EMO-NET ARTIFICIAL NEURAL NETWORK: A ROBUST AFFECTIVE COMPUTING PREDICTION SYSTEM FOR EMOTIONAL PSYCHOLOGY USING AMIGOS

Bakkialakshmi V. S[1]
Research Scholar, Department of Computer Science & Engineering, Hindustan University,
OMR, Padur, Chennai, Tamilnadu, 603103, India
bakkyam30@gmail.com
Orcid ID - 0000-0002-0886-0553

T. Sudalaimuthu[2]
Professor, Department of Computer Science & Engineering, Hindustan University,
OMR, Padur, Chennai, Tamilnadu, 603103, India
sudalaimuthut@gmail.com
Orcid ID - 0000-0003-0371-9371

Abstract

Affective computing has become an increasingly popular area of study that focuses on developing a robust system that automatically recognizes human emotions. Any changes in human emotion directly impact brain stimulation and physiological parameters. Emotions are critical parameters that directly impact the behaviour of an individual. Collecting the neurophysiological data from humans is utilized here. The ultimate goal of the presented work is to develop a robust methodology to predict human real affect. The present system considers the Amigos data set in which physiological signals such as ECG, EEG, and Galvanic Skin Response (GSR) are considered. The proposed framework is modelled using Gaussian mixture models to produce an expectation-maximization technique (GEM). Along with the measurement of statistical parameters such as mean, standard deviation, and Sigma, these are helpful for the system to identify the real class. The comprehensive analysis of various participant data collected through the AMIGOS dataset was split into training data and testing data. The raw data preprocessing using the Synthetic Minority Oversampling Technique (SMOTE) model in which the data has cleaned up random values or removed junk values or removed. Since data is provided to the GEM algorithm in which the expectation-maximization parameters such as mean median standard deviation and sigmoid are calculated. Based on the evaluated model, part of the test signals are given from the amigo dataset. The system can compare an interpreter to validate the parameters-based emotion labelling. A novel EmoNet_ANN (ENA) system is further improved by including deep learning models to find the detailed covariate values helpful to identify the personality traits of the participants. The proposed optimized Novel EmoNet_ANN (ENA) perceives the accuracy benefit of 92.5% with less computational time. A novel EmoNet_ANN(ENA) Proposed system is comparatively studied and further improved by evaluating deep learning models to find the detailed covariate values present in the data set. The statistical measures on Sigma, Variance from the GEM model concerning the correlation metric from ANN are further used to validate the emotion detection. Accuracy, Precision, Recall and F1score form the analysis module which is used to determine the overall performance statistics. Emotion analysis and affect impacted parameters are modelled using Novel EmoNet_ANN (ENA). The AMIGOS dataset analyses physiological signals to determine the actual emotions. With reduced computation time and iteration run till Zero error on complete analysis.

Keywords: **Affective computing, Emotion analysis, Subject identification, Personality detection, Mental health matters, Emotional Psychology.**

1. Introduction

Affective computing has emerged as an interesting area of development for systems that can automatically recognize, interpret and model the emotions of humans. Emotions are important parameters that impact the behaviour of humans directly. The emotional reflection of an individual depends on various factors such as perception, decision-making, creativity, thoughts, social interaction etc. Many Research Developments are emerging every year that deeply analyze the emotional factors behind affective computing [1]. Irrespective of the application, the area of affective computing considers both emotional classifications and emotional detection. When it comes to emotional classification, two approaches are used in the Discrete and Dimensional models. Emotions are correlated with voice, face, social texting, Neuro-imaging, and physiological signals coming from the human body. In terms of emotional elicitation, ethically ignoring the affective states in the experiment is a critical challenge [26]. Two kinds of emotions, active and passive are discussed. Active emotions are reflected immediately, passive emotions are hidden emotions. Image data sets are available to analyze emotions. DEAP, the publicly available human emotion dataset contains the ECG recording of various channels with interpreter labels for analysis [2][19]. The growth of artificial intelligence and machine learning technology created various test scenarios for evaluating the human real affect status using standard datasets. Human emotion is identified with many parameters like capturing physiological data, speech patterns, face expressions, contextual expressions etc. Emotions are easily captured with facial expressions, whereas the hidden emotions of humans are typical to understand. In the current digital world, people engage their minds towards interacting with smart devices rather than speaking with other people [3]. Sometimes, emotional triggers are not addressed. People often express their accumulated emotions either in a positive way, such as focused, determined, and hard work or in a negative manner like arrogance, anger, depression, etc. In the case of psychological diagnosis, the doctors must identify an individual's real emotions to give them better treatment.

A systematic analysis incorporating artificial intelligence is discussed to detect human emotion with the physiological data that cross validates the psychological interpretation of consultants. The proposed research work is organized as data collection, preprocessing, classification and performance analysis etc. [4]. Emotions are direct reflections of the brain's response to certain incidents. Real emotion is sometimes hidden and it cannot be held for a long time. The impact of chronic emotional suppression causes stress and hypertension. Spontaneous reflections of thoughts are expressed as emotions. Affective computing is formulated with a two-dimensional emotion model that contains valence and arousal [27]. The three-dimensional model contains valence, arousal and dominance. Emotions such as Alertness, Excitement, Elated mood, Happiness and Pleasure come under the arousal category. Contentment, Serenity, Relaxed mode and Calmness come under the valence category. Negative emotions such as tension, nervousness, stress, Upset, Unpleasantness, Sadness, Depression, a Lethargic mood, Fatigue and Deactivation are considered negative emotions [5][18].

In many affective computing-enabled emotion detection frameworks, the drawback persists with the multi-modality in decision making. Emotions of different dimensions fall under a similar category due to the algorithmic issue of labelled invalid spatial-temporal features [28]. The impact of invalid data needs to be reduced in further implementations. Emotion data are massive in size since the ECG, EEG, and GSR values are the sequences of recorded signal peaks. A discriminative model is focused on research implementations. Computing all the features available in the real-time dataset seems complex and it consumes more computation time. On the other hand, it evaluates multi-modality in features mapping [6][20]. The present research work is focused on developing a robust and lightweight architecture that skim the massive AMIGOS dataset, by considering the EEG, ECG, GSR parameters and the Self-assessment reports to evaluate emotion detection.

- Systematic analysis of affective computing that helps the physiologist to determine the real emotional impact of the subject under test.
- Considering the automated prediction as prior work, with the reduced computational steps, a robust algorithm needs to be created.
- Emotional highlights that reflect in EEG, ECG, and GSR parameters are keenly analyzed to produce a framework that competes with the state-of-the-art approaches.
- The detailed study is performed, with the acceptable statistical parameters formulated to validate the present work.

The rest of the paper is organized as a background study in **Section 2.** The existing methodologies for emotion detection in the area of affective computing and the results obtained using certain techniques are discussed. **Section 3** discusses the various materials and the methods required to initiate the development of prediction models, such as tool selection, Dataset selection, experimental plans etc. **Section 4** discusses the detailed system architecture and the implementation summary, followed by **Section 5** which explains the results obtained with the proposed model and the discussions that led to the interpretations. **Section 6**concludes with the suggested future scope.

