# *Recognition of Emotion Through Facial Expressions Using EMG Signal*


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***Abstract*— Emotion recognition play important role in human-computer interfacing and a treatment of a person under depression. Facial expressions of a person reflect his emotional status. Electromyogram (EMG) based emotion recognition systems able to recognize true emotions of a person.**

**Current research on EMG based emotion recognition reports overall accuracy in the range 69% to 91% in a particular emotional environment. In case of posed expressions, emotions were recognized with accuracy range from 91% to 97%. There is a scope for improvement for enhancing accuracy of emotion recognition in emotional environment. In this research work EMG dataset acquired under emotional environment by Augsburg University is analyzed. From 96 EMG signals representing four emotions, four features including Root mean square, Variance, Mean absolute value and Integrated EMG are calculated. These parameters are given to 3 different classifier namely Elman neural network (ENN) classifier, Back propagation neural network (BPNN), and Nonlinear autoregressive exogenous network (NARX) for classification of emotion. NARX neural network gave maximum overall accuracy of 99.1%.**



***Keywords*— *Emotion recognition, EMG, neural network classifier***


## I. INTRODUCTION

Human-computer interface has become habitual part of our daily life like hospitality industry, automatic tutoring application, game, and entertainment industry; however this communication has several limitations in recognizing non verbal cues of attitudes, intellectual states and emotions. In current emotion recognizing systems, researchers are attempting to detect emotion mainly from the following modalities: audio (voice) [1], [2], image (facial expression) [3], body posture, physiological information, text, and multimodal cues [4, pp. 26-36]. Out of these methods audio mode is affected with noisy conditions. Many researchers used video and image processing for facial expression detection; however these methods required proper sensor alignment and light condition. Out of these methods, the natural movements of the self-directed nervous system are easily detected by physiological signals such as Electrocardiogram (ECG), skin temperature (SKT), blood pressure (BP), electroencephalogram (EEG), electromyogram (EMG), and respiration change (Rsp) [5]. Out of above physiological signals, EMG signals are directly related to muscles movement. Signal of the brain retrenched a human muscle. Activated signal causes electrical potential on muscles; which normally occurs in facial expression and body movements [6]. Current research on EMG based emotion recognition reports accuracy in the range 69% to 91%, [7], [8] in a particular emotional environment. Some emotions were recognized with high accuracy range from 91% to 97%, [9], [10], but in posed expressions. There is a scope for improvement for enhancing accuracy of emotion recognition in a particular emotional environment.

Fig. 1 shows basic block diagram of recognition of emotion through facial expressions using EMG signal. EMG signals are taken from human face muscles. After sensing this signal, signal preprocessor is used for amplification, filtering, and digital conversion. This signal is applied to feature extractor to extract quantitative information from signal. This information is applied to classifier for classification of emotional signal [11].

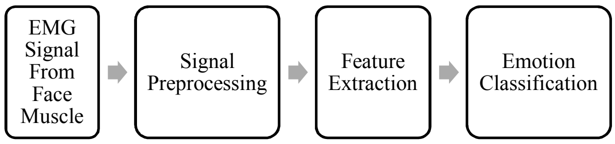


Fig.1. Basic block diagram of recognition of emotion through facial expressions using EMG signal [11].

## II. LITERATURE REVIEW ON EMG BASED EMOTION RECOGNITION

EMG based emotion recognition is carried out in two different situations namely in posed expression and in emotional environment.

### *A. Posed expression*

In this type, during acquisition of EMG signals, subjects need to be posed in particular expression. Hamedi et al. [12, pp. 11] reported in his thesis that in 1966, Hardyck and his researchers used surface EMG signal for the first time. In 1976 Ekman and Friesen [13] invented facial action code for measuring facial movement. In 2004, Ang et al. [14] recognized only three facial expressions namely angry, happy, and sad using 3 channel facial EMG signal with 94.44% recognition rate. Gibert et al. [9] used 8 channel facial EMG signals for human- computer interaction. Authors recognized happy, disgust, angry, surprise, neutral and sad emotions with 91% accuracy using Gaussian model. Chen et al. [10] recognized five emotions using Elman neural networks (ENN) based model and reported 97.12% accuracy. Hence in case of posed expressions, emotions were recognized with accuracy range from 91% to 97% [9], [10]. This posed expression is not considered as true emotions because it's not stimulated in

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emotional environment. Hence there are need to be considered particular emotional environment in emotion detection.

