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# Emo-Gem: An Impacted Affective Emotional Psychology Analysis through Gaussian Model using AMIGOS

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***Abstract—***

**Objectives: Analysis of human affect (feelings) that directly release on human emotions is mandatory to rival many psychological impacts. Human emotions are more precious and real. The history of Effect Theory implies on the idea of detecting the feelings and emotions seems needful to predict behaviour. The proposed research work is based on predicting the real emotion using a robust model with neurophysiological data. To design a robust affective computing model to determine the human emotions for an enhanced experience of understanding.**

**Methods: Machine learning-based existing research are helpful in deriving the idea of affect detection, in which the proposed system keeps the statistical analysis as a unique idea, Using AMIGOS Dataset, Gaussian distribution enabled analysis model is developed.**

**Findings: ECG, EEG signals are highly impacted by noise factors and motion artifacts. In spite of emotion detection, the Similarity of emotional results and multi-modality of results leads to neutral responses. In order to overcome the issue, a cross-modality approach is used here, which make the dual validation of the training data with the test inputs.**

**Novelty: The presented system utilizes the concept of Gaussian mixture models to create a novel prediction algorithm named the Gaussian expectation maximization technique (GEM) using the AMIGOS dataset. The dataset considered physiological signals such as Electrocardiography (ECG), Electroencephalography (EEG), Galvanic Skin Response (GSR). The statistical response after the processing of the data, measurable results on emotion labels those coincidence responses with training samples directly impacts the obtained results. The presented system is comparatively discussed with a state-of-the-art approach in terms of statistical parameters like standard deviation, the population mean etc. The comparative analysis on various participants and their unique covariate points are extracted for deep emotion analysis. The proposed system achieves the detection of emotional affects such as anger, contempt, disgust, happiness and sadness. Based on various iterative learning with improved expectations and maximization value extraction, the proposed system detects the ssemotion with minimum iterations of 5 with Mean=0.62, SD=0.88 etc.**

*Index Terms*—**Affective computing, Emotion analysis, Subject identification, Machine learning, Artificial intelligence, Emotional Psychology.**

## I. Introduction

### A. Need for Affective Computing

The sociology of emotions has a long history of better identifying the effect produced from human emotions in formulating contagious questions and self-assessment tests. The conscious and unconscious forms of emotion directly impact human behaviour. Subjected to psychological facts affective computing is the challenging area of research that created with many ideological Pathways. Audio signals can clearly define the emotional impact since the variations in the pitch determine the emotional factor. Many cross-modal emotion embedding systems incorporate audio and video correlations to determine the actual emotion explode by the subject through the ensemble learning process [1].

Depression and anxiety are chronic mental disorders that start small and continue to affect human emotion in a large span. Affect sensing is a wide area of challenging research. While discussing the affect scenario, it is obvious to include the term called emotion contagion. Emotional contagion is a kind of social contagion that transits the emotions and related behaviours from one person to another. This convergence of expressed emotions can happen to reflect from one person to another in a certain environment [2]. Emotions are the outcome of serial events. Reactions of a series of events enable the person to behave differently at an irrelevant time [3].

### B. Need Technology Support

The emerging growth of artificial intelligence technology creates a way for much interactive analysis to understand the emotions of people through various sources. Standard datasets are available for research purposes and many publicly available data are used for the research work. Speech signals are used to determine the emotional impacts. Changes in pitch, tone are the direct reflectors of emotional change or affect notification. Neuro-fuzzy logic-based resilient evaluations are used to recognize the speech patterns that change concerning emotional affect [3].

