Affect Recognition for Biometric Surveillance using Multilayered Support Vector Machine Binary Tree

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Abstract - **Affect recognition plays an important role in biometric surveillance systems. In biometric surveillance the physiological and behavioral characteristics can be determined from physiological parameters, face expressions, voice, gesture, iris, which can be used to improve the performance of security system. The biometric surveillance can also be used to predict human intention and diseases which helps to prevent them in advance. The main objective of this work is to determine human emotions automatically with high efficiency. Thus, to automate the emotion detection process, the first step is to model the emotion and in this work emotion is modeled 2-dimensionally with valence along x-axis and arousal along y-axis. The first factor on which the classification efficiency depends is the reliable data, hence in this work the data is acquired experimentally from 200 participants which increases the efficiency of the system. The second factor on which the classification efficiency depends is, the features used for classification. In this work HRV time domain and frequency domain parameters are used which is proved to be an efficient parameter for classification thus it improves the classification efficiency of the system. The third important factor which increases efficiency of classification is suitable classification algorithm. Thus in this work, Multilayered SVM Binary Tree (MSBT) algorithm is proposed to efficiently classify multiclass problem. This MSBT algorithm is a modified SVM algorithm which uses SVM in two levels and also utilizes the advantages of binary tree structure, thus dividing valence in the first level and arousal in the second level. Thus the proposed methodology with the combined advantage of experimental data, efficient HRV features and robust MSBT algorithm classifies the emotions into four categories of relax, happy, sad and angry with an accuracy of 91%.**

Keywords: ***Affect, Emotions, Biometric Surveillance, MSBT, SVM, ECG***

INTRODUCTION

Affect identification is a methodology to understand the type of emotion a person expresses and to develop an efficient automated system to identify emotions in human beings is a major challenging task. The development of the system is based on the inter relationship between quantity of inducement of emotion by video and audio content and human response [1]. The emotional changes in human beings bring changes in facial expression, speech, iris and also in physiological signals like EEG, ECG and GSR [2]. This helps in the development of automatic prediction of human emotions with respect to the multimedia content.

The first step in the development of affect identification is to model the emotions. Psychological researchers have categorized emotions into discrete form [3]. One of the models classifies emotions in 1-dimensional scale as six basic types surprise, happiness, sad, anger, fear and disgust [4]. Emotions are perceived by the people regardless of the culture [5]. Another methodology to split the emotions in discrete manner is based on daily life [6]. The main drawback of using discrete model for emotion is that more circumstance and realistic analysis required to describe emotions [3] which is difficult to develop an automatic emotion recognition system.

The drawback can be overcome by modeling the emotions in a 2-dimensional scale. There are two types, one is emotional wheel model suggested by Plutchik [7] and other model proposed by Russell is valence-arousal model [8]. The valence-arousal model is commonly used since emotions can be well defined using this model [7] with valence defining the positive or negative feelings and arousal define the emotions on the scale of bored or excited. The 2-Dimensional model used in this work is shown in Figure 1. Different types of machine learning techniques are used to identify the affect, which requires data acquisition of a participant for a particular period when that type of emotion is expressed. In literature, different methods are employed to acquire emotional data, like facial expressions, speech signals, fMRI [2], physiological signals as ECG, EEG, EMG and GSR, thermal infrared imaging [9].

