Emotion recognition by EEG and physiological data in patients with schizophrenia: a study with wearable devices

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Abstract. In this study, we explore emotion recognition in schizophrenia patients by analyzing biometric signals. This research is part of the SPECTRA project, which aims to support clinicians in the early identification of Treatment-Resistant Schizophrenia (TRS) patients, a subset of individuals with schizophrenia who do not respond to standard pharmacological treatments. Early diagnosis of TRS is crucial for improving therapeutic outcomes and quality of life. To address this challenge, we developed an experimental protocol that collects physiological signals via wearable devices, including electroencephalogram (EEG) and related physiological data. The protocol includes two steps: a cognitive test and the viewing of three 120-second video clips selected to evoke specific emotions. The collected data were preprocessed through a pipeline in MATLAB, with a subsequent feature extraction step in Python. The analysis focuses on the activity of the alpha and beta bands of the EEG, correlated with valence and arousal dimensions derived from frontal brain asymmetry (FBA), a key neuromarker for emotional states. Results showed a group classification accuracy of up to 95% in distinguishing between healthy controls and treatment-resistant or responsive schizophrenia patients and were used to support the training of predictive models. This could provide an objective tool to improve the understanding of emotional responses in schizophrenia patients, with potential clinical applications in improving diagnostic accuracy and predicting the efficacy of drug treatments. While promising, this study represents an initial investigation with a limited sample size and a constrained set of emotional stimuli. Future work will expand the dataset and incorporate additional physiological modalities to enhance diagnostic capabilities.

Keywords: Emotion recognition · EEG · Schizophrenia · Biometric signals · frontal brain asymmetry (FBA) · Treatment-Resistant Schizophrenia (TRS) · machine learning

1 Introduction and State of the Art

Emotion recognition through biometric signals is a rapidly growing research field with significant applications in human-computer interaction (HCI) and artificial intelligence (AI) systems [1]. The ability to analyze electroencephalographic (EEG) signals and physiological parameters provides valuable insights into individuals' emotional and cognitive states, enabling the development of adaptive and personalized technologies. In particular, EEG, with its high temporal resolution, allows for the identification of neural activity associated with emotions, making it a key tool for affective computing [2]. EEG is widely used for emotion recognition due to its ability to capture direct neural activity. The frequency band analysis (delta, theta, alpha, beta, gamma) provides crucial information on emotional states, with specific patterns linked to different affective responses. For example, increased power in the alpha band is often correlated with relaxation, while an increase in beta activity is associated with stress or cognitive load [3]. Additionally, frontal brain asymmetry (FBA) is considered a key neuromarker for valence and arousal dimensions, crucial for emotion characterization [4] [5]. The acquisition of EEG signals follows the international 10-20 system, ensuring standardized electrode placement for consistency across studies. Data preprocessing is a fundamental step to remove artifacts caused by eye blinks, muscle movements, and external noise. Established techniques, such as those implemented in the EEGLAB toolbox [6], allow effective signal cleaning. Once preprocessed, relevant features are extracted and analyzed for emotion classification. In addition to EEG, wearable devices such as smartwatches and biometric wristbands enable continuous and non-invasive monitoring of physiological signals. These devices measure parameters including electrodermal activity (EDA), heart rate (HR), and skin temperature (ST), all of which reflect autonomic nervous system responses to emotional stimuli [7]. The fusion of EEG and wearable data enhances emotion classification accuracy by integrating neural and physiological responses into a multimodal framework [8] [9]

1.1 Emotion Recognition in Schizophrenia

In psychiatric research, emotion recognition is particularly relevant for disorders such as schizophrenia. Schizophrenia affects approximately 1% of the global population and is characterized by cognitive, emotional, and behavioral impairments, including deficits in emotion recognition and affective flattening [10]. These deficits can negatively impact patients' social interactions and quality of life. Recent studies suggest that biometric signal analysis could provide an objective method to assess emotional responses in schizophrenia, offering valuable support for clinical decision-making [11][12]. Despite advances in affective computing, the management of schizophrenia remains complex, particularly for treatment-resistant patients (TRS). Current diagnosis and treatment selection heavily rely on subjective clinical evaluations, leading to uncertainties and delays in therapeutic decisions. By analyzing EEG and physiological signals, it is possible to identify distinctive patterns of emotional response among different subject

groups, potentially improving personalized treatment strategies. This study is part of the **SPECTRA project**, which aims to improve the early diagnosis of Treatment-Resistant Schizophrenia **TRS** [13], a subtype of schizophrenia where patients do not respond to standard treatments, leading to prolonged ineffective care and a decline in quality of life. The goal of the SPECTRA project is to aid clinicians in identifying TRS patients by applying advanced machine learning and multimodal biometric analysis. Emotion recognition through EEG and physiological signals is central to this effort, as distinct neurophysiological patterns may emerge in TRS patients in response to emotional stimuli. This research specifically focuses on distinguishing TRS from treatment-responsive patients (SCZ) using EEG data. The study compares three participant groups:

- **TRS patients** – those unresponsive to standard treatments.
- **SCZ patients** – those responsive to pharmacological treatment.
- **Healthy controls (HC)** – neurotypical individuals serving as reference.

While the results are promising, this study represents an initial investigation with a limited sample size and emotional stimuli. Future work will expand the dataset and integrate additional physiological modalities to further improve diagnostic accuracy and predictive capabilities.

2 Methods And Materials

Fig. 1: Phases of the experimental protocol

The study involved **21 participants**, 7 HC , 8 TRS and 6 SCZ. The classification was performed by the psychiatric medical staff according to established diagnostic criteria. Participants were recruited from a psychiatric clinic and a university research center. Before the experiment, informed consent was obtained from each participant. The experimental protocol consisted of three phases as shown in the Figure 1. At the beginning of the test, a 30-second EEG baseline was recorded, divided into 15 seconds of relaxation with eyes open and 15 seconds with eyes closed. After that, participants completed a memory game designed to stimulate cognitive functions and induce emotional states related to concentration and stress. In the last phase, participants watched three video clips selected to elicit distinct emotions: "Positivity", "Negativity", and "Neutrality". The clips were taken from the E-MOVIE database [14]. After each video, participants completed a self-assessment questionnaire rating their emotional response on a scale from 1 to 9, based on Ekman's six basic emotions [15]: "Joy, Sadness, Anger, Disgust, Fear, Surprise", plus a neutral condition.

2.1 Data Recording

EEG data were acquired using the Emotiv Epoc X headset, a wireless EEG system featuring 14 channels positioned according to the international 10-20 system. This configuration enables high-precision recording of EEG signals, with the following channels being recorded: *AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4*. Reference sensors were placed at P3 (CMS) and P4 (DRL), and the signals were sampled at a frequency of 256 Hz. The EEG data were acquired using the Emotiv Pro software, which ensured accurate signal recording and synchronization.

In addition to EEG, physiological signals were continuously monitored using the Empatica Embrace Plus smartwatch. The recorded parameters included Electrodermal Activity (EDA), Heart Rate (HR), and Skin Temperature (TEMP). These physiological data were acquired simultaneously with the EEG recordings using the Empatica Care App.

Fig. 2: A test acquisition on a control patient during the experimental session.

Furthermore, participants' facial expressions were recorded using a video camera throughout the experimental session. This additional data source will allow for future analyses of facial expressions and their correlation with EEG and physiological responses. However, in the present study, only EEG data were analyzed.

3 EEG Data Analysis

As shown in Figure 3, after data acquisition, the raw signals undergo a preprocessing pipeline to remove artifacts and noise, ensuring clean and reliable data. Finally, relevant features are extracted from the preprocessed signals for further analysis. This structured approach ensures the integrity and quality of the data, enabling accurate emotion recognition and group classification.

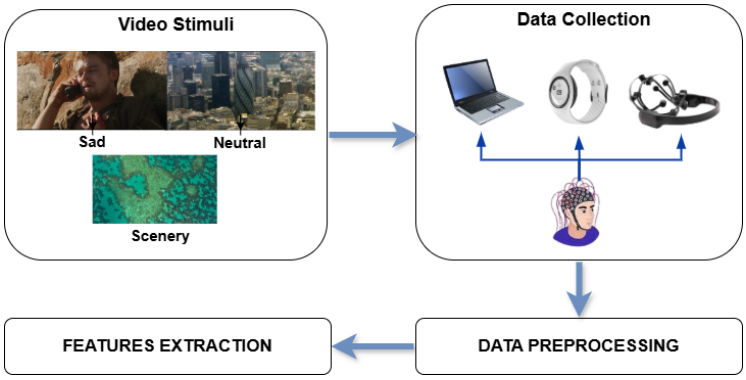


Fig. 3: General schema of the acquisition phase.