The face is the foremost mirror of emotional impacts. Expressions are a common principle for all. It is clear to

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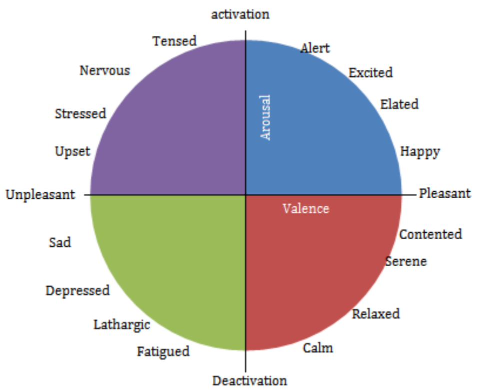
understand the emotion through facial expression. Often, hidden emotions are difficult to find out based on face emotions only in certain cases. Virtual facial vectors and landmark extractions are another way of expression formulation [4]. The growth of Machine learning technology manipulates the existing difficulties in neural networks toward improved algorithms creation. Linear discriminant analysis (LDA) models are used to evaluate the large set of feature vectors created from subject analysis data. After the number of trials, emotion analysis results are getting improved with LDA [5].

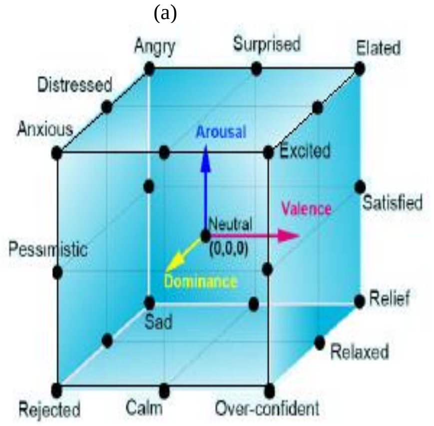
Multi-label learning algorithms help analyze the emotional affects in various modalities. Major polarity concerns the happiness and sad expressions, where multiple modality scenarios offer to extend the emotional impact factors to different angles [6].

### *C. Dimensions of Emotions*

Emotion is the real expression of feedback from the brain on the given input. It directly expresses the spontaneous feeling in the given instance. In terms of dimensionality, the emotion model can be classified into two types, such as 2D or two-dimensional models and 3D or three-dimensional models. In the 2D model, the most impactful emotion lies within the Valance and arousal dimension. Whereas the 3D model contains the major emotion as Valence, arousal Dominance etc. Fig. 1. (a). Shows the 2D model of emotion and Fig. 1. (b). Shows the 3D model of emotion dimensions.




(a)




(b)

Fig. 1. (a) 2D model of emotion [9] (b) 3D model of emotions [9]

Existing research works, the drawbacks and guidelines are summarized in Sec II. On Background study to further proceed with the model selection and design constraints evaluation in Sec III. The proposed methodology, data collection and algorithm are discussed. Sec IV. Describe the system architecture and Sec V. Describe the results and further discussions.

## II. Background Study

M. Li et al., (2020) multi-step enabled deep emotion detection framework is used to detect multiple polarities about emotions. Based on publicly collected databases, videos and physiological signals are extracted using deep neural networks (DNN). Pattern comparison is done concerning training features and testing features [7].

M. -H. Hoang et al., (2021) multi-task cascaded neural network with primary agent stream to detect the posture, face and reasoning stream detection using a virtual semantic module is evaluated. The reasoning stream is extracted using a multi-level perceptron (MLP). EMOTIC datasets with modelled heat stream maps are involved to improve the detection mechanism [8].

M. R. Islam et al., (2021) Emotion detection is the process of detecting and expanding the mental state of the individual. Deep learning and shallow learning-based spontaneous feeling detection and comparison are implemented. ECG and EEG signals are incorporated to reveal the correlated performance on emotion identification. The technique of PRISMA which includes identification, screening, eligibility is considered for detailed analysis [9].

A. Albraikan et al., (2019) presented a system, where MAHNOB dataset is used to analyze the emotion using weighted multi-dimensional DWT and the K-Nearest neighbour algorithm is applied. Video clips of various emotions are ensemble together and after the levels of training iterations, a Meta classifier detects the final emotional affect. Using different simulations using MW-DWT, 9 emotions are highlighted [10].