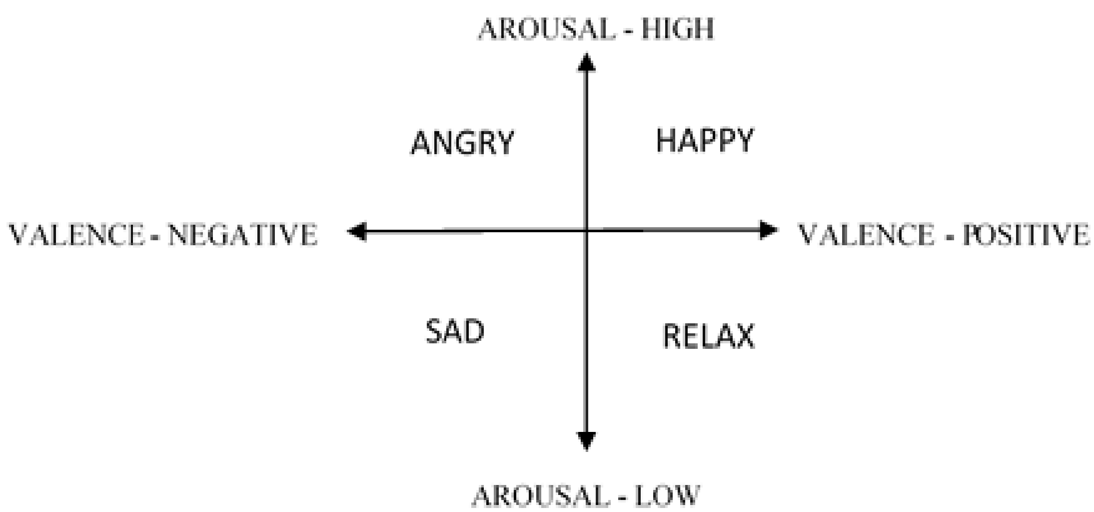

Figure 1: 2 – Dimensional Emotion Model

There are different types of features extracted either in time domain or in frequency domain or the features considered from both time and frequency domain are used [10]. In [11] Hjorth proposed use of features in time domain which is used to explain the activity and complexity of time series. The most important frequency domain parameter PSD is analysed in [13].The author highlighted the importance of HOC features which explained the oscillatory pattern of time domain features [12]. The spectrum transform functions such as Hilbert-Huang transform [10] and Short-Time Fourier Transform (STFT) [14] are also used to analyze emotions. The classification process is performed by many classifiers among which more efficient results are obtained by using k-Nearest Neighbour (kNN) [16] and by using Support Vector Machine (SVM) [15]. Another important parameter to be considered is the stimuli which is used to stimulate emotions which may be audio only, video only or a combination of both.

MATERIAL AND METHODS

Subjects

200 volunteers in the age range of 17-25 with equal distribution of males and females are considered.

Experimental setup

The experimental procedure and also the self-assessment questionnaire is described in detail to all the participants and a consent form which contains all the necessary information about the experiment is signed by each participant before commencement of the experiment. The temperature and light of the room is maintained same throughout the experiment and also same for all participants. After getting the concern from the participants that they are clear about the experimental process, sensors were placed in the correct position and after all the signals appeared to be normal, the signals were recorded. The stimuli video clips were displayed using a projector and the audibility of the audio is checked for comfortable hearing. They were played in a random order. The self-assessment rating with respect to emotions of respective videos was conducted at the end after the participants removed all the sensors. Participants were allowed to view the videos which is played and after completion, they were asked to fill the Positive and Negative Affective Scheme (PANAS) questionnaire. The other questionnaire Self-Assessment Manikin (SAM) were also asked to be filled. The self-assessment questionnaire Differential Emotions Scale (DES) were also filled by the participants.

MODULES

The different modules in the identification of individual affect state are: Data acquisition, Feature extraction and Classification. The different modules are shown in Figure 2.

Data acquisition

The ECG electrodes were connected for lead II, the subjects were asked to sit comfortably and relax by closing their eyes for 10 minutes and then Blood Pressure (BP) was measured. Biopac data acquisition system was used to record ECG signals in lead II setup. The signals were recorded at the rate of 200 samples / second for a duration of 5 minutes, with a breath rate in normal condition of 12-18 / minute, which is the rest position. Video clips were played in a random order for 10 minutes for each emotional state which contains the complete content to elicit the target emotion. ECG sensors are connected in lead II set up and ECG was recorded for last 5 minutes during viewing the video clips with 10 minutes of rest in-between different types of emotional video clipping to avoid interference between emotions. The improper ECG signal recordings were removed from analysis.

The participants after viewing the video, they were asked to fill the questionnaires truthfully such that the signals acquired could be correlated with their emotions. Different types of questionnaires were asked to be filled such that the validity of the answers could be verified. The three different type of standard emotion questionnaire used are PANAS [17], which is proved as efficient, valid and reliable for two different aspect of mood positive and negative affect. They were also asked to fill the SAM [18], which can effectively determine the arousal and valence of the participant. Similarly another questionnaire DES [19], proved to efficiently determine emotions in different dimensions.

