ORIGINAL ARTICLE

Decoding Pain Dynamics: EEG Insights into Neural Responses and Classification Via RQA Analysis

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Abstract

Purpose: Pain detection remains a challenging aspect of medical diagnosis, necessitating innovative approaches to address existing limitations. Current pain detection methods often lack precision and efficiency, prompting the exploration of alternative methodologies. This study focuses on investigating dynamic Electroencephalogram (EEG) patterns during pain states, aiming to fill gaps in the current understanding of pain detection mechanisms.

Materials and Methods: EEG recordings were conducted on a cohort comprising ten participants (5 men, and 5 women) who were free from drug usage and underlying ailments. The participants underwent EEG recording sessions during both resting and phasic pain states induced by immersing their left hand in ice-cold water. The EEG data were subjected to rigorous analysis using Recurrence Quantification Analysis (RQA). Additionally, a rough neural network classifier, with specific parameters tailored to the dataset characteristics, was employed for pain state classification.

Results: Our analysis revealed dynamic EEG features during phasic pain states, elucidated through RQA. Notably, the rough neural network demonstrated a high classification accuracy of 95.25% in distinguishing between pain and non-pain states. While specific numerical results such as p-values are not provided, the robust accuracy of the classification underscores the discernibility of cerebral responses during painful experiences.

Conclusion: This study contributes to the advancement of pain detection methodologies by introducing an innovative approach that leverages EEG analysis and neural network classification. While further investigation is warranted to validate these findings, they hold promise for enhancing pain assessment accuracy and ultimately improving patient care outcomes.

Keywords: Cold Pressor Test; Electroencephalogram; Phasic Pain; Rough Neural Network; Recurrence Quantification Analysis; Electroencephalogram Dynamics; Pain Assessment.

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1. Introduction

Pain, often regarded as an unpleasant sensation accompanying illness or physical injury, plays a critical role in determining an individual's quality of life and overall functionality. Despite its significance, accurately detecting and assessing pain remains a complex endeavor in medical practice. Existing methodologies for pain detection are fraught with limitations, necessitating innovative approaches to enhance precision and efficacy. Understanding the dynamic changes that occur in the brain during pain perception is crucial for advancing pain detection techniques. Various brain regions, including the somatosensory, insular, cingulate, and prefrontal cortices, as well as the thalamus, subcortical areas, and brainstem, are known to be involved in processing pain signals [1, 2]. Electroencephalogram (EEG) recordings offer a unique opportunity to capture these dynamic neural responses during pain induction. EEG, a well-established electrophysiological monitoring technique, has traditionally been utilized for diagnosing a range of neurological conditions, such as sleep disorders, epilepsy, and Alzheimer's disease [3-5]. More recently, researchers have begun exploring its potential in pain assessment. While previous studies have demonstrated the brain's ability to perceive pain through EEG analysis [6-9], there remains a need for further investigation into the specific EEG patterns associated with different types and intensities of pain.

Phasic pain, characterized by its short duration, serves as a valuable model for studying pain perception in controlled laboratory settings. Studies utilizing phasic pain induction methods, such as the Cold Pressor Test (CPT), have yielded insights into the neural correlates of pain processing [10-24]. Additionally, Garcia-Larrea *et al.* [11] evaluated phasic pain via EEG, while Lorenz *et al.* [12] and Mouraux *et al.* [13] found that the induction of pain could modulate neural activity in various frequency bands. Furthermore, Gross *et al.* [14] reported that phasic pain stimulation affects gamma frequencies. Accordingly, the obtained results based on different methods demonstrated that the brain could sense the pain [11-25]. Usually, the frequency band is used as a pain-related feature [10-25]. Some studies use classifiers to classify pain leveling (i.e. pain and no-pain) [15-17]. Several studies have used classifiers to diagnose pain based on its severity [18-20], [23-28]. For instance, Mansoor *et al.* [19] differentiated pain from non-pain states using KNN and SVM classifiers, while Bonotis *et al.* [23] classified pain into five intensity levels using a stochastic forest algorithm. Elsayed *et al.* [24] found a direct correlation between alpha frequency band power and pain intensity and used an ANN classifier to classify data into four classes. Cao *et al.* [23] demonstrated the utility of the alpha band as a tool for sudden pain detection using laser stimulation. Moreover, recurrence quantification analysis (RQA) has emerged as a powerful tool for visualizing and analyzing the dynamic behavior of complex systems [27]. This research aims to investigate dynamic changes in the brain for pain detection using EEG during phasic pain episodes with the RQA method. The implications of accurate pain detection extend beyond research settings to clinical practice, where timely and precise pain assessment is essential for guiding treatment decisions and improving patient outcomes [31, 32]. By elucidating the neural mechanisms underlying pain perception, this research has the potential to inform the development of more effective pain management strategies.

In summary, this study seeks to address gaps in our current understanding of pain detection by leveraging EEG technology and advanced analytical methods. By elucidating the dynamic neural responses associated with pain, we aim to contribute to the refinement of pain assessment techniques and ultimately enhance patient care.

2. Materials and Methods

In this study, the nonlinear features were extracted using the RQA method [27-30] to detect the pain state from the non-pain state. Then, the Rough neural network [31,32] was applied for pain classification. Figure 1 displays the general process in EEG classification.

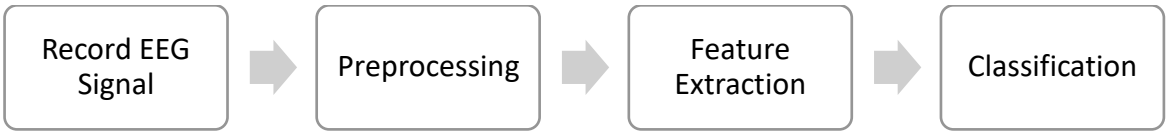

Figure 1. General process in EEG classification

2.1. Participants

2.1.1. Sample Size and Demographics

The study involved a total of 10 participants, consisting of five men and five women. The participants were selected based on the following criteria: they were drug-free and had no history of acute or chronic diseases. The selection criteria for participants in the study were carefully considered to ensure the reliability and validity of the findings. Participants were selected based on specific inclusion and exclusion criteria. Inclusion criteria included being drug-free and having no history of acute or chronic diseases. Exclusion criteria were not having any pre-existing medical conditions or taking any medications that could potentially affect pain perception. Participants were recruited through advertisements and word-of-mouth referrals within the local community. Individuals who expressed interest in participating underwent a screening process to determine eligibility based on the inclusion and exclusion criteria outlined above. The mean age of the participants was 33.9±6.07 years. Ethical considerations were taken into account throughout the study, including obtaining informed consent from each participant. To assess pain perception, participants provided pre- and post-test responses using the Visual Analogue Scale (VAS) method, which rates pain on a numerical scale from 0 (no sensation) to 10 (pain tolerance threshold).