### *B. Emotional environment*

In this type, during acquisition of EMG signals, subjects need to be placed in emotional environment. Cheng et al. [15] adopted wavelet transform and classified joy, angry, sadness, and pleasure emotions with 75% accuracy. Jerritta et al. [7] achieved 69.5% classification accuracy using single channel EMG data acquisition unit, in audio visual stimulus condition. Picard et al. achieved 83% classification accuracy for 3 emotions [16]. From 2012 to 2014 Gruebler et al. [17], [18] recognized smiling, biting, and frowning expressions with 87.52% accuracy using wearable device. Anger and frustration were missing in expressions. In 2016, Charlyn et al. [19] identified six emotions namely fear, anger, happy, disgust, sad and neutral with 78.56% accuracy. Yang et al. [8], [20] used EMG signal data bank, generated from the Augsburg University in German and recognized emotion with 87.5% accuracy using support vector machine with back propagation algorithm with (BP_SVM). In same year author used support vector machine with least squares algorithm (LS_SVM). Due to this method recognition rate improved to 91.67%. Hence EMG based emotion recognition reports overall accuracy in the range 69% to 91% in a particular emotional environment [7], [8]. From literature it is observed that there are lots of improvement is needed in emotional environment.

In this research work Augsburg bio-signal toolbox dataset (AUBT) made available by Augsburg University is analyzed [8]. This dataset is generated in musical emotional environment. From 96 EMG signals representing four emotions, four time- domain features including Root mean square (RMS), Variance (VAR), Mean absolute value (MAV) and Integrated EMG (IEMG) are calculated. Three artificial neural network namely Elman neural network (ENN) classifier, Back propagation neural network (BPNN), and nonlinear autoregressive exogenous network (NARX) are used for classification. NARX neural network is used first time for facial emotion recognition using EMG signal. As described above Yang et al. [8] used AUBT dataset and achieved accuracy of 91.67% emotion recognition with least squares Support Vector Machine. This research work attempts to improve emotion recognition accuracy by selecting best performance neural network out of ENN, BPNN and NARX classifiers.

## III. RESEARCH IMPLEMENTAION

### *A. Data collection*

This research work has used datasets created by University of Augsburg (AUBT). It contains 4 physiological data namely respiration change (Rsp), ECG, skin conductivity (SC), and EMG of a single person in four diverse expressive states namely angry, joy, pleasure, and sad under musical circumstance [21]. These data were collected at 25 different sessions; however data in one session was not properly recorded, so this research considers only 24 sessions' data. We have also investigated emotion recognition for five subjects by extracting EMG signals with circuit developed in laboratory; however due to limitation of pages, EMG dataset acquired by Augsburg University is analyzed. The length of the recording is restricted up to two minutes per session per emotion and sampled at 32Hz [22], [23]. Out of these signals, this research work considers only EMG signal for all emotions. 24 EMG signals are collected for each emotion. Hence total 96 EMG signals are collected from AUBT dataset.

### *B. Signal preprocessing and feature extraction*

In this research, MATLAB is used for feature extraction and classification. As mentioned in [21], [23] feature extraction based on 256ms window duration of facial EMG signal gives better result. Hence in this research EMG signal frame of 256ms is used. Each signal has 192 samples, hence after framing 24 frames are formed, and for 96 EMG signals 2304 frames are formed. From each of the frames, eight time domain features are calculated. Table I gives a mathematical formulas of features.