2. Background Study

A multi-featured model for extracting the Heart Rate Variability (HRV) ratio for emotion recognition. Emotional dimensions such as arousal, violence and dominance are synthesized with the evaluated standards. The demonstration method considers the Heartbeat rate as a test signal and it finds the emotion. The accuracy of 96.87 % is achieved for the detection of violence and 85.4 % is achieved for the arousal dimension and 81.25% is achieved for violence arousal combined synthesis. ECG data are comparatively built small for analyzing emotions with the successive differences in the heartbeat [7][21].

T.Song et al., (2018), Using DREAMER dataset, EEG multichannel based emotion recognition system with a novel dynamic graph convolutional neural network method is evaluated here. The GCNN differs from the traditional approach of Convolutional Neural Network (CNN) which uses the graphical mode of multichannel EEG data. Using discriminative features for improving the EEG-based emotion recognition. The adjacent matrix is learnt using neural network architecture for better accuracy [29]. The presented system achieves the recognition accuracy of 90.4 % for the subject-dependent experiment, while 79.5 %accuracy for the subject-independent network that is cross-validated with the SEED dataset [8].

A multimodal dataset for analyzing the affective emotional states of humans using ECG data. The physiological signals of 32 different participants are recorded concerning the videos of different emotions tested. Despite the exposure to the video, the level of arousal, violence, like, dislike, dominance and familiarity of 32 participants are keenly recorded. A novel method records the stimuli of the brain and it correlates with the data signal in terms of frequencies. DEAP is a publicly available dataset for the research purpose that is used for test on affective states. Different modalities of emotional highlights are impacted in the present study [9]. R. Jenke et al., (2014) Emotion recognition from ECG signals depends on the direct assessment of the mental state of the subject in which placing of electrodes and features occurred from the brain wave data also are considered. Based on 33 studies a feature extraction technique is evaluated. The experiment comprises of machine learning technique for feature selection on the self-recorded data. While using a multivariate method, the system outperforms comparatively [10][22].

Micro facial expressions are uniquely identified with the revolutionary moments of the phase when a person expresses a Real Emotion. In the case of hiding the Real Emotion, small facial movements could be reflected even in an adverse situation. A novel micro facial moment dataset is considered here for detecting the emotions of the patients. Using spatial-temporal descriptors and machine learning techniques these micro-moments are identified from non-moments. The outcome of the presented system using the machine learning approach is compared with the state-of-art approach and it achieves a recall of 0.91 [11][23].

J. Shukla et al., (2021) (EDA) Electrodermal activity is the direct integrative of psychological process happening to the human and the emotional effect. In the presented study, the author utilizes 40 different feature parameters and their frequency, and time-frequency values using the publicly available AMIGOS dataset. The author completely depends on the processed dataset available, using a machine learning technique named Mutual information maximization algorithm is utilized [25]. The author also considers the statistical features using Mel Frequency Sepal Coefficients (MFSC) were explored. Using the area signal, the feature group outperforms the common skin conductance responses comparatively [12][13].

3. Materials & Methods

3.1. *Data collection*

Amigos a dataset for the multi-model research on identifying the real effective states of humans concerning personality driving mood of individuals and groups. The dataset context is formulated with the recorded information of ECG, GSR, and EEG using wearable sensors. 40 participants are intended for the present research work with 16 short emotional videos and four long videos presented. The participants watch the full videos and express their emotions freely. They are also allowed to respond to a question provided by the SAM tool for the self-assessment. Using the Self-assessment manikins SAM tool, PANAS positive and negative affect schedule is also performed. On the other hand, the AMIGOS dataset also records the body portion of the participants while responding to the self-assessment as well as their videos live.

Videos are provided to find out the emotions such as violence, arousal, control, familiarity, and liking and basic emotions such as happiness, sadness, disgust and fear are also included in that. Amigos dataset can be categorized into two kinds of analysis modes, the personality for the emotional trait and the social context. The dataset is completely formulated as a personal treat as anger, happy, sad, contempt, disgust etc. The social context means, how familiar the video should be, liking or disliking and the neutral values are recorded over it. In the present research work, Amigos data set is completely studied in that EEG, ECG, and GSR values are considered for analysis. The cross-validation process is performed using self-assessment reports provided by Amigos [30]. The preprocessed values are considered for modelling the robust system. Further, the real-time raw data provided by the amigo data set is considered for testing purposes [14][15].

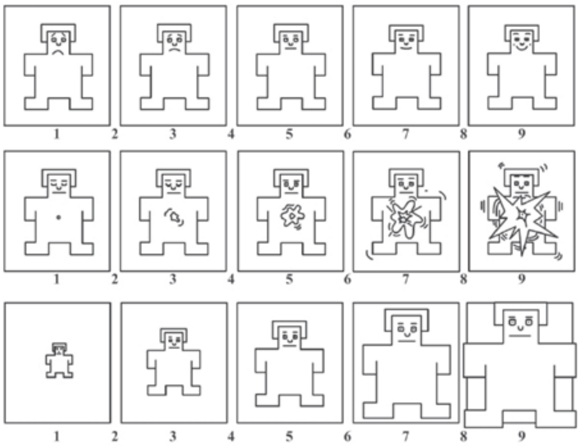

Fig. 1. Self-Assessment manikins' chart for the Valence, arousal and dominance

Fig. 1. shows the Self-Assessment manikins chart for Violence, arousal and dominance. [24] SAM tool consists of an affective slider designed to represent the pictorial representation of pleasure on the top row, arousal in the middle row, and further dominance on the bottom scale is defined. During the emotion analysis process, the participants are allowed to make a marking in the chart shown above to make them self-assess the exposed inputs. For testing the emotions, randomly formulated videos, images and audio are used for testing. During the test performance, the physiological data are dynamically collected. Any sudden rise in emotion is directly reflected in the physiological data and also it helps the participant self-assess the real feel in the record. The regularly adopted SAM laboratory practices this self-assessment method for the detection of behavioural traits. In the present system, the experimental setup formulates as 1 to 7 emotional affect parameters are considered. 5 social contexts are included. Based on the SAM tool, the user perspective and systematic analysis is verified.

3.2. *EEG Data Collection*

EEG acts as a direct reflection of the brain's stimuli that happened by the human while responding to certain actions. Electroencephalogram data consists of brain waves such as Alpha wave, Beta wave, Gamma wave, Theta wave and Delta wave. Most of the ECG signals are measured in terms of frequency that determines the wave category. The most commonly studied waveforms as Delta which falls between the ranges of 5 to 4 Hz, Theta 4 to 7 Hz, alpha 8 to 12 Hz, Sigma 12 to 16Hz, and beta 13 to 30 Hz. It is reflected as a small electrical activity of the brain from the scalp which is recorded using as many as a maximum of 256 electrodes. The commonly used sensor ranges are 64cm on the scalp. Even though ECG signals are accurate in performance, in terms of the societal susceptible drawback is detected in motion artefacts. ECG Signals and noise are mixed up with the signal peaks.