2.1.2. Data Acquisition

The EEG data were recorded according to the standard 10-20 protocol, utilizing 19 channels (Fp1, F7, T3, T5, Fp2, F8, T4, T6, F3, C3, P3, O1, F4, C4, P4, O2, Fz, Cz, Pz). Referential electrodes were bilaterally connected to the two earlobes and then averaged. The acquired EEG signals were filtered using a hardware 4th-order band-pass filter with a bandwidth of 0.1 to 35 Hz [29], and a sampling frequency of 500 Hz. The study was conducted at Golestan Hospital of Ahvaz, following the necessary approvals from Ahvaz Jundishapur University of Medical Sciences and the local institutional ethics committee. Stringent ethical and safety procedures were implemented, given the possibility of inducing pain in volunteers. These procedures included appropriate considerations and contractions [33]. The EEG recordings were conducted in both resting and phasic pain states [34,35], induced by cold exposure, with the cooperation of ten participants (comprising five men and five women) who were drug-free and free from acute or chronic diseases. The average age of the participants was 33.9 years, with a standard deviation of 6.07. Informed consent was obtained from all participants before the test, and a series of questions were administered both before and after the test to ensure that the pain experienced by the volunteers was measurable and assessable. Pain intensity was assessed using the Visual Analogue Scale (VAS) method [36], allowing participants to rate the painfulness of the stimuli on a numerical scale ranging from 0 (no sensation) to 10 (pain tolerance threshold). During the experiment, all participants kept their eyes open. EEG recordings were performed using the reference method and passive electrodes, eliminating the need for gel application. A Nihon Kohden electroencephalograph machine, specifically the Neurofax model, was used to record EEG data. Key settings on the machine included the activation of a power line filter and a sensitivity of five microvolts. Additionally, the Neurofax machine applied a digital notch filter at 50 Hz. Impedance was consistently maintained at less than 5 Kohm to ensure data quality. The experimental procedure took place in a semi-dark room, where volunteers were seated in chairs. EEG recordings in the resting state were collected for 30 seconds. For the cold pain condition [8], participants submerged their left hand in ice water until they could no longer tolerate the cold-induced pain. This process was repeated five times, and the durations of both pain and non-pain states were accurately recorded.

2.2. Pre-processing

After EEG recording, the signals of pain and non-pain states were categorized according to the time of occurrence, recording of signal, and sampling frequency (500 Hz). Then, signal processing was performed using Fz, Cz, and Pz channels. In this study, three midline channels (Fz, Cz, and Pz) were selected to fulfill global activation of the brain (both hemispheres). In addition, the complexity and time-consuming analysis of all channels are avoided [27]. Finally, the zero-phase filter was used to remove the noises [26].

2.3. Feature Extraction

RQA is considered a method of evaluating nonlinear data for applications in dynamic systems. The selection of Recurrence Quantification Analysis (RQA) over other nonlinear analysis methods in our research was based on several factors that are relevant to our study's objectives and the nature of the data we collected. RQA is a widely recognized and effective method for evaluating nonlinear data in dynamic systems. Our research aimed to investigate dynamic changes in the brain during pain induction using EEG signals. RQA is particularly suited for capturing and quantifying recurrent patterns and dynamical features in time series data. Its focus on recurrence and the structure of data points aligns well with our goal of detecting changes in brain activity associated with pain. EEG data is inherently complex and often exhibits nonlinear patterns. RQA is known for its ability to uncover hidden nonlinear dynamics in such data, making it a suitable choice for our study. While other nonlinear methods, like wavelet analysis or fractal analysis, have their merits, they may not have been as well-suited to our specific dataset and research question. After recording EEG in participants in pain and resting states, features were extracted and data were analyzed using the dynamic analysis of these two states based on EEG signals and the RQA method. The reconstructed signal in the phase space is required for calculating RQA. The values of RQA extremely rely on embedded parameters including dimension and delay time [28]. Another parameter is the threshold distance (radius). Euclidean distance was considered via 0.1 of the threshold regarding finding the neighbor. Further, the value of the minimum diagonal and vertical line was equal to 2, and the window size was 1000 milliseconds [28]. Therefore, 13 features were extracted from the EEG signals for each channel in non-pain and pain states for each person. Our goal in extracting these specific features is to capture and quantify the dynamic changes in EEG data during pain perception. By analyzing these features, we aim to gain a deeper understanding of how the brain responds to painful stimuli.

Equations 1-13 demonstrate features extracted according to RQA. In these equations, ε represents a predefined threshold, and N is the number of points in the phase space trajectory. The variables l and v denote the lengths of the diagonal and vertical lines in the recurrence plot, respectively. The parameters l_{min} and v_{min} specify the minimum lengths of diagonal and vertical lines to be considered in the analysis. P(l) denotes the frequency distribution of diagonal lines of length l, and P(v) represents the frequency distribution of vertical lines of length v [27-30]. Figure 2 displays one of the RQA plots of EEG channels.

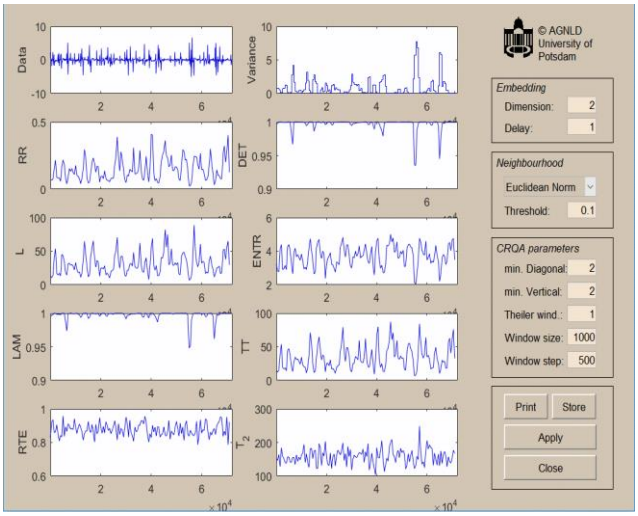

Figure 2. One of the RQA plots of EEG channels

1. *Recurrence Rate:* The density of recurrence points in a recurrence plot (Equation 1);

$$RR(\varepsilon) = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{i,j}(\varepsilon) \quad (1)$$

2. *Determinism:* The percentage of recurrence points from the diagonal lines in the recurrence plot of the minimal length ($l_{\min}$) (Equation 2);

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)} \quad (2)$$

3. *Averaged diagonal length* (Equation 3)*:*

$$L = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=l_{min}}^{N} P(l)} \quad (3)$$

4. *Length of the longest diagonal line* (Equation 4)*:*

$$Lmax = max(\{L_i; i = 1,2 \dots, N_L\}) \quad (4)$$

5. *Entropy of diagonal length:* The Shannon entropy rate with the probability of $P(l)= P(l)/ Nl$ for finding the diagonal line exactly with length l in the recurrence plot (Equation 5);

$$ENTR = -\sum_{l=l_{min}}^{N} P(l) \ln p(l) \quad (5)$$

6. *Laminarity:* The rate between the recurrence points formed in the vertical structure and the internal data of the recurrence points is calculated as follows (Equation 6):

$$LAM = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)} \quad (6)$$

7. *Trapping time:* The stopping time based on the average length of the vertical structure (Equation 7):

$$TT = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=v_{min}}^{N} P(v)} \quad (7)$$

8. *Length of the longest vertical line* (Equation 8)*:*

$$Vmax = max(\{v_i; i = 1, \dots, N_v\}) \quad (8)$$

N_v equals the absolute number of vertical lines.