R. Qayyum et al., (2021) Due to frequent interaction with smartphones, an android application-based emotion identification system is presented. The combination of convolutional neural network (CNN) with recurrent neural network (RNN) is evaluated to create a strong model for emotion detection. CNN attains an accuracy of 65% and RNN attains an accuracy of 41% respectively. The presented recommendation platform is used for new content etc. [11].

Sarkar, P et al., (2021) presented a system based on a self-supervised learning approach in which unlabeled data are mapped to the bias weights based on the iterative learning and feedback updating. ECG based emotion recognition system is evaluated using the hardware sensors collected with various temporal properties. Considering the standard emotion dataset namely AMIGOS, SWELL, WESAD AND DREAMER the maximum accuracy achieved was 97% [12].

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Many existing implementations are considered for algorithm selection. Self-supervised learning models act as an intermediate approach between supervised learning and unsupervised learning. The beneficial thing in the self-supervised learning approach is the learning scenario of many unlabeled data. Because of these unlabeled data, the biased weights are continuously updated and enable the downstream version of raw data [13]. Deep belief networks are considered as the robust method in analyzing complex data connections. Multi-Feature analysis models need complex structures that rely on unique combinations of data [14]. Convolutional neural network (CNN) algorithms are considered as the automated feature mapping blocks that can be tuned to attain deeper analysis. By changing the preceding layers of the CNN structure, an adaptive network is created. Selection of filter blocks, improvising the feature selection blocks such as fully connected layers, ReLu layer and Max-pooling layers, adaptive design is formed [15]. Gaussian mixture models find out the all-probabilistic data that is generated from the finite Gaussian distribution of data in the random space. The model converges the relative data into the grouped structure to make the regression better [16].

*Datasets Available:*

OMG emotion dataset: OMG-emotion behaviours a dataset consists of category information of volunteers with emotional classifications are 12567 videos from YouTube and an average length of 1 minute. These videos are divided into various emotion-based classifications: happiness, sadness, surprise, fear, and disgust. The dataset consists of standard 1-minute videos that triggered the emotion mentioned above. OMG emotion dataset used as one of the standard emotions grabbing models [17]. Instead of emotion rating, the keyword tagging based emotion identification standard module is available with the MAHNOB-HCI dataset. The collection of 24 participants is involved in organizing the dataset in which they are allowed 20 different brain-stimulating videos to prevail their real emotions [18].

The proposed methodology considers the drawbacks of similar polarity in decision making and evaluated a Gaussian mixer model-based ensemble algorithm to improve the prediction quality.

## III. Methodology

### *A. Data collection*

Amigos is a standard data set used for affect personality and mood research done with the individuals and groups of peoples based on personality profiles and external annotations created neurophysiological recordings such as ECG, EEG, and GSR signals are recorded from the individual during the test. During the test short and long video experimental videos are given to the volunteers. 40 volunteers watched a set of 16 different effective videos that trigger the brain stimulus deals concerning the emotions namely valance, arousal dominance, familiarity and liking. Selected basic emotions such as neutral, happiness, sad, surprise, fear, anger, and disgust that they feel during the videos. Based on this information and the kinematics of patients the evaluation of emotion needs to be determined. Amigos is a robust recorded dataset, validated with a self-assessment test. In the proposed system ECG, EEG, GSR signals are considered from the AMIGOS data set.

### *B. GEM algorithm*

The expectation-maximization algorithm is based on the Gaussian mixture model that is not advertised of probabilistic clustering model allows describing the given selected data into equivalent groups. Each observation and density of the given groups validate a set of classes. It has the capability of grouping the concentrated main of data that belongs to the same class. The Gaussian Expectation-Maximization (GEM) algorithm is an iterative way to find maximum-likelihood estimates for model parameters when the data is inadequate with misclassified data feature points or has some Eigen variables. GEM initiates from any random values for the missing data points and evaluates a new set of data. These new values are then recursively used to learn and find out the better covariate data, by filling up missing points, until the values get fixed.