TABLE I. MATHEMATICAL FORMULAS OF FEATURES, R IS THE SIZE OF THE FRAME, C IS THE PRESENT FRAME, $Y_M$ IS THE PRESENT POSITION OF SIGNAL AND M IS THE INDICATOR OF THE PRESENT POINT $Y_M$ [11].

| **MATHEMATICAL FORMULAS OF FEATURES** | |
|---|---|
| $RMS_c = \left(\sqrt{\frac{1}{R}\sum_{m=1}^{R} y_m^2}\right)$ (1) | $MAV_c = \frac{1}{R}\left(\sum_{m=1}^{R}\lvert y_m\rvert\right)$ (5) |
| $VAR_c = \frac{1}{R}\left(\sum_{m=1}^{R}(y_m-\bar{y}_m)^2\right)$ (2) | $MMAV1_c = \frac{1}{R}\left(\sum_{m=1}^{R}s\lvert y_m\rvert\right)$ (6) <br> $s=1$ if $0.25L<m<0.75L$ <br> $s=0.5$ otherwise |
| $IEMG_c = \left(\sum_{m=1}^{R}\lvert y_m\rvert\right)$ (3) | $MMAV2_c = \frac{1}{R}\left(\sum_{m=1}^{R}s\lvert y_m\rvert\right)$ (7) <br> $s=1$ if $0.25R< m<0.75R$ <br> $s=4m/R$ if $m<0.25R$ <br> $s=4(m-R)/R$ otherwise |
| $SSI_c = \left(\sum_{m=1}^{R}\lvert y_m\rvert^2\right)$ (4) | $MPV_c = max(y_m)$ (8) |

It includes RMS, MPV, MAV, MMAV1, MMAV2, IEMG, VAR and simple square integral (SSI) formulas. RMS contains average power of signal and it is easy for speedy training and running of the classifier [12]. VAR feature is used to identify variation of signal [10]. IEMG feature is used to determine a raise in signal power and amplitude due to higher muscle fiber mobilization for a rigid external force. MAV is good estimator of EMG amplitude [24]. MMAV1 and MMAV2 is extension of MAV with weighting factor. SSI used to describe energy of EMG signal [25]. MPV described maximum amplitude level of EMG signal. To begin with this research, all parameters are compared for their performance with different emotions. Fig.2. shows time domain feature of 96 EMG signals for different classes of emotions namely class 1 for joy, class 2 for angry, class 3 for sad, and class 4 for pleasure. Out of these, SSI feature do not show significant changes in different emotions. Hence RMS, MPV, MAV, MMAV1, MMAV 2, IEMG, and VAR are selected for further feature comparison.

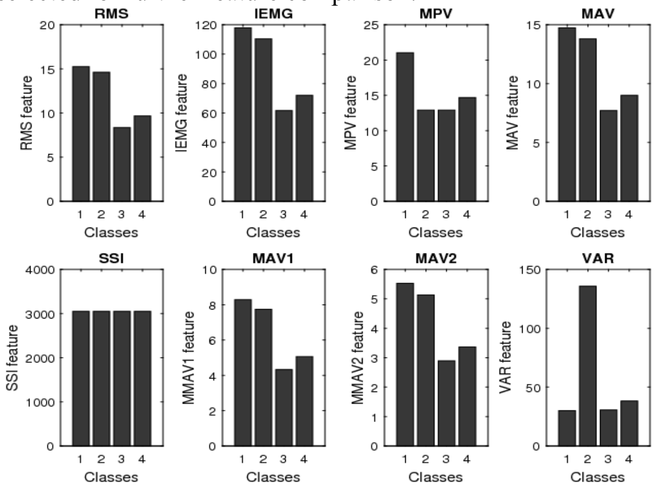


Fig. 2 Time domain feature of 96 EMG signals for different classes of emotions namely class 1 for joy, class 2 for angry, class 3 for sad, and class 4 for pleasure.

Table II shows performance of different combinations of seven features. RMS, MAV, VAR, and IEMG gave minimum MSE. Hence these four features are selected to train neural networks.

