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RESEARCH ARTICLE

Multiscale Fluctuation Dispersion Entropy of EEG as a Physiological Biomarker of Schizotypy

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ABSTRACT Altered electroencephalography (EEG) activity in schizotypal individuals is a powerful indicator of proneness towards psychosis. This alteration is beyond decreased alpha power often measured in resting state EEG. Multiscale fluctuation dispersion entropy (MFDE) measures the non-linear complexity of the fluctuations of EEGs and is a more effective approach compared to the traditional linear power spectral density (PSD) measures of EEG activity in patients with neurodegenerative disorders. In this study, we applied MFDE to EEG signals to distinguish high schizotypy (HS) and low schizotypy (LS) individuals. The study includes several trials from 29 participants psychometrically classified as HS (n=19) and LS (n=10). After preprocessing, MFDE was computed in frontal, parietal, central, temporal and occipital regions for each participant at multiple time scales. Statistical analysis and machine learning algorithms were used to calculate the differences in MFDE measures between the HS and LS groups. Our findings revealed significant differences in MFDE measures between LS and HS individuals in the delta frequency band (at time scale 100 ms). HS individuals exhibited increased complexity and irregularity compared to LS individuals in the delta frequency band particularly in the occipital region. Furthermore, the MFDE measures resulted in high accuracy (96.55%) in discriminating between HS and LS individuals and outperformed the models based on power spectrum, demonstrating the potential of MFDE as a neurophysiological marker for schizotypy traits. The increased non-linear fluctuation in delta frequency band in the occipital region of HS individuals implies the changes in cognitive functions, such as memory and attention, and has significant potential as a biomarker for schizotypy and proneness towards psychosis.

INDEX TERMS Schizotypy, EEG, nonlinear analysis, complexity, multiscale fluctuation dispersion entropy.

I. INTRODUCTION

Schizotypy is a mild stage of psychosis consisting of three dimensions, namely positive syndrome (paranormal beliefs, delusional beliefs, hearing voices, magical thinking and near-death experiences), negative syndrome (social and physical anhedonia) and disorganisation (illogical thinking and speech, poor concentration and memory) [1], [2], [3], [4]. Disorganisation also consists of poor selective attention and anxiety in social interaction [5], [6], [7]. These traits are common in the general population [8], [9]. Schizotypy denotes psychosis-like experiences but remains latent in the sub-clinical population [2]. Thus, studying schizotypy is important for understanding the risk factors for subsequent onset of schizophrenia (or other spectrum disorders).

Electroencephalography (EEG) is a non-invasive and inexpensive neuroimaging technique and it provides reliable indicators for proneness towards psychosis [10], [11]. Several

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studies have identified altered resting-state EEG activity in schizotypal individuals [11], [12], [13], [14], [15]. Fuggetta et al. [11] observed higher alpha oscillation in the parieto-occipital brain regions in high schizotypy (HS) individuals which may be related to abnormal heightened attention. Frontal alpha asymmetry is another potential biomarker of vulnerability for psychosis. Two studies examined frontal EEG asymmetry in alpha [12], beta2 and gamma frequency bands at rest [13]. Both studies reported a reduction in left, relative to right, frontal asymmetry for HS individuals. These findings align with the prevailing research on decreased motivation and consciousness, and emotional impairment in individuals with schizotypal traits [4], [16]. Additionally, Chen et al. [14] examined gamma frequency power in the first-degree relatives of schizophrenia patients, and they were assessed for schizotypal personality traits. They found an inverse association between gamma frequency band power in the mid-line brain region in resting-state eyes-closed and eyes-open EEG and schizotypal personality traits in the first-degree relatives, thus implicating diminished gamma frequency power as an intermediate phenotype of underlying genetic liability for schizophrenia.

