Iraqi Journal of Information and Communications Technology(**IJICT**)
Vol. 7, Issue 3, December 2024
www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

A DATASET FOR EMOTION RECOGNITION FOR IRAQI AUTISM INDIVIDUALS AS A STEP TOWARDS EEG-BASED THERAPEUTIC INTERVENTION

Israa Laith Salim [1], **Ali Sadeq Abdulhadi Jalal** [2], **Osama Ali Awad** [3]
[1,2] Department of Information and Communication Engineering, College of Information Engineering, Al-Nahrain University, Jadriya, Baghdad, Iraq
[3] Department of Medical Instrumentation Techniques Engineering, Al-Mustaqbal University, Babylon, Iraq
israa.phd23@ced.nahrainuniv.edu.iq[1], ali.jalal@nahrainuniv.edu.iq[2], osama.ali.awad@uomus.edu.iq[3]
Corresponding Author: **Ali Sadeq Abdulhadi Jalal**

Received:24/05/2024; Revised:16/07/2024; Accepted:27/07/2024
DOI:**10.31987/ijict.7.3.284**

***Abstract*- In this work, Emotion Recognition for Iraqi Autism Individuals (EmoReIQ) is presented, a dataset of Electroencephalogram (EEG) signals recorded during various sessions for Autism Spectrum Disorder (ASD) participants. Since individuals with ASD often have difficulty understanding and expressing their own emotions, which leads to difficulties in social interactions, communication, and overall well-being; therefore, recognizing and understanding emotions is crucial for them during therapy sessions to provide appropriate support and interventions. Developing, being done for the first time in Iraq country, a dataset that is more specific to the cultural and linguistic context of Iraqi ASD individuals will help treat and try to get them to safety. EEG signals from 28 ASD participants were recorded while they were exposed to visual emotion-eliciting stimuli that evoked one of the five emotions (calm, happiness, anger, fear, and sadness) in different experiment sessions. The classification algorithm, Artificial Neural Network (ANN), is applied and analyzed for emotion recognition. EEG signals were recorded using BrainAccess, a portable and wireless kit that allows the use of effective Brain-Computer Interface (BCI) techniques in everyday applications. A dataset construction protocol is proposed, with emotional stimuli specifically designed to evoke the emotional responses of ASD individuals. EEG data preprocessing and analysis framework is developed to select and combine various EEG-based emotional-relevant features efficiently. With the proposed ANN classifier model, the mean accuracy values are 78.86%, 83.32%, and 72.98% for valence, arousal, and dominance respectively. The EmoReIQ dataset is validated and outperforms state-of-art datasets.**

***keywords:* Emotion recognition, Autism Spectrum Disorder (ASD), EEG, BCI, Dataset, ANN.**

I. INTRODUCTION

The emphasis on using assistive technology for people with physical or mental conditions, limiting movements, senses, or activities is increasingly popular within various technology solutions. Assistive technology refers to any device, software, or equipment designed to help individuals with disabilities or impairments perform tasks that might be difficult or impossible [1]. With the help of Internet of Things (IoT) hardware and software components, these technologies can provide smart diagnosis systems at home, school, or medical centers to improve communication, mobility, sensory integration, and other areas of daily living [2]. Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder; individuals with ASD often have difficulties with communication, social interaction, and sensory processing; therefore, assistive technology has a promising prospect to address these challenges. Due to the unique and diverse nature of ASD, it can be challenging even for medical experts to estimate an individuals emotional state through therapeutic sessions accurately. One of the advanced assistive technologies for ASD is Brain-Computer Interface (BCI) applications, which can provide social interaction and feedback, support emotional regulation, and improve communication skills. This direct bridge between the machine and the human brain has many applications, especially in the medication field for autism or disabled cases; for instance, the

Iraqi Journal of Information and Communications Technology(**IJICT**)
Vol. 7, Issue 3, December 2024
www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

use of Electroencephalography (EEG) sensing technology works by recording the brain's electrical activity information. The EEG signals can be analyzed to provide information about brain conditions and can potentially be used to develop assistive technology devices to help individuals with ASD. EEG technology is particularly appropriate for emotion recognition for those who cannot speak clearly, have physical disabilities, or whose facial expressions and body postures are impossible to interpret [3], which is the case with ASD. This technology is a non-invasive BCI that uses external sensors (electrodes) placed on the scalp, making it generally safe and widely applicable. To make EEG technology applicable, the evolution of Artificial Intelligence (AI) can provide a better understanding of the functional operation of the human brain, creating intelligent machines that can mimic human thinking and actions using various techniques, including Machine Learning (ML). On the other hand, the Deep Learning (DL) technique, a subset of ML, uses an Artificial Neural Network (ANN) to mimic the neuron network structure of the human brain and its learning process, it show outstanding performance for various studies employing classification techniques [3].

This paper presents the EmoReIQ dataset that explores the possibility of classifying emotion with EEG technology for ASD individuals. The remainder of this paper proceeds as follows: Section II explains the potential of using EEG technology for emotion recognition systems and the main steps to implement such systems. Section III literature reviews the most common emotional dataset and related research papers that use machine learning algorithms for classifying emotions. Section IV illustrates the proposed experimental design, data acquisition protocol, and information for the participants included in constructing the EmoReIQ dataset. Section V shows the roadmap for classifying emotion, including the preprocessing of EEG signal, proposed emotion-relevant features extracting method, features selection method and the used ML model. Results are discussed in Section VI, and the conclusion in Section VII.

II. EEG TECHNOLOGY FOR EMOTION RECOGNITION

The high temporal resolution of EEG signals allows the detection of changes in brain activity within milliseconds, making EEG well-suited for studying emotional responses that happen quickly and may be missed with other techniques [4]. EEG signals can provide personalized emotion recognition based on individual brain activity patterns. The EEG technique has fixed electrode placement systems used in neurophysiological studies; one of them is the international 10-20 system shown in Fig.1, a standardized method for locating electrode positions relative to anatomical landmarks on the scalp. The electrodes are placed at specific locations corresponding to different brain regions. Characters like: F, T, C, P, and O, refer to the frontal, temporal, central, Pelvic, and occipital areas, respectively. Even numbers (2,4,6,8) refer to electrode positions on the right hemisphere. Odd numbers (1,3,5,7) refer to electrode positions on the left hemisphere. EEG waveform is characterized by different frequency sub-bands, which are called EEG rhythms (Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ)), each one associated with a mental state or a specific activity [5].

www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

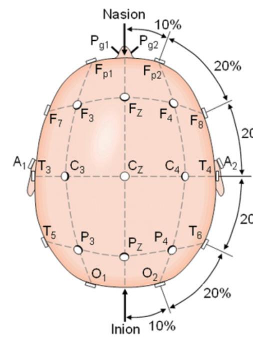

Figure 1: International 10-20 system, above head view.