These are the two basic steps of the GEM algorithm, namely E Step or Expectation Step or Estimation Step and M Step or Maximization Step. The initial process starts with the Normal distribution analysis discussed below.

*Normal Distribution:*

In a Gaussian space, the expectation-maximization algorithm enables to initiation of the random location to pick the covariate points from the given data. The iterative loops tend to continue to search for the newly obtained data from the statistical measures like standard deviation of the initiated pattern, and variance, mean of the population. In general, the normal distribution is given by,

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

$$Where, -\alpha < x < \alpha,$$
$$\lambda \rightarrow Varience,$$
$$\mu \rightarrow Mean\ of\ the\ population$$

The normal distribution curve acts as an important and strong phenomenon in psychology. Normal distribution on initially helpful in finding the symmetry of the given dataset. the function f(x) determines the initial symmetric relationships between the given dataset. Standard deviation represents the number of variations available within the given dataset. The initial phenomenon of variation in the test data is derived from the above formula (1). The symmetric case of a normal distribution is called standard distribution, or unit normal distribution, in the case of multivariate distribution, the mean and standard deviation points are not stable. The higher the complexity of the input data pattern, the distributed curve get varied.

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## IV. System Architecture

### A. Design Architecture

The system architecture consists of preprocessing stage, analysis stage and performance evaluation stage. The preprocessing consists of steps such as reading the AMIGOS dataset as a whole CSV file and storing each data into appropriate variables say ECG, EEG, and GSR separately. The SMOTE process mentioned in the architecture is common for all the input types. The SMOTE process resizes the data and samples the data into 1000 frames of arrays to reduce the processing delay effectively. Once the preprocessed data is ready as a sequence of frames, then the Gaussian expectation-maximization algorithm is initiated. The algorithm randomly selects the initial data to start finding the maximum value at each frame and keep the expectation value as the initial data. The procedure is repeated until the best error rate is achieved. Based on the training process, a set of labels have arrived at the given dataset. 25% of data from the given dataset is considered for testing and the testing process is initiated. The complete system architecture captures the relative score value to the training value. These score values are labelled uniquely for happy, normal, anger, contempt and disgust.

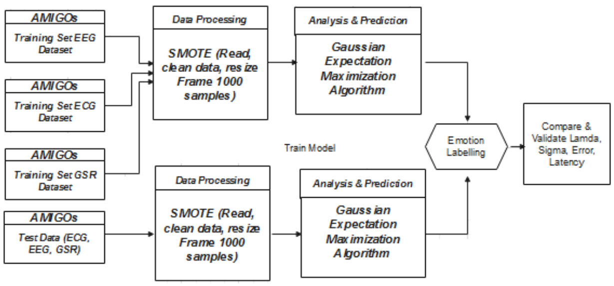


Fig. 2. System Architecture of Proposed Emo-Gem model

Fig. 2 Shows the system architecture of the proposed Gaussian expectation-maximization model that depends on the normal probabilistic distribution and analysis. The input data such as ECG, EEG, and GSR are the preprocessed recorded information of physiological signals. These patterns are unique for the certain emotional affect that determines the variations. The impact point is forbidden as per the given test record is concerned. The normal distribution of random data of overall physiological information helps attain the correlated points only.

### B. Summary Implementations:

The AMIGOS dataset consists of a recorded data sequence of a large scale of values containing ECG, EEG, GSR and self-assessment data covering the emotional effect of volunteers. The proposed Emo-Gem model is comprised of two-phase of operations. The first phase gets the processed data from the AMIGOS, preprocess and reorganize the fast-flowing data into frames of samples. These samples are fetched into the Gaussian Expectation maximization rule for analyzing the covariate points in the given data and formulate the lambda (λ) and sigma (Σx) values. The model is iteratively tested to achieve less latency and 0% Error rate. The better the number of learning iterations, the better the parametric weights are obtained. The trained model is tested with the new data formulated from 25% of the raw data. The covariate points are plotted and visualized. A better correlation occurs when train data and test data get maximum expected covariate points.