3.1 Signal Pre-Processing

The EEG data were pre-processed using the **EEGLAB** toolbox [6] and **MATLAB**. The pre-processing pipeline included several steps aimed at preparing the data for further analysis. The recorded EEG data were segmented based on the timestamps corresponding to the game phases and video clips [14]. A Python video player automatically sent signals to the Emotiv Pro recording program to synchronize these segments with the respective experimental phases. After segmentation, the baseline signal was removed from the complete dataset to minimize intra-subjective differences and normalize individual variability in EEG signals. This was achieved using the `pop_rmbase()` function from the EEGLAB toolbox. [6] Next, a bandpass filter was applied to the data, maintaining frequencies of interest in the range from 1 to 45 Hz. This filter was used to exclude components outside the typical EEG analysis range. Additionally, a notch filter at 50 Hz was employed to remove any noise associated with the electrical network. Artifact removal was the following step, where automatic signal cleaning was performed using the `pop_clean_rawdata` function. Independent Component Analysis (ICA) was then conducted using the **PICARD** algorithm to isolate cerebral components from non-neural artifacts, such as muscular movements or ocular signals (EOG). The `pop_iclabel` function was used to classify each component based on its nature. Any component identified as an artifact with a high probability was removed from the EEG signal. To ensure signal integrity, the variance of signal segments was checked. Segments exhibiting anomalous variance were excluded if they exceeded a pre-defined threshold. Finally, if necessary, channels were interpolated to maintain the spatial coherence of the EEG signal. [16]

After preprocessing, the input data (Figure 4) are segmented and filtered to remove unwanted artifacts. In the input directory, different data types are identified by the subject's ID. This structure allows for easy association of multimodal data with each participant. The resulting cleaned and processed segments are then stored in the structured output directory (Figure 5), where all data are systematically segmented. Specifically, for each subject and for each clip, sepa-

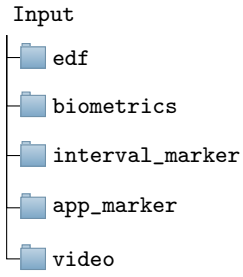


Fig. 4: Input Hierarchy

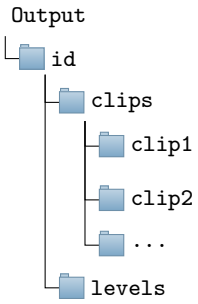


Fig. 5: Output Hierarchy

rate segments are created for EEG signals, biometric data, and video recordings. This ensures a well-organized dataset, facilitating subsequent feature extraction and classification.

3.2 Feature Extraction

Once the data were pre-processed, feature extraction was performed using Python. The first feature extracted was the Power Spectral Density (PSD), which was computed using Welch's method. This provided a measure of the signal's power distribution across different frequency bands. Next, bandpower (BP) was calculated in several frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-100 Hz). These bands are typically associated with different cognitive states, and the analysis of their power allowed for the identification of various neural processes. Additionally, frontal brain asymmetry (FBA) metrics were calculated using the power in the alpha and beta bands for the F7 and F8 channels. The following equations were used to compute these metrics [4]:

$$v_1 = \frac{\alpha_{F8}}{\beta_{F8}} - \frac{\alpha_{F7}}{\beta_{F7}} \qquad a_1 = \frac{\alpha_{F7} + \alpha_{F8}}{\beta_{F7} + \beta_{F8}} \tag{1}$$

$$v_2 = \ln(\alpha_{F7}) - \ln(\alpha_{F8}) \qquad a_2 = -\big(\ln(\alpha_{F7}) + \ln(\alpha_{F8})\big) \tag{2}$$

$$v_3 = \frac{\beta_{F7}}{\alpha_{F7}} - \frac{\beta_{F8}}{\alpha_{F8}} \qquad a_3 = \log_2\left(\frac{\beta_{F7} + \beta_{F8}}{\alpha_{F7} + \alpha_{F8}}\right) \tag{3}$$

$$v_4 = \alpha_{F8} - \alpha_{F7} \qquad a_4 = \frac{\beta_{F7} + \beta_{F8}}{\alpha_{F7} + \alpha_{F8}} \tag{4}$$

The metrics of valence and arousal were calculated to characterize emotional dimensions. Valence represents the positivity or negativity of an emotion, while arousal reflects the level of physiological activation associated with the emotion [17]. For all features, the EEG signals were divided into 4-second time windows, with a 50% overlap, ensuring a fine-grained analysis of the data. Prior to classification, the extracted features were normalized to ensure consistency across subjects and prevent any individual feature from dominating the analysis. Specifically, features were scaled between 0 and 1 by subtracting the mean, dividing by the standard deviation, and then adding 0.5.