If recurrence data were assumed as S=$\{x_{t1},x_{t2},\dots,x_{ti},\dots\}$, then the corresponding recurrence time T equals $\{T(i) = t_{i+1} - t_i, i = 1,2, \dots\}$. Features 9 and 10 are achieved accordingly.

9. *Recurrence time of 1st type* (Equation 9)*;*

10. *Recurrence time of 2nd type* (Equation 10)*;*

$$T_1 = \frac{1}{N}\sum_{i=1}^{N} T_i^{(1)} \quad (9)$$

$$T_2 = \frac{1}{N}\sum_{i=1}^{N} T_i^{(2)} \quad (10)$$

11. *Recurrence period density entropy* (Equation 11)*;*

$$H_{norm} = (\ln T_{max})^{-1} \sum_{t=1}^{T_{max}} P(t) \ln P(t) \quad (11)$$

12. *Clustering coefficient* (Equation 12)*;*

$$Clust = \sum_{i=1}^{N} \frac{\sum_{j,k=1}^{N} R_{i,j}R_{j,k}R_{k,i}}{RR_i} \quad (12)$$

13. *Transitivity:* The transfer of a complex network is related to the probability that two neighbors in each case are still neighbors, indicating how much the network is clustered locally (Equation 13).

$$Trans = \frac{\sum_{j,k=1}^{N} R_{i,j}R_{j,k}R_{k,i}}{\sum_{i,j,k=1}^{N} R_{i,j}R_{k,i}} \quad (13)$$

In the current study, recurrence quantification analysis is done using MATLAB Toolbox [28]. (available at: http://tocsy.pik-potsdam.de/).

2.4. Apply T-Test

We took several steps to assess and ensure the normality of our data distribution. Firstly, we visually inspected the data using histograms and Q-Q plots, which allow for a preliminary assessment of data normality. This step provided an initial indication of whether our data points followed a normal distribution. Subsequently, we employed statistical tests for normality, such as the Shapiro-Wilk test and the Kolmogorov-Smirnov test. These tests are commonly used to assess if a dataset significantly deviates from a normal distribution. Our results from these tests indicated whether the data significantly departed from normality. To enhance the robustness of our analysis, we applied data transformations when necessary. These transformations can include logarithmic, square root, or Box-Cox transformations, among others, to make the data conform more closely to a normal distribution. It's important to note that not

all data needs to be perfectly normally distributed for certain statistical analyses to be valid. However, when violations of normality were identified, we employed appropriate statistical techniques, such as non-parametric tests or data normalization, to mitigate the effects of non-normality on our results. This allowed us to choose the most suitable statistical methods for our data based on its distribution characteristics. A statistical paired T-test [25] by GraphPad Prism software was conducted after extracting features, and P-values were obtained for each feature that are less than the significance level (0.05). The signal classification was performed after applying the T-test and ensuring that features in both pain and non-pain states were different.

2.5. Signal Classification

The Rough neural network is used to classify the signals. These networks are neural structures that include rough neurons [31,32]. The neural network based on rough neurons can improve the network performance and reduce errors [31]. The output could be obtained for the second layer (output layer) similar to the multilayer perceptron neural network. Equations 14-20 represent the neural network algorithm.

$$net_L^1 = X \cdot W_L^1 \tag{14}$$

$$net_U^1 = X \cdot W_U^1 \tag{15}$$

$$O_L^1 = min(f^1(net_L^1), f^1(net_U^1)) \tag{16}$$

$$O_U^1 = max(f^1(net_L^1), f^1(net_U^1)) \tag{17}$$

$$O^1 = \frac{O_U^1 - O_L^1}{average(O_U^1, O_L^1)} \tag{18}$$

$$net^2 = O^1 \cdot w^2 \tag{19}$$

$$O^2 = f^2(net^2) \tag{20}$$

In this study, the feature matrix had a dimension of 13×60. Additionally, Dataset is split into a 50/50 ratio. Also, we used 2-fold cross-validation [37] to divide the data into 2 folds with 20 times iterations. We kept the same dimension for both the training and testing sets. The Rough neural network was used in such a way that the number of neurons in the middle layer was equal to 10. The gradient descent method was used for learning and weight updates in the neural network. Furthermore, bias values in the first and last layers were randomly considered based on input and target data. Eventually, the maximum value for each step of training in the network was equal to 50. Then, the LogSig activation function was utilized for training and testing the data. The decision to employ a 2-fold cross-validation technique was based on the limited size of our dataset. While 2-fold cross-validation is less common than, say, 5 or 10-fold cross-validation, it was necessary due to the constraints of our dataset. With a limited number of samples, we aimed to ensure that both the training and testing sets were as diverse and representative as possible. A 50/50 split was chosen to prevent any bias toward one class or the other, given the nature of our binary classification task. The exact size of the training and test datasets would depend on the total number of samples available in the dataset, which is not specified in this context. However, the 50/50 split suggests an equal distribution between the two sets. We opted for a 2-fold cross-validation to ensure that both training and testing sets were adequately representative of the data distribution. In summary, while we acknowledge that 2-fold cross-validation and a 50/50 data split may not be typical in all scenarios, these choices were made to address the specific challenges of our dataset, ensuring that the neural network model was trained and tested as effectively as possible given the available data.

3. Results

EEG variation during pain and no pain condition is studied in various research works. In the present study, all P-values in the paired T-test for 13 features were obtained using the RQA method and were less than the significance level (0.05), indicating the difference between pain and non-pain states. Therefore, these differences in features demonstrate a sign of the difference in cerebral performance in pain and non-pain states and thus can be used for pain detection and classification in participants (Figure 3). The mean and standard deviation of VAS were 4.2 and 1.25. Pain level estimation is shown in Figure 4. The obtained values from the paired T-test are presented in Table 1. After training the neural network and considering the network as a recurrent neural network, a confusion matrix based on comparing the neural network output