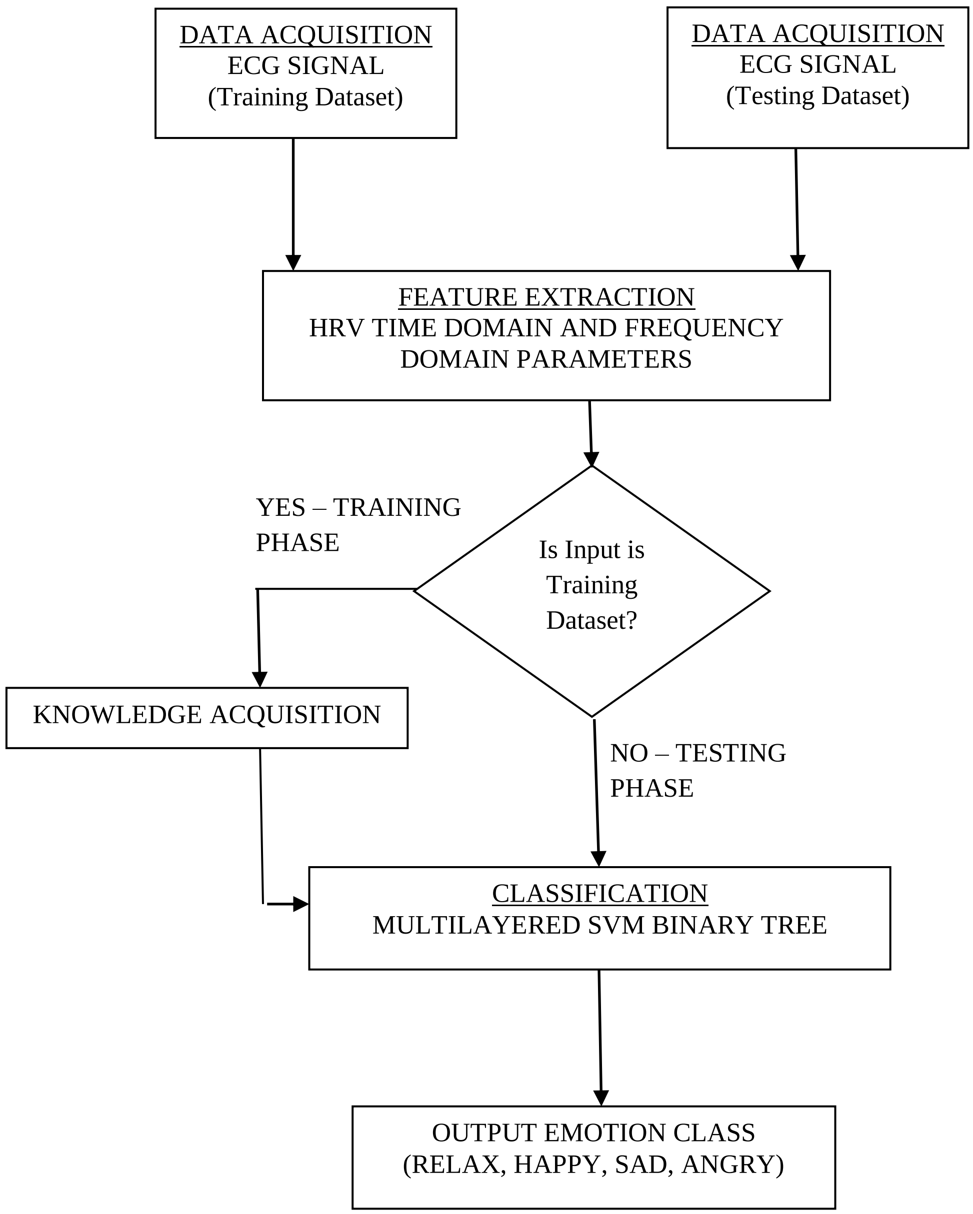

Figure 2: Block diagram of different modules in the proposed work

Feature Extraction

Heart Rate Variability Analysis

HRV analysis is calculated by following the recommendation of Task Force and 5 minutes HRV is sufficient for analysis [28]. The RR series are resampled at frequency 4 Hz, and power spectrum between 0.15 Hz and 0.4 Hz is integrated to obtain High Frequency (HF) spectral powers and 0.04 Hz and 0.15 Hz is integrated to obtain Low Frequency (LF) spectral powers. The sum of LF and HF powers were also calculated. The time domain parameters of HRV are meanRR, meanHR, the normal beat intervals termed as NN, the RR intervals which varies by more than 50ms termed as NN50. The percentage value of NN50 intervals is termed as pNN50. The other time domain parameters are Standard Deviation of all NN intervals (SDNN). The value of square root of the mean of the squares of the differences between consecutive NN intervals (RMSSD) is also calculated. The frequency domain analysis is calculated by determining the Fast Fourier Transform (FFT). This estimates the Power Spectral Density (PSD) of RR series. The HRV parameters are defined and tabulated [29] in Table 1.

