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Effective Prediction System for Affective Computing on Emotional Psychology with Artificial Neural Network

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***Abstract*— Human emotions reveal mental health. Understanding people's emotions help make vital decisions. With recent improvements in AI and machine learning, affective computing has become an interesting topic of research that adapts human emotional behavior and increases learning outcomes connected to behavioral psychiatry. Machine learning algorithm evaluation improves prediction quality, yet problems arise with connected decisions. The suggested research predicts true emotion using neurophysiological data. Emotional changes trigger physiological responses. The suggested system uses Gaussian mixture models to develop a novel prediction algorithm utilizing the AMIGOS dataset. The dataset included ECG, EEG, and GSR (GSR). The findings affect the statistical response following data processing, measurable emotion labelling, and training samples. The provided system is compared to state-of-the-art statistical measures like standard deviation, population mean, etc. The system can compare an interpreter to validate emotion labelling parameters. A unique Emotional detecting artificial Neural Network (EMONN) system is improved by using deep learning models to find covariate values that help identify participant personality traits. Novel Emotional detecting artificial Neural Network (EMONN) achieves 93% accuracy with reduced computing time. A new Emotional detecting artificial Neural Network (EMONN) system is researched and developed by analyzing deep learning models to detect covariate values in the data set.**

Keywords*— Affective computing, Emotional Psychology, Emotion prediction, Amigos, Personality detection, Mental health matters.

I. Introduction

A. Affective Computing

Using common datasets, AI and ML constructed test scenarios to evaluate human genuine affect. Physiological data, speech patterns, face expressions, contextual expressions, etc. are used to identify human emotion. Facial expressions quickly capture emotions, hidden emotions are difficult to identify [1]. A scientific investigation using AI to determine human emotion from physiological data verifies an expert's psychological interpretation. Data collection, pre-processing, categorization, and performance analysis are a part of the proposed research [2]. Emotions reflect the brain's response to particular experiences. The real feeling is sometimes suppressed and cannot be retained for long. The impact of continuous emotional suppression promotes stress and hypertension. Reflections of thoughts are expressed as emotions. Affective computing uses a two-dimensional emotion model containing valence and arousal [3]. In subsequent implementations, it will be necessary to take steps to lessen the impact of invalid data. Since the values of the ECG, EEG, and GSR are sequences of recorded signal peaks, the magnitude of the data associated with emotions can be extremely large. The implementation of research is the primary emphasis of a discriminative model. The process of computing all of the features that are present in the real-time dataset appears to be complicated, and it requires more time for processing. On the other hand, it analyses multi-modality in the mapping of features [4].

B. Datasets Analysis

An EEG multichannel-based emotion recognition system with an innovative dynamic graph convolutional neural network technique is examined here using the DREAMER dataset. The conventional method of the Convolutional Neural Network (CNN), in which the graphical form of multichannel EEG data is utilized, is not the same as the GCNN method. Implementing discriminative characteristics to enhance EEG-based emotion recognition To achieve higher levels of accuracy, the adjacent matrix is taught using neural network architecture. [5].

The Digital Emotional Assessment Program (DEAP) is a research dataset that is open to the public and is used for evaluating different emotional states. The current study affects a variety of modalities of emotionally significant highlights. The direct evaluation of the subject's mental state, as well as the placement of electrodes and any features that emerge from the analysis of brain wave data, is required for emotion recognition based on ECG signals. This evaluation is done in conjunction with the ECG signals. A technique for the extraction of features is determined based on 33 different studies. The experiment uses a machine learning technique to identify features to apply to the data that was recorded by the participant. When utilizing a multivariate approach, the system performs exceptionally well in comparison. [6].

For the subject-dependent experiment, the given system achieves a recognition accuracy of 90.4%, whereas the subject-independent network that is cross-validated with the SEED dataset [8] achieves a recognition accuracy of 79.5%. A multimodal dataset that utilizes electrocardiogram information to analyze the affective and emotional states of human beings. Regarding the videos of varying emotions, the physiological signals of 32 different participants are recorded and analyzed. Despite having seen the video, each of the 32 participants had their levels of arousal, aggression, like, dislike, dominance, and familiarity meticulously documented. The stimuli of the brain are recorded using an innovative way, and the method corresponds with the data signal in terms of the frequencies [7].