While spectral power analysis techniques have revealed alterations in brain EEG activity in schizotypy [12], [13], [14], [15], research rarely combines comprehensive EEG analysis and machine learning techniques. For instance, we have observed this gap in the research in our previous work [17]. This gap was addressed by utilizing a directed transfer function, which was obtained from multivariate autoregressive coefficients, to assess effective brain connectivity within the same sample as the present study. This approach successfully distinguished between the HS and low schizotypy (LS) groups with an accuracy of 89.21%. The study revealed that individuals with HS had reduced brain connectivity between the parietal and prefrontal lobes than those in LS in the beta frequency band. It is worth noting that beta power is associated with greater cognitive workload [18]. These findings suggest low synchrony between regions and diffuse connectivity. Another study [19] revealed that the alpha brain connectivity is decreased in the right frontoparietal region for the HS group, and lower frontal alpha power implies more wakefulness and consciousness [20]. They classified HS and LS groups with 74.3% accuracy based on brain connectivity in the alpha frequency band. Thus, reduced connectivity between frontoparietal regions is consistently found in HS in several studies. Jeong et al. [21] employed a shrinkage linear discriminant algorithm to classify participants during an audiovisual emotion perception task. Their classification algorithm attained a zero false positive rate between the schizotypy and healthy control groups, indicating high degree of accuracy in group classification. Quite recently, Zandbagleh et al. [22] utilized machine learning approaches to differentiate between the HS and LS groups in the same sample as the present study during an auditory oddball task. They achieved an accuracy of 93.1% based on the P300 event-related potential (ERP) subcomponents derived from tensor factorization.

Prior research has shown that nonlinear dynamics are not only pivotal in adaptive cortical functioning and linked to various brain disorders but also often considered more powerful than linear methods [23], [24]. Complexity measures have the capability to reveal complex neuronal processes of the brain, which may not be possible using linear approaches [25]. To our knowledge, there is no paper studying the effect of schizotypy on the complexity of brain activity based on nonlinear dynamical analysis. Complexity refers to the amount of irregularity or randomness observed in a time series across different temporal scales and is computed by evaluating the entropy of a signal at different scales or resolutions [26]. Higher-level perceptions often arise from the combined activity of numerous neurons within cortical circuits and throughout the brain's large-scale systems [27]. By employing nonlinear dynamical methods rooted in information theory, such as entropy, it is possible to model the expansive brain activity and integrate data from diverse experimental modalities into a unified framework. Previous studies have demonstrated that collective, nonlinear dynamics play a crucial role in adaptive cortical functioning and area associated with various brain disorders [27], [28]. Consequently, entropy-based approaches have been utilized to identify nonlinear dynamics in EEG data [29]. So far, existing entropy techniques have mainly focused on measuring signal irregularity at a single temporal scale, potentially disregarding the presence of multiple inherent time-scales in EEG recordings or complexity [26], [30], [31]. To this end, we chose to apply a recently introduced complexity method, multiscale fluctuation dispersion entropy (MFDE) [23]. The MFDE technique is effective in assessing the complexity of signal fluctuations since it estimates the entropy across multiple scales [28], [29]. The significance of MFDE resides in its capacity to quantify the complexity of time series, particularly in cases where the mean value of a time series undergoes significant changes alongside the signal. While the analysis of signal fluctuations holds importance, MFDE outperforms other methods such as Multiscale Dispersion Entropy (MDE), Multiscale Fuzzy Entropy (MFE), and Multiscale Sample Entropy (MSE) in the detection of more meaningful patterns. Additionally, MFDE demonstrates robustness in the presence of baseline wanders or trends in the data and avoids the problem of undefined MSE values [32]. This measure can identify both local (at lower scale factors) and global (at higher scale factors) information within a time series [33], [34]. This characteristic makes it particularly suitable for analyzing signals of diverse domains, including biological [23], [35], mechanical [36], and financial time series [37]. These signals often exhibit intricate patterns, non-periodic fluctuations, and interactions among various components, making their analysis challenging using linear techniques. Given its capacity to capture the intricate dynamics that underlie brain function, this method has become an important tool for researchers seeking to better understand the complex brain function [23], [31].

This study aims to explore the complexity of brain activity in various frequency bands in HS and LS groups for the first time. The MFDE method is utilized to estimate the complexity of EEG fluctuations. Then, several classifiers are utilized to evaluate the efficacy of the proposed method in detecting cases of HS.

Our objective is to demonstrate the potential of MFDE as a non-linear measure compared to the commonly used traditional measure known as power spectral density (PSD). Besides using MFDE to classify HS and LS groups, for exploratory purposes, we will calculate the correlation between Schizotypal Personality Questionnaire (SPQ) scores and MFDE. We anticipate a strong correlation between this nonlinear measure and SPQ scores, in comparison to the PSD measure based on the literature reviewed above which typically reveals an association between diminished power in different frequency bands and schizotypal traits [14]. The main focus of this study is to answer two key questions: (a) How do nonlinear features differentiate between groups with HS and LS? (b) Which brain regions and frequency range play a significant role in the relationship between nonlinear measures of entropy and schizotypy?