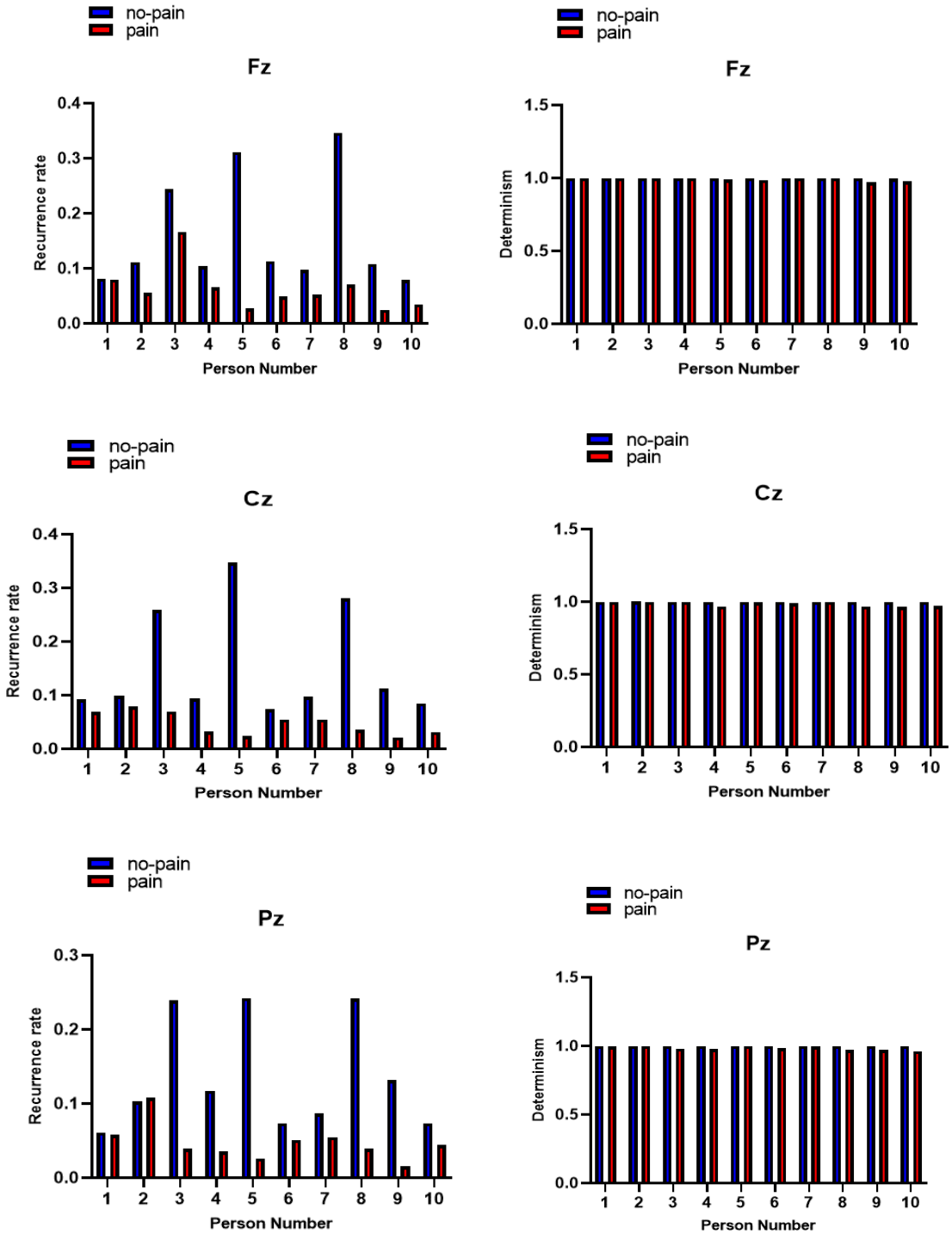

Figure 3. A) Recurrence rate across 3 channels for 10 subjects. B) Determinism across 3 channels for 10 subjects

with the target matrix was calculated to evaluate each step of the classifier. Figure 5 shows one confusion matrix of 20 times of running the classifier.

All feature in Figure 3 is shown in no-pain and pain conditions. Recurrence rate, determinism, averaged diagonal length, length of longest diagonal line, entropy of diagonal length, laminarity, trapping time, length of longest vertical line, recurrence times of second type, clustering coefficient, transitivity is lower in the pain state than the non-pain state. Recurrence times of the first type and recurrence period density entropy is lower in the no-pain state than in the pain state.

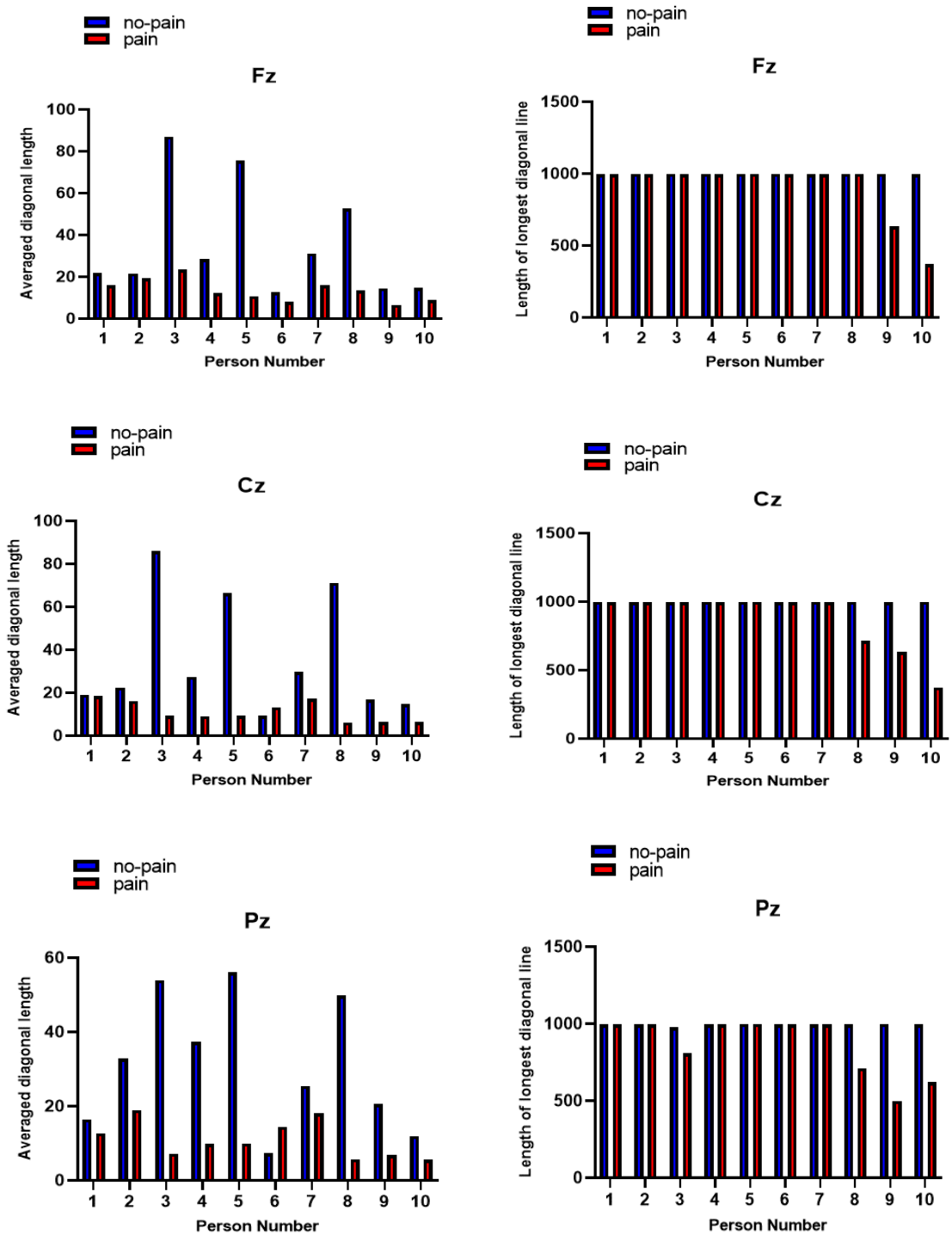

Figure 3. C) Averaged diagonal length across 10 subjects. D) Length of longest diagonal line across 10 subjects

Therefore, the accuracy of the Rough neural network classifier was obtained by the confusion matrix [38]. Table 2. Depicts the Mean and standard deviation of the values of the confusion matrix, for two steps of classification using 20 times of the running classifier, which was equal to 95.254%. Accordingly, extracting dynamic features and using the neural network based on rough neurons is appropriate for classifying and detecting pain from non-pain states. This test aims to detect and classify pain from non-pain states in volunteers using features that are extracted from EEG and the RQA method [28]. In the present study, CPT was applied to create phasic pain.