A multimodal dataset that contains detailed annotations of continuous emotions during genuine interactions. The dataset contains multimodal measures that were gathered with off-the-shelf devices from 16 sessions of around 10-minute-long paired debates on a social topic. These measurements include audiovisual recordings, EEG, and peripheral physiological signals. It differs from other datasets in that it includes annotations of feelings from all three perspectives that are now available: the self, the debate partner, and external observers. While watching the discussion film, raters took notes on emotional displays at regular intervals of five seconds. These notes were organized according to arousal valence and 18 other categories of emotions. The K-EmoCon database that was produced as a result is the first multimodal dataset that allows for the multi-perspective evaluation of emotions while people are interacting with one another [8].

Dataset to monitor drivers in natural driving circumstances such as rest, driving in the city, and driving on the highway, researchers used four different types of physiological sensors. The total time spent driving was close to one hour and ninety minutes. Data were recorded with the use of an electromyogram that was positioned on the shoulder, a rhythm trace from an electrocardiograph, a sensor that detected respiration by monitoring the expansion of the chest cavity, and skin conductance sensors put on both the hand and the foot. Several video cameras were employed the whole time to record the driver's facial expression, as well as his or her body movement and the conditions of the road. To give an accurate basis for analysis, these movies were time-stamped to correspond with the physiological data. These videos are currently in the process of having some hand annotations added to them. This data has been donated so that it can be made freely available for researchers to use on PhysioNet, and the annotations, whenever they are finished, will do the same thing. The data were compiled using readings of four physiological signals and eight affective states. These readings were obtained daily during a session that lasted around twenty-five minutes. The recordings spanned over twenty days. Blood volume pulse, electromyogram, respiration, and skin conductance are the four physiological signals. Skin conductance is the fifth physiological signal [9].

II. LITERATURE STUDY

Q Zhou et al., (2017) based on the theory of affective psychology, investigated the aspects and transitions of emotional state was carried out. After that, an affective decision model with multiple layers was suggested by developing a mapping relation between character, mood, and motion. The model captured the shifts in sentiment and emotional space. As a result of the experiment demonstrating that human emotion traits are consistent with theory and law, a reference point has been established for the modelling of human-computer interaction systems. A multi-layer affective computing model by constructing a mapping relationship between three different regions, the model can reasonably depict the relationship between the stimulation from the outside world, an individual's character, mood, and emotion. The findings demonstrate that the method by which emotions and moods change generally conforms to the law governing the transformation of human emotions. As a result, the applicability and efficiency of the model are validated through experimentation, which paves the way for a novel approach to the autonomous production and computing of affective models. [10].

Sánchez-Reolid et al., (2018) The assessment of human feelings is an essential component in the creation of contemporary brain-computer interface devices such as the Emotiv EPOC+ headset, in which the application programming interface of the headset accurately classifies a user's emotional state (API). These responses are given in the form of a self-assessment manikin questionnaire. Several artificial neural networks (ANNs) based on the multilayer perceptron architecture are put to the test to determine how accurately they can classify the emotional outcomes produced by the Emotiv EPOC+ API. The greatest results can be obtained using an ANN configuration that has three hidden layers, with 30, 8, and 3, respectively, for the number of neurons in each of the first three layers. Accuracy of classification of 85%, which indicates emotional estimation provided by the headset may be utilized in real-time applications that are based on the emotional states of users with a high level of confidence. [11].

The problems faced with ample sequential text information with emotion analysis using psychiatrist text to be analyzed. Problems are the most significant aspects of emotion recognition using long text data on mental health-care-oriented texts. This leads to a new direction for exploring emotion analysis in mental health care using the DL models. Extracted the emotions from psychiatric data with long text sequences and reduced loss function using the DL models. MHA-BCNN model for emotion analysis with GloVe Embedding model gives decent outcomes to the long sequence text. The model is trained on a dataset from mental-health questions posted by the patients on Webmd and Healthtap websites. Concluded by experimental results that model MHA-BCNN by GloVe300 with Healthtap dataset achieved the most acceptable accuracy, about 97.8%, of any other DL models, including state-of-the-art methods [12].