3.3. *ECG Data collection*

Electrocardiogram (ECG) utilizes 12sensors placed on the chest and Limb area of the subjects. These electrodes are sticky and are adhered to the chest area through an adhesive patch. It is connected to the human body on one side; on the other hand, it is connected to the monitor. To record the electrical signals that are generated through the Heartbeat. The computer records all the electrical pulses coming over from the Heartbeat. This electrical signal consists of important points represented as the PQRST wave. Using various kinds of analysis such as RR interval formulation, QR interval formulation, and QRS peaks the evaluation of ECG-based abnormality is done. Here, the ECG data is collected from the Amigos dataset. The dataset contains the recorded information of 40 participants ECG data 6 channeled/separately. The data is also segregated as preprocessed data and raw data provided by the Amigos dataset.

3.4. *GSR Data collection*

Galvanic Skin Responses (GSR) are also referred to as Electro Dermal Activity (EDA) ready for skin conductance. The skin simply expresses the information in the form of heat, cold, warm etc. Any kind of

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positive or negative emotional effect directly impacts the skin temperature. The brain-stimulating activities are also directly proportional to the skin system. The conductivity of the skin varies concerning the emotions such as stress, nervousness, fearfulness, soaked mood, surprise, happiness and sadness. Galvanic skin response created from the automatic sweat glands in the skin itching on hand and the feet is triggered by the emotional stimulation happening in the brain. Whenever a person is emotionally aroused, the GSR data responds to distinctive variations in the patterns which are visible and that can be quantified statistically also. GSR value is based on the immune system in which the environment of the person belongs, thermoregulation, the skin controls the temperature through the regulated values Goosebumps sensing and perception in which the organs detect the relevant changes in the environment based on the activity of pressure and pain. In the present study amigo, the data set collects the GSR value of 40 participants in which each Channel 1 unique GSR parameter sequence is recorded and this pattern is helpful for us to find out the emotional state.

3.5. *Sample data of Self-assessment records*

			Initial_SelfAssessment											
UserID	VideoID	p_Ind	arousal	valence	dominance	liking	familiarity	neutral	disgust	happiness	surprise	anger	fear	sadness
1	'10'	6	5	6.733792	8.235496	9	1	0	0	0	0	1	0	0
1	'13'	7	2.938568	5	8.235496	1	1	1	0	0	0	0	0	0
1	'138'	9	6.488056	9	2.829352	9	9	0	0	0	0	1	0	0
1	'18'	13	6.542664	1	4.549488	9	9	1	0	0	0	0	0	0
1	'19'	11	4.959048	6.706488	6.433448	8.53584	1	0	0	0	0	1	0	0
1	'20'	4	1.382256	1.382256	8.180888	8.2628	9	1	0	0	0	0	0	0
1	'23'	14	2.965872	8.59044	8.098976	8.208192	9	0	0	0	0	1	0	0
1	'30'	15	6.488056	1.382256	3.402728	1	9	0	1	0	0	0	1	0
1	'31'	3	6.6	1	1.027304	1	9	0	1	1	0	0	1	0
1	'34'	2	4.931744	6.65188	8.044368	8.972696	9	0	0	0	0	1	0	0
1	'36'	12	6.460752	1	2.856656	1	9	0	1	0	0	0	1	0

3.5 Sample data of Self-assessment records

The expectation-Maximization algorithm relies on the Gaussian mixture model enabling the probabilistic clustering data which allows discussing the structured equivalent groups of a given dataset. The provided data have a specific observation and density that validates the set of a category associated with it [17]. The Gaussian Expectation-Maximization (GEM) algorithm repeatedly tests the given pattern of training data and testing data to find the maximum relativity present with the two variables. GEM algorithm also enables the system to predict the hidden data. The algorithm starts initializing with the Gaussian value of evaluation considered as a new set of data then it learns from the iterative process to find better covariant data within the given data set. The Gaussian mixture model is based on the normal distribution. Without normal distribution of the data, the specific probability and the Gaussian space cannot resemble the expected maximization value. In general, the normal distribution of the given pattern of data is evaluated by the equation (1) given below.

$$f(x) = \frac{1}{\lambda\sqrt{2\Pi}} e^{-\frac{1(x-\mu)}{2\lambda}} \tag{1}$$

$$Where \ \ -\alpha < x < \alpha$$

$$\lambda \rightarrow Varience,$$

$$\mu \rightarrow mean\ of\ population$$

The comprehensive analysis of various participant data collected through the AMIGOS dataset was split into training data and testing data. The raw data preprocessing using the Synthetic Minority Oversampling Technique (SMOTE) model in which the data has cleaned up random values or removed junk values or removed. Since data is provided to the GEM algorithm in which the expectation-maximization parameters such as mean median standard deviation and sigmoid are calculated.

4. System Model

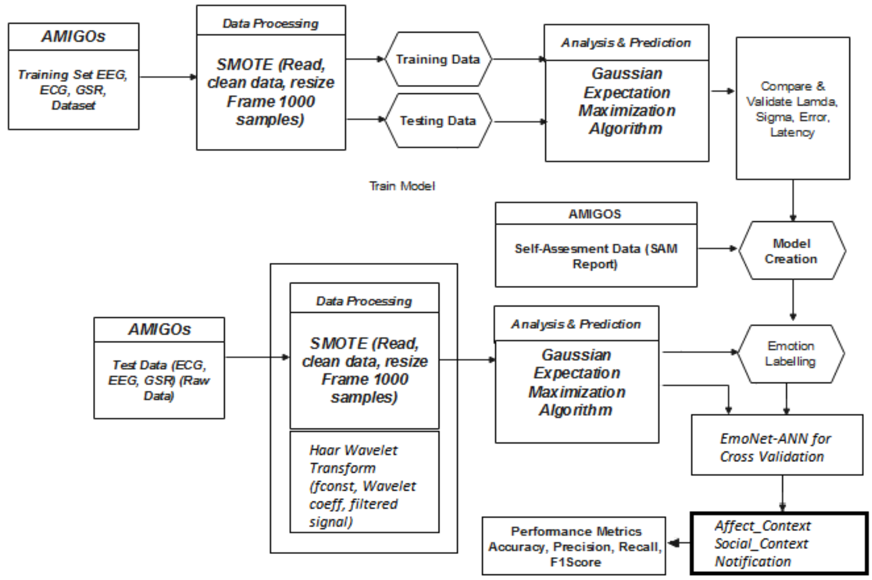

Fig. 2 System architecture of proposed EmoNet_ANN (ENA) model

Fig. 2 shows the system architecture of the proposed EmoNet-ANN enabled the emotional affect prediction using the AMIGOS dataset. The input data is divided into two modes, preprocessed data and raw data. The raw data is the AMIGOS recorded signal points using EMOTIV Epoch for EEG, and Shimmer tool for GSR with ECG recorded with the ECG sensors of 6 channels. The preprocessed data from AMIGOS is given as .Mat file from the bandpass filter applied at 60Hz. The SMOTE process or the synthetic minority oversampling technique is used to down sample the large-scale dataset. It performs the initial scaling steps of input data by which reading the data from AMIGOS, resizing the data into a constant down sample scale of 1000 samples in each frame, and cleaning data by removing the junk values and Nan (not a number) values, INF (infinite) values are done. The SMOTE process takes the necessary steps toward formulating the raw data input into the scaled data for normalization Fig. 3.