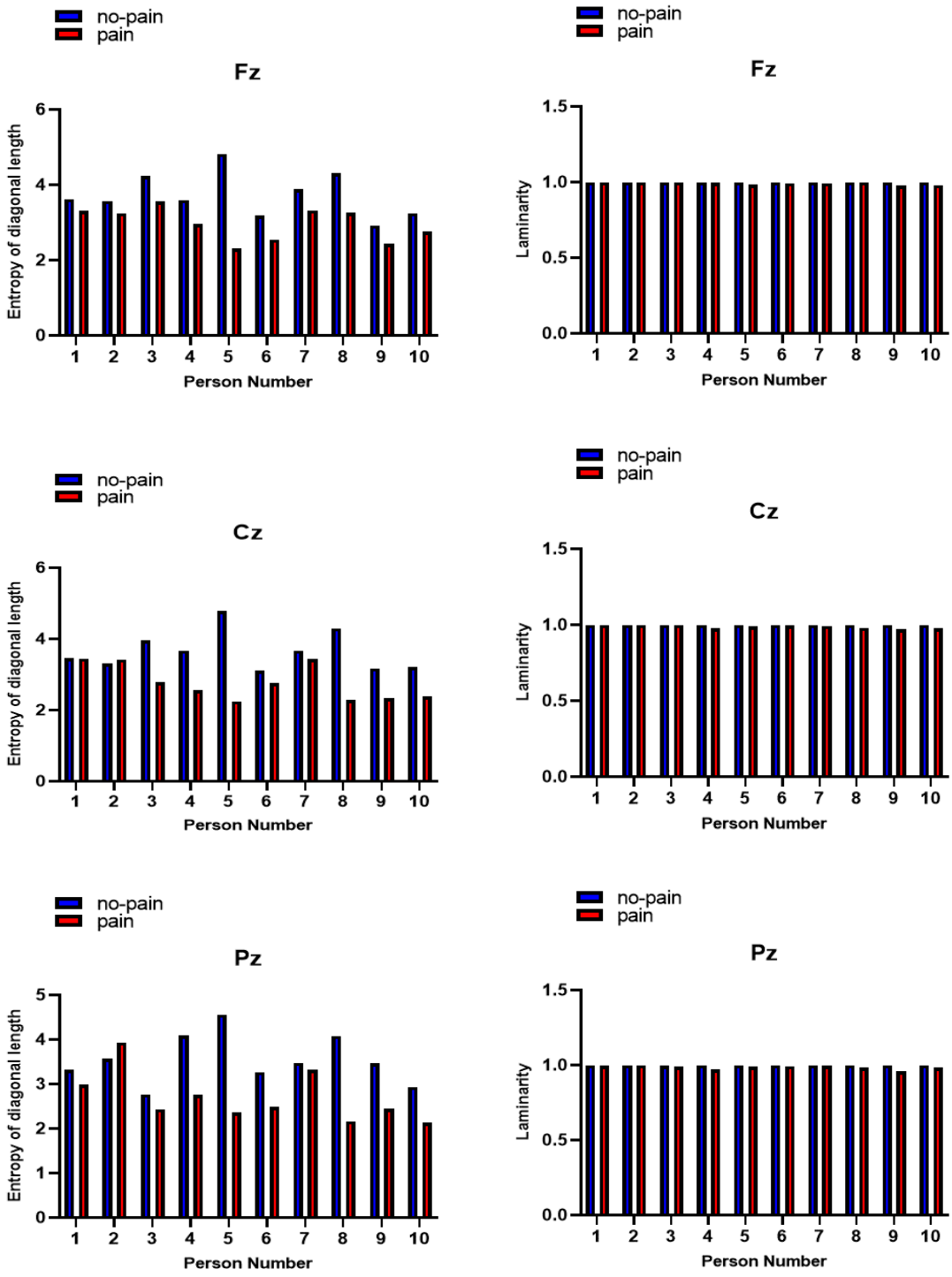

Figure 3. E) Entropy of diagonal length for 10 subjects. F) Laminarity for 10 subjects

Implementation of proposed methods performed using MATLAB R2017a software.

4. Discussion

The detection and differentiation of pain states have garnered significant attention in research globally. In this study, we have demonstrated substantial alterations in the dynamic features of the brain when comparing pain and non-pain states. We also propose the utilization of the Recurrence Quantification Analysis (RQA) method to investigate these dynamic brain changes. Importantly, we have achieved highly accurate pain differentiation using a Rough Neural Network classifier. Prior research has explored EEG signal processing and related methods for automatic