Table 1: Definition of Time Domain and Frequency Domain Features of HRV

Variable Name	Definition
Mean RR (ms)	Distance between RR peaks
Mean HR (1/min)	The mean of heart rate
SDNN	The value of Standard Deviation of normal to normal RR intervals
RMSD (ms)	The value of the square root of the mean of the sum of the squares of differences between the neighbouring NN intervals
L.F. (normalized unit)	0.04-0.15 Hz Low Frequency power
H.F. (normalized unit)	0.15-0.4 Hz High Frequency power
LFHF	LF /HF

The reliability of the video clippings displayed is verified by correlating the videos with the questionnaire, whether the video clippings have induced the expected emotions in the participants. To determine their reliability the statistical evaluation parameter sensitivity and specificity is used, which is defined as given by the equation (1) and (2).

$$Sensitivity = \frac{True\ Positive}{True\ Positive + Fale\ Negative} \quad (1)$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad (2)$$

The sensitivity and specificity are obtained as 99.05 and 99.76 respectively which proves the reliability of using video clipping to stimulate emotions.

The time domain parameters Mean RR, Mean HR, SDNN, RMSD, NN50, pNN50 and the frequency domain parameters LF, HF and LF/HF are determined for all the participants. The average value is tabulated in Table 2 and the graphical representation is shown in Figure 3.

Table 2: The Average Experimental Values of HRV Features for Four Emotional States

HRV Time Domain Parameters	Mean RR	Mean HR	SDNN	RMSD	NN50	pNN50
Relax	749.39 ± 88	87.04 ± 11	72.01 ± 48	65.08 ± 32	99.48 ± 88	32.18 ± 86
Happy	738.22 ± 72	91.01 ± 22	62.07 ± 38	55.76 ± 32	89.28 ± 55	27.36 ± 56
Sad	734.07 ± 72	94.32 ± 91	59.36 ± 39	49.71 ± 41	79.45 ± 45	23.16 ± 17
Angry	719.12 ± 75	95.04 ± 18	56.08 ± 13	41.61 ± 11	69.17 ± 51	21.46 ± 45

HRV Frequency Domain Parameters	L.F. (normalized unit)	H.F. (normalized unit)	LFHF
Relax	32.18 ± 86	49.65 ± 56	1.21 ± 1
Happy	27.36 ± 56	41.56 ± 39	1.64 ± 1
Sad	23.16 ± 17	33.65 ± 68	2.27 ± 1
Angry	21.46 ± 45	27.79 ± 43	2.96 ± 1

RR - The distance between subsequent R wave peaks in ECG
HR - Heart Rate,
SDNN - Standard Deviation of normal to normal RR interval,
RMSSD - Root Mean Square Standard Deviation,
NN50 - Normal to Normal RR interval differing more than 50ms,
pNN50 - Percentage of NN50,
LF - Low Frequency,
HF - High Frequency,