### C. Algorithm Pseudocode

*Start*
*Initialize Model;*
*E1=Read_data (Amigos);*
*Scale_data(N_frames(E1));*
*Select random Variable k=x;*
*Formulate Pram(k);*
*Update weight;*
*If(pram(E1) =Exp_Max)*
        *E1=parm_E1;*
*Else*
*Update_data;*
*End loop;*
*Visualize New_data;*
*Plot regression;*
*End*

The Pseudocode above briefly defines the process of expectation maximized value extraction through the continuous process of iterative learning. The process starts from the initial value selected randomly from the given data. As per equation (1), the distribution probability is evaluated with respect, $\mu, \lambda \ and \ \Sigma$.The shape of the distributed data is uni-modal; any maximum variations in the given pattern of data cumulatively change the distributed graph. The interpretation of that lies at the positive and negative functions based on the variance.

## V. Results And Discussions

### A. Convergence analysis on ECG, EEG, GSR

From the given dataset on each category, the convergence point extracts the sensitive data alone that is required to ensure the decision. To the repeated iterations of the expected maximum value search process, the only value that is closely related to the expected value is converged or grouped in the geometrical space. These values are plotted using the Convergence scatter graph shown below.

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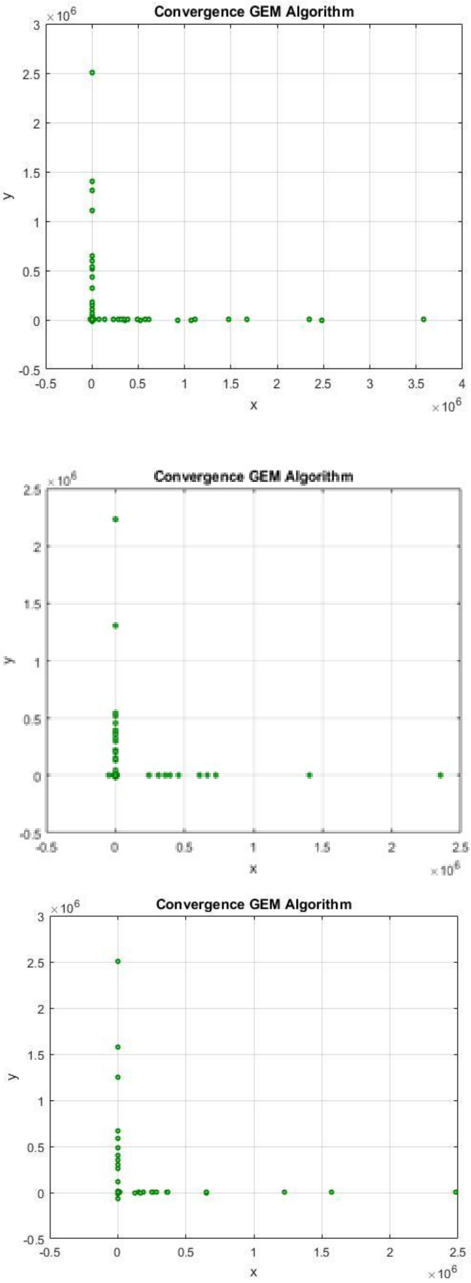


Fig.3. Convergence analysis on ECG, EEG, GSR

Fig. 3. Shows the convergence analysis on ECG, EEG, and GSR data on various iterations. The iterations are repeated for different participants to analyze the unknown labels. The formulated results are tabulated for verification in TABLE I.