However, developing and implementing an EEG-based emotion recognition system typically involves deciding the number of used electrodes/locations and defining and analyzing characteristics of a particular EEG frequency sub-band. There are four fundamental steps. The first is data acquisition, which collects EEG data from participants while they experience different emotional stimuli or scenarios. This data serves as the foundation for training and testing emotion recognition algorithms. The second step involves filtering, signal normalization, artifact removal techniques, and any necessary pre-processing of the EEG signal to remove noise and artifacts. The physiological artifacts of eye movement and blinking Electrooculogram (EOG) and movement of the head and muscle Electromyography (EMG) are mostly considered for studies of BCI [6]. The next step is extracting features from the EEG data relevant to emotional states. Among several extracted features, the most emotion-relevant features are selected, which have better emotion classification performance. In the fourth step, the extracted information is now used to train and test the ML model after annotating the EEG data with corresponding emotional labels.

For ASD individuals, emotions are important since they refer to their internal reactions, including their ability to focus, remember, attain objectives, recognize priorities, feel motivated to gain knowledge, interact with others, enhance their learning abilities, regulate their mood, and stay motivated to put in the effort. A 3D emotion model is illustrated in Fig. 2, which combines three emotion dimensions valence, arousal, and dominance [7]. Valence refers to the positivity or negativity of emotion, ranging from pleasant (positive valence) to unpleasant (negative valence). Arousal, on the other hand, refers to the level of physiological activation or stimulation associated with an emotion, ranging from low arousal (calm and relaxed) to high arousal (excited and agitated). Dominance ranges from submissive to dominant, indicating the level of control that a person possesses over a particular emotion. For example, Anger and fear emotions have similar negative valence and high arousal values, but different dominance values differentiate them; anger emotion has a higher dominance than fear

ISSN:2222-758X
e-ISSN: 2789-7362

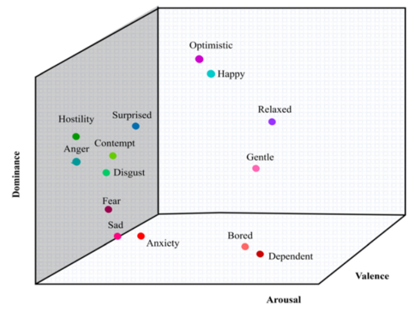

Figure 2: Three-dimensional valence-arousal-dominance model.

III. **RELATED WORK**

Several studies created their own datasets for emotion recognition using EEG technology methods, achieved different levels of success, and became more and more popular due to available commercial off-the-shelf EEG wirelessly recorded devices and the use of powerful AI techniques. The Database for Emotion Analysis using Physiological Signals (DEAP) dataset [1] is a valuable resource for emotion research. It contains physiological data collected from 32 participants (18 males and 14 females, aged between 19 and 37) who watched a set of 40 music videos that induced a range of emotional responses. DEAP records EEG data at a sampling rate of 512 Hz using 32 active AgCl electrodes. It also measures several physiological signals, including Galvanic Skin Response (GSR), Blood pressure, Heart Rate Variability (HRV), skin temperature, respiration, EMG, and EOG. DEAP measures emotions through EEG signals using the 3-D scale: valence, arousal, and dominance, besides the liking and familiarity evaluation. After watching each video, participants were asked to provide emotional ratings using the Self-Assessment Manikin (SAM) [8] to give labels (valence, arousal, dominance, liking, and familiarity) for the watched videos.

DEAP provides researchers with a rich source of information to study the relationship between physiological signals and emotional states, making it a valuable tool for emotion recognition and it has been used in several studies [9]. The most applied emotion classifier on the DEAP dataset is the Support Vector Machine (SVM) classifier, with a high classification accuracy of 89.45% in the study [10], due to the use of Gaussian Process Latent Variable Models (GP-LVM), through which latent points were extracted as dynamical features to train the classifier.

In the study [11], MAHNOB-HCI is a multimodal dataset that records data for emotion recognition and implicit tagging experiments. The recorded signals are EEG, GSR, ECG, respiration, skin temperature, face and body videos using six cameras, eye gaze, and audio signals. A total of 27 participants are included in the rate for 20 emotion-specific stimuli video clips.

SAM scale was used in [8], to facilitate the self-assessments of valence and arousal scales, with a rating scale between 1 and 9. The authors stated that they achieved emotion classification by fusion of the two best modalities, EEG and Eye Gaze, with a classification accuracy of 67.7% and 76.1% for arousal and valence scales respectively.

The study [12] achieved an emotion classification accuracy of 73% for valence and 72.5% for arousal when using the MAHNOB dataset. The fusion of EEG and facial expression modalities for implicit, affective tagging is implemented.

www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

In decision-level classification fusion, Regression-Estimated Weights Fusion (W-REG) combined with Recursive Feature Elimination (RFE) obtained the best results of 73% for valence and 72.5% for arousal.

The SEED dataset provided by [13] contains two parts: EEG data in addition to eye movement data. EEG data from 15 participants (7 males and 8 females, with an average age of 23 years) was recorded using 62 EEG electrodes using the ESI NeuroScan system with a 1000 Hz sampling rate, each participant watching 15 film clip stimuli trails for only a valence label with three values (-1 for negative, 0 for neutral, and +1 for positive). SEED uses deep belief network (DBN) SVM, linear regression (LR), and KNN models to compare the performance of EEG-based emotion recognition.

The study [14] suggests using a novel Group Sparse Canonical Correlation Analysis (GSCCA) method for EEG channel selection and emotion recognition using the SEED dataset. They found that the GSCCA model could reach an emotion classification accuracy of 82.45% with only 20 EEG channels, while the Support Vector Machine (SVM) classifier needed to use 62 channels to get the same results.

Another more recent dataset, DREAMER (Database for Emotional Analysis in Music and Electroencephalogram Recordings) [15] is a comprehensive resource designed for research in emotion recognition, particularly focusing on the audio-visual stimuli content, EEG brain activity, and ECG records. EEG records were sampled at 128 Hz using an Emotiv EPOC headset with 16 electrodes. DREAMER with self-assessment emotional responses from 23 participants (14 males, 9 females, aged: 22 – 33) who watched a set of 18 short music videos designed to induce different emotions within three dimensions: valence, arousal, and dominance. This dataset has been used as a benchmark dataset for comparing different emotion recognition approaches.