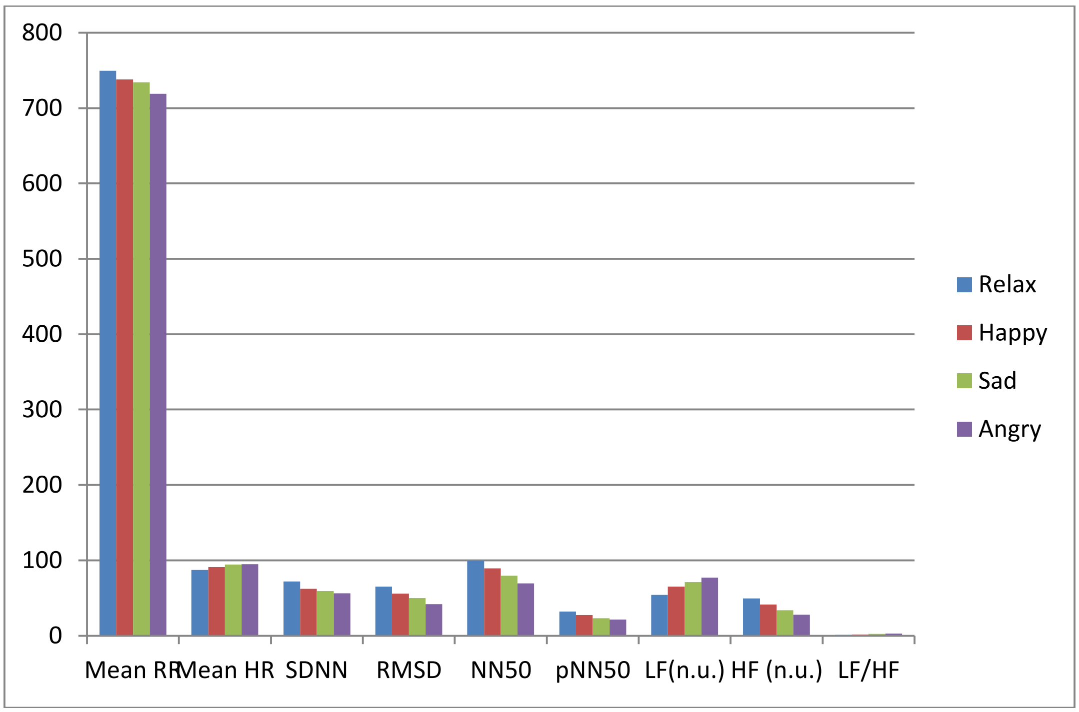

Figure 3: Graphical Representation of Experimental Values of HRV Features

SVM CLASSIFICATION

The support vector machine is basically designed to classify between two classes by Vapnik [20], [21], which was further improved [22]. The basic operation of SVM is that the input vectors are projected into high dimensional feature space. The main objective of SVM is to determine the decision boundary to separate two classes determining an optimal hyperplane which is linear and also maximizes the distance between two classes.

If the given problem is 2-class, then for a given set of training samples, $(\boldsymbol{x}_i, d_i)$

Where $\boldsymbol{x}_i$ is the input feature vector
d_i is the corresponding output class
i = 1,2, …, N
The objective is to determine an estimate d, which is denoted by y in equation (3)

$$y_i = \sum_{j=0}^{m_i} w_j \varphi_j(\boldsymbol{x}) \quad (3)$$

the objective of SVM is to define optimal hyperplane which is given in equation (4) and (5)

$$d_i - \boldsymbol{w^T} \boldsymbol{\varphi}(\boldsymbol{x_i}) \leq \boldsymbol{\epsilon} + \xi_i \quad (4)$$

$$\boldsymbol{w^T} \boldsymbol{\varphi}(\boldsymbol{x_i}) - d_i \leq \boldsymbol{\epsilon} + \xi_i{}' \quad (5)$$

Where w is the normal vector
$\boldsymbol{\epsilon}$ is the insensitive loss function
$\xi_i, \xi_i{}'$ are slack variables, $\xi_i \geq 0$, $\xi_i' \geq 0$
that satisfy the condition given in equation (6)

$$\min \frac{1}{2} \|w\|_2^2 \quad (6)$$

Kernel function is defined accordance with Mercer's theorem is given in equation (7)

$$\boldsymbol{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) = \boldsymbol{\varphi^T}(\boldsymbol{x_i}) \boldsymbol{\varphi}(\boldsymbol{x_j}) \quad (7)$$

The different kernel functions used in SVM are listed in equations (8), (9) and (10):

Polynomial Function $K(x, y) = (1 + x.y)^d$ (8)

Exponential RBF $K(x, y) = \exp(-\frac{\|x-y\|}{2\sigma^2})$ (9)

Gaussian RBF $K(x, y) = \exp(-\frac{\|x-y\|^2}{2\sigma^2})$ (10)

In this work Gaussian RBF kernel is used which classifies more efficiently compared to other kernels.

For the new data point x, the classification is then performed as given by equations (11) and (12)

$$y = sign\ (f(x)) \quad (11)$$

$$f(x) = \sum_{i=1}^{N_{sv}} \alpha_i y_i K(x. x_i) + b \quad (12)$$

Where N_{SV} is the number of support vectors.

MULTI-CLASS CLASSIFICATION METHODS

SVMs were developed for 2-class problem and many approaches were proposed for N-class problem [23]. One approach is 'One-Against-All' method, in which the kth SVM, the kth class is grouped as positive and the all the other class is grouped as negative. During the testing phase, all N samples are given to SVMs and they are classified based on the maximum output. The major drawback of this methodology is that it requires large training samples. The other method is 'One-Against-One' in which there are N(N-1)/2, 2-class classifiers. In this method, first classifier is trained by positive samples and the second classifier considered as negative samples. The classifier results are combined by using voting algorithm [24]. The drawback of this method is that the training phase is fast but testing phase is slow when there are large number of classes [25]. Another N-class methodology known as Directed Acyclic Graph SVM (DAGSVM), in which N(N-1)/2 classifiers are trained as One-Against-One, but during testing phase, the decision starts from root and final decision ends in leaf [26]. Thus a sample is given as input to SVM only N-1 times. The Binary Tree SVM (BTS) [27] is N-class SVM in which all nodes of the tree are trained using 2-classes. The probabilistic outputs are used to determine the resemblance among the samples and trained using two classes. The samples of a node are allotted to two sub nodes derived from previous class. This step is repeated for all nodes. The drawback of this method is large training time.