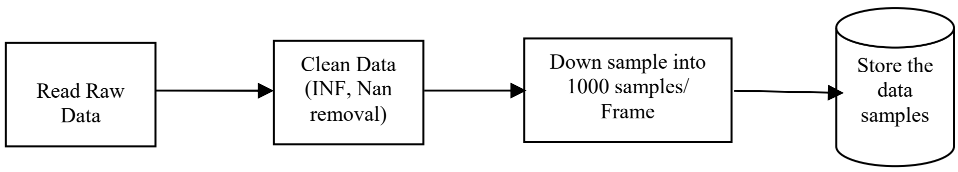

Fig. 3. Steps involved in SMOTE process

4.1 Summary of Implementation

Once the input data is ready, the data is split up into training data and testing data. The overall preprocessed data of 40 participants with 16 short emotional videos and 4 long videos and their equivalent recordings from the channels are given. The preprocessed data concerning the self-assessment made by the 40 participants using the SAM tool are considered. The self-assessment is the direct responsibility of the participant about the video exposed to them. The labels are divided into two perspectives. In a Social context, the familiarity and knowledge about the video are exposed by the participant. Affect context in which the emotion felt by the participants is asked in the questionnaire. The direct response data is further compared with the raw data after the Haar Wavelet transform. The statistics beyond the correlation process depend on the unique covariate points that exist with the input data patterns. Not all the values are correlated with the training data. The relative covariate is identified purely by the GEM algorithm. The proposed classification and validation process is created with the Novel EmoNet_ANN system in which the results of the GEM algorithm such as lambda (λ) and sigma (Σ) values are mapped into an array of vectors. These vectors are organized for all the training data and the test data split from the AMIGOS dataset. Once the model is created with the GEM algorithm, the raw data is fetched to the channel filters using the Haar Wavelet transform.

4.2 EmoNet_ANN formulation

The result of the GEM algorithm provides the statistical equivalent of the given pattern of data. Further with the cross-validation process artificial neural network architecture with the Scaled Conjugate Gradient Optimized (SCG) as training function. The data is split up into training data of 70%, testing data of 10% and validation data of 10%. If the GEM algorithm provides the emotion label concerning self-assessment data, the ANN model cross validates the pattern recognition as a stacking process to a certain extent. The concept behind the ANN is quite simple, the higher the correlation present with the training data and testing data, the regression is fair and the accuracy is good. 10 hidden layers are configured with the ANN model, thereby the percentage of error is calculated with the correctly classified data concerning the given data elements. The generalized subtract (gsubtract) is performed by ANN to find the element-wise difference between the data. If the data values are in the form of cells, then cell them to matrix format needs to be converted. (Error=gsubtract(input, output)) as in equation (2).

$$x^* = \sum_{i=1}^{n} \alpha_i d_i \qquad (2)$$

$$he\{d_1, d_2, d_3, \ldots \ldots d_n\} be\ the\ n\ \ orthogonal\ vectors\ as\ input\ x^*$$
$$\rightarrow Minimum\ scaled\ input\ f(x)(1)$$

$$\boldsymbol{Pseudocode\ of\ EmoNet_{ANN}}$$

$$etGet\ data_{inp} = AMIGOS(ECG, EEG, GSR)$$
$$Execute\ x1 = SMOTE\big(ECG_{datinp}\big);$$
$$vecorize\ [x1, x2, x3]$$
$$perform\ GEM = f(x1)[Eq.(1)]$$
$$Repeat\ for\ EEG_{datainp}, GSR_{datainp}\ as\ x2, x3$$
$$Sigma_{Gem} = \sum_{i=1}^{n} f(x1)$$
$$Lamda_{Gem} \rightarrow \frac{x1}{n} \quad ;$$
$$Repeat\ for\ x2, x3;$$
$$if\ Max[Sigma_{Gem}, Lamda_{Gem}] then$$
$$store \rightarrow Stats = [Sigma_{Gem}, Lamda_{Gem}]$$
$$at\ Corresponding\ iteration\ else$$
$$REPEAT\ till\ err_{gem} = 0$$
$$end$$
$$Vectorize\ [stats(x1, x2, x3)]$$
$$Split\ Trainin\,g_{data}, \quad Testing_{data}$$
$$Y \rightarrow Ann(Trainin\,g_{data}, Testing_{data})$$
$$onmeasure\ correlation(Trainin\,g_{data}, Testing_{data})$$
$$EmoNet_{ANN} = \sum_{i=1}^{n} f(b + x_i)$$
$$if\ MSE < 0\ save\ _{trainingmodel}\ ;$$
$$Get\ raw_{data}\ z1 \rightarrow Haar(raw_{data})$$
$$repeat\ above\ steps\ SMOTE, EmoNet_{ANN}$$
$$End$$

Considering the self-assessment records from the processed data with the corresponding input correlations, further the raw data is tested. Once the EmoNet model is created, further the raw data of ECG, EEG, and GSR are tested and evaluated as tabulated in Table 2**.**

4.3 Formulation of ENA

Fig. 4. determines the ANN model formulation for EmoNet_ANN. The parameters from the GEM algorithm are considered as the environmental vectors x(n) samples, further using the Artificial neuron blocks to find the correlation between the input discrete samples and the iteration results of the previous loop are fetched continuously until less Mean Square Error value (MSE) is found. The neurons are adjusted automatically concerning the weights fetched from the feedback loop. Further, the ANN process performs the expression,

$$EmoNet_{ANN} = \sum_{i=1}^{n} f(b + x_i) \quad (3)$$

to the maximum iteration of 1000 epochs allowed.