Authors in [16] obtained an average emotion classification accuracy of 86.23%, 84.54%, and 85.02% for valence, arousal, and dominance labels respectively, on the EEG data of DREAMER. This study outcome with a novel Dynamical Graph Convolutional Neural Network (DGCNN) which can dynamically learn the effective relationship between EEG channels, to get more discriminative EEG feature extraction, and improve the overall emotion recognition process.

The study [17] experiments with the use of a Broad Learning System (BLS) for enhancing features for the GCB-net (Graph Convolutional Broad Network) classifier, results reached high accuracy of 86.99%, 89.32%, and 89.20% on valence, arousal, and dominance dimensions respectively.

Another study [18] proposes a combination of Long Short-Term Memory (LSTM) and 1D-CNN architecture to improve the emotion recognition performance while exploiting the significance of various modalities provided by DREAMER and AMIGOS datasets such as Galvanic Skin Response (GSR), EEG, and ECG. With the multi-modal fusion of the DREAMER dataset, this study achieves a maximum of 90.8% emotion classification accuracy.

Authors in [19] suggest using only a valence label for deciding either positive or negative emotion; they use a logistic regression-based recursive feature selection technique based on featuresâ performance and computational efficiency, with Linear Support Vector Classifier (LSVC) as an emotion classifier, they evaluate their proposed method using the Area Under the receiver operating characteristic Curve (AUC) performance parameter, DREAMER valence outcome with 0.83 score of AUC.

Another multimodal dataset for affect, personality, and mood on individuals based on neurophysiological signals EEG,

ISSN:2222-758X
e-ISSN: 2789-7362

ECG, and GSR is the AMIGOS dataset [20]. AMIGOS experimental data is collected within two protocols; the first one, a total of 40 participants (17 and 12 female) with a mean age of 28.3, watched 16 short emotional video clips, each with less than 250 sec. Participants self-assessed basic emotion space valence, arousal, dominance, familiarity, and liking. The second one investigates the impact on the participants when being in groups watching a long emotional video (duration > 14 minutes), which has an important effect on the valence and arousal levels. In general, when the participant is in a group, he/she shows a higher level of valence (high positive emotions), a higher level of arousal for high-arousal clips, and a lower level of arousal for low-arousal clips than when alone. AMIGOS recorded EEG data using 14 electrodes (channels) on an Emotiv EPOC Neuroheadset measuring device, and the data were preprocessed with a sampling frequency of 128 Hz.

A Deep Convolutional Neural Network (DCNN) is applied in [21], to evaluate the arousal and valence on detection of ECG features (time-domain, frequency domain, nonlinear) and GSR features (Mean, standard deviation, max, min, kurtosis, skew) of AMIGOS dataset. The authors suggest using DCNN, which involves a sequence of fully connected CNN layers that are used to automatically extract features utilizing fuzzy filters to reduce noise and extract morphological patterns in peaks of the ECG and GSR signals. Classification accuracy of DCNN based on GSR signals shows a value of 0.71% for both valence and arousal. Meanwhile, the classification accuracy of DCNN based on ECG signals shows a value of 0.68% for valence and 0.81% for arousal.

Another study on the AMIGOS dataset, [22] suggests using bidirectional Long Short-Term Memory Recurrent Neural Network (LSTM-RNNs) for automatically capturing the best temporal features from EEG signal, then fed to Deep Neural Network (DNN) classifier to predicate emotion along with a decision level fusion strategy. The experimental results show that bidirectional LSTM-RNNs can achieve an emotion classification accuracy of 67.8% and 73.5% for valence and arousal respectively.

The abovementioned datasets have major limitations in not being personalized to an individual's unique EEG brain activity patterns, there is a lack of standardization in terms of experimental protocols, stimuli, and emotion induction methods across different datasets, and the limitation of being a single-session EEG records that capture a snapshot of emotional states dismisses evolving nature of emotions over time. These datasets also do not examine their strategies for individuals with mental health disorders such as ASD. Studying emotion recognition variations has implications for fields of mental health, education, and psychology; emotions can vary among individuals due to several factors:

1) Genetics influences the development of the brain, which can affect how it processes emotions. Furthermore, neurodiversity, which describes the diversity and variation of cognitive functioning in individuals, may include conditions like autism [23], which can result in unique patterns of emotion recognition and processing.
2) Cultural, personality, and temperament differences also impact how individuals perceive and express emotions, as well as different life experiences can shape the brain's ability to recognize and respond to emotions.
3) Context and situational factors can also influence brain activity patterns. For example, emotions recognized in an experimental setting differ from those recognized in real-world situations.

Iraqi Journal of Information and Communications Technology(**IJICT**)
Vol. 7, Issue 3, December 2024
ISSN:2222-758X
e-ISSN: 2789-7362
www.ijict.edu.iq

IV. EXPERIMENTAL DESIGN AND DATA ACQUISITION

The EmoReIQ was conducted and tested with 28 ASD individuals participating from Baghdad, Iraq. EEG signals are recorded for each one in a separate experiment. All experiments follow the same protocol, five different sessions for each participant on different days. Each session consisted of 5 trials, the trial is a short video clip destined to a specific emotion, and the emotion stimuli for these trials were completely different. For the emotion recognition process, the intersection of the 3D emotion domain Valence-Arousal-Dominance (V-A-D) is utilized to give several emotions; in this work, five emotion measurements (calm, happy, anger, fear, sad) are chosen. Calm is (PV, LA, HD): Positive valence, low arousal, high dominance. Happy is (PV, HA, HD): Positive valence, high arousal, high dominance. Anger is (NV, HA, HD): Negative valence, high arousal, high dominance. Fear is (NV, HA, LD): Negative valence, high arousal, low dominance. Sad is (NV, LA, LD): Negative valence, low arousal, low dominance. These emotions are appropriate and sufficient during ASD therapy sessions. EEG signal recording, preprocessing, and emotion classification were performed using MATLAB (vR2023a).