Initial investigations have demonstrated that it is possible to deduce, using computational methods, the degree to which an image is memorable based on the intrinsic qualities of the image itself. The computational model for predicting the memorability of images is based on deep learning and has been fine-tuned. According to the state of the art, the model's performance obtains a relative increase of 32.78% higher than that of the model considered the best-performing model. This model's performance is much better than that of any previous work. We also test how well our model generalizes to a new dataset consisting of 150 images. The model achieves a higher predictive performance for arousing negative pictures than neutral or arousing positive ones [13].

III. Methodology

A. AMIGOS Dataset

A data set for use in multimodal studies of the effects of affect, personality traits, and mood on individuals and groups. Using short and lengthy videos makes it possible to do multimodal research on affective responses using neuro-physiological signals of individuals in connection to their personality and mood, as well as concerning the duration of films and the social setting. The data are gathered from two distinct experimental environments. Wearable sensors are used to get recordings of the individual's signals, specifically electroencephalograms (EEG), electrocardiograms (ECG), and galvanic skin responses (GSR). The participant's feelings have been annotated with self-assessment and external assessment of the affective levels (valence, arousal, control, familiarity, liking, and basic emotions) they experienced while watching the videos [14].

B. Self-Assessment Manikin (SAM) Tool & PANAS

Participants view the entire video and then discuss their feelings openly and honestly. Participants are also allowed to answer the questions posed by the SAM tool throughout the self-evaluation process. In addition, the PANAS positive and negative affect schedule is carried out using the Self-assessment manikins SAM tool. The self-assessment manikins SAM tool is used to chart the force of stimulation and dominance [15]. The SAM tool consists of an affective slider that is supposed to depict the pictorial representation of pleasure on the top row, arousal in the middle row, and further dominance on the bottom scale. When fetching the emotion analysis, the participants are allowed to make a marker in the chart displayed above to self-evaluate the inputs. The physiological data are dynamically collected while the test is being performed on the subject. Any abrupt increase in emotion is directly represented in the physiological data, and it also lets the participant self-assess how the record makes them feel. This self-assessment method is regularly practised at the SAM laboratory to identify behavioural characteristics. The experimental setting in this system considers anything from one to seven emotional effect characteristics, depending on the situation. There are five different social settings offered [16].

C. Distribution

Iterative loops tend to keep looking for new data from statistical measurements, such as the population mean and the initial pattern's standard deviation and variance. The specified probability space can't approximate the expected maximizing value if there is no normal data distribution. In general, equation (1) presented below can be used to determine whether or not the data pattern in question follows the distribution method.

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

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

$$\lambda \rightarrow Varience,$$

$$\mu \rightarrow Mean\ of\ the\ populanation$$

IV. System Architecture

A. Design Architecture

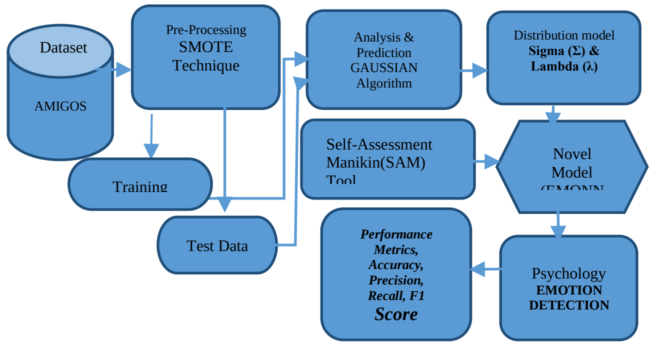

Figure 1. EMONN Model - Emotional detecting artificial Neural Network

Figure 1. shows the proposed Gaussian model algorithm system architecture and analysis, which is based on the distribution model using sigma(Σ) & Lambda(λ). The input data, such as ECG, EEG, and GSR, are preprocessed physiological signal recordings [17]. The self-assessment Manikin (SAM) tool inputs the reading and the Novel EMONN model is generated.