MULTILAYERED SVM BINARY TREE (MSBT)

In this work MSBT algorithm is proposed to classify the input signals efficiently to determine the affect state. In this methodology two layered SVM and also the binary tree structure is combined to make decisions. The classification problem is subdivided into two layers such that classification efficiency is increased. The emotion is modeled in 2-dimension with valence across x-axis and arousal along y-axis. In the first level the problem is defined to differentiate between positive valence and negative valence. In the second level the problem is reduced to differentiate between high and low arousal. Thus MSBT classifies efficiently compared to other multiclass SVM methods. The architecture of the methodology is described in Figure 4.

ALGORITHM

1. Experimentally the ECG signals are acquired from participants.
2. HRV time domain and frequency domain parameters are extracted from ECG signals.
3. The database is divided into 75% of training dataset and 25% testing dataset.
4. With the training dataset $\{(\boldsymbol{x}_i, d_i)\}_{i=1}^{N}$, Gaussian kernel, Lagrange multipliers α and α' are determined to maximize the objective function

$$Q(\alpha_i, \alpha_i') = \sum_{i=1}^{N} d_i \, (\alpha_i - \alpha_i') - \epsilon \sum_{i=1}^{N} (\alpha_i + \alpha_i') - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (\alpha_i + \alpha_i') \left(\alpha_j + \alpha_j'\right) K(x_i, x_j) \tag{13}$$

with the following constraints

a. $\sum_{i=1}^{N} (\alpha_i + \alpha_i') = 0$
b. $0 \leq \alpha_i \leq C$
c. $0 \leq \alpha,' \leq C$

Where i = 1,2,…N

5. Step 4 is level1 SVM which separates valence as positive and negative.
6. Step 3, 4 is repeated with level2 SVM to separate arousal as high and low.
7. Thus from step 6, the estimated class of training dataset is determined.
8. Classification efficiency is determined using confusion matrix
9. Similarly from step 4 to 8 is repeated for 25% testing dataset and classification efficiency determined.
10. The classification efficiency is determined for other multiclass algorithm and compared with proposed MSBT algorithm.