A. Instruments

Stimuli were played using a Samsung Galaxy Note 10 Android tablet positioned in front of the participant, with a resolution of 1280 by 720 pixels. Additionally, a PC is employed to monitor and record EEG data captured by a wearable EEG headset. The headset connects wirelessly to the PC via Bluetooth. For each video, the data stream is saved in a single file, including the necessary details for later processing. EEG was recorded at a sampling rate of 250 Hz using BrainAccess portable EEG solution Fig. 3, including a cap with 8 dry-contact EEG electrodes plus reference and bias electrodes. The electrode location of BrainAccess is based on the 10-20 international system, with the possibility of adapting the electrodeâs location, making it suitable for other applications. BrainAccess is lightweight (70 grams), head shape-conforming cap, and no-gel electrodes make them comfortable compared to other traditional EEG devices, which is crucial in applications for individuals with neurological conditions, including ASD.

Figure 3: BrainAccess cap with dry-contact EEG electrodes.

Iraqi Journal of Information and Communications Technology(**IJICT**)
Vol. 7, Issue 3, December 2024
www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

B. Participant

To protect personal privacy, the participants' names are hidden; in Table I, the participant's information is listed, including ID, gender, and age.

TABLE I
PARTICIPANTS STATISTICS

Subject	**ID Gender**	**Age**
Subj01	male	6
Subj02	female	7
Subj03	male	6
Subj04	male	4
Subj05	male	4
Subj06	male	12
Subj07	male	8
Subj08	male	7
Subj09	male	7
Subj10	male	9
Subj11	male	10
Subj12	male	6
Subj13	female	7
Subj14	male	5
Subj15	male	10
Subj16	male	5
Subj17	male	6
Subj18	male	6
Subj19	male	8
Subj20	male	8
Subj21	male	9
Subj22	male	9
Subj23	male	8
Subj24	male	7
Subj25	male	7
Subj26	female	8
Subj27	male	7
Subj28	male	10

C. Stimuli Selection

The video clips are carefully selected, considering that they are presented to young children, among them those with ASD, scenes manually selected from commercially produced movies. Each video elicits precisely only one emotion (calm, happy, anger, fear, sad); for example, avoid scenes of blood while presenting fear videos so as not to evoke disgust. The videos are chosen to be understood without speech or explanation to be understandable to different cultural groups. Since ASDs are involved in these emotion recognition experiments, the videos are chosen not to be too long, so they do not

www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

feel fatigued or lose focus. The details of the chosen video clip stimuli are listed in Table II. The valence, arousal, and dominance values for each video stimuli are determined by asking for ratings from volunteers who did not take part in the experiment and were unaware of the purpose of it to make the emotions evaluation valid and authentic. They perform the SAM [8] for each video clip with scale numbers between 1 and 5. The values or labels of valence, arousal, and dominance for each video are then fused using the Mean Opinion Score (MOS) as shown in Table II. The assessment of videos for valence, arousal, and dominance should not present a high variation, the relative standard deviation (RSD), the ratio of standard deviation to mean, is also measured. The lower RSD is preferable, with low variability between ratings, proving that the video election is right and it presents one target emotion.

TABLE II
Video List with (MOS) and (RSD) for each Valence, Arousal, and Dominance scale

Video ID	Target Emotion	Duration (sec)	Valence (MOS, RSD)*	Arousal (MOS, RSD)	Dominance (MOS, RSD)
Vid01	Calm	26	4.26, 0.176	1.85, 0.195	3.71, 0.195
Vid02	Happy	35	4.57, 0.112	4.78, 0.194	3.73, 0.184
Vid03	Anger	47	2.33, 0.131	4.46, 0.106	4.33, 0.181
Vid04	Fear	30	2.27, 0.154	4.69, 0.133	1.53, 0.161
Vid05	Sad	38	1.58, 0.147	2.03, 0.151	1.34, 0.184
Vid06	Calm	36	3.817, 0.197	2.05, 0.334	3.75, 0.209
Vid07	Happy	34	4.68, 0.102	4.05, 0.119	4.10, 0.187
Vid08	Anger	41	1.67, 0.170	4.49, 0.128	4.13, 0.192
Vid09	Fear	31	1.93, 0.145	4.24, 0.166	2.08, 0.167
Vid10	Sad	30	1.44, 0.132	1.51, 0.169	1.93, 0.184
Vid11	Calm	31	3.63, 0.164	1.52, 0.300	3.58, 0.169
Vid12	Happy	37	4.24, 0.101	3.82, 0.188	3.90, 0.130
Vid13	Anger	43	1.43, 0.189	4.51, 0.115	3.89, 0.167
Vid14	Fear	43	2.17, 0.198	4.66, 0.114	1.40, 0.193
Vid15	Sad	50	1.49, 0.124	1.82, 0.154	1.18, 0.198
Vid16	Calm	37	3.72, 0.133	2.166, 0.285	3.82, 0.190
Vid17	Happy	31	4.33, 0.127	4.78, 0.176	4.17, 0.166
Vid18	Anger	52	2.08, 0.120	4.65, 0.173	3.91, 0.172
Vid19	Fear	34	1.89, 0.115	3.58, 0.145	1.91, 0.194
Vid20	Sad	41	1.15, 0.109	1.91, 0.192	1.80, 0.150
Vid21	Calm	28	4.02, 0.135	1.9, 0.414	3.60, 0.245
Vid22	Happy	36	4.96, 0.118	4.81, 0.207	4.03, 0.138
Vid23	Anger	40	2.68, 0.180	3.62, 0.109	3.88, 0.194
Vid24	Fear	32	1.00, 0.116	4.11, 0.122	2.02, 0.117
Vid25	Sad	38	1.70, 0.132	1.61, 0.168	1.45, 0.165

Note: *Ratings as follows: 1: very low, 2: low, 3: medium, 4: high, and 5: very high.

D. Data Acquisition

The chosen electrodes locations are at FP1, FP2, F7, F8, F3, F4, T3, and T4 according to the international 10-20 system, as depicted in Fig. 4, which are the most significant EEG locations for recognition emotion according on our main findings in [24]. The reference and bias electrodes are placed at O1 and O2 locations. Each participant was asked to watch the emotional video clips and to keep minimum movement or eyeblink, participants were in a relaxed state to record as much

ISSN:2222-758X
e-ISSN: 2789-7362

noise-free EEG data as possible. Each participant is included in five sessions, each session with five video clips for a particular emotion (calm, happy, angry, fearful, sad). The recording protocol starts with displaying a 5-sec fixation cross image, then displaying a varying-duration effective video clip separated from the next video clip by another 5-sec fixation cross image, which is used as the baseline to reset the stimuli effect.