## B. Convergence analysis on ECG, EEG, GSR

For every individual test data, the convergence points are mapped. In the same way, the secondary set of unique values is extracted after the first level of the GEM algorithm. The comparison of raw data of single frame with unique values and equivalent covariate points extracted after GEM algorithm is plotted together using Stem plot as shown in Fig. 4.

| Iterations | Error Rate | uMin | uMax |
|---|---|---|---|
| 1 | 3548.8753 | 0.623 | 2443.95 |
| 2 | 11941.6081 | 3.6651 | 10652.47 |
| 3 | 4149.7602 | 4.0671 | 13505.42 |
| 4 | 2796.9045 | 4.2713 | 15428.54 |
| 5 | 2027.8982 | 4.449 | 16822.77 |
| 6 | 942.3074 | 4.5347 | 17470.45 |
| 7 | 372.3683 | 4.5476 | 17726.56 |
| 8 | 126.5081 | 4.5489 | 17813.63 |
| 9 | 0.00 | 4.5489 | 17813.63 |

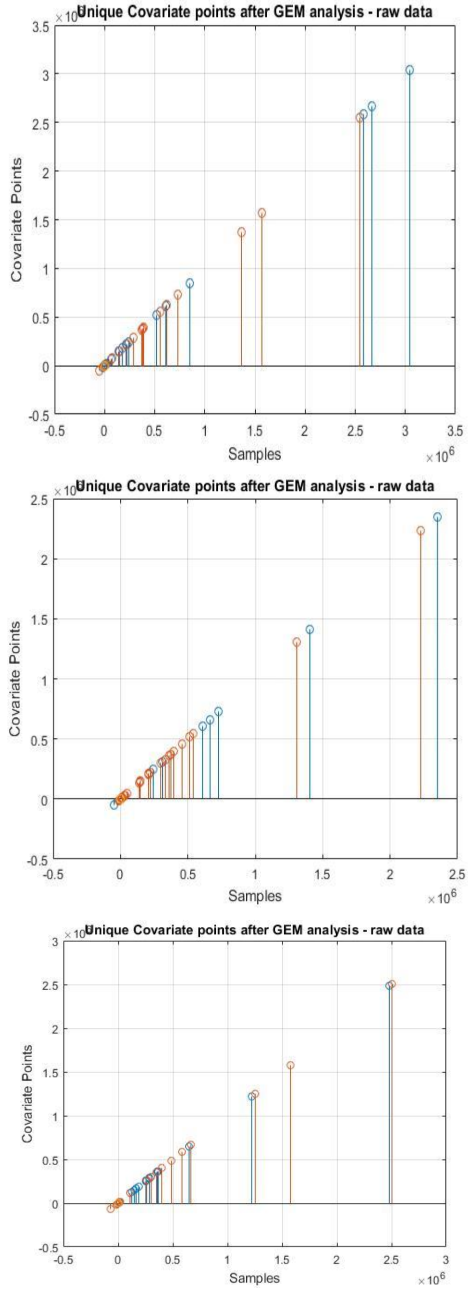


Fig. 4. ECG, EEG, GSR Unique covariate of Single participant

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Fig. 4. shows the unique covariate points of a single participant under test analyzed using the GEM algorithm. These points are unique and extracted from the overall distributed random data. The points are extracted after the error rate reaches the minimum from the given iterations. The iterations are initially started with maximum error and *u* value gets organized according to error rate until the expectation algorithm search for the maximum value. The complete process provides easy capturing of unique points from the large dataset. The difference between the expected value and the obtained maximum value enables the system to iteratively learn and run for the new data search. The complete process takes a maximum of 500 milliseconds to finish the complete given test data. The training process forms the working model concerning the initial maximization value obtained.

TABLE I. ITERATIONS VS. ERROR RATE (E), MEAN(U)

TABLE I. Shows the number of iterations taken for the given test sample started with an error rate at the random selection of initial location at 3548.8753 to the error rate of 0.00 at the end of the 9th iteration. In the meanwhile, corresponding statistical points are evaluated.

### C. *Statistical evaluations*

Each data after the evaluation of the prediction process provides the transformed data. These data are initially calculated with mean, standard deviation etc. at the initial stage of the process, the error rate is maximum and the GEM algorithm finds the expected value until the error rate becomes zero. Meanwhile average, statistical values are obtained to cross-correlate the matching label.