TABLE II. PERFOMANCE OF DIFFERENT COMBINATION OF FEATURES

| Sr. No | Features | MSE |
|---|---|---|
| 1 | RMS,VAR, IEMG | 0.00055102 |
| 2 | RMS, MPV,VAR, IEMG | 0.01694 |
| 3 | RMS, MAV,VAR, IEMG | 0.00002877 |
| 4 | RMS, MAV, MMAV1, VAR, IEMG | 0.06177 |
| 5 | RMS, MAV, MMAV1, MMAV2, MPV, VAR | 0.0077 |
| 6 | RMS, MAV, MMAV1, MMAV2, MPV, VAR, IEMG | 0.0071 |

*B. Classification*

Three Artificial neural networks namely ENN, BPNN and NARX are used for classification. BPNN used back propagation rule [26]. Elman neural network has feedback path. Hidden layer inserts an undertake layer act as memory, so that network system is suitable for time varying dynamic condition like emotion detection in natural conversation [27]. NARX is normally used for nonlinear dynamical system. Output is recurrently connected to hidden layer, so network can interconnect two events that are far way from each other. Due to this characteristic, network suitable for continuous natural emotion recognition [28]. Many researchers [8], [9], [13], [27], [28] used these classifiers and succeed good emotion recognition. Hence in this research, we first compared their performance with different emotions. All selected classifiers consists of four input neurons for four features, four output classes for four emotions, and one hidden layers. For selection of hidden node in hidden layer, run these three models for different values of hidden nodes and selected hidden node with minimum mean square error (MSE). For BPNN, ENN and NARX networks, 7, 9 and 3 hidden nodes are selected. Fig. 3 to 5 shows structures for all three neural networks generated using MATLAB.

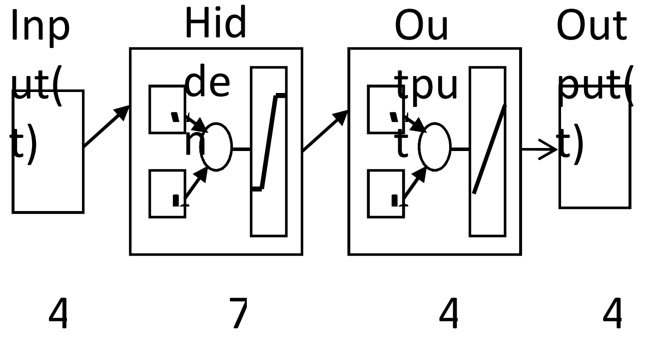


Fig.3. Structure of BPNN [29]

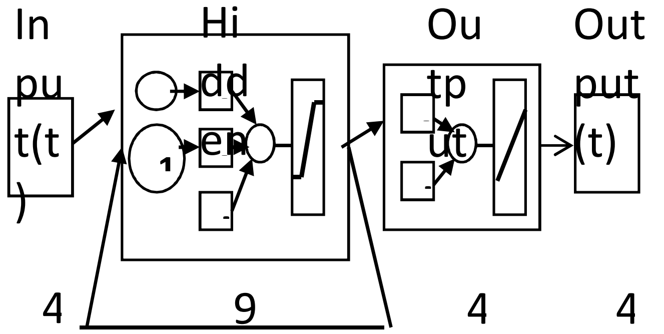


Fig.4. Structure of ENN [29]

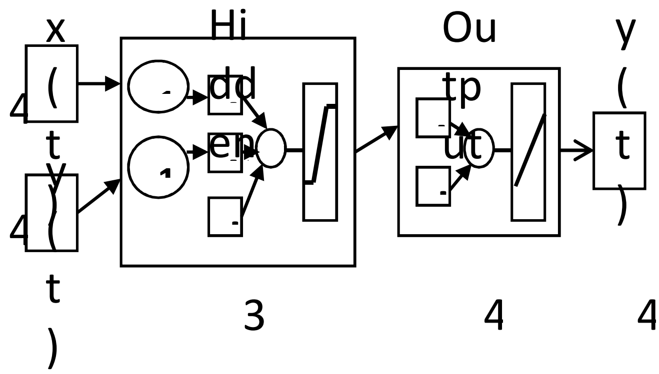


Fig.5. Structure of NARX neural network [29]

Levenberg-Marquardt algorithm (trainlm) is used for training of BPNN and NARX models and adaptive and momentum learning rate algorithm (traingdx) is used to train ENN model [29].