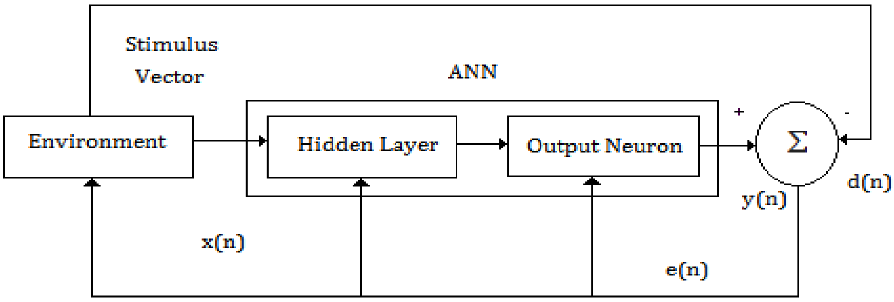

Fig. 4. Formulation of ANN for Emonet_ANN

5. Results and Discussions

ROC graph concerning Training data and Testing data

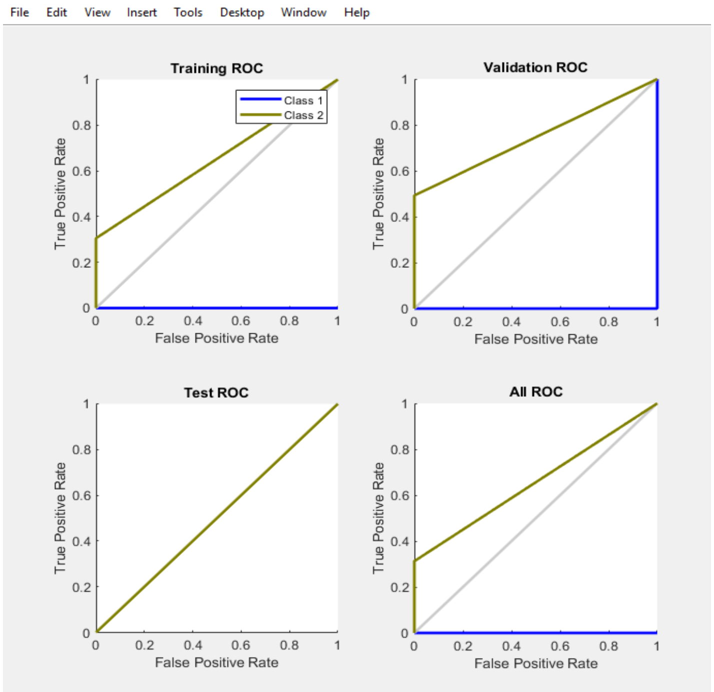

Fig. 5. ROC graphs showing overall confusion matrix performance

Fig. 5 shows the Receiver Operating Characteristic (ROC) graph of ANN analysis incorporated with Emo_Net. The accuracy calculation is based on true positive, true negative rate, false positive and false negative rate obtained by the given training and testing process. There are two classes of data given in the dataset that split the pattern into a social context and affect context.

5.1 Confusion Matrix

Fig. 6. shows the confusion matrix of the proposed EmoNet_ANN for the cross-validation process. A confusion matrix is formed from the artificial neuron blocks, while comparing the input pattern with the trained patterns. The confusion matrix determines the performance of the prediction model. It is simple to understand that in the automated EmoNet_ANN model after the comparison of these data inputs, the actual expected results need to be compared with the predicted results.

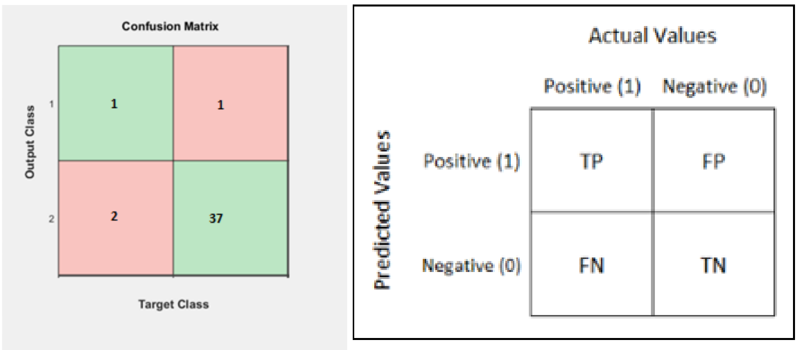

Fig. 6. Confusion matrix of proposed ENA model

Fig. 6. shows the confusion matrix of the proposed EmoNet_ANN for the cross-validation process. A confusion matrix is formed from the artificial neuron blocks, while comparing the input pattern with the trained patterns. The confusion matrix determines the performance of the prediction model. It is simple to understand that in the automated EmoNet_ANN model after the comparison of these data inputs, the actual expected results need to be compared with the predicted results.

True positive rate determines the amount of the predicted results is the same as that of the expected results.

True Negative rate determines the fact that the expected value and the predicted value on false data state the real information on the reflected data. Despite the stated result being negative, it is predicted as negative only.

False-positive determine the incorrect classification of false data as true data reflected as a prediction result.

False-negative determines the incorrect classification of true data as false data that is reflected as a prediction result with the presented system.

Based on these TP, TN, FP, and FN the actual classification performance is evaluated. The accuracy of the prediction model is important to measure the performance of training and testing.

Accuracy, Precision, Recall, F1Score, Sensitivity and Specificity are determined by the formula given below:

$$Accuracy = \frac{TN+TP}{TP+TN+FP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$F1Score = 2 * \frac{Precison*Recall}{Precision+Recall} \quad (6)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (7)$$

$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

From the proposed ENA model, the parameters are mapped as shown in Table 1.

Table 1. Parameters of Confusion Matrix concerning TP, TN, FP, FN

Parameter	Value	TP	TN	FP	FN
Accuracy	0.9268	1.00	37.00	2.00	1.00
Precision	0.3333	1.00	37.00	2.00	0.00
Recall	1.0000	1.00	37.00	2.00	0.00
F1Score	0.5000	1.00	37.00	2.00	0.00
Sensitivity	1.0000	1.00	37.00	2.00	0.00
Specificity	0.9487	1.00	37.00	2.00	0.00

Table 1. provides the quantitative measure obtained from the proposed ENA model. Sensitivity determines the capability of the ENA model to classify the matching emotions correctly. Specificity determines the quality of the ENA model on certain result reflections and precise outcomes.

5.2 Error Histograms

Fig.7. shows the error histograms generated concerning the training, testing and validation process at the EmoNet_ANN process. To the maximum extent of the training data and testing data, the least error of -6.877 occurred. At every instant of samples, the least difference occurred which is depicted in the above figure as only negative values lie in the error histogram. In the initial instances, a small part of the test value is considered.