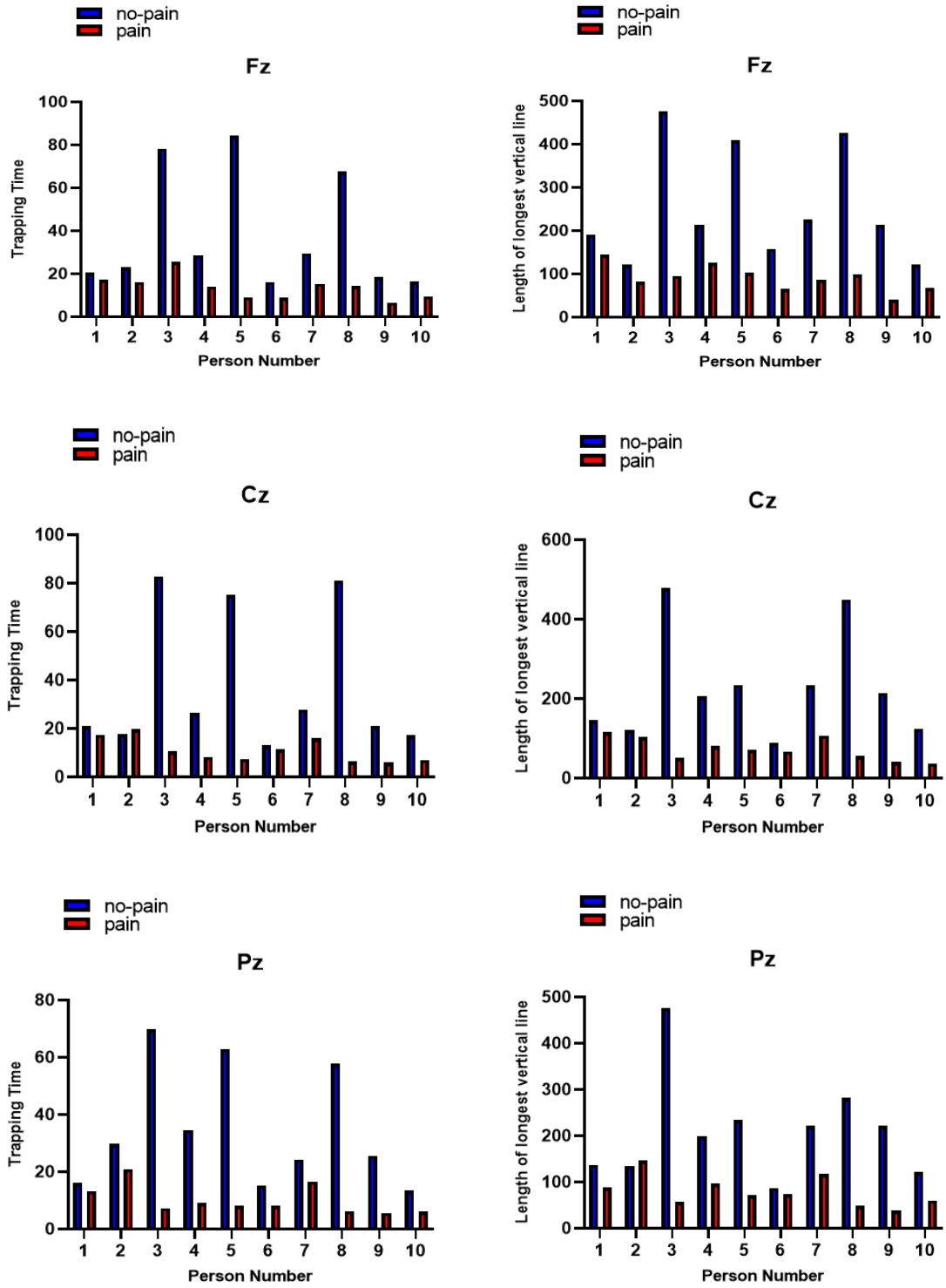

Figure 3. G) Trapping time across 10 subjects. H) Length of longest vertical line across 10 subjects

pain detection, but the results have not been consistently conclusive. For instance, studies by Vatankhah *et al.* [13,14], Alazrai *et al.* [15], and Nezam *et al.* [16], Bonotis *et al.* [21], Elsayed *et al.* [22], Mosares-Haghighi *et al.* [24], Wang *et al.* [25], and Lin Lin Y *et al.* [39] employed the Cold Pressor Test (CPT), similar to our study, to induce pain in participants and recorded data using EEG. Each of these studies utilized different features and techniques for pain detection. For example, Vatankhah *et al.* [13] and [14] focused on nonlinear and spectral features, while Alazrai *et al.* [15] concentrated on the beta

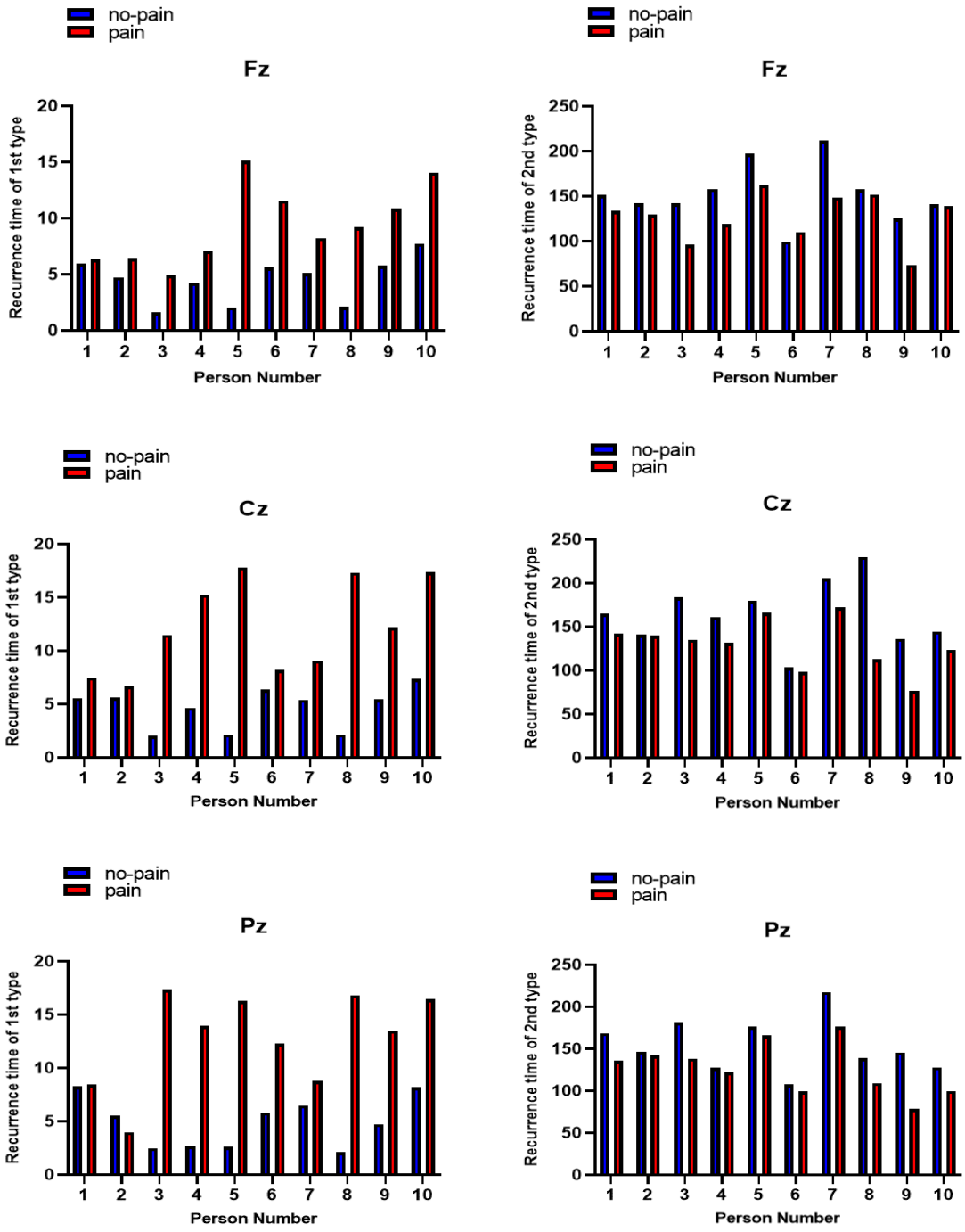

Figure 3. I) Recurrence times of the first type across 10 subjects. J) Recurrence times of the second type across 10 subjects

frequency band. Nezam *et al.* [16] achieved multi-level pain differentiation, and Bonotis *et al.* [21] classified pain into five intensity levels based on band power. Elsayed *et al.* [22] found a direct correlation between the alpha frequency band power and pain intensity, while Mosares-Haghighi *et al.* [24] differentiated pain and non-pain states by examining differences in connectivity graphs in the alpha band. Wang *et al.* [25] used a paired T-test to investigate the significance of EEG power differences between pain and non-pain states, revealing higher power in the pain state across most frequency bands. Lin Lin Y *et al.* [39] used SVM for classifying three levels of pain using various physiological signals, including EEG, with a focus on frequency-domain features.

