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YAAD: Young Adult's Affective Data Using Wearable ECG and GSR sensors

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***Abstract*—Emotions play a significant role in human-computer interaction and entertainment consumption behavior, which young adults commonly use. The main challenge is the lack of a publicly available dataset for young adults with emotion labeling of physiological signals. This article presents a multi-modal data set of Electrocardiograms (ECG) and Galvanic Skin Response (GSR) signals for the emotion classification of young adults. Signal acquisition was performed through Shimmer3 ECG and Shimmer3 GSR units wearable to the chest and palm of the participants. The ECG signals were acquired from 25 participants, while GSR signals were acquired from 12 participants while watching 21 emotional stimulus videos divided into three sessions. The data was self-annotated for seven emotions: happy, sad, fear, surprise, anger, disgust, and neutral. These emotional states were further self-annotated with five very low, low, moderate, high, and very high-intensity levels of felt emotion. The participant also annotated valence, arousal, and dominance scores through Google form against each provided stimulus. The base experimental results for classifying four classes of high valence high arousal (HVHA), high valence low arousal (HVLA), low valence high arousal (LVHA), and low valence low arousal for ECG data is reported with an accuracy of 69.66%. Our baseline method for the proposed dataset achieved 66.64% accuracy for the eight-class classification of categorical emotions. The significance of data lies in the more emotional classes and less intrusive sensors to mimic real-world applications. Young adult's affective data (YAAD) is made publicly available, and it is valuable for researchers to develop behavioral assessments based on physiological signals.**

***Index Terms*—Electrocardiograms (ECG), Galvanic Skin Response (GSR), Emotion recognition, Affective computing, Human computer interaction, Biomedical signals.**

I. Introduction

Emotions play a significant role in the decision-making of advanced human-computer interaction and automated health care. The intrinsic behavior of Electrocardiogram (ECG) and Galvanic skin response (GSR) manifest the actual emotional experience of a person with the help of newly developed wearable and low-cost sensors. Affective computing through the processing of these biomedical signals recently improves the quality of psychological healthcare monitoring [19, 14], emotion regulation, stress management, affect-aware tutor [5], aid patients with cognitive disorders with the advancement of deep learning algorithms [28, 15, 7, 16]. Existing datasets such as AMIGOS [4], and MAHNOB-HCI [29] (that correlate ECG and GSR signals with emotional states) have a significant impact on affective computing research, came up with the challenges of the limited number of emotion classes, intrusive sensors for data acquisition, and specified for adult age range only. However, our dataset produced more emotion classes with wearable sensors from young adults having the significance for affective computing.

The advancement of technology [9, 20, 12, 27, 26] and distance learning proposes more technology users in the age range of children, and young adults [3, 2, 10]. The emotion elicitation problem is more challenging for children and young adults as they are more physically active and emotionally sensitive than adults. The existing emotion annotated datasets with physiological signals incorporate only adults above 19 years. Therefore, the researchers are more focused on the emotion elicitation of adults due to the lack of a publicly available dataset for children and young adults. Similarly, the available datasets usually acquire Electroencephalogram (EEG) signals in addition to ECG and GSR signals making it more intrusive to users to be applicable in real-world applications. The existing datasets are also limited to various emotion classes and self-annotation labels. In this work, we collected the self-annotated multimodal dataset of young adults with more emotion classes and less intrusive wearable sensors of ECG and GSR.

This study provided a publicly available [1] Young Adults

[1] Identification Number: doi.org/10.17632/g2p7vwxyn2.4; Direct URL to data: https://data.mendeley.com/datasets/g2p7vwxyn2/4

