification for valence with the FSVM classification.

	Fractal	Theta	Alpha	Beta	Gamma	Passageway	Average	Variance	entropy	Energy	Violet	Total
Linear	59.1 (14.3)	57.6 (22)	59.86 (22)	55.93 (6.65)	58.63 (13)	58.17 (14)	57.7 (1.49)	57.23 (11.5)	66.31 (31.4)	54.84 (7.8)	60.06 (11.6)	59.13 (10.1)
Square	59.1 (14.3)	58.5 (25)	57.79 (19)	56.63 (12)	56.6 (5)	57.1 (20)	54.62 (8.8)	57.45 (11.5)	59.48 (19.4)	55.22 (18)	60.93 (21)	58.15 (7.5)
Polynomial	59.1 (14)	56.45 (12)	55.14 (4.7)	55.33 (13.)	54.7 (11)	54.7 (14)	54.64 (21.5)	59.73 (11)	61.65 (3.28)	56.13 (29)	61.49 (19)	58.52 (16.5)

Multi-layer Percep-tron	59.1 (14.3)	56.7 (18)	55.7 (26)	55.74 (20)	53.8 (13)	55.1 (22)	53.11 (17)	55.57 (18.7)	51.21 (5.3)	55.72 (31)	53.73 (10.1)	54.54 (16)
Gauss-ian (RBF)	59.1 (14.3)	55.7 (13)	56.24 (20)	56.9 (10)	55.8 (5.4)	60.57 (32)	58.54 (9.9)	59.66 (12.7)	59.08 (13)	59.1 (13)	59.1 (14)	59.1 (14.3)

4.4. The results of the classification of brain signals

In the previous sections, we discussed various methods for feature extraction of EEG signals. A category of features in the time domain contains average and variance, and another in the frequency and time-frequency domain contains Fourier and wavelet. Moreover, the fractal feature is a nonlinear feature that is extracted. We applied linear and nonlinear SVM for classification with square, polynomial, multi-perceptron, and Gaussian kernels. Tables 5 and 6 present the correctness percentage of these kernels for arousal and valence index. According to table 5, for the arousal index, extracted entropy feature with linear kernel has the best response %66.42.

Table 6 presents the results of SVM classification for the valence index. According to this table, the entropy feature for the valence index has the highest accuracy rate of %64.26, which is related to the Gaussian kernel.

Table 5: The average validity (and maximizing) of the brain signals classification for arousal by the classification of FSVM.

	Fractal	Theta	Alpha	Beta	Gamma	Passageway	Average	Variance	entropy	Energy	Violet	Total
Linear	60.83 (10.5)	60.93 (10.2)	59.85 (7.52)	60.97 (14.3)	58.49 (6.5)	63.61 (21.4)	59.04 (13.9)	63.43 (24.9)	66.42 (22.1)	59.83 (15.2)	61.69 (7.75)	61.99 (17.4)
Square	60.83 (10.5)	60.34 (13.7)	60.4 (4.5)	59.22 (6.6)	60.02 (11.9)	57.06 (18)	55.64 (9. 7)	63.5 (28.1)	60.58 (20.1)	57.67 (5.2)	62.91 (19.3)	61.75 (23.8)
Polyno-mial	60.83 (10.5)	60.32 (10.3)	61.04 (14.2)	61.74 (20)	60.76 (18.3)	56.87 (17.7)	58.36 (29.1)	61.36 (31.2)	60.84 (9.2)	54.31 (24.3)	63.07 (17.3)	63.18 (15.1)
Multi-layer Percep-tron	60.83 (10.5)	57.48 (15.7)	59.35 (20.3)	57.48 (18.9)	58.36 (40.1)	55.93 (13.4)	52.96 (15.8)	55.53 (11.2)	53.59 (14)	56.78 (13.4)	54.28 (12.8)	55.99 (25.6)
Gauss-ian (RBF)	60.83 (10.58)	61.34 (6.75)	60.22 (5.83)	62.95 (13.94)	61.67 (14.91)	61.8 (14.1)	61.96 (15.9)	62.27 (13.5)	65.3 (10.7)	60.73 (10.4)	60.83 (10.5)	60.83 (10.5)

Table 6: The mean percentage accuracy (and standard deviation) of the Brain Signal Classification for Valence by the classification of FSVM.