In our study, we have made noteworthy advancements by utilizing the Rough Neural Network

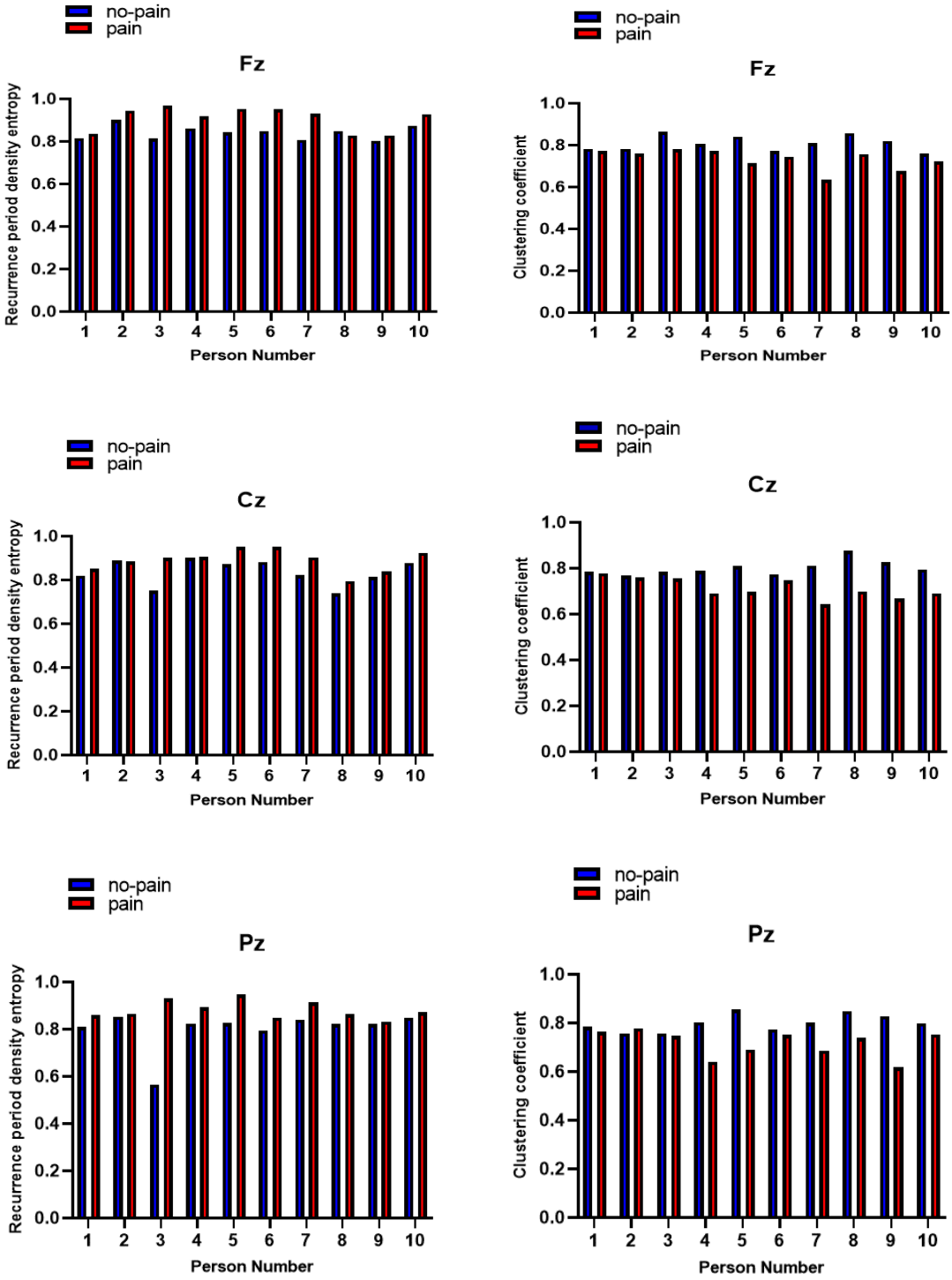

Figure 3. K) Recurrence period density entropy across 10 subjects. L) Clustering coefficient across 10 subjects

and nonlinear features, leading to increased accuracy in pain differentiation. However, the primary focus of these studies has been on distinguishing different levels of pain, which was not the primary objective of our research. Mansoor *et al.* [17] induced pain using cold and heat stimuli and achieved 100% accuracy using frequency and time-domain features with classifiers like SVM and KNN. While their overall accuracy surpassed our results, they did not incorporate nonlinear features. Panavarnan *et al.* [18], Misra *et al.* [19], Vijayakumar *et al.* [20], and Cao *et al.* [23] induced pain through heating stimuli. Panavarnan *et al.* [18] used power spectral density in alpha and beta frequencies for pain classification.