Dataset	**AMIGOS** [22]	**DEAP** [21]	**DECAF** [1]	**DREAMER** [18]	**MAHNOB-HCI** [29]	**SEED-IV** [30]	**YAAD**
Participants	40 (27M, 13F)	32 (16M, 16F)	30 (16M, 14F)	23 (14M, 9F)	30 (13M, 17F)	15 (7M, 8F)	25 (15M, 10F)
Modalities	EEG, ECG, GSR and audio-visual	EEG, GSR and peripheral signals	ECG and peripheral signals	EEG, ECG	EEG, ECG, GSR and peripheral signals	EEG	ECG and GSR
Self-Assessment Annotations	Dimensional: valence, arousal, dominance, liking, familiarity. Categorical: Six basic emotions.	Dimensional: arousal, valence, liking, dominance and familiarity.	Dimensional: valence, arousal and dominance.	Dimensional: Valence, arousal and dominance.	Dimensional: valence, dominance.	Categorical: Happy, Sad, Neutral and Fear.	Dimensional: valence, arousal, dominance, familiarity. Categorical: six basic emotions, five levels of each of the six basic emotion categories, neutral and mixed emotion state.
Dimensional Scale	1 to 9	Continuous scale 1 to 9	0 to 5 and -2 to +2	1 to 5	1 to 9	None	0 to 10
Acquisition	14 Channel EEG, Wireless ECG and GSR	32 Channel EEG and wired GSR	3 channel ECG	14 Channel EEG, Wireless ECG	32 Channel EEG and wired ECG, GSR	62-Channel ESI Neuroscan System	Shimmer 3 Wireless
Age (years)	21-40 (μ=28.3)	19-37 (μ=26.9)	(μ=27.3, σ= 4.3)	22-33 (μ= 26.6, σ=2.7)	19-40 (μ=26.06, σ=4.93)	20-24	8-25 (μ=15.23, σ=4.84)
Stimuli	20 Videos	40 Videos	32 Videos	18 Videos	20 Videos	24 Videos	21 Videos
Duration of signal	51-150 s	60 s each	(μ=80 s, σ=20 s)	65-393 s (μ=199 s)	12-22 s (μ=17.6 s, σ=2.2 s)	120 s each Approx	39 s each

TABLE I: Comparison of state-of-the-art emotion databases using physiological signals. M represented male, F represent female, μ represents mean and σ represents standard deviation.

Affective Data (YAAD) dataset for emotion recognition. Researchers can use this data to develop emotionally intelligent software to provide product customization, emotion regulation, stress management, and monitoring anomalies in psychological and emotional behavior. The provided data can help improve the quality of distance learning and healthcare services to people suffering from alexithymia, autism, and other related conditions by providing a baseline for emotion recognition. The data significantly augment the available datasets by providing more emotional categories (35 emotional categories: 7 emotions with five levels each, simultaneously provided with the dimensional scale of valence, arousal, and dominance values) and the associated psychological environment. Section II compares the proposed dataset with existing datasets, while the description of data and experimentation setup is provided in sections III and IV, respectively. Section V is dedicated to the baseline affective computing results, and a conclusion is provided in section VI.

II. Related Work

The induced emotion through stimuli is highly subjective, often represented by self-annotation. The available data is characterized by various variables, such as number of participants, type of stimuli, number of emotion classes, type of acquisition sensor, number and type of modalities, ease of data acquisition, and variation in annotation models. This section will review critical databases that tried to generalize these parameters for affective computing in real-world applications. The comprehensive comparison of these parameters between state-of-the-art databases and provided publicly available database are presented in Table I.

There are two approaches to model emotions through annotations: the dimensional and the categorical. Plutchnik [24, 13] emotion wheel and Russel circumplex model [25] are based on dimensional approach. The circumplex model is based on two-dimensional space with the scale of valence and arousal. This two-dimensional space is divided into four quadrants of high valence high arousal (HVHA), high valence low arousal (HVLA), low valence high arousal (LVHA), and low valence low arousal (LVLA). The participants can annotate in a range of scalar values for valence and arousal, which can then be classified in one of these four quadrants. Ekman [8] proposes the categorical approach with six basic emotion categories: happiness, sadness, anger, fear, disgust, and surprise. Most databases such as [21], [18] and [30] use only one of these approaches to annotate emotion labels. Only AMIGOS [22] database incorporate both approaches for annotation to generalize their data for comparative analysis in the domain of affective computing. In our dataset collection, we also incorporated both dimensional and categorical approaches with the addition of five levels of each of the six basic emotions during self-annotation. Similarly, the annotation provided in YAAD is on the larger dimensional scale of 0 to 10 compared to previous datasets for more accurate modeling of self-