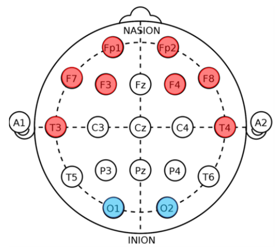

Figure 4: EEG electrodes location indicated with red circles, reference, and bias with blue circles.

V. EMOTION CLASSIFICATION PROPOSED METHOD

Recognizing emotions using EEG brain signals requires accurate and efficient signal processing and feature extraction methods as mentioned in Section II. The main steps involved in the proposed model for constructing the EmoReIQ dataset for this study are explained next and illustrated in Fig. 5.

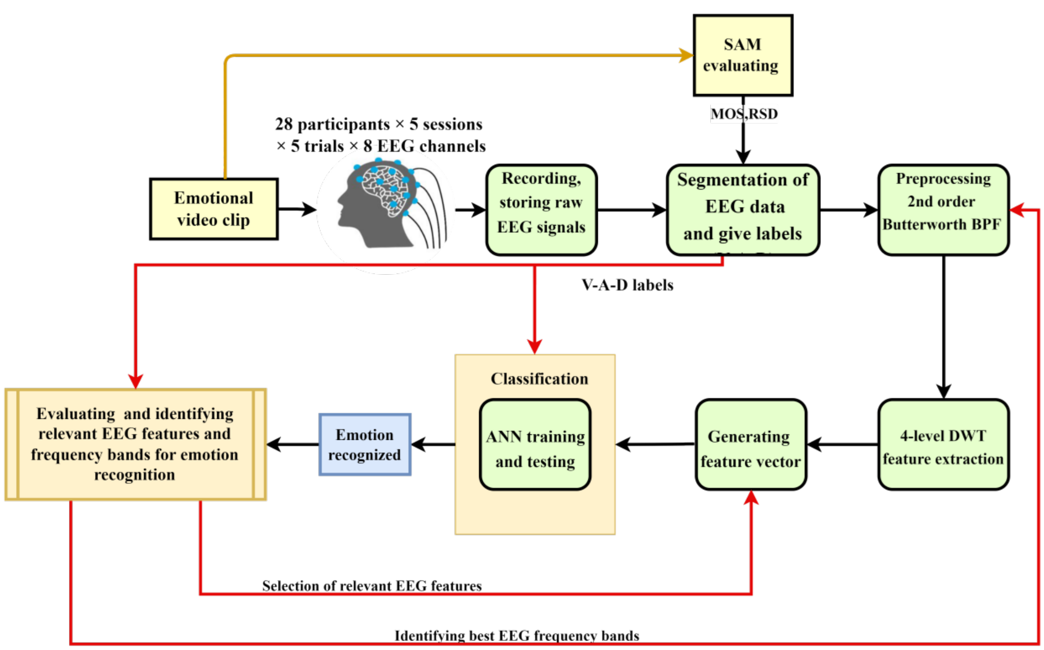

Figure 5: Flowchart of the methodology of EmoReIQ dataset.

ISSN:2222-758X
e-ISSN: 2789-7362

A. EEG Preprocessing and Feature Extraction Method

After EEG data were recorded from participants while they experienced different emotional stimuli, the data must processed to remove the undesirable signals including physiological artifacts such as EMG and EOG, and non-physiological artifacts such as AC electrical lines interference and bad contact electrodes while keeping as much EEG information as possible. To cater to the need to remove both physiological and non-physiological artifacts while retaining the EEG signals within the particular band of interest, the delta and high Gamma features are dropped out. For bandpass filtering, A 2nd-order Butterworth band Pass Filter (BPF) is applied to extract only the Theta, Alpha, and Beta EEG frequency bands (i.e. 4-30 Hz) from the acquired EEG recordings. It is necessary to reduce the dimensionality of the input features to the classifier to get lower computational power, as well as to improve classification system performance. Discrete Wavelet Transform (DWT) decomposition, a type of time-frequency signal analysis, is utilized in this study to implement a features extraction approach. In this wavelet decomposition method, the EEG signal is decomposed in coefficients for different scales and drifts of a selected wavelet called "mother", the coefficients are filtered with a threshold by applying a Low-Pass Filter (LPF) and High-Pass Filter (HPF) iteratively, then the filtered EEG signal is reconstructed using inverse-DWT. For input signal x(n), the DWT is defined using:

$$DWT(p,q) = |p|^{-\frac{1}{2}} \int_{-\infty}^{\infty} x(n)\,\phi\left(n - \frac{q}{p}\right) dn \tag{1}$$

Where p represents the scale factor, q represents the shift factor, and $\phi(n)$ is the wavelet function. A four-level-decomposition Discrete Wavelet Transform (4-level DWT) function with Daubechies as the "mother wavelet" with six vanishing moments (db6) is applied in this study. This results in two vectors for each decomposition level: Approximation Coefficients (ACs), using the scaling function $\phi(n)$ to capture the low-frequency content of the EEG signal. Detail Coefficients (DCs), using the wavelet function $\psi(n)$ to capture the high-frequency content of the EEG signal. The successive four decomposition levels produce five coefficients: DC1, DC2, DC3, DC4, and AC4.

B. Statistical Feature Selection Method

Common emotion-related EEG feature extraction methods after applying wavelet transform are statistical measures, where features are extracted from the 4-level DWT coefficients at each decomposition level. Six statistical features, along with their formalities, are illustrated in Table III and are used in this study.

C. Deep Learning Model

Once features are measured, the information is then prepared to be fed into the DL model for emotion classification. This classifier identifies correlations between extracted EEG features and emotions. The exploited DL technique used in this study is ANN, designed ANN architecture that is found to be suitable for the emotion classification task is shown in Fig. 6. One input layer, two hidden layers (100/100 neurons), and one output layer. 60% of the total data is used to train the ANN, adjusting its weights and biases to minimize the error between its predictions and the actual labels. 40% of the

www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

TABLE III
SELECTED STATISTICAL FEATURES

Feature	Formula
Minimum value (min)	min = X_{min}
Maximum value (max)	max = X_{max}
Mean (μ)	$\mu = \frac{\sum_{i=0}^{N-1} X_i}{N-1}$
Variance (σ^2)	$\sigma^2 = \frac{\sum_{i=0}^{N-1} \lvert X_i-\mu\rvert^2}{N-1}$
Energy (E)	E = $\sum_{i=0}^{N-1} \lvert X_i\rvert^2$
Log entropy energy (E_{log})	$E_{\text{log}} = \sum_{i=0}^{N-1} \log(X_i^2)$

total data, is used to evaluate the performance of the ANN after it has been trainet. The Tansig activation function is used at the hidden layers. This architecture results in a minim loss function; the Least Mean Square Error (MSE) is chosen, which measures the difference between the predicted label and the true label. The backpropagation training algorithm is used to optimize the weights and biases of ANN. The classifier output is one of five combinations: (PV, LA, HD), (PV, HA, HD), (NV, HA, HD), (NV, HA, LD), or (NV, LA, LD). This output is compared with valence, arousal, and dominance label values for each video taken from MOS shown in Table II, and used as the ground truth; these labels are essential for training and validating the ANN classifier. The MOS ratings of these labels ranged from 1 to 5 and are mapped into two classes: low and high, with a 3.5 threshold.