4 Classifiers and Statistical Analysis

The data analysis was conducted in several stages. Initially, a descriptive analysis was conducted to examine the distribution of variables in the **HC, SCZ, TRS** groups, highlighting the differences between these groups. The results are shown in Figure 6 with bar graphs of the mean features for each group. Next, an ANOVA test was applied to see whether significant differences existed between the averages of EEG features among the groups. The results, including F-values and p-values for each feature, are summarized in Table 2.

The analysis identified the EEG features that varied the most between groups, helping to better understand the differences between the **HC, SCZ, TRS** groups. This guided the selection of features for classification.

4.1 Classification Models

The classification was implemented in Python, utilizing libraries such as Scikit-learn[18]. The experiments were conducted on a machine equipped with an AMD Ryzen 7 2700X CPU and 32 GB of RAM. The first classifier employed was the Support Vector Machine (SVM)[19]. SVMs are particularly effective in high-dimensional spaces, making them ideal for EEG data, where each feature represents a different dimension. Various kernel types were tested, including linear, polynomial, radial basis function (RBF), and sigmoid kernels. Next, K-Nearest Neighbors (KNN) was used, effective in classifying based on the nearest feature points. In addition, a Multilayer Perceptron (MLP) was used, which is a type of neural network with one or more hidden layers. MLP is suitable for handling non-linear decision boundaries. Other classifiers tested included Decision Trees (DT) and Random Forests (RF).

4.2 Hyperparameter Optimization

Feature selection was performed using **SelectPercentile** method with the **F-test**, allowing for the selection of the most relevant features before training. Hyperparameter optimization was conducted using **RandomizedSearchCV**, which efficiently explores a subset of possible hyperparameter values for each classifier. The best hyperparameters were selected based on classification accuracy. The tested hyperparameters for each model are summarized in Table 1.

Table 1: Hyperparameter distributions used for optimization.

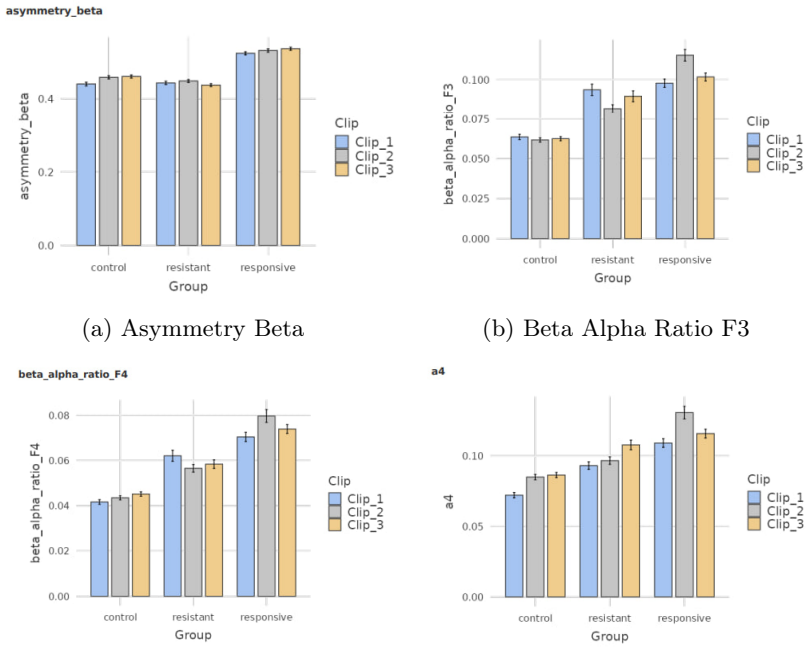
Classifier	Hyperparameters
SVM (linear)	C: $U(0.1, 10)$, gamma: scale, auto
SVM (poly)	C: $U(0.1, 10)$, gamma: scale, auto, degree: $U(2, 4)$
SVM (RBF)	C: $U(0.1, 10)$, gamma: scale, auto
SVM (sigmoid)	C: $U(0.1, 10)$, gamma: scale, auto
MLP	Hidden layers: (50,), (100,), alpha: $U(0.0001, 0.01)$, solver: adam, sgd
KNN	n_neighbors: $U(3, 7)$, weights: uniform, distance
Random Forest	n_estimators: $U(50, 200)$, max_depth: 10, 20, None
Decision Tree	max_depth: 10, 20, None, min_samples_split: $U(2, 10)$

The models were evaluated using **Stratified K-Fold cross-validation (5 folds)** to ensure each fold maintained the overall class distribution. Additionally, prediction time was recorded to evaluate computational efficiency. The final results, including accuracy, precision, recall, and F1-score for each model, are presented in Table 3 and Table 4.