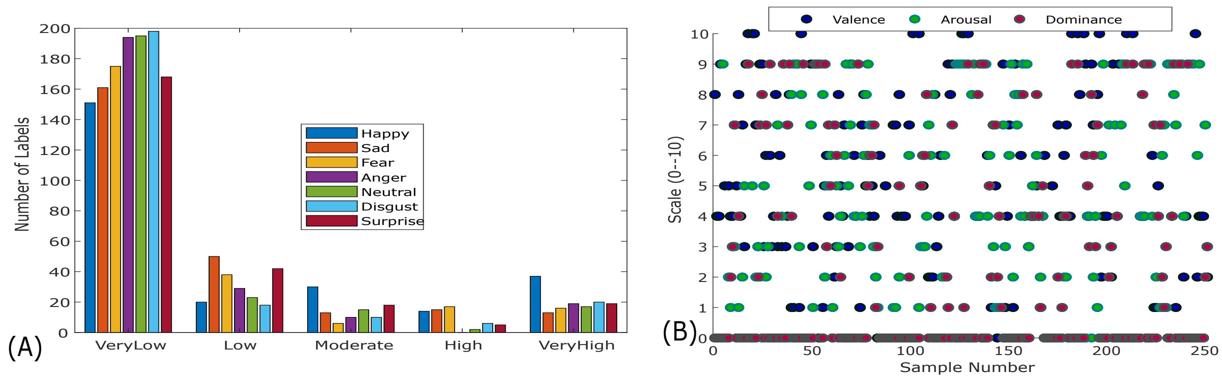

Fig. 1: Dataset statistics for emotion classes and valence, arousal, dominance model (A) Number of samples labelled with seven emotion classes of happy, sad, fear, anger, neutral, disgust and surprise with five levels of very low, low, moderate, high and very high states (B) Sample from 1-252 with the score of valence, arousal and dominance.

annotation.

Few state-of-the-art databases with facial emotion expressions are provided for young adults and teenagers [23, 11], [6]. However, the databases for emotion recognition using physiological signals are focused on adults age groups only as provided in Table I. YAAD is provided for emotion elicitation of young adults with a higher standard deviation. Another critical problem is the collection of data through non-invasive wireless devices with a minimum number of electrodes. In previous databases, EEG is incorporated in addition to ECG, GSR, and other peripheral signals, making it intrusive to the participants compared to the real-world environment. Our dataset acquires only ECG and GSR signals with single electrodes and wireless devices for non-invasive data acquisition compared to previous datasets.

III. Data Description

Our dataset consists of two configurations, one with single modal ECG signals and the other with multi-modal ECG and GSR signals. The provided multi-modal dataset comprises seven emotional states (happy, sad, anger, fear, disgust, surprise, and neutral). Each of these seven states consists of five levels of very low, low, moderate, high, and very high annotations representing the intensity of the felt state with a total of 35 states. The annotation is considered a mixed emotional state for the participant who self-annotates the same level of felt emotion for more than one emotional state.