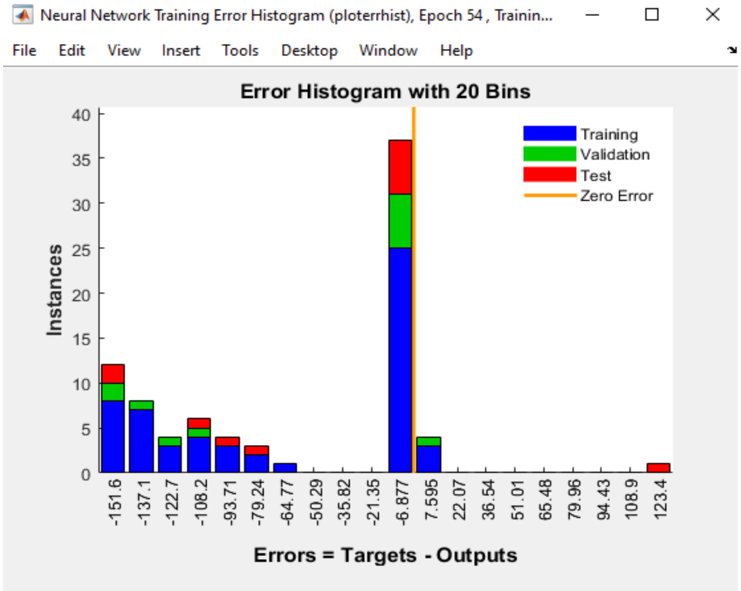

Fig.7. Error histograms obtained with ENA analysis (Participant ID:7)

5.3 AMIGOS Processed vs. Raw Data

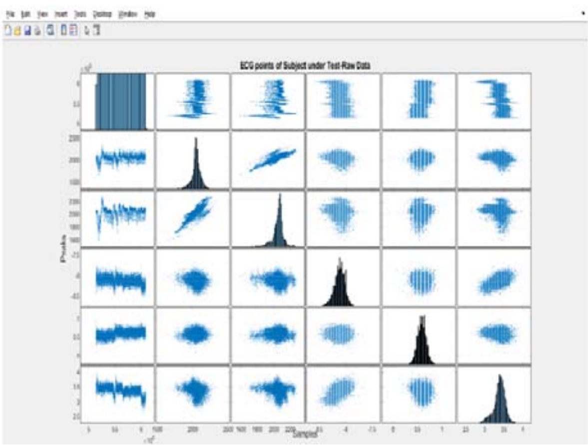

Fig. 8 Data visualization of ECG points processed data

Fig. 8. shows the data visualization - Plot Matrix of AMIGOS preprocessed data points of the subject under test selected randomly and they are displayed here. The plot persists the various ranges of ECG data at overall 6 channels of the recording provided, 2 channels are considered for analysis. A matrix of individual axes to handle the histogram plots.

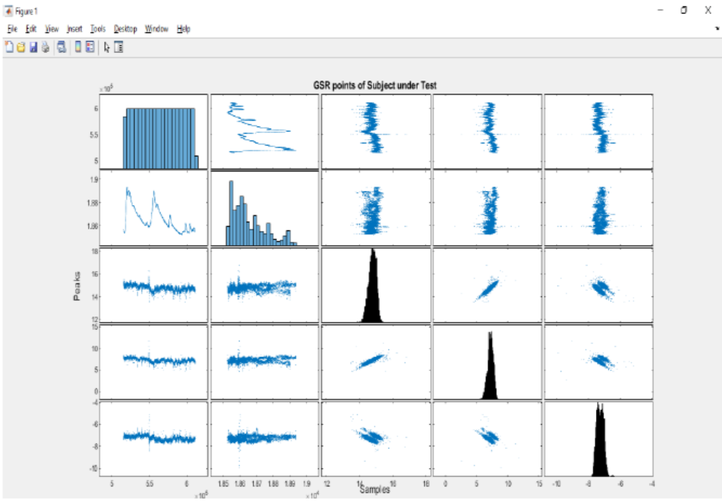

Fig. 9. Data visualization of GSR points processed data

Fig. 9**.** shows the Plot Matrix of AMIGOS preprocessed data points of subjects under test selected randomly and they are displayed here. The plot persists the various ranges of GSR data at overall 40x5 channels of the recording provided, 1 channel is considered for analysis. A matrix of individual GSR axis points is displayed in the histogram plot shown above.

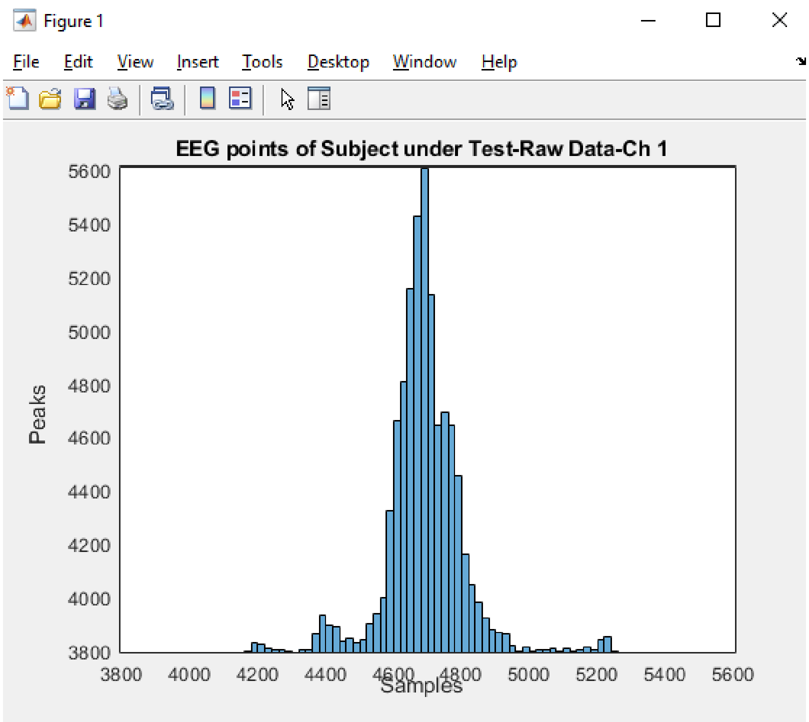

Fig.10. Data visualization of GSR points processed data

Fig.10. shows the single-channel EEG data recorded from AMIGOS – preprocessed values, showing the data aligned into histograms. The EEG data was provided with 25 channels of 40 participants. For the testing purpose, the scaled data size of 14 channels is considered.

VIDEO-ID	Statistical Parameters				Social Context		Affect Status	
	Lamda1	Lamda2	sigma 1	Sigma 2	Actual	Predicted	Actual	Predicted
1	0.9275	0.0725	9.7905	11.1695	3	3	1	1
2	0.88425	0.1157	7.4507	48.35	2	2	5	5
3	0.799	0.20025	7.5495	32.67	4	4	6	6
4	0.733	0.26625	6.0865	33.65	3	3	5	5
5	0.702	0.298	7.3773	33.6	4	4	7	6
6	0.551	0.449	5.75	26.4031	4	3	6	6
7	0.906	0.09325	8.5928	29.2249	4	4	6	6
8	0.7155	0.2845	7.342	31.958	4	4	4	3
9	0.7688	0.2312	6.045	22.9322	5	2	6	6
10	0.5793	0.4207	6.782	32.5063	2	2	5	5
11	0.9215	0.0785	16.2836	133.406	5	5	1	1
12	0.731	0.269	5.9156	26.149	4	4	5	5
13	0.8235	0.1765	7.3935	27.988	4	2	1	1
14	0.7525	0.2475	7.4847	33.83	5	5	5	5
15	0.832	0.168	6.2846	31.34	2	2	5	5
16	0.7702	0.2298	7.0491	33.52	4	4	5	5

Table.2 Statistical parameters of the GEM model for the given Sample test data

The affect detection framework from the AMIGOS dataset presented here focuses on two kinds of context detection. Social context determines the actual opinion and knowledge about the test video to the particular participant. Another emotional category here is represented as affect context in which the real emotion of the participant as per the self-assessment record is displayed here. The training input vectors and their equivalent self-assessment data are considered to validate the test data. The correlation between the self-assessment records relevant to the given test input and the conventional prediction approach is not same always. Considering the above table, there is less difference in covariate for the social context and affects the status of the test case for participant ID 7. labelled above, Table 3**.** shows the labelling sequence of the emotional parameters. Each emotion and social context are assigned a weight concerning the self-assessment data. Further, the training data is validated with the same weights.