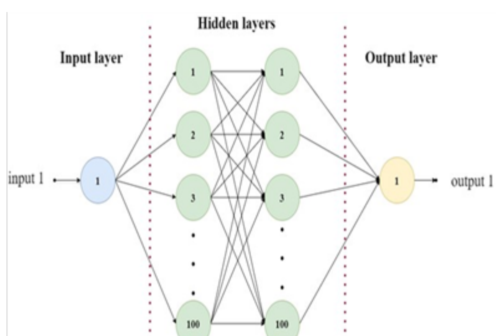

Figure 6: Designed ANN

VI. RESULTS

The results reported in this study focus on the classifier accuracy for the valence, arousal, and dominance emotions dimensions. Accuracy is measured using:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100\% \tag{2}$$

Where TP: true positive decision, TN: true negative decision, FP: false positive decision, and FN: false negative decision made by the classifier (predicated output label) compared to the actual data label. The higher TP and TN, the predicted

ISSN:2222-758X
e-ISSN: 2789-7362

label (positive/negative) is the same as the actual label (positive/negative), which means good classifier performance. A raw EEG and artifact-free EEG segments from a random subject data are visualized in Fig. 7, to emphasize the strength of the implemented 2nd order Butterworth BPF filtering along with the 4-level DWT method used for EEG feature extraction, it is found that the 4-level DWT function was efficient in the proposed model for EEG-based emotion recognition. In Fig. 8, the valence classification accuracy for each subject for the 8 electrode channels (FP1, FP2, F7, F8, F3, F4, T3, and T4), averaged over 25 trials (5 sessions each with 5 trials).

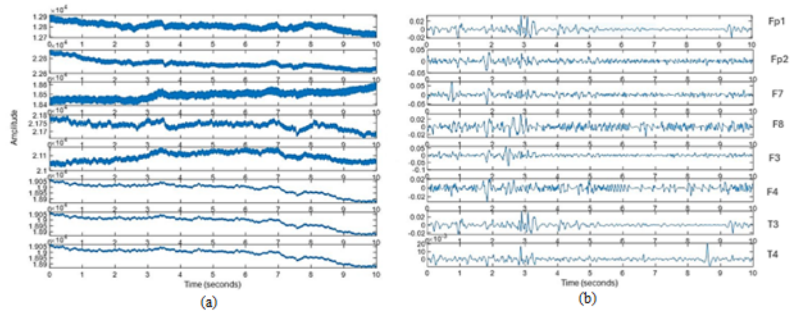

Figure 7: (a) raw EEG segment , (b) artifact-free EEG segment.

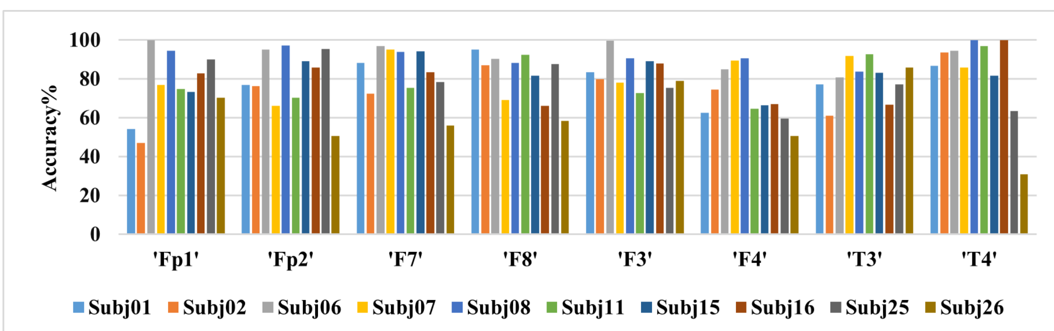

Figure 8: Valence classification accuracy for 10 random subjects.

Similarly, Fig. 9 shows arousal classification accuracy and Fig.10 shows dominance classification accuracy findings. Subj06 and Subj08 both exhibit a strong engagement with positive negative presented stimuli, with valence classification accuracy reaching a maximum of 99.94% with the (Fp1) channel. This associates the valence emotional state with the left frontal region of the brain. High valence values for some ASD subjects indicate that they perceive events and experiences higher than others, no matter if these events are positive or negative. Other subjects, like Subj26, exhibiting low engagement with the presented stimuli, seemed distracted confused during the recording session, resulting in a low valence classification accuracy of 30.95%. The valence emotion state is important; during ASD therapy sessions, a therapist can create a more responsive and effective treatment plan, enhancing positive emotions and managing negative emotions as much as possible.

Iraqi Journal of Information and Communications Technology(IJICT)
Vol. 7, Issue 3, December 2024
www.ijict.edu.iq
ISSN:2222-758X
e-ISSN: 2789-7362

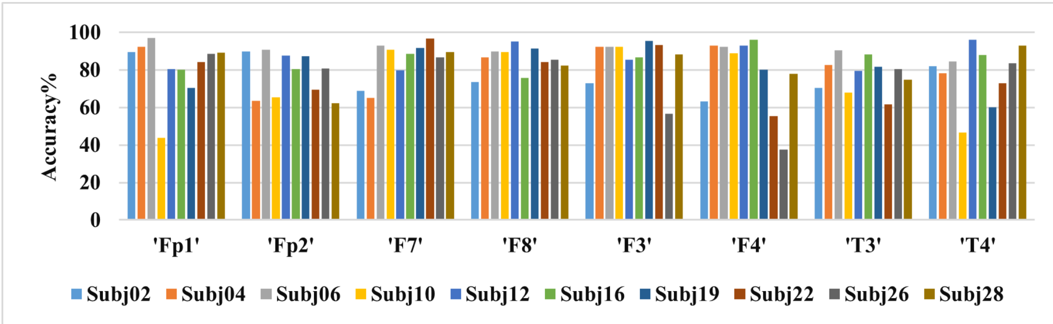

Figure 9: Arousal classification accuracy for 10 random subjects.