The dataset contains two folders, namely raw data and self annotations. The ***raw data*** folder contains two sub-folders namely single modal and multi-modal. The ***multimodal*** sub-folder contains raw data of both ECG and GSR signals in separate sub-folders. Both ECG and GSR signals were collected simultaneously from 12 participants. Each ECG and GSR folder contains 252 files (3 sessions x 12 persons x 7 emotions). The set of experiments performed for a single modal contains only ECG signals. Therefore, the ***single modal*** sub-folder of raw data consists of 154 ECG samples comprising 13 participants (other than that used in multi-modal experiments) watching seven stimulus videos for the variable number of sessions. Participants of the single modal dataset with ID numbers 1, 3, 4, 5, 6, 7, 10, and 13 participated in the first session only, and ID number 2 participated in the first two sessions, participants with ID numbers 8, 9, 11 and 12 participated in all the three sessions. Each ECG and GSR sample size 1 x 5000 with a 128 Hz sampling frequency (39-sec data) has a unique ID based on session number, person ID, and video stimulus ID. For example, sample ID of ***ECGdata_s3p11v2*** represent ECG data sample of session 3 of participant ID 11 with video ID 2. ***self annotation labels*** folder contains the self annotated labels (emotions) against all the raw data signals of single modal and multi-modal (two separate excel files). Therefore, each of these 39-sec raw data samples correlates with one of these 35 emotional states provided in self annotation excel file. The distribution of samples against these 35 emotional labels are present in Fig. 1(a), the highest number of very low values in encouraging because most of the participants felt strong emotions against the provided stimuli.

The provided data incorporated 25 volunteer participants, ten females and 15 males. The age varies from 8 to 25 years, and each participant completed a questionnaire in the form of a self-assessment (url). The self-assessment excel file contains the sample with the session, participant, and video ID, the rating of 35 emotional states, also provided 3D valence, arousal, and dominance model on a scale of 0 to 10 (from lowest to highest). The number of samples provided with scores of valence, arousal, and dominance is represented in Fig. 1(b), which shows equal distribution of these values among the provided scale. The valence score represents the positiveness or negativeness of emotion, and the arousal score represents excitement level, while the dominance score represents the control and influence level felt by emotional stimuli. The Self-Assessment Manikin (SAM) is used for 3-dimensional emotional assessments of subjects in the questionnaire. SAM is a non-verbal pictorial assessment technique that is quick, inexpensive, and easy, which directly measures the pleasure, arousal, and dominance associated with a person's affective reaction to a wide variety of stimuli. These manikins are