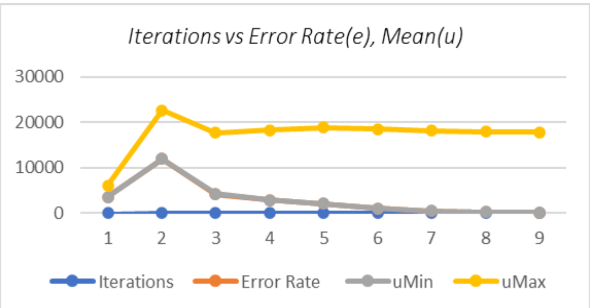


Fig. 5. Visualization of Population of Mean (u) estimation.

Fig. 5. Shows the graphical representation of population search concerning the number of iterations for the given test sample. Each sample has the unique and correlated points of mean, maximum mean comparatively. At the decision-making process, these mean values are considered for final labelled match scores.

The parametric values of different participants are analyzed at each emotion affect reflected from the given ECG, EEG, and GSR dataset. These parameters help find the correlation points. At every emotional point, these patterns of parametric values are equally compared to relativity. Higher the pattern matches with the training data, and then higher the match score of the parameters measured.

TABLE II. PARAMETRIC VALUES ON DIFFERENT PARTICIPANTS

| Physio-Data | Emotion Label | Lamda($\lambda$) (Varience) | Sigma 1 (SD $\Sigma x$) | Sigma 2 ($\Sigma x$ Max) |
|---|---|---|---|---|
| ECG | anger | 0.8925 | 8.7022 | 134903.2056 |
| ECG | anger | 0.893 | 9.6402 | 193923.7399 |
| EEG | anger | 0.879 | 9.9524 | 66890.2988 |
| EEG | anger | 0.88375 | 11.8962 | 191742.3546 |
| GSR | anger | 0.88875 | 5.7734 | 125302.4221 |
| GSR | anger | 0.8845 | 6.2729 | 134375.2957 |
| ECG | Contempt | 8.2213 | 0.88825 | 116364.1597 |
| EEG | Contempt | 0.87025 | 10.8091 | 130774.1179 |
| GSR | Contempt | 0.9 | 6.4912 | 115197.8651 |
| ECG | Disgust | 0.892 | 7.141 | 178349.1068 |
| ECG | Disgust | 0.89 | 7.3346 | 66622.7735 |
| EEG | Disgust | 0.8775 | 10.8876 | 171178.1147 |
| EEG | Disgust | 0.88525 | 11.1879 | 113150.0861 |
| GSR | Disgust | 0.89675 | 7.0367 | 102351.8506 |
| GSR | Disgust | 0.89875 | 6.6059 | 179998.2492 |
| ECG | happy | 0.882 | 9.0123 | 164960.485 |
| ECG | happy | 0.8905 | 8.7424 | 105189.2817 |
| EEG | happy | 0.87375 | 10.2731 | 109640.1184 |
| EEG | happy | 0.88125 | 11.283 | 164761.7216 |
| GSR | happy | 0.9005 | 6.7607 | 158058.2385 |
| GSR | happy | 0.8935 | 6.777 | 50920.1948 |
| ECG | Normal | 0.8895 | 10.838 | 86024.0168 |
| EEG | Normal | 0.868 | 10.6751 | 145732.2119 |
| GSR | Normal | 0.89825 | 6.4408 | 129405.7874 |

TABLE II. Shows the overall analysis results with parametric measurements such as μ,λ and Σx etc. is calculated concerning the obtained emotion label. The parametric data above generate a unique combination of patterns that reflect each emotion. Say example, the ECG value of Σx during the anger is 8.7022 whereas, at the Contempt affect, the ECG goes down to 0.88825. sudden fall of stimulus value impacts the emotional impact finding scenarios. Also, considering the Normal and Happy emotions, the ECG values raise more than 10. These kinds of unique variants are more helpful in differentiating the emotional affect from the massive processing dataset.