	Fractal	Theta	Alpha	Beta	Gam-ma	Passage-way	Aver-age	Vari-ance	entropy	Energy	Violet	Total
Linear	59.1 (14.35)	58.95 (13.84)	58.19 (11.23)	60.92 (16.38)	57.74 (8.87)	61.01 (17.77)	57.86 (7.35)	58.4 (20.94)	61.42 (8.47)	54.86 (17.28)	60.75 (10.6)	58.97 (11.72)

Square	59.1 (14.35)	57.28 (10.91)	58.28 (15.9)	56.45 (14.4)	56.33 (7.48)	56.67 (10.47)	58.98 (14.67)	59.73 (30.4)	63.4 (20.23)	53.85 (23.74)	56.14 (5.35)	57.94 (10.09)
Polyno-mial	59.1 (14.35)	56.86 (13.97)	57.65 (22.65)	56.24 (12.91)	55.54 (5.12)	58.44 (10.31)	56.83 (16.16)	60.32 (14.13)	60.11 (4.94)	57.39 (27.09)	59.41 (14.98)	57.27 (6.3)
Multi-layer Percep-tron	59.1 (14.35)	56.17 (21.29)	56.12 (16.14)	54.8 (25.37)	56.19 (30.17)	53.29 (11.9)	55.72 (18.69)	56.48 (24.27)	52.27 (30.03)	56.34 (22.16)	53.48 (9.11)	56.23 (29.7)
Gauss-ian (RBF)	59.1 (14.35)	57.96 (11.77)	59.47 (25.23)	57.75 (11.42)	57.49 (11.26)	61.1 (25.91)	58.56 (18.88)	60.49 (25.22)	64.26 (21.7)	59.34 (15.05)	59.1 (14.35)	59.1 (14.35)

By comparing the results of physiological signals (EEG and peripheral) with only EEG signals, it is evident that the range of accuracy rate is similar with very little difference. It can be stated that the feature space of EEG signals is rich with information related to emotion. Therefore, 32 EEG channels of the physiological signal can be used instead of 40 channels. Regarding selecting the appropriate feature extraction, it is notable that the valuable feature is selected according to the kernel because the extraction of features by various kernels is different, and it is impossible to have a decisive decision. However, the features which are selected give a relevant answer.

4.5. The comparisons of proposed methods with recent works

The following Table 7 provides a comparative analysis of the latest literature research provided in (Egger, M., Ley, M., & Hanke, S., 2019) and our proposed forecasting method. The main keywords used in (Egger, M., Ley, M., & Hanke, S., 2019) for reviewing the literature research include emotion recognition, classification, prediction, and arective computing. The results in Table 7 include the methods name, number of participants (n), measured emotion, stimulus, extracted features, classification method, and achieved accuracy. The literature researches with imprecise details regarding the features or accuracy calculation were excluded from this comparison. Utilizing the proposed method, the arousal and valence parameters obtained reach a suitable accuracy compared to the other methodologies. Given the number of attributes and participants, it can be concluded that the proposed method is more accurate and stable than the other mentioned methods.

Table 7: Comparison results of the proposed method along with the recent studies related to emotion recognition measuring physiological data (Electrocardiography (ECG), Heart Rate Variability (HRV), Electroencephalography (EEG), Facial Recognition (FR), Forehead Bio-Signal (FBS), Speech Recognition (SR), Electrodermal Activity (EDA), Skin Temperature (SKT), Blood Volume Pulse (BVP), Respiration (RSP))

	Year	Method n		Emotion	Stimulus	Feature	Classification	Accuracy
Agrafioti, F., Hatzinakos, D., & Anderson, A. K. (2011)	2012	ECG	31	Excitement, erotica, disgust, fear, gore, neutral	Passive: IAPS Active: Video games	Instanta-neous frequency, local oscillation	Linear discriminants, leave-one-out cross-valida-tion	52.41 % passive, 78.43 % active