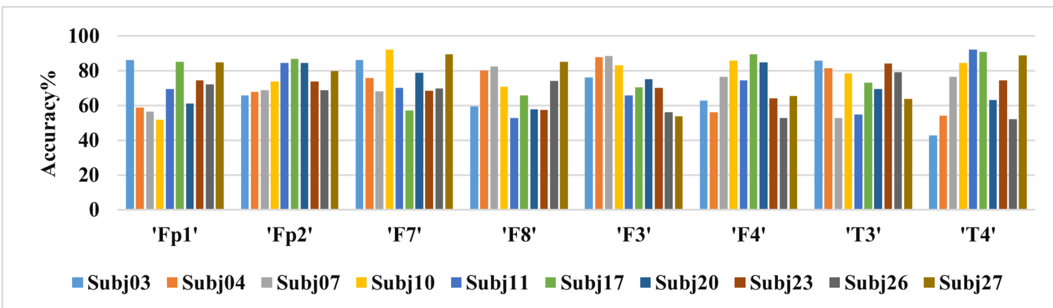

Figure 10: Dominance classification accuracy for 10 random subjects.

On the other hand, results show that arousal classification accuracies are higher compared with valence ones; Subj6 shows the highest arousal accuracy of 96.96%, which indicates a good response to the presented excitement alertness (high arousal) stimuli or relaxation calmness (low arousal) stimuli. The highest mean arousal classification accuracy is presented over channels (F3, F8, and Fp1), the frontal lobe. In general, dominance emerges to be the least well-defined dimension compared to valence and arousal. This could arise from various factors, some of the elected emotional stimuli are not well suited to ASD individual differences. Since ASD individuals have difficulties in social interactions, this can impact their sense of control, feeling powerless. Also, the high levels of anxiety and stress of ASD individuals can interfere with feelings of confidence and control. These factors make the labelled data used to train the classification model mismatched with the actual truth labels. However, the maximum dominance classification accuracy is 94.15%, and the mean dominance classification accuracy over all subjects is about 72.98%.

Table IV summarizes the differences between existing emotional datasets and EmoReIQ constructed in this study. As observed, other datasets do not include ASD participants; EmoReIQ specifically targets a homogeneous group of 28 ASD individuals. It also planned to record EEG signals with a portable and lightweight device suitable for further daily life applications. This study, compared with others mentioned in Table IV, utilizes a reduced set of EEG electrodes while achieving a high emotion classification performance.

ISSN:2222-758X
e-ISSN: 2789-7362

TABLE IV
Comparison of EEG Datasets and Methods Used

Dataset	#Subj	Including mental conditions?	#Trials /length (sec)	# EEG Channels /Fs	EEG headset/weight	Emotion states	Classifier	Findings (EEG modality only)
DEAP [1]	32	No	40 / 60	32 / 512 Hz	Biosemi active II / 1.1 kg	valence, arousal, dominance, liking, familiarity	Gaussian NB	Accuracy: Valence (57.6%) Arousal (62%) Liking (55.4%)
MAHNOB-HCI [11]	27	No	20 / 34-117	32 / 256 Hz	Biosemi active II / 1.1 kg	valence, arousal, dominance, predictability	SVM	Accuracy: Valence (57%) Arousal (52.40%)
SEED [13]	15	No	10 / 240	62 / 1000 Hz	ESI NeuroScan	positive, negative, neutral	DBN, SVM, LR, KNN	Best accuracy: 86.08%
DREAMER [15]	23	No	18 / 65-393	14 / 128 Hz	Emotiv EPOC / 170g	valence, arousal, dominance	SVM	Best accuracy: 61.84%
AMIGOS [20]	40	No	16 / <250	14 / 128 Hz	Emotiv EPOC / 170g	valence, arousal, dominance, liking, familiarity	Gaussian NB, SVM	Mean F1-score: 0.572
EmoReIQ	28	Autism	25 / 26-50	8 / 250 Hz	BrainAccess / 70g	valence, arousal, dominance	ANN	Average Accuracy: Valence (78.86%) Arousal (83.32%) Dominance (72.98%)

VII. CONCLUSIONS

In this work, an analysis of emotions evoked by visual stimuli is presented with autistic individuals. The construction of the EmoReIQ dataset includes EEG recordings from 28 participants during 5 sessions, each watching 25 video clips elicited carefully to evoke specific emotions. EEG recording was done using a portable and lightweight device with a minimum number of EEG electrodes that would allow for a wide range of BCI applications. The performance of the ANN classifier is evaluated for the valence, arousal, and dominance emotion scales. Raw EEG signal is preprocessed, and a 4-level DWT is implemented as a feature extraction method. Based on the best performance, specific statistical features are selected from EEG data to give the most emotional-relevant information. The findings suggest that Theta, Alpha, and Beta EEG frequency bands reflect important aspects of brain activity including emotional responses. The experimental results show that the use of a minimum number of 8 EEG channels can provide efficient emotion recognition rates while preserving cost, minimizing hardware weight, and fast initialization and processing time. ANN classifier model resulted in mean values of 78.86%, 83.32%, and 72.98% for valence, arousal, and dominance respectively.

Funding

None

ACKNOWLEDGEMENT

The authors would like to thank the reviewers for their valuable contribution in the publication of this paper.

The authors extend their sincere gratitude to all individuals who participated in this study and their families. Their time and efforts were indispensable to the success of our research. We also express our sincere appreciation to [Bassmet Amal Center For Special Needs] and [Baghdad Autism Center] for their invaluable support and collaboration throughout this study.

CONFLICTS OF INTEREST

The author declares no conflict of interest

REFERENCES

[1] S. Koelstra et al., "DEAP: A Database for Emotion Analysis ;Using Physiological Signals," IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18-31, Jan. 2012, doi: https://doi.org/10.1109/t-affc.2011.15.

[2] E. K. Jassim and E. H. AL-Hemiray, "COGNITIVE INTERNET OF THINGS USING MQTT PROTOCOL FOR SMART DIAGNOSIS SYSTEM," Iraqi Journal of Information Communications Technology, vol. 2, no. 3, pp. 30–37, Dec. 2019, doi: https://doi.org/10.31987/ijict.2.3.77.