5 Statistical Analysis of Features: Methods and Results

This section presents the results obtained from the statistical analysis of the features extracted from the EEG signals and evaluates their discriminative power. The primary goal is to examine how the features can most effectively distinguish between groups (HC, SCZ, TRS) as opposed to variations between clips (presented stimuli). This work focuses exclusively on EEG data, but future studies will incorporate other signal types for a multimodal approach.

5.1 Visualizations



(a) Asymmetry Beta

(b) Beta Alpha Ratio F3

(c) Beta Alpha Ratio F4

(d) Value A4

Fig. 6: Distribution of main EEG features for subject groups.

The bar charts, generated from the descriptive analysis, were grouped by clip and group. These plots, shown in Figure 6, illustrate the distribution of key EEG features such as Beta Asymmetry, Beta/Alpha Ratio (F3 and F4), and the A4

metric. The plots reveal that, within each group, the differences between clips are minimal, while significant variations are observed between groups. This outcome suggests that EEG features are more indicative of the subject's intrinsic condition (e.g., patients versus controls) rather than subtle variations between stimuli. It is likely that the selection of clips with less divergent stimuli contributed to this result, indicating that future studies could improve discrimination at the clip level by selecting stimuli with greater emotional differences.

5.2 Inferential Analysis

To compare the mean feature values grouped by clip and by group, ANOVA was applied. The results, summarized in Table 2, indicate that the differences in feature means were more pronounced between groups than between clips. This confirms the association between EEG abnormalities and the intrinsic characteristics of the subjects. The ANOVA results reveal significant differences in EEG features between groups (HC, SCZ, TRS) ($p < 0.001$), particularly for Alpha and Beta Asymmetry, suggesting these features are strongly linked to the intrinsic neurological conditions of the subjects. In contrast, differences between clips were less pronounced, with only a few features (e.g., Beta Asymmetry, A1, A2) showing significant variations, indicating that the selected stimuli may not have elicited sufficiently distinct emotional responses. This highlights the potential of EEG as a diagnostic tool for schizophrenia, while suggesting the need for more emotionally divergent stimuli in future emotion recognition studies.

Table 2: ANOVA Results for Clips and Groups

ANOVA - Clips				**ANOVA - Groups**			
Feature	**F**	**df1**	**p-value**	**Feature**	**F**	**df1**	**p-value**
Theta Asymmetry	0.0404	2	0.960	**Theta Asymmetry**	148.04	2	**< 0.001**
Alpha Asymmetry	0.4447	2	0.641	**Alpha Asymmetry**	278.91	2	**< 0.001**
Beta Asymmetry	4.1305	2	**0.016**	**Beta Asymmetry**	378.20	2	**< 0.001**
V1	2.6699	2	0.069	**V1**	54.69	2	**< 0.001**
A1	20.2986	2	**< 0.001**	**A1**	135.43	2	**< 0.001**
V2	14.1778	2	**< 0.001**	**V2**	7.03	2	**< 0.001**
A2	37.1981	2	**< 0.001**	**A2**	12.01	2	**< 0.001**
V3	4.4488	2	**0.012**	**V3**	23.10	2	**< 0.001**
A3	22.7179	2	**< 0.001**	**A3**	141.28	2	**< 0.001**
V4	4.3625	2	**0.013**	**V4**	26.06	2	**< 0.001**
A4	17.8308	2	**< 0.001**	**A4**	137.46	2	**< 0.001**
Beta/Alpha AF3	1.3351	2	0.263	**Beta/Alpha AF3**	164.06	2	**< 0.001**
Beta/Alpha F7	16.7248	2	**< 0.001**	**Beta/Alpha F7**	84.32	2	**< 0.001**
Beta/Alpha F3	0.1483	2	0.862	**Beta/Alpha F3**	285.91	2	**< 0.001**
Beta/Alpha F4	0.1590	2	0.853	**Beta/Alpha F4**	268.35	2	**< 0.001**
Beta/Alpha F8	8.3556	2	**< 0.001**	**Beta/Alpha F8**	130.20	2	**< 0.001**
Beta/Alpha AF4	6.4043	2	**0.002**	**Beta/Alpha AF4**	180.68	2	**< 0.001**