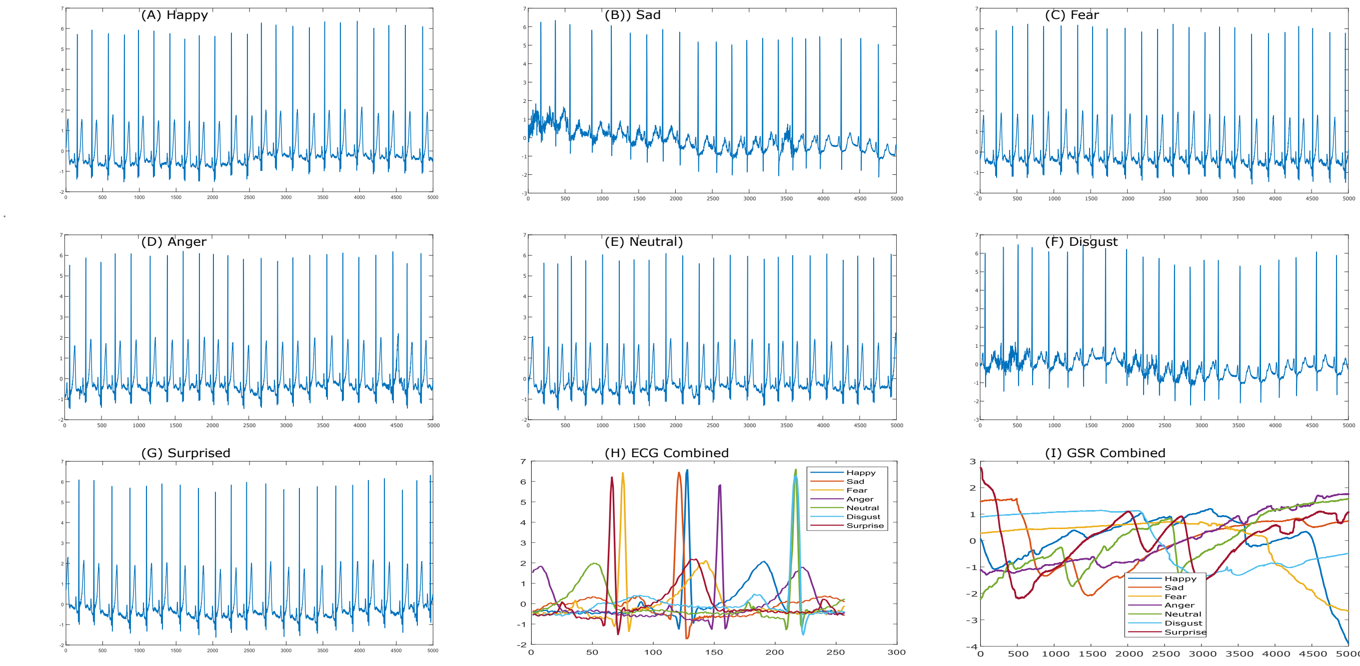

Fig. 2: Raw data samples of ECG and GSR for various emotion classes (A) Raw ECG data for happy class, (B) Raw ECG data for sad class, (C) Raw ECG data for fear class, (D) Raw ECG data for anger class, (E) Raw ECG data for neutral class, (F) Raw ECG data for disgust class, (G) Raw ECG data for surprised class, (H) Raw ECG data combined for seven emotion classes with 2-sec window, (I) Raw GSR data combined for seven emotion classes.

Stimulus ID	**Target Emotion**	**Video Title**	**Stimulus ID**	**Target Emotion**	**Video Title**	**Stimulus ID**	**Target Emotion**	**Video Title**
S1V1	Happy	Babies Laughing	S2V1	Happy	Funny babies	S3V1	Happy	Funny panda
S1V2	Sad	Barely there	S2V2	Sad	Life is beautiful	S3V2	Sad	The Pianist
S1V3	Neutral	National Park Alaska	S2V3	Neutral	Abstract shapes	S3V3	Neutral	Color bars
S1V4	Surprise	Highest Waterfall	S2V4	Surprise	Bungee jump	S3V4	Surprise	Alpha jetman
S1V5	Disgust	Disgust compilation	S2V5	Disgust	Open diabetic ulcer	S3V5	Disgust	Disgusting eating
S1V6	Anger	Triggering OCD	S2V6	Anger	Schindler's List	S3V6	Anger	Kashmir protest
S1V7	Fear	Horror scene diet	S2V7	Fear	The moonlight man	S3V7	Fear	Whisper

TABLE II: 21 Stimulus videos with ID, target emotion and video title.

mapped with numbers. Ten levels from 0 to 10 are defined for each dimension, representing an increase in intensity as shown in the questionnaire attached in the Appendix. For valence, it is unpleasant to pleasant; for arousal, it is from calm to activated; and for dominance, it is from no control to in control. The participant's name, age, gender, and familiarity score (with stimulus video from level 0 to 10, 10 means more familiar and 0 means never watched the video before) is also present in the excel sheet.

The raw ECG data for samples of seven emotion categories are represented in Fig. 2(a) to Fig. 2(g). Raw ECG signals representing these emotional categories are combined for 2-sec and shown in Fig. 2(h). Similarly, Fig. 2(i) shows the combined representation of seven emotion classes of raw GSR data. These raw signals against self-annotation labels would help the researchers preprocess, extract features using biomedical signal processing, and then classify emotional categories to develop emotion-related applications.

IV. Experimentation Protocol

Shimmer3 ECG and Shimmer3 GSR units are used to capture ECG and GSR signals, respectively. The sampling frequency for the ECG signal is set to be 256 Hz. Similarly, the sampling frequency for the GSR signal is set to be 128 Hz, and a total of 5000 samples are considered for each signal. The electrode placement for the wearable Shimmer3 ECG unit is represented in Fig. 3(a), where there is no need to place gel on the chest. GSR signals are acquired by placing one electrode on the palmar surface of the medial phalange and the other on the palmar surface of the distal phalange and an ear clip on the side, as shown in Fig. 3(b). Emotional stimuli are provided after 5-sec of signal acquisition; these 5-sec should be considered as baseline signals of neutral state in the absence of emotional stimuli. Participants are allowed to recover and relax by providing a 3-5 minute gap between the trials and provided seven stimulus videos. The same environmental setup is used for each signal acquisition