[3] X. Wang, Y. Ren, Z. Luo, W. He, J. Hong, and Y. Huang, "Deep learning-based EEG emotion recognition: Current trends and future perspectives," Frontiers in Psychology, vol. 14, Feb. 2023, doi: https://doi.org/10.3389/fpsyg.2023.1126994.

[4] Priyadarsini Samal and Mohammad Farukh Hashmi, "Role of machine learning and deep learning techniques in EEG-based BCI emotion recognition system: a review," Artificial intelligence review, vol. 57, no. 3, Feb. 2024, doi: https://doi.org/10.1007/s10462-023-10690-2.
[5] G. Arnulfo, Jonni Hirvonen, L. Nobili, Satu Palva, and J. Matias Palva, "Phase and amplitude correlations in resting-state activity in human stereotactical EEG recordings," NeuroImage, vol. 112, pp. 114–127, May 2015, doi: https://doi.org/10.1016/j.neuroimage.2015.02.031.
[6] A. G. Correa, E. Laciar, H. D. Patino, and M. E. Valentinuzzi, "Artifact removal from EEG signals using adaptive filters in cascade," Journal of Physics: Conference Series, vol. 90, p. 012081, Nov. 2007, doi: https://doi.org/10.1088/1742-6596/90/1/012081.
[7] A. Mehrabian, "Comparison of the PAD and PANAS as models for describing emotions and for differentiating anxiety from depression," Journal of Psychopathology and Behavioral Assessment, vol. 19, no. 4, pp. 331–357, Dec. 1997, doi: https://doi.org/10.1007/bf02229025.
[8] M. M. Bradley and P. J. Lang, "Measuring emotion: The self-assessment manikin and the semantic differential," Journal of Behavior Therapy and Experimental Psychiatry, vol. 25, no. 1, pp. 49–59, Mar. 1994, doi: https://doi.org/10.1016/0005-7916(94)90063-9.
[9] N. Thammasan, K. Moriyama, K. Fukui, and M. Numao, "Familiarity effects in EEG-based emotion recognition," Brain Informatics, vol. 4, no. 1, pp. 39–50, Apr. 2016, doi: https://doi.org/10.1007/s40708-016-0051-5.
[10] H. F. Garcia, M. A. Alvarez, and A. A. Orozco, "Gaussian process dynamical models for multimodal affect recognition," Aug. 2016, doi: https://doi.org/10.1109/embc.2016.7590834.
[11] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic, "A Multimodal Database for Affect Recognition and Implicit Tagging," IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 42–55, Jan. 2012, doi: https://doi.org/10.1109/t-affc.2011.25.
[12] S. Koelstra and I. Patras, "Fusion of facial expressions and EEG for implicit affective tagging," Image and Vision Computing, vol. 31, no. 2, pp. 164–174, Feb. 2013, doi: https://doi.org/10.1016/j.imavis.2012.10.002.
[13] Wei-Long Zheng and Bao-Liang Lu, "Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks," IEEE Transactions on Autonomous Mental Development, vol. 7, no. 3, pp. 162–175, Sep. 2015, doi: https://doi.org/10.1109/tamd.2015.2431497.
[14] W. Zheng, "Multichannel EEG-Based Emotion Recognition via Group Sparse Canonical Correlation Analysis," IEEE Transactions on Cognitive and Developmental Systems, vol. 9, no. 3, pp. 281–290, Sep. 2017, doi: https://doi.org/10.1109/tcds.2016.2587290.
[15] S. Katsigiannis and N. Ramzan, "DREAMER: A Database for Emotion Recognition Through EEG and ECG Signals From Wireless Low-cost Off-the-Shelf Devices," IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 1, pp. 98–107, Jan. 2018, doi: https://doi.org/10.1109/jbhi.2017.2688239.
[16] T. Song, W. Zheng, P. Song, and Z. Cui, "EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks," IEEE Transactions on Affective Computing, vol. 11, no. 3, pp. 532–541, Jul. 2020, doi: https://doi.org/10.1109/taffc.2018.2817622.
[17] T. Zhang, X. Wang, X. Xu, and C. L. P. Chen, "GCB-Net: Graph Convolutional Broad Network and Its Application in Emotion Recognition," IEEE Transactions on Affective Computing, pp. 1–1, 2019, doi: https://doi.org/10.1109/taffc.2019.2937768.
[18] M. N. Dar, M. U. Akram, S. G. Khawaja, and A. N. Pujari, "CNN and LSTM-Based Emotion Charting Using Physiological Signals," Sensors, vol. 20, no. 16, p. 4551, Aug. 2020, doi: https://doi.org/10.3390/s20164551.
[19] A. Menon et al., "Efficient emotion recognition using hyperdimensional computing with combinatorial channel encoding and cellular automata," Brain Informatics, vol. 9, no. 1, Jun. 2022, doi: https://doi.org/10.1186/s40708-022-00162-8.
[20] J. A. Miranda Correa, M. K. Abadi, N. Sebe, and I. Patras, "AMIGOS: A Dataset for Affect, Personality and Mood Research on Individuals and Groups," IEEE Transactions on Affective Computing, pp. 1–1, 2018, doi: https://doi.org/10.1109/taffc.2018.2884461.
[21] L. Santamaria-Granados, M. Munoz-Organero, G. Ramirez-Gonzalez, E. Abdulhay, and N. Arunkumar, "Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset (AMIGOS)," IEEE Access, vol. 7, pp. 57–67, 2019, doi: https://doi.org/10.1109/access.2018.2883213.
[22] C. Li, Z. Bao, L. Li, and Z. Zhao, "Exploring temporal representations by leveraging attention-based bidirectional LSTM-RNNs for multi-modal emotion recognition," Information Processing Management, vol. 57, no. 3, p. 102185, May 2020, doi: https://doi.org/10.1016/j.ipm.2019.102185.
[23] E. Pellicano and J. den Houting, "Annual Research Review: Shifting from "normal science" to neurodiversity in autism science," Journal of Child Psychology and Psychiatry, vol. 63, no. 4, Nov. 2021, doi: https://doi.org/10.1111/jcpp.13534.
[24] Israa Laith Salim, Osama Ali Awad, and A. Sadeq, "EEG-Based Emotion Recognition Using DWT and Artificial Neural Network: A Case Study on Autism Spectrum Disorder," Dec. 2023, doi: https://doi.org/10.1109/honet59747.2023.10374719.