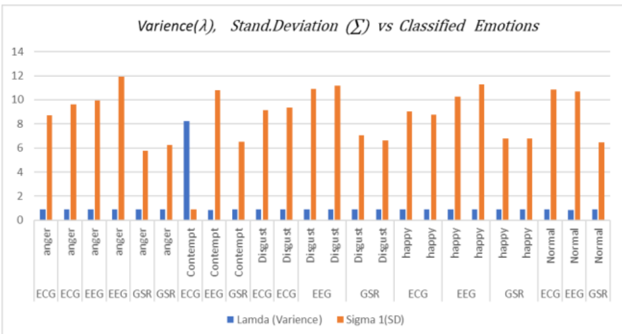


Fig. 6. Classification of emotional affect based on Test samples.

Fig. 6. Shows the Classification of emotional affect for the given test samples. The proposed model classifies the given test data into categories such as Anger, Contempt,

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Disgust, Happy and Normal. The statistical parameters such as Variance (λ), Stand Deviation ($\Sigma$ x) and Error Rate (e), Mean (u) help categorize the unique covariates.

### D. Comparison of existing works

Emotional affect detection is implemented with neural networks in [5] considering EEG dataset and K-nearest neighbour algorithms in [10] considering EDA dataset, Heart rate and Temperature are collectively compared with the proposed performance of GEM algorithm.

TABLE III. COMPARISON OF PROPOSED GEM ALGORITHM PERFORMANCE WITH EXISTING METHODS

| S.No | Input Type | Ref. | Method | Categories | Statistical Measure |
|---|---|---|---|---|---|
| 1 | EEG | [5] | Neural Networks | Pleasant, Unpleasant, Neutral | Mean=0.43, SD=0.16 |
| 2 | EDA, HR, TEMP | [10] | KNN, WMD-DTW | neutral, cheer, sad, erotic and horror | Mean=0.71, SD=0.12 |
| 3 | ECG, EEG, GSR | Proposed | GEM | anger, contempt, disgust, happiness, normal | Mean=0.62, SD=0.88 |

TABLE III. Shows the comparison table of existing implementation on emotional affect detection with proposed GEM algorithm performance and analysis. The proposed work considers the ECG, EEG and GSR datasets of AMIGOS, in which the average impacted emotional affects arrived, are tabulated above. The minimum impacted standard deviation value $\Sigma$ x=0.88 and the Mean μ = 0.62. likewise, each dataset for unique emotions varies from its minimum to the maximum value.

## VI. CHALLENGES

The main challenge of the presented work is the big data handling and processing latency consumed for the purpose of training and testing. The Gaussian expectation-maximization model determines the relative convergence of grouped data through probabilistic distribution and similarity mapping. The system model needs to be focused on improvising the preprocessing stage and feature extraction steps to scale the data before processing.

## VII. CONCLUSION

Emotion identification through the Gaussian expectation-maximization algorithm is evaluated here. AMIGOS dataset is considered for analysis. Physiological signals such as ECG, EEG and GSR is considered for analysis. The proposed research work is focused on detailed analysis and creating a lightweight model for emotion analysis that produce less latency comparatively is evaluated here. The participants are selected randomly and tested with ECG, EEG, GSR data covariance analysis using Emo-Gem and Gaussian expectation-maximization model that depends on the regression of the data. The higher the processing depth-wise convergence that produces equality in data size, produce unique correlation points to determine the emotions. The proposed model achieves less latency of approximately 435mSec for the overall processing with 0% error to the maximum iterations. From TABLE III. The statistical measures highlighted as Mean μ =0.62, SD=0.88, concerning the detection of emotions like anger, contempt, disgust, happiness and normal. Further, the system needs to be classified using a deep learning model to find the detailed variations etc.

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