Social Context		Affect Status	
Arousal	1	Neutral	1
Valence	2	Disgust	2
Dominance	3	Happiness	3
Liking	4	Surprise	4
Familiarity	5	Anger	5
		Fear	6
		Sadness	7

Table 3. Labels and Weights assigned

Fig. 11. shows the Lambda 1 and Lambda 2 values of the GEM algorithm for the given test sample of Participant ID 7, for the given 16 short emotional videos. The corresponding social context and affect variable are depicted in the figure. Fig. 12. shows the simulated GEM algorithm generated by Sigma variables 1 and 2 for 16 short emotional videos under test with certain participant ID:7.

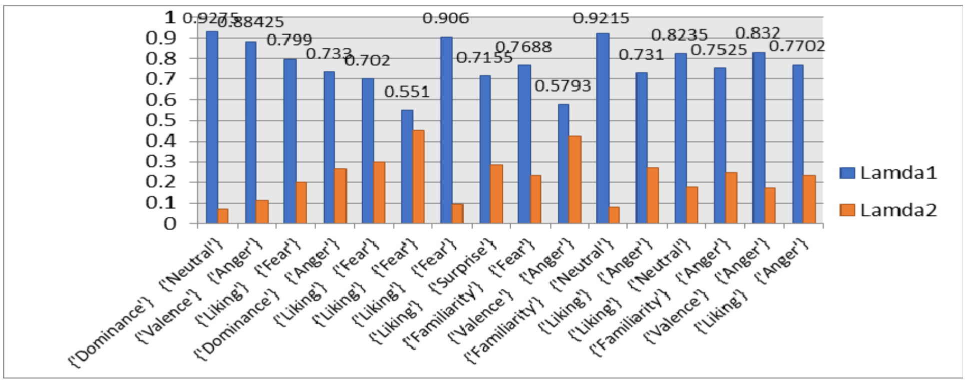

Fig. 11 Emotion labels of GEM algorithm

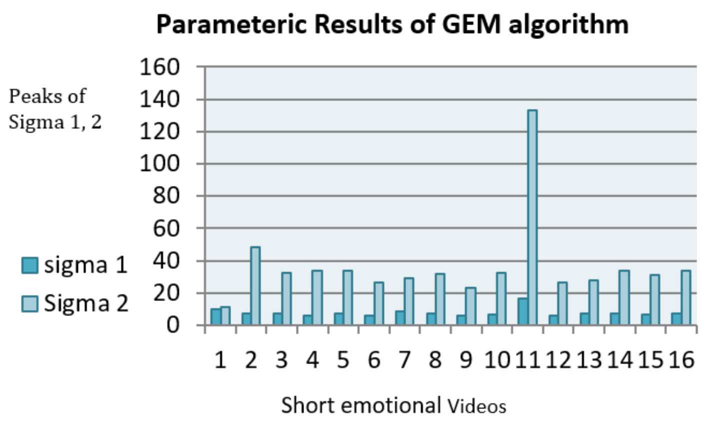

Fig. 12 Parametric Results of GEM algorithm

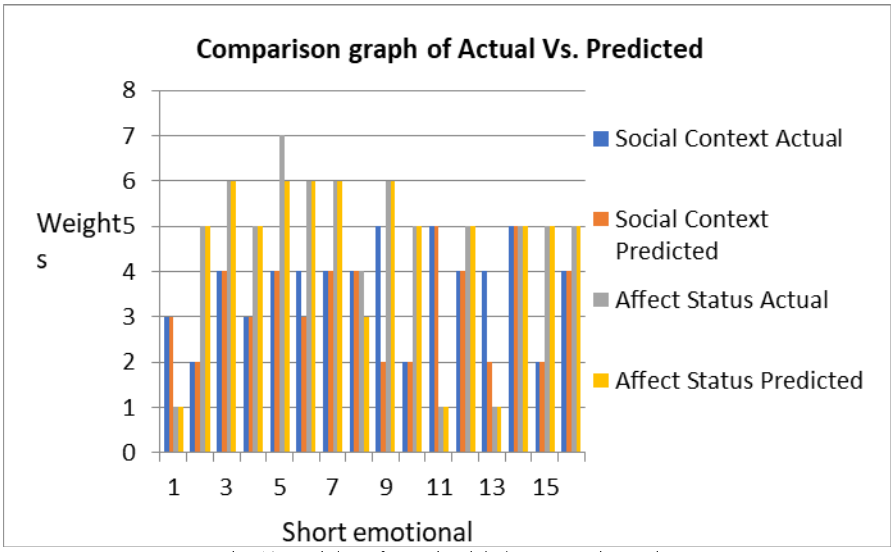

Fig. 13. Weights of Emotion labels systematic results

Fig. 13. shows the weights of the obtained social context result and the affected status concerning 16 emotional videos concerning actual results vs. the predicted labels in context.

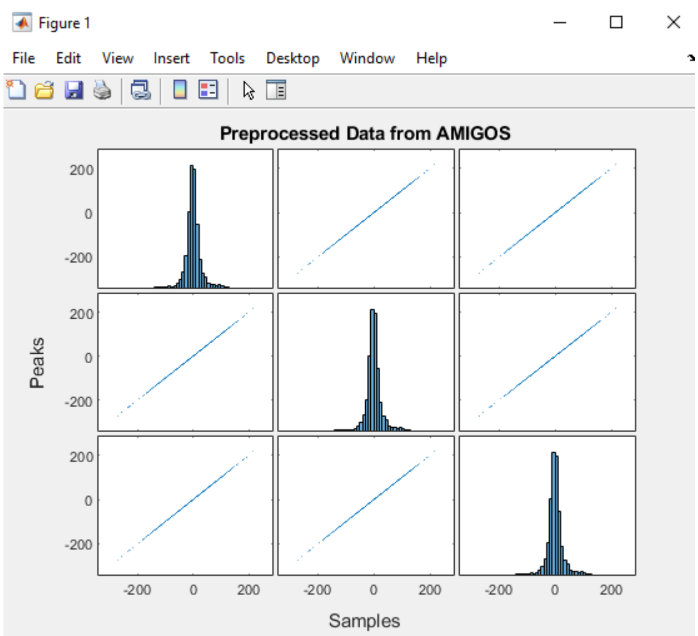

Fig.14. Preprocessed EEG data (Baseband filter)

Fig.14**.** shows the preprocessed AMIGOS data on EEG test input as a plot matrix. As per the AMIGOS dataset, the data is processed at 128 kHz, concerning a common reference. Using a Bandpass filter with a cut-off frequency of 4.0-5.0 Hz is applied. The training data is recorded with Video orders from 1-20 videos. ECG data is filtered with a low frequency as a 60Hz cut-off frequency. GSR data is also recorded with low-level electrical impulses; hence the GSR data is down sampled to 60Hz.