Fig. 3: Dataset acquisition procedure (A) Shimmer3 GSR unit, (B) Shimmer3 ECG unit, (c) Participant watching stimulus video with wearable ECG and GSR sensors communicated with MATLAB for data streaming and storage through bluetooth.

process to standardize the dataset. The environmental setup with a participant watching emotional stimulus is shown in Fig. 3(c), while both wearable ECG and GSR sensors were paired with PC and communicated the acquired signal with MATLAB software through Bluetooth.

There were 21 stimulus videos shown to each participant for 39-sec. Table II represent all the stimulus videos shown to participants during data acquisition. For example, stimulus ID S1V1 represents the first stimulus video used for the first session, and S3V5 represents the fifth stimulus video used for the third session. The details of these videos and their links are also provided in supplementary material with the dataset. The real-time streaming of data from a Shimmer device to MATLAB incorporated the Shimmer MATLAB Instrument Driver. Each sensor has its COM port number through which their signals are shared over the Bluetooth to PC and saved as mat files. The ECG data is pre-filtered with a second-order Chebyshev low pass filter (LPF) with a corner frequency slightly smaller than the Nyquist frequency and a second-order Chebyshev high pass filter (HPF) with a corner frequency of 0.5 Hz to minimize the effect of environmental noise and muscle movement before data storage. The interference noise is minimized during signal acquisition; mobile phones and all other electronic devices were removed from the environment and asked the subject to stay static without unnecessary movements.

TABLE III: Confusion matrix of ECG modality with four classes classification of dimensional self-annotation.

Output Class \ Target Class	HVHA	HVLA	LVHA	LVLA
HVHA	278	14	5	14
HVLA	28	720	41	217
LVHA	20	127	655	241
LVLA	41	220	278	1242

TABLE IV: Confusion matrix of eight emotion categories.

Output Class \ Target Class	Anger	Disgust	Fear	Happy	Mixed	Neutral	Sad	Surprise
Anger	140	2	0	8	8	0	1	0
Disgust	0	252	47	52	66	0	11	14
Fear	4	0	197	11	11	2	7	1
Happy	24	21	38	912	122	75	30	30
Mixed	117	71	72	185	660	111	111	30
Neutral	1	0	0	30	0	189	0	1
Sad	0	0	3	25	30	0	309	3
Surprise	0	1	0	1	1	0	0	105

V. Affective Computing results

This section presents the baseline results of affective computing with ECG signals using the deep learning methodology proposed in [7]. The proposed dataset has both dimensional and categorical self-annotations. Therefore, we computed emotion classification in two different schemes. Firstly, with four classes of HVHA, HVLA, LVHA, LVLA by dividing the scales of valence and arousal into half. Secondly, with 8 class categories of happiness, sadness, anger, fear, disgust, neutral, surprise, and mixed emotion were classified.

The initial exploratory results of classification were computed using ECG signals by combining single modal (154 samples) and multi-modal (252 samples) data with a total of 406 samples from 25 subjects. Each sample contains 39-sec of ECG data, while the first five seconds of ECG recording is the baseline signal without any provided stimuli. The last 34-sec of each sample contains the data with the provided stimuli of target emotion. The data from each sample is converted to a 1-sec segment and subtract the average baseline from each 1-sec segment. Total number of 1-sec segments were 406 x 34 = 13,804 samples. These 13,804 samples are divided into 70 percent training (9,663 samples) and 30 percent testing (4,141 samples). After baseline removal and z-score normalization, the CNN-LSTM architecture was trained and then tested with these samples based on the methodology provided in [7].

The methodology employed for classification is based on three one-dimensional convolutional layers with 16 filters of size 1 x 8 each followed by LSTM layer. The model was trained with batch size of 64 and learning rate of 0.001 with adam optimizer.