5.3 Classification Results

The performance of various classifiers in distinguishing between the three groups (HC, SCZ, TRS) is presented in Table 3. The Multilayer Perceptron (MLP) achieved the highest accuracy (97.2%), followed by Random Forest (RF) with 95.6% accuracy. These results demonstrate that EEG features are highly effective in differentiating between healthy controls and patients with schizophrenia, as well as between treatment-resistant and treatment-responsive patients.

Classifier	**Percentile**	**Accuracy**	**Precision**	**Recall**	**F-score**	**pred_time(s)**
SVM_linear	100	0.901	0.902	0.901	0.901	0.65
SVM_poly	50	0.905	0.906	0.905	0.905	0.15
SVM_RBF	50	0.947	0.948	0.947	0.947	0.22
SVM_sigmoid	100	0.487	0.484	0.487	0.480	0.23
MLP	70	**0.972**	0.972	0.972	0.972	3.90
KNN	100	0.945	0.946	0.945	0.945	0.04
RF	70	0.956	0.957	0.956	0.956	9.18
DT	100	0.830	0.831	0.830	0.830	0.75

Table 3: Best results for each model (Classification by Groups)

The performance of the classifiers in distinguishing between emotional stimuli (clips) is shown in Table 4. While the MLP also performed well in this task (84.6% accuracy), the overall performance was lower compared to group classification. This suggests that the currently used EEG features are more effective in characterizing intrinsic differences between subjects than variations in individual stimuli.

Classifier	**Percentile**	**Accuracy**	**Precision**	**Recall**	**F-score**	**pred_time(s)**
SVM_linear	100	0.644	0.648	0.644	0.642	2.77
SVM_poly	100	0.547	0.686	0.547	0.508	0.23
SVM_RBF	100	0.801	0.802	0.801	0.800	0.36
SVM_sigmoid	70	0.441	0.457	0.441	0.434	0.26
MLP	70	**0.846**	0.847	0.846	0.846	7.59
KNN	70	0.786	0.787	0.786	0.786	0.03
RF	70	0.819	0.821	0.819	0.819	9.95
DT	100	0.719	0.721	0.719	0.719	0.84

Table 4: Best results for each model (Classification by Clip)

6 Conclusions

In this study, we explored the relationship between emotions and biometric signals in patients with schizophrenia by analyzing EEG and physiological data to achieve emotion recognition. We focused on distinguishing between healthy individuals and schizophrenia patients, specifically comparing treatment-resistant and treatment-responsive subgroups. To this end, we developed a structured

dataset by acquiring EEG and physiological signals during exposure to standardized emotional stimuli.

The results revealed significant differences in EEG frequency bands across groups, suggesting distinct neural patterns associated with emotional processing. Physiological responses also indicated varying levels of emotional regulation between healthy subjects and schizophrenia patients, supporting the hypothesis that emotional perception abnormalities manifest in biometric signals.

This study is part of the SPECTRA project, which aims to support clinicians in the early identification of Treatment-Resistant Schizophrenia (TRS), a condition that prevents patients from responding to conventional pharmacological therapies, leading to ineffective treatments and a decline in quality of life. The multimodal analysis of biometric signals, including EEG monitoring and the integration of machine learning algorithms, can contribute to improving diagnostic accuracy and predicting therapeutic efficacy in TRS patients. The obtained results, with classification accuracy of up to 95% among groups, suggest that the proposed approach could provide objective tools for improving diagnosis and clinical management of treatment-resistant schizophrenia.

Although promising, these results represent an initial step in investigating emotion recognition in schizophrenia patients. Future studies should expand the analyzed sample, incorporate additional physiological modalities, and optimize machine learning models for even more accurate classification. Furthermore, integrating multimodal approaches, such as facial expression analysis, could enhance the understanding of emotional responses and their connection to the pathology. With the advancement of neuroscientific technologies, we hope that studies like this will contribute to a deeper understanding of schizophrenia, paving the way for new diagnostic and therapeutic avenues, positively impacting patient quality of life and clinical intervention effectiveness.

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