## IV. RESULT AND DISCUSSION

To train neural network, four features of 96 EMG signals are applied at input of model and set target matrix of 4 emotions. Entire dataset is divided in seven parts. One part is considered for testing and other parts considered for training and validation. To find out average of classification accuracy, repeated this process seven times by considering different testing part. Table III shows performance of three neural networks with different testing input. Best performance of

BPNN, ENN and NARX are 41.2%, 33.7% and 99.1% respectively. From this table it's observed that NARX gave best classification accuracy

TABLE III. PERFORMANCE OF CLASSIFIER FOR DIFFERENT TEST INPUT

| Test input | BPNN | ENN | NARX |
|---|---|---|---|
| | *Accuracy (%)* | *Accuracy (%)* | *Accuracy (%)* |
| 1 | 39.6 | 25.8 | **99.1** |
| 2 | 35.4 | **33.7** | 98.8 |
| 3 | **41.2** | 27.3 | 99.1 |
| 4 | 37.8 | 29.1 | 99.1 |
| 5 | 35.4 | 24.8 | 99.1 |
| 6 | 37.5 | 28.8 | 99.1 |
| 7 | 29.2 | 28.1 | 97.2 |
| Average Accuracy (%) | 36.58571 | 28.22857 | 98.78571 |

Detail performance evaluated by mean square error (MSE) [29] which is squared difference of output and target value and plotted confusion matrix to find out classification accuracy. Fig. 6 to 8 shows performance of neural networks. As shown in figures, Blue solid plot is for training, green dash plot for validation and red dotted plot for testing. Training data is to train the network. Test set is used for prediction to unknown class. Validation set is used to control the learning rate and training period. All training data is passed to the network in one epoch. In each epoch, weight of network is updated and MSE is calculated. Best performance indicates that iteration at which validation performance reached minimum [29]. In this case, for BPNN network, Minimum mean square error (MSE) of validation plot is 0.1678 at 97 epochs. For ENN network, Minimum MSE of validation plot is 0.18949 at 48 epochs, and for NARX network, Minimum MSE of validation plot is $2.8776e^{-5}$ at 12 epochs. The training continued for 6 more iteration before the training stopped. NARX network is achieved minimum MSE as compared to BPNN and ENN model.

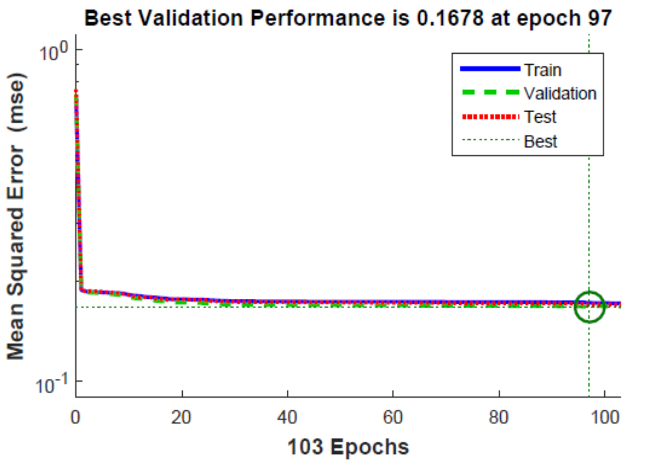


Fig.6. BPNN training performance generated in MATLAB neural network tool. Blue solid plot is for training, green dash plot for validation and red dotted plot for testing.

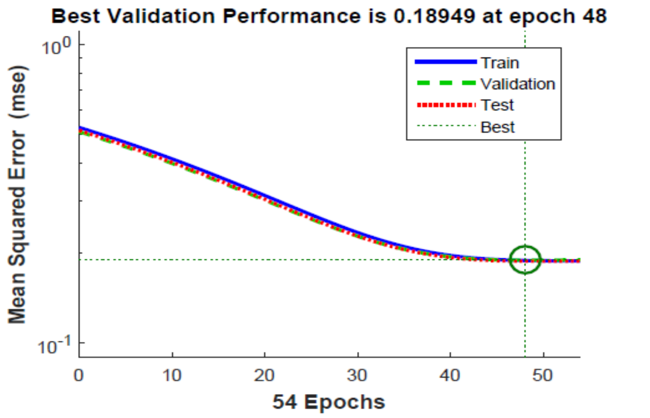


Fig.7. Elman neural network training performance graph is generated in MATLAB neural network tool. Blue solid plot is for training, green dash plot for validation and red dotted plot for testing.