Guo, H. W., Huang, Y. S., et al. (2016, October)	2016	ECG	25	Sad, angry, fear, happiness, relax	Movie clips	Time, frequency, poincare, statics	SVM	56.9 %
Guo, H. W., Huang, Y. S., et al. (2016, October)	2016	EEG	21	Sad, scared, happy, calm	IAPS	5 Frequency bands (delta, theta, alpha, beta, gamma)	KNN, SVM	55 % KNN, 58 % SVM
Den Uyl, M. J., & Van Kuilenburg, H. (2005, August)	2005	FR	1	Happy, angry, sad, surprised, scared, disgusted, neutral	Video clips	AAM appearance vector (locations of key points and texture)	ANN (Noldus FaceReader)	89 %
Naji, M., Firoozabadi, M., & Azadfallah, P. (2014)	2013	ECG, Forehead Bio-Signal (FBS)	25	Soothing, engaging, annoying, boring	Music	4 FBS, 8 ECG features	Binary SVM	88.87 % (FBS: 47.2 % ECG: 86.63 %)
Dai, K., Fell, H. J., & MacAuslan, J. (2008)	2008	SR	7	Neutral, hot anger, happiness, sadness, interest, panic	Reading emotional speech and transcripts	62 Features	Bayesian network	80.46 % (happy and sadness), 62 % (4 emotions), 49 % (6 emotions)
Kessous, L., Castellano, G., & Caridakis, G. (2010)	2009	FR, SR, gestures	10	Anger, despair, interest, pleasure, sadness, irritation, joy, pride	Guided acting according to experiment script	26 (FR), 18 (SR), 18 (gestures)	Bayesian network	48.3 % (FR), 57.1 % (SR), 67.1 % (gestures), 78.3 % (multimodal)
Haag, A., Goronzy, S., Schaich, P., & Williams, J. (2004, June)	2004	EMG, EDA, SKT, BVP, ECG, RSP	1	Arousal, valence	IAPS	7 Features	ANN	89.73 % (arousal), 63.76 % (valence)
Katsis, C. D., Katertsidis, N., Ganiatsas, G., & Fotiadis, D. I. (2008)	2008	EMG, ECG, RSP, EDA	10	High stress, low stress, disappointment, euphoria	Simulated racing condition	13 Features	SVM, ANFIS	79.3 % (SVM), 76.7 % (ANFIS)
Maaoui, C., & Pruski, A. (2010)	2010	BVP, EMG, EDA, SKT, RSP	10	Amusement, contentment, disgust, fear, neutral, sadness	IAPS	30 Features	SVM	46.5 %
		Proposed Method	32	Arousal, valence	Audio-Visual Stimuli (musical video)	40 Features	FSVM	70.09 % (arousal), 74.47 % (valence)

An overview of the benefits, limitations, and application area of the methods compared with the proposed approach is shown in Table 8.

Table 8: An overview of the methods' benefits, limitations, and application area compared with the proposed approach (Egger, M., Ley, M., & Hanke, S., 2019).

Modality	Benefits	Limitations	Application Area
EEG	allows measurements on impaired patients	complex installation, maintenance of equipment prone to movement artifacts	lab conditions
FR	contact-less, tracking of multiple persons possible	requires a camera frontal to the face, prone to be deliberately falsified	lab conditions, work-place, intelligent homes, public spaces
VR	contact-less, casual measurement	microphone necessary, prone to background noise	the broad field of application
SR	contact-less, casual measurement	communication necessary	the broad field of application
ECG	data acquisition during cardiac check-up possible, mobile measurements	higher accuracy in stationary measurement, movement artifacts in mobile systems	lab conditions, every day use, sports activities
BVP	highly versatile method due to the small size of sensors allows assess-ment of other health-related parameters	depending on application area prone to artifacts (i.e., movement during sport)	lab conditions everyday use, sports activities
EDA	a good indicator of stress, the distinction between conflict and no-conflict situation	measures only arousal, influenced by temperature, needs In calibration	lab conditions, everyday activities
RSP	simple installation, can indicate panic, fear, con-centration or depression	the distinction of broad emotive spectrum discult	the broad field of application
SKT	versatile data acquisition possible	measures only arousal, the relative-ly slow indicator for emotive states depend on external temperature	lab conditions, workplace, smart homes, public spaces
EMG	allows measurements on patients with atypical communication	measures only valence, discult installation, amplitudes vary on chosen measurement location	lab conditions

A full review of the above methods is presented in (Egger, M., Ley, M., & Hanke, S., 2019).

5. Summaries and Conclusions

This paper proposes a modified FSVM classification-based approach to recognize emotional states based on the physiological signal in the FSVM method. The main contribution of this study includes applying various data extraction indexes and proper kernels for the FSVM classification method and evaluating the signal's richness in experimental tests. In the proposed method, FSVM is applied to solve the problem of emotional state diagnosis by using physiological signals. Initially, while the signals are preprocessed, various indexes in time and frequency domains are used for data extraction. Then, by formulating the FSVM classifier, proper nonlinear kernels are used to improve results, and free parameters r and C are considered. The obtained result shows that the performance of FSVM concerning the conventional SVM is impressive.

Furthermore, the results show that proper values for free parameters are r=1 and C=40. Another significant result obtained from this study is that EEG signals were rich enough for data classification, and 8 peripheral signals did not affect the correctness percentage of classification. The developed emotional recognition method is also compared with the existing state-of-the-art techniques for accuracy. The results show an accuracy improvement for the proposed model.

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