B. Summary of Implementations

Using the AMIGOS dataset, the emotional affect prediction was made possible by the system architecture of the proposed Emotional detecting artificial Neural Network (EMONN). The input data are separated into two distinct modes: the raw data mode and the pre-processed data mode. The raw data consists of the signal points recorded by AMIGOS utilizing EMOTIV Epoch for EEG and the Shimmer tool for GSR [18]. Additionally, the data for the ECG was recorded using ECG sensors with 6 channels. The pre-processed data from AMIGOS is supplied as a (.Mat) file generated by the bandpass filter with the frequency set to 60 Hz. The synthetic minority oversampling method (SMOTE) process is utilized to reduce the number of samples taken from the comprehensive dataset. Initial scaling steps of input data perform, reading the data from AMIGOS, resizing the data into a constant down sample scale of 1000 samples in each frame, and cleaning the data by removing the junk values and Nan (not a number) values, INF (infinite) values. These steps are carried out to prepare the data for further processing.

V. Results and Discussions

A. Analysis on ECG, EEG, GSR

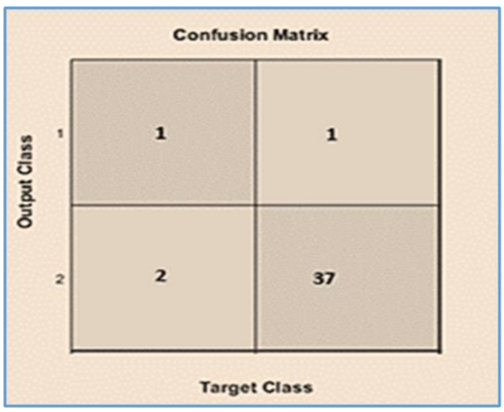

Figure 2. Analysis on ECG, EEG, GSR

Figure 2. shows ECG, EEG, and GSR data convergence analysis on several iterations. To examine the unknown labels, the iterations are repeated for different individuals.

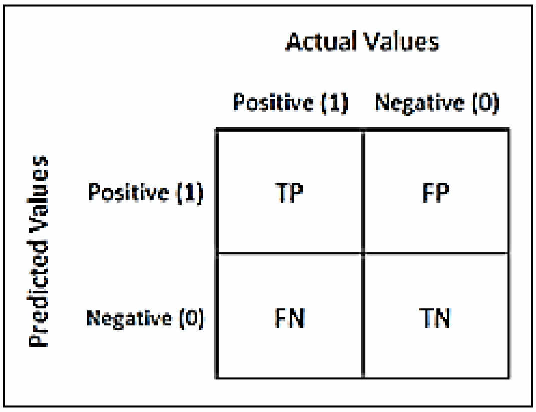

Figure 3. Predicted values compared to Actual values

Figure 3. explains the automated Emotional detecting artificial Neural Network (EMONN), after comparing these data inputs, the actual expected results need to be compared with the predicted results. This is an easy concept to grasp, as it is explained in the previous sentence.

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

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

Accuracy, Precision, Recall, F1Score, Sensitivity and Specificity are determined by equations (2) and (3). The actual categorization performance is evaluated based on these TP, TN, FP, and FN scores [19]. When evaluating the effectiveness of training and testing, the accuracy of the prediction model is an essential metric to consider.

B. AMIGOS Processed vs. Raw Data

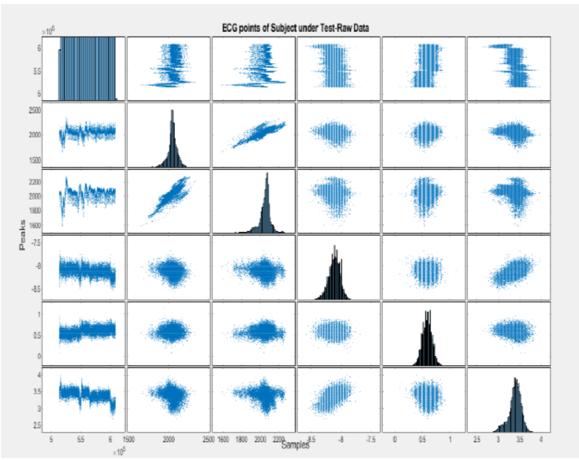

Figure 4. Data Visualizations of Processed Data vs Actual Data

Figure 4. shows the single-channel EEG data that was recorded by AMIGOS together with the raw data and the preprocessed values. The Plot Matrix of AMIGOS preprocessed data points of subjects under test selected randomly and they are displayed here. The data from all 40x5 channels of the recording provided a single channel taken into consideration for the study.