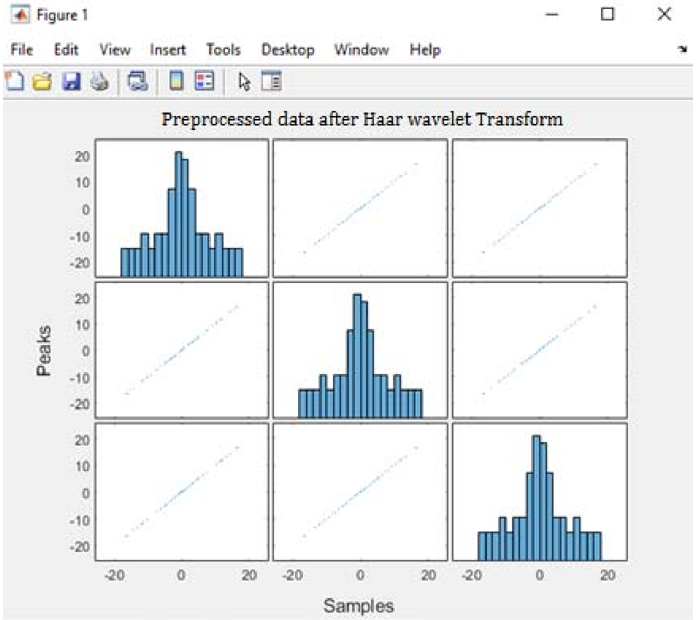

Fig. 15. Preprocessed EEG data (Haar Wavelet transform)

Fig. 15. shows the raw data from the AMIGOS dataset. The three major modalities ECG, EEG, and GSR data are recorded concerning the video showcase process for 40 participants and they are stored as separate variables. The EEG data is recorded via EMOTIVE Epoch with a sampling frequency of 128 Hz, ECG data is sampled at 256 Hz, GSR values are the same as EEG data, and it is sampled at 128 Hz.

S No	Input Parameters	Reference	Method	Emotions detected	Accuracy
1	EEG	T. Song et al., (2020) [8]	GCNN	Valence, Arousal, Dominance	90.40%
2	EEG, PPG	B. H. Kim et al., (2020) [16]	ConvLSTM	Valence, Arousal, Dominance	82%~
3	EEG	Liu, et al., (2022) [24]	DCNN	arousal, valence like, dislike, dominance and familiarity	92.50%
4	ECG, EEG, GSR	Proposed Work	EmoNet_ANN (ENA)	Valence, Arousal, Dominance, liking, familiarity, Neutral, Disgust, Happiness, Surprise, Anger, Fear, Sadness	92.95%

Table 4. Comparative analysis of the existing and the proposed methodology

Table 4. shows the comparative study of the existing work related to the presented analysis. T. Song et al., (2020) [8] with EEG data, using Graphical Convolution neural network model on finding the emotional affect arousal, dominance and violence achieved the accuracy of 90.4%. B. H. Kim et al., (2020) [16] the author used the Conventional LSTM model and achieved an accuracy of 82% on affective computing. Liu, et al., (2022) [24] discussed the Deep Convolution Neural Network for affect state analysis and achieved an accuracy of 92.5%. From the table above, the proposed EmoNet_ANN (ENA) model achieved an accuracy of 92.95% with multiple parameters with reduced computations.

6. Challenges and discussions

The major challenge of the presented system is the massive dataset that needs to be integrated with the EmoNet_ANN algorithm. At every iterative learning process, the Gaussian mixture model analyzes the given training data and the test data until it reaches zero error. Similarly, the ANN model with SCG optimizer runs iteratively to the scaled statistical data completely for a 40x20x16 combination of inputs with ECG, EEG and

GSR parameters separately. Hence, the longer the learning process takes place in case of a new data entry. The Code integrity is focused much and hence the stimulated model performs with flexible iterations that can be customized. Whereas, further extension of the presented system should ensemble one or more machine learning models for classification, The Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) for the input dimensionality reduction is suggested. Further utilizing the XGboost models, the overall iteration steps are reduced. The transformed data performs better while comparing the statistical approach despite the automated analysis.

7. Conclusion

Human behaviours are the direct outcome of their emotions, where the feeling of sadness, happiness, excitement and disgust are the emotional impacts related to the individual personality. As a test case participant number 7 is considered and the above analysis is derived through training all the participant's responses. Focusing on the lightweight emotion analysis model using the Gaussian Expectation-Maximization algorithm Ensemble Optimized Novel EmoNet_ANN(ENA) is simulated here. The Novel EmoNet is designed in such a way the massive data pattern of the AMIGOS dataset is formulated concerning the self-assessment data. The model is created with the preprocessed data to validate the performance of the ENA. The raw AMIGOS samples with filter tool as Haar wavelet function is created. Based on the statistical parameters generated through the GEM model, the stacked analysis framework is developed here. The goal of the research work is to reduce the similarity in decision making that is highly reduced with the presented system, clearly depicted in the readings of test case 7 shown in Table 2. Based on the stacked analysis with ENA, an accuracy of 92.5% is achieved. The presented system is further improved by utilizing more machine learning models such as LDA, and PCA, furthermore with tunable XGBoost models, the research work is explored with the more unique covariate points analysis.

Conflicts of interest

The authors have no conflicts of interest to declare.

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Authors Profile

V.S. Bakkialakshmi received the Master of Science degree in Computer Science from Anna Adarsh College for Women’s of India in 2004 and received the Master of Philosophy degree in Computer Science from the Bharathidasan University of India in 2005. She received the Master of Engineering degree in Computer Science Engineering from Anna University Affiliation college, India in 2011. Currently, she is a Researcher at the Hindustan University of Technology and Science. Also, she served as a resource person in many Seminars and workshops. She is pursuing her research work in the field of Affective computing on emotional psychology. She can be contacted at email: bakkyam30@gmail.com.

Sudalaimuthu Thalavaipillai is working as a Professor in the School of Computing Science, Hindustan Institute of Technology and Science, Chennai, India. He had completed his PhD degree from the Hindustan Institute of Technology and Science, Chennai, India. He is a Certified Ethical Hacker. He has published 50 research articles in reputed International Journals and conferences. He is granted both Indian and Australian patents. He obtained many awards in his career including Pearson Award in the Best Teacher category, and the Top innovator Award for patent rights. His research areas include cyber network security, grid and cloud computing, and machine learning. He is a lifetime member of CSI, ACM and IEEE. He can be contacted at email: sudalaimuthut@gmail.com.