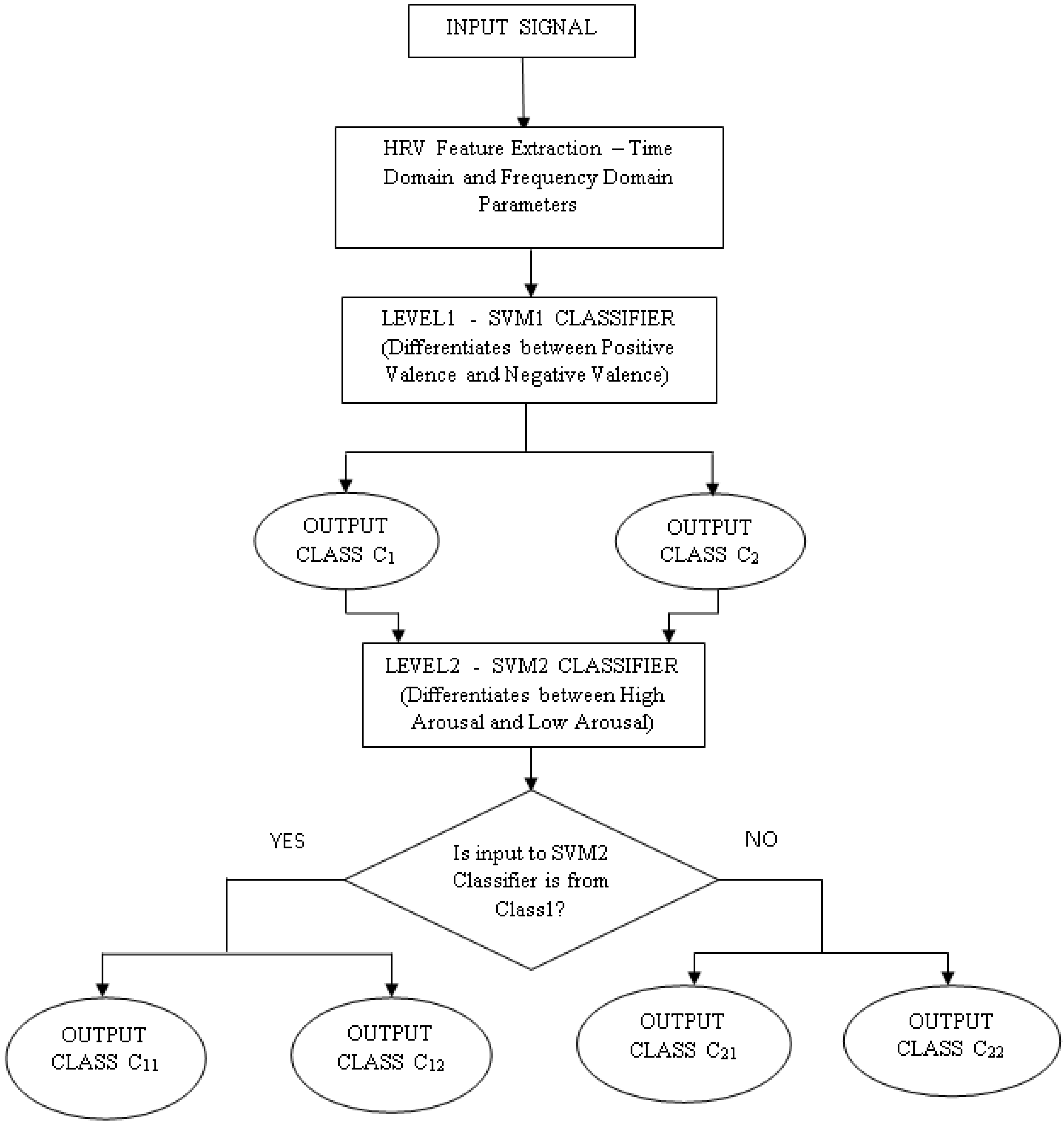

Figure 4: Multilayered SVM Binary Tree

RESULTS AND DISCUSSION

The classifier performance is evaluated using multi-class evaluation measure applying statistical methods. The confusion matrix is used to evaluate the performance of multiclass problem. The result of the expected class from the input forms the rows of the matrix while the columns are true classes. The actual class represented as C_i, and the expected classes are represented as $\widehat{C_j}$ $(1 \leq i \leq k)$, where the values are in the range of $1 \leq i, j \leq k$, which represents the matrix values for class i by the classifier but when it is actually belongs to class j. Thus from the confusion matrix it can be interpreted that the diagonal values $i = j$ represent the number of data which are correctly classified by the classifier but the off-diagonal values $i \neq$

j shows the number of data which are not properly classified. Table 3 lists the formula which is used to build 4-class confusion matrix. For example, let E_{11} represents the number of data whose actual class is class I and the expected class is also class I. Consider E_{12} which is the number of data whose actual class is class I but the expected class is class II. Similarly the other variables are also defined in the similar way.

Table 3 Formulae to Calculate Confusion matrix for four classes

		Estimated Class				Efficiency	Error
		Class I	Class II	Class III	Class IV		
Actual Class	Class I	E_{11}	E_{12}	E_{13}	E_{14}	$\frac{E_{11}}{E_{11}+E_{12}+E_{13}+E_{14}} * 100$	$\frac{E_{12}+E_{13}+E_{14}}{E_{11}+E_{12}+E_{13}+E_{14}} * 100$
	Class II	E_{21}	E_{22}	E_{23}	E_{24}	$\frac{E_{21}}{E_{21}+E_{22}+E_{23}+E_{24}} * 100$	$\frac{E_{21}+E_{23}+E_{24}}{E_{21}+E_{22}+E_{23}+E_{24}} * 100$
	Class III	E_{31}	E_{32}	E_{33}	E_{34}	$\frac{E_{31}}{E_{31}+E_{32}+E_{33}+E_{34}} * 100$	$\frac{E_{31}+E_{32}+E_{34}}{E_{31}+E_{32}+E_{33}+E_{34}} * 100$
	Class IV	E_{41}	E_{42}	E_{43}	E_{44}	$\frac{E_{41}}{E_{41}+E_{42}+E_{43}+E_{44}} * 100$	$\frac{E_{41}+E_{42}+E_{43}}{E_{41}+E_{42}+E_{43}+E_{44}} * 100$

The accuracy is calculated by using the formula in equation (13)

$$\text{Total Classification accuracy} = \frac{E_{11}+E_{22}+E_{33}+E_{44}}{n} * 100 \qquad (13)$$

where n is the total number of dataset.