The affect detection methodology derived from the AMIGOS dataset described here primarily emphasizes identifying two distinct types of contexts [20]. The participant's actual attitudes and knowledge about the test video are determined by the social environment in which they were viewed. Another emotional category displayed here is known as the affected context. It depicts the actual emotion that the participant was feeling at the time of the self-assessment, which may be seen here. When validating the test data, the training input vectors and their equivalent self-assessment data are considered [21].

Table.1. Shows the statistical parameter of long videos referred to with 10 different video IDs. The distribution model analysis of each video is sampled Lamda 1, Lamda 2, sigma 1, sigma 2

Table.1 Statistical parameters Test data

	Statistical Parameters			
VIDEO-ID	Lamda1	Lamda2	sigma 1	Sigma 2
1	0.9275	0.0725	9.7905	11.1695
2	0.88425	0.1157	7.4507	48.35
3	0.799	0.20025	7.5495	32.67
4	0.733	0.26625	6.0865	33.65
5	0.702	0.298	7.3773	33.6
6	0.551	0.449	5.75	26.4031
7	0.906	0.09325	8.5928	29.2249
8	0.7155	0.2845	7.342	31.958
9	0.7688	0.2312	6.045	22.9322
10	0.5793	0.4207	6.782	32.5063

Table 2. shows the number of iterations for the given test sample ranging from 3548.8753 at the start of the random selection of the beginning position to 0.00 at the end of the 9th iteration. The statistical points related to the mean are assessed.

Figure 4. Shows the parametric results of the short emotional videos with 16 participants. Sigma 1 & Sigma 2 are calculated with the distribution model and evaluate the peak limit.

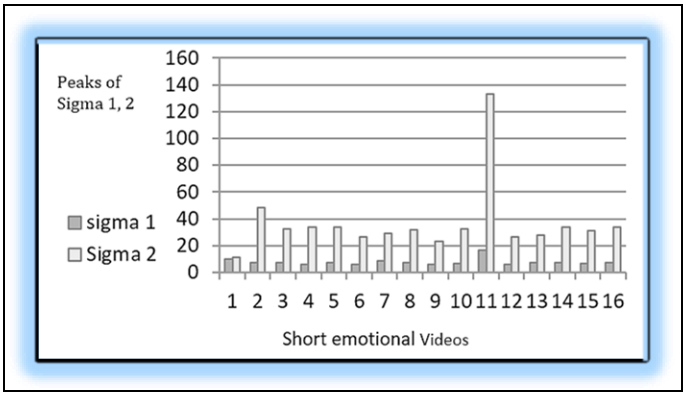

Figure 4. Parametric results Novel EMONN

VI. CHALLENGES

The massive challenge of the presented system is the vast dataset that needs to be integrated with the Emotional Artificial neural network (EMONN). The ANN model runs iteratively to the scaled statistical data until it is independently obtained for a 40x20x16 combination of inputs with ECG, EEG, and GSR parameters. If new data is entered, the learning process takes place over a more extended period. Even though the automated analysis was performed, the altered data performed better when compared to the statistical method.

VII. CONCLUSION

The feelings of unhappiness, happiness, excitement, and disgust are the emotional effects of an individual's personality. The behaviours that humans engage in are the direct result of emotions. In this simulation, the lightweight emotion analysis model that uses the Gaussian algorithm with Smote technique is the focus of attention. The Emotional detecting artificial Neural Network (EMONN) model is simulated. In terms of how the vast data pattern of the AMIGOS dataset is structured concerning the self-assessment data, the Novel Emotional detecting artificial Neural Network (EMONN) was developed with such a design in mind. The pre-processed data are used to construct the model, and the layered analysis performed using EMONN reveals an accuracy of 93% being obtained overall. The presented system can be improved further by using additional deep learning models.

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