The number of epochs to train the model was set to 200 epochs, and the experimental setup was followed by [7]. For four-class classification with the dimensional label, the emotion recognition performance of 69.66% is achieved. Similarly, for eight class classification with categorical emotion labels, the emotion recognition performance of 66.64% is achieved. The detailed class-wise results are presented as confusion matrices of four class classification in Table III. Similarly, the detailed class-wise results for eight classes are presented in Table IV. This proposed dataset is based on a single electrode of ECG. The recording was performed for a limited duration of 39-sec for the minimal intrusion to the participant. Therefore, due to less number of total training samples and single electrodes, the recognition performance is less compared to [7], however, comparable to the baseline results of many state-of-the-art approaches. The proposed dataset allows researchers to improve the ECG and GSR-based emotion recognition performance with less intrusive data collection and larger classes of emotions.

VI. Conclusion

In this work, a multimodal YAAD database is presented and made publicly available to the research community of affective computing. The lack of a physiological signal-based emotion database for young adults makes it understudied for the prime consumers of the latest technology. This database contains ECG and GSR recordings using wireless sensors for 25 participants, with dimensional and categorical scales self-annotation. The audio-visual stimuli of 21 selected videos are used to induce target emotions. The wide range of self-annotations and larger classes of emotions with less intrusive data collection make it valuable to explore the potential of ECG and GSR for emotion elicitation in young adults. The limitation of this work is to incorporate ECG and GSR signals only compared to EEG based emotion analysis [17]. The baseline results are provided for ECG signals, enabling the researchers to explore the potential of GSR and the multimodal fusion of both signals for comparison and improvement of emotion elicitation in the domain of affective computing.

VII. Ethics Statement

Data acquisition was performed in a controlled environment with subjects' consent, where they agreed to volunteer for this data collection to support research. The study did not add any patients to collect data, and the data is collected from students who volunteer for data collection. All subjects signed a consent form. The NUST ethical review committee initially approved the study with protocol number 03-2021-02/20, the collection of data was performed in a dedicated controlled environment. The data provided online is wholly anonymized and contains no information revealing the subject's identity.

VIII. Acknowledgements

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References

[1] Mojtaba Khomami Abadi et al. "DECAF: MEG-based multimodal database for decoding affective physiological responses". In: *IEEE Transactions on Affective Computing* 6.3 (2015), pp. 209–222.

[2] Hussain Ahmad et al. "Futuristic Short Range Optical Communication: A Survey". In: *IEEE International Conference on Information Science and Communication Technology (ICISCT)* (2020).

[3] Jozenia Torres Colorado and Jane Eberle. "Student demographics and success in online learning environments." In: (2012).

[4] Juan Abdon Miranda Correa et al. "Amigos: A dataset for affect, personality and mood research on individuals and groups". In: *IEEE Transactions on Affective Computing* (2018).

[5] Ailbhe Cullen et al. "Creaky voice and the classification of affect". In: *Proceedings of WASSS, Grenoble, France* (2013).

[6] Kirsten A Dalrymple, Jesse Gomez, and Brad Duchaine. "The Dartmouth Database of Children's Faces: Acquisition and validation of a new face stimulus set". In: *PloS one* 8.11 (2013), e79131.

[7] Muhammad Najam Dar et al. "Cnn and lstm-based emotion charting using physiological signals". In: *Sensors* 20.16 (2020), p. 4551.

[8] Paul Ekman and Wallace V Friesen. *Unmasking the face: A guide to recognizing emotions from facial clues*. Vol. 10. Ishk, 2003.

[9] Khush Naseeb Fatima et al. "Fully automated diagnosis of papilledema through robust extraction of vascular patterns and ocular pathology from fundus photographs". In: *Biomedical optics express, Vol. 8, Issue 2, pp. 1005-1024* (2017).

[10] Bilal Hassan et al. "Automated retinal edema detection from fundus and optical coherence tomography scans". In: *IEEE 5th International Conference on Control, Automation and Robotics (ICCAR), pp. 325-330* (2019).