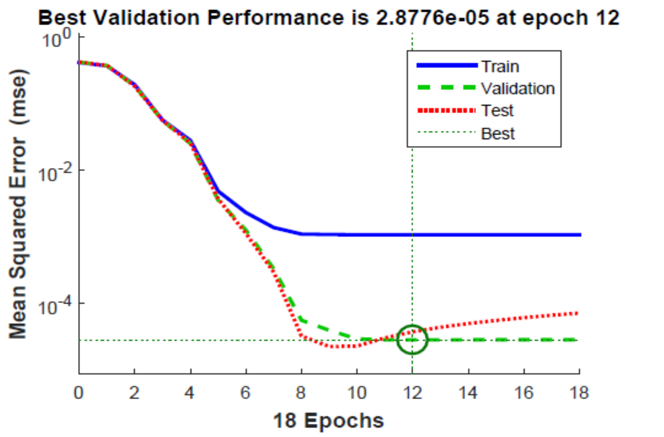


Fig.8. NARX neural network training performance graph is generated in MATLAB neural network tool. Blue solid plot is for training, green dash plot for validation and red dotted plot for testing.

To find out classification accuracy, confusion matrix is plotted. Fig. 9 to 11 shows confusion matrices for BPNN, ENN and NARX models. Confusion matrix column represents target class and row represents output class. Class1 for joy, class2 for angry, class 3 for sad and class 4 for pleasure.

Bottom corner of matrix represents overall classification accuracy and misclassification accuracy. Precision and specificity of individual classes are given in last row and last column respectively.

Prediction of each data in percentage is given in each box of confusion matrix. Individual emotion accuracies were calculated using "(9)," and written in table IV

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Positive + True\ Negative + False\ Positive + False\ Negative)} \tag{9}$$

Where
True positive= right positive guess
True negative= right negative guess
False positive= wrong positive guess
False negative= wrong negative guess

Diagonal values of confusion matrix represent true positive and true negative value. Other values considered as false positive and false negative.

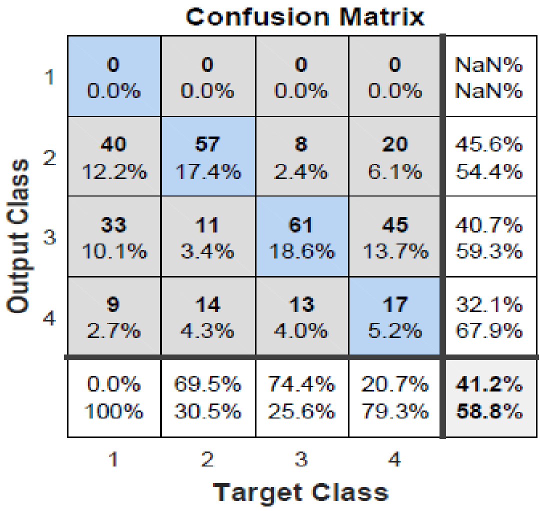


Fig.9. Confusion Matrix for BPNN generated in MATLAB neural network tool.

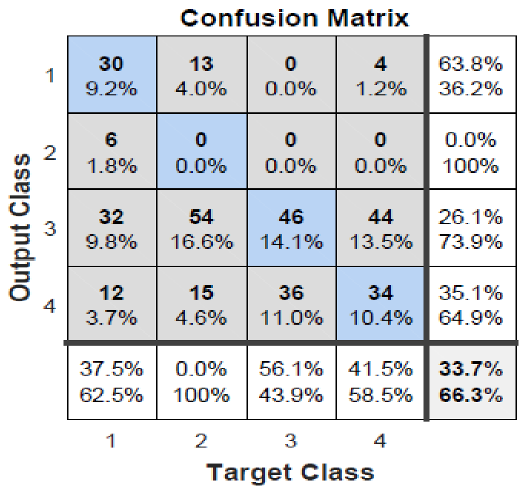


Fig.10. Confusion Matrix for ENN generated in MATLAB neural network tool.