Table 4: Confusion Matrix for Training Dataset

		Estimated Class				Classification Efficiency (%)	Error Efficiency (%)
		Relax	Happy	Sad	Angry		
Actual Class	Relax	142	8	0	0	94.67	5.33
	Happy	7	140	2	1	93.33	6.67
	Sad	0	3	137	10	91.33	8.67
	Angry	0	2	8	140	93.33	6.67

Table 5: Confusion Matrix for Test Dataset

		Estimated Class				Classification Efficiency (%)	Error Efficiency (%)
		Relax	Happy	Sad	Angry		
Actual Class	Relax	46	3	1	0	92	8
	Happy	2	46	1	1	92	8
	Sad	1	2	44	3	88	12
	Angry	0	1	4	45	90	10

Table 4 shows the confusion matrix for training database and Table 5 shows the confusion matrix for test database. The dataset which is correctly classified are along the diagonal elements of the matrix. Table 6 compares the classification efficiency of different types of multiclass classification methodology along with the proposed methodology. The graphical comparison is shown in Figure 5. The tabulation proves that proposed methodology outperforms other methods and hence the MSBT algorithm can be effectively used to determine the different types of emotions.

Table 6: Comparison between different types of Multiclass classification Algorithms

Multiclass Algorithm	CLASSIFICATION EFFICIENCY (%)				
	Relax	**Happy**	**Sad**	**Angry**	Average
One-Against-All	85	85	82	80	83
One-Against-One	86	85	82	82	83.75
DAGSVM	88	88	85	85	86.5
BTSVM	90	90	86	86	88
Proposed MSBT	93	92	90	90	91.25

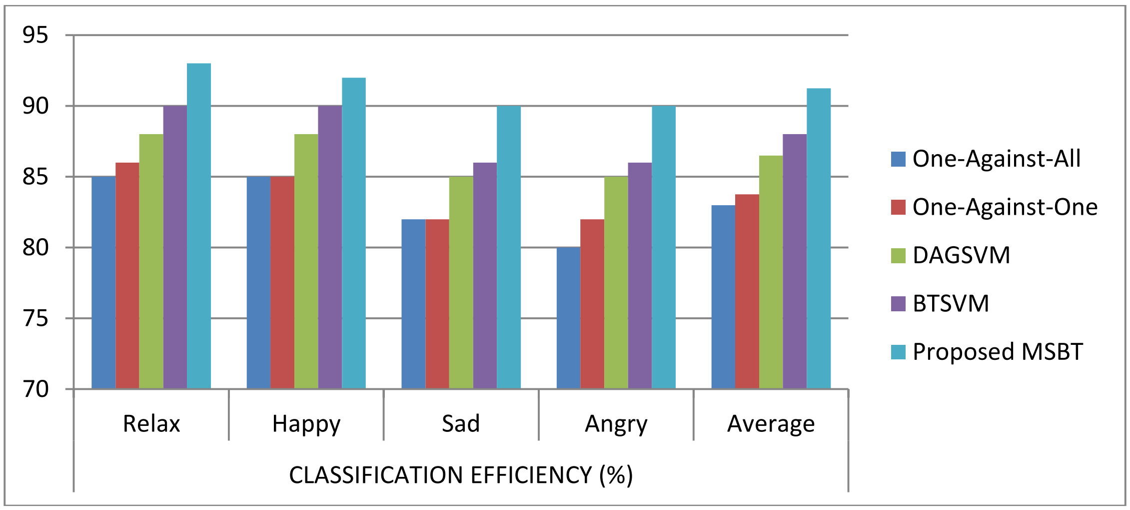

Figure 5: Graphical Representation of Comparison between different types of Multiclass Classification Algorithms

CONCLUSION

Biometric surveillance applications are widely used in security, medical diagnosis and behavioral analysis. Affect is feeling which arises due to environmental conditions. In this work a system is proposed to identify human emotions automatically using human-computer interaction. Emotion is modeled using 2-dimensional valence-arousal method, thus defining the four emotional states, relax, happy, sad and angry. The reliable system is designed by conducting experiments and acquiring data from 200 participants. The participants were displayed with relevant video clippings and ECG signals are acquired from them. The reliability of video clippings is proved by correlating with the questionnaire method. The HRV time domain and frequency domain parameters are extracted from ECG signals which is proved to be an efficient parameter for classification. The features are given as input to the proposed MSBT classifier. The modified SVM, Multilayered SVM Binary Tree is designed with two SVM is two layers which separate valence in the first layer and arousal in the second layer. The classification results proves that the proposed classifier classifies with an accuracy of 91%.

In future the efficiency can be increased by using multi modal input data, such as combining face images with physiological signals. The methodology can be extended to determine more number of emotional states.

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