[11] Bilal Hassan et al. "Autonomous Framework for Person Identification by Analyzing Vocal Sounds and Speech Patterns". In: *IEEE 5th International Conference on Control, Automation and Robotics (ICCAR), pp. 325-330* (2019).

[12] Bilal Hassan et al. "Deep learning based joint segmentation and characterization of multi-class retinal fluid lesions on OCT scans for clinical use in anti-VEGF therapy". In: *Computers in Biology and Medicine, August* (2021).

[13] Bilal Hassan et al. "Structure tensor based automated detection of macular edema and central serous retinopathy using optical coherence tomography images". In: *Journal of Optical Society of America A, Vol. 33, Issue 4, pp. 455-463* (2016).

[14] Taimur Hassan, Saleem Aslam, and Ju Wook Jang. "Fully automated multi-resolution channels and multithreaded spectrum allocation protocol for IoT based sensor nets". In: *IEEE Access, Vol. 6, pp. 22545-22556* (2018).

[15] Taimur Hassan et al. "RAG-FW: A hybrid convolutional framework for the automated extraction of retinal lesions and lesion-influenced grading of human retinal pathology". In: *IEEE Journal of Biomedical and Health Informatics*. January 2021.

[16] Taimur Hassan et al. "Structure tensor graph searches based fully automated grading and 3D profiling of maculopathy from retinal OCT images". In: *IEEE Access, Vol. 6, pp. 44644-44658* (2018).

[17] Zhongyang He et al. "Cross-Day EEG-Based Emotion Recognition Using Transfer Component Analysis". In: *Electronics* 11.4 (2022), p. 651.

[18] Stamos Katsigiannis and Naeem Ramzan. "DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices". In: *IEEE journal of biomedical and health informatics* 22.1 (2017), pp. 98–107.

[19] Samina Khalid et al. "Automated segmentation and quantification of drusen in fundus and optical coherence tomography images for detection of ARMD". In: *Journal of Digital Imaging, Vol. 31, Issue 4, pp. 464-476* (2018).

[20] Samina Khalid et al. "Fully automated robust system to detect retinal edema, central serous chorioretinopathy, and age related macular degeneration from optical coherence tomography images". In: *BioMed research international, pp. 217-220* (2017).

[21] Sander Koelstra et al. "Deap: A database for emotion analysis; using physiological signals". In: *IEEE transactions on affective computing* 3.1 (2011), pp. 18–31.

[22] Juan Abdon Miranda-Correa et al. "Amigos: A dataset for affect, personality and mood research on individuals and groups". In: *IEEE Transactions on Affective Computing* 12.2 (2018), pp. 479–493.

[23] Behnaz Nojavanasghari et al. "Emoreact: a multimodal approach and dataset for recognizing emotional responses in children". In: *Proceedings of the 18th acm international conference on multimodal interaction*. 2016, pp. 137–144.

[24] Robert Plutchik. "The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice". In: *American scientist* 89.4 (2001), pp. 344–350.

[25] James A Russell. "A circumplex model of affect." In: *Journal of personality and social psychology* 39.6 (1980), p. 1161.

[26] Muhammad Shafay et al. "Deep Fusion Driven Semantic Segmentation for the Automatic Recognition of Concealed Contraband Items". In: *SoCPaR, pp. 550-559* (2020).

[27] Muhammad Shafay et al. "Temporal Fusion Based Multi-scale Semantic Segmentation for Detecting Concealed Baggage Threats". In: *IEEE International Conference on Systems, Man, and Cybernetics (SMC), August* (2021).

[28] Lin Shu et al. "A review of emotion recognition using physiological signals". In: *Sensors* 18.7 (2018), p. 2074.

[29] Mohammad Soleymani et al. "A multimodal database for affect recognition and implicit tagging". In: *IEEE transactions on affective computing* 3.1 (2011), pp. 42–55.

[30] Wei-Long Zheng et al. "Emotionmeter: A multimodal framework for recognizing human emotions". In: *IEEE transactions on cybernetics* 49.3 (2018), pp. 1110–1122.