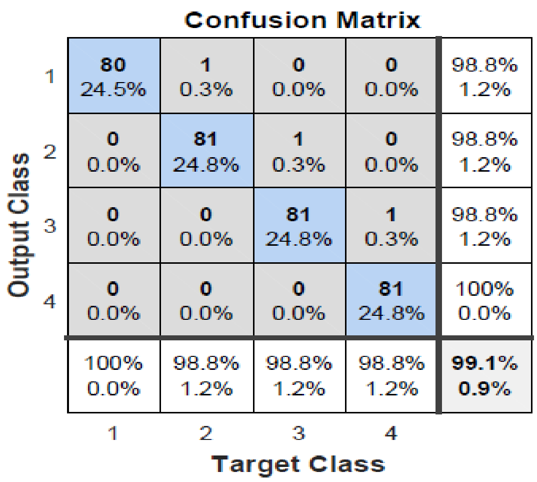


Fig.11. Confusion Matrix for NARX generated in MATLAB neural network tool.

TABLE IV. CLASSIFICATION ACCURACY, SENSITIVITY AND PRECISION IN (%) FOR ALL EMOTIONS USING BPNN, ENN , AND NARX CLASSIFIERS

| **Classifier** | **Emotion** | **Joy** | **Angry** | **Sad** | **Pleasure** | **Overall Accuracy %** |
|---|---|---|---|---|---|---|
| BPNN | Accuracy | 62.21 | 59.21 | 55.10 | 57.2 | 41.2 |
| | Sensitivity | NAN | 45.6 | 40.7 | 32.1 | |
| | Precision | 0 | 69.5 | 74.4 | 20.7 | |
| ENN | Accuracy | 62.14 | 55.55 | 39.85 | 49.7 | 33.7 |
| | Sensitivity | 63.8 | 0 | 26.1 | 35.1 | |
| | Precision | 37.5 | 0 | 56.1 | 41.5 | |
| NARX | Accuracy | 99.69 | 99.38 | 99.38 | 99.6 | 99.1 |
| | Sensitivity | 98.8 | 98.8 | 98.8 | 100 | |
| | Precision | 100 | 98.8 | 98.8 | 98.8 | |

TABLE V. CLASSIFICATION ACCURACY OBTAINED BY YANG ET AL.[8]FOR ALL EMOTIONS USING LS_SVM CLASSIFIER

| **Classifier** | **Emotion** | **Joy** | **Angry** | **Sad** | **Pleasure** | **Overall Accuracy %** |
|---|---|---|---|---|---|---|
| LS_SVM | Accuracy % | 100 | 83.3 | 83.3 | 100 | 91.67 |

Table IV shows classification accuracy for all emotions using different classifier. From this table it's observed that NARX gave best classification accuracy. Also, individual emotion recognition is very high in NARX method as compared to BPNN and ENN method. Another online dataset made available by MIT laboratory is used to check cross validation and found that classification accuracy is still 99.1%. From precision and sensitivity, it is proved that BPNN and ENN are not good to recognize joy and anger emotion respectively. However NARX shows good sensitivity and precision for all emotions. As shown in table V, Yang et al. [8] used AUBT dataset and classified four emotions using least square support vector machine with 91.67% accuracy. NARX neural network with four time domain features namely RMS, MAV, IEMG, and VAR improved accuracy by 8.1%.

## V. CONCLUSION

The four features extracted from EMG signals namely RMS, MAV, IEMG, and VAR shows better variations for the four emotions under study. After comparing performance of three different classifiers namely BPNN, ENN, and NARX neural network, found that NARX neural network gave maximum 99.1% classification accuracy. This system achieved classification accuracy 8.1% more than accuracy achieved by Yang et al [8].

## VI. FUTURE SCOPE

This research work has used online EMG based data set. In future, we can plan to acquire and process EMG signal for different emotions. To improve classification accuracy, we can plan to consider head motion and facial gesture along with facial expression.

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