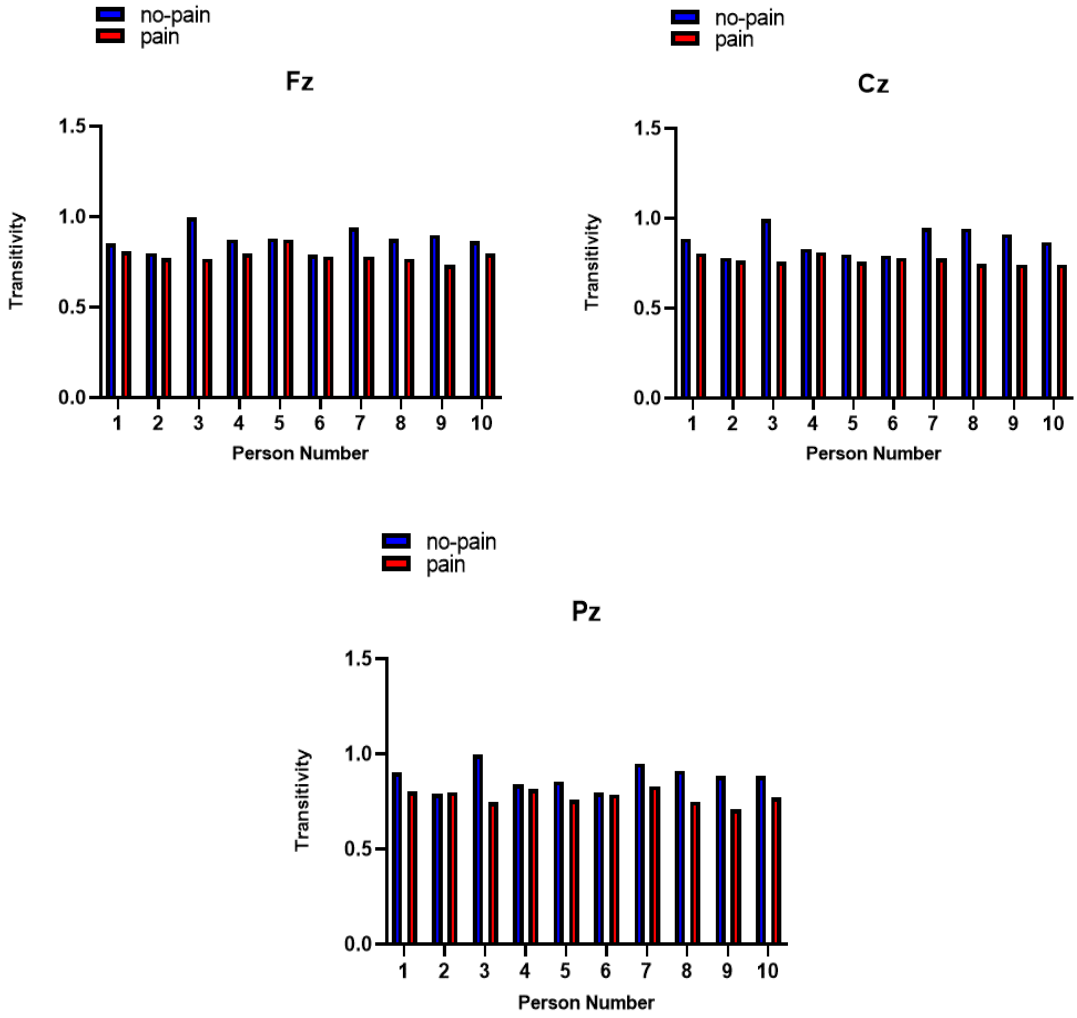

Figure 3. M) Transitivity across 10 subjects

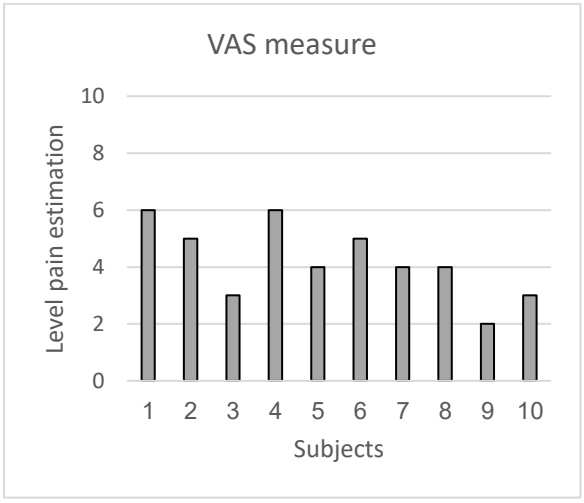

Figure 4. Pain level estimation of 10 subjects using the VAS method

Table 1. P-values (paired T-test) of RQA Measures

Features	P-value
Recurrence rate	0.0002
Determinism	0.03
Averaged diagonal length	0.003
Length of longest diagonal line	0.008
Entropy of diagonal length	0.008
Laminarity	0.02
Trapping time	0.001
Length of longest vertical line	0.0001
Recurrence times of first type	0.002
Recurrence times of second type	0.02
Recurrence period density entropy	0.04
Clustering coefficient	0.001
Transitivity	4.67E-06

Misra *et al.* [19] analyzed independent components and localization in EEG to classify pain, concluding that gamma and theta power increase in the prefrontal area and beta power decreases in the cortical region

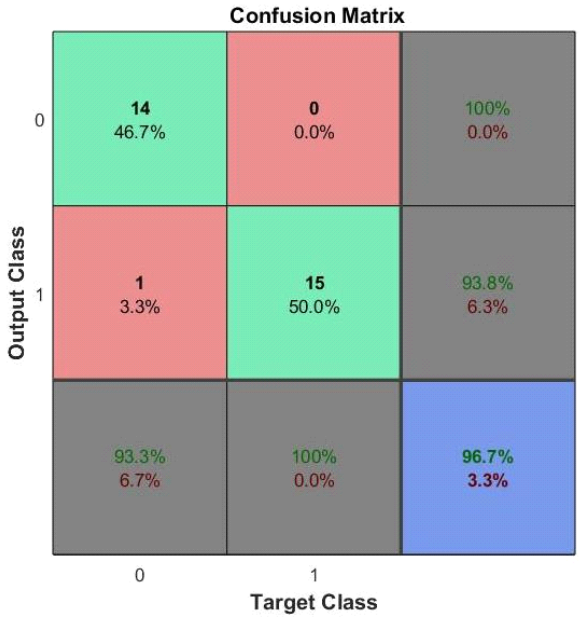

Figure 5. One confusion matrix obtained from 20 iterations of running the classifier.

Table 2. The mean and standard deviation of confusion matrix measurements

	Accuracy value for First input	Accuracy value for Second input
Mean of Confusion Matrix	95.5005	95.001
Standard Deviation of confusion Matrix	4.506915	4.014004

with increased pain sensation. Vijayakumar *et al.* [20] used time-frequency wavelet transformation of EEG and the random forest algorithm to assess pain. Cao *et al.* [23] employed laser stimulation and found that alpha band amplitude was an effective objective tool for sudden pain detection. Zolezzi DM *et al.* [40] successfully differentiated three levels of pain severity in chronic neuropathic pain patients, focusing on the sampling rate. Notably, studies such as Panavarnan *et al.* [18], Misra *et al.* [19], Nezam *et al.* [16], Cao *et al.* [23], and Zolezzi DM *et al.* [40] have reported contradictory results based on spectral features. This highlights the insufficiency of relying solely on spectral features from EEG for pain processing. Future studies should consider incorporating both dynamic and spectral features to enhance the accuracy and robustness of pain detection methods.

In summary, our study contributes to the growing body of research in the field of pain detection by highlighting the significance of dynamic features, nonlinear analysis, and the potential for improved accuracy in pain differentiation using the Rough Neural Network method. This underscores the importance of further exploration of a holistic approach that combines dynamic and spectral features for more robust and accurate pain processing.

4.1. Limitation

It should be mentioned that the test was applied based on phasic pain by the CPT test. In this study, only nonlinear features were extracted, and it is suggested that the effect of both linear and nonlinear features be investigated.

5. Conclusion

In Figure 3, a comprehensive set of features was examined in both no-pain and pain conditions. It is evident that various dynamic features, including recurrence rate, determinism, averaged diagonal length, length of the longest diagonal line, entropy of diagonal length, linearity, trapping time, length of the longest vertical line, recurrence times of the second type, clustering coefficient, and transitivity, were observed to be lower in the pain state compared to the non-pain state. On the other hand, recurrence times of the first type and recurrence period density entropy were found to be lower in the no-pain state compared to the pain state.

This analysis underscores the significance of extracting dynamic features and employing neural networks based on rough neurons for the accurate classification and detection of pain from non-pain states. The observed differences in these dynamic features serve as valuable insights into the distinctive brain activity patterns associated with pain perception, offering a promising avenue for the development of robust pain detection methodologies.

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