Some EEG patterns associated with schizotypy traits may overlap with those observed in clinical conditions, such as schizophrenia or other psychiatric disorders [38], [39]. Distinguishing schizotypy-related EEG patterns from those associated with other clinical conditions is very challenging. On the other hand, late diagnosis or treatment of such psychosis symptoms may lead to unfavorable outcomes [39]. The highlights of the proposed method for addressing the aforementioned problems are summarized as follows:

1) The MFDE approach represents a novel method for quantifying the complexity of signal fluctuations.
2) Significant differences in MFDE measures between individuals with HS and LS are observed in the occipital brain region, primarily at temporal scale 25, which is associated with nonlinear EEG fluctuations related to the delta frequency band.
3) The positive correlations between MFDE and schizotypal traits are stronger compared to those between relative power and schizotypal traits.
4) This enhancement in MFDE could serve as a valuable supplementary or alternative tool to the SPQ, particularly during the initial risk of experiencing psychosis.
5) The machine learning results offer supporting evidence for the efficacy of the proposed method utilizing a single feature, thereby suggesting the potential consideration of MFDE as a biomarker for schizotypy.

II. MATERIALS AND METHODS

A. PARTICIPANTS

In this work, we employed the same dataset used in our previous study [17], [22]. A total of fifty participants were screened (aged 18-48 years) from the general population in Nottingham Trent University (NTU) based on their scores on the SPQ [40]. This test is commonly used to identify individuals with LS and HS traits in the general population. HS participants were defined as individuals who scored above 31 (out of 74) for their SPQ, whereas LS participants were those who scored below 13 (out of 74) for their SPQ. Prior to data collection, ethical approval was granted by the School of Social Sciences Research Ethics Committee at NTU (approval number 2017/232), and all participants provided informed consent before participating in the experiment. The data were collected during an emotional auditory odd-ball task [22], and post-ERP recordings were used for subsequent analysis. Specifically, we focused on the data obtained after the ERP waveform had stabilized. This ensured that the variability in the signals due to initial stimulus processing was minimized.

B. EEG DATA ACQUISITION AND PREPROCESSING

Continuous EEG signals were recorded using a BioSemi Active-Two amplifier with 64 channels and a sampling rate of 2048 Hz (Biosemi Inc., Amsterdam, Netherlands). EEG data were preprocessed using the EEGLAB toolbox [41] to remove the artifacts effectively. Following down-sampling of the EEG data to 256 Hz, all channels were re-referenced to the Cz electrode. Then, a zero-phase shift bandpass finite impulse response (FIR) filter with cutoff frequencies of 1 and 30 Hz was implemented. Visual inspection was conducted to detect and eliminate any artifactual time points, such as those related to body-movement artifacts. To eliminate any remaining ocular artifacts, independent component analysis (ICA) was performed [42]. Following artifact rejection, we selected four-second segments for each trial to be used in subsequent analysis steps.

C. MULTISCALE FLUCTUATION-BASED DISPERSION ENTROPY

The MFDE approach is based on the coarse-graining process developed by Costa et al. [30] and the concept of fluctuation dispersion entropy (FDispEn) introduced by Azami et al. [34]. To clarify, let's assume we have a univariate time series of length L: $a = a_1, a_2, \ldots, a_L$.

In the MFDE algorithm, we first divide the time series $\mathbf{u}$ into non-overlapping segments of length τ, known as scale factor. Then, the mean value of each segment is computed to derive a coarse-grained data as follows [30]:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} a_i, \quad 1 \leq j \leq \left\lfloor \frac{L}{\tau} \right\rfloor = N \tag{1}$$

It is worth noting that at this step, other coarse-graining processes can be employed [43]. However, in order to ensure clarity, we consider the principal definition within this article. Finally, the FDispEn of each coarse-grained time series $y_j^{(\tau)}$ is computed.

Now, moving to the calculation of FDispEn for univariate signal of length N: $b = b_1, b_2, \ldots, b_N$, we proceed through the following steps:

Step 1) Firstly, we map b_j ($j = 1, 2, \ldots, N$) to c classes with integer indices from 1 to c. In order to accomplish this, we employ the normal cumulative distribution function (NCDF) to deal with issues related to assigning the majority of b_i to only a few classes, particularly when the minimum/maximum values significantly differ from the mean/median value of the data [32], [34], [44]. The NCDF maps $\mathbf{b}$ into $x = x_1, x_2, \ldots, x_N$ from 0 to 1 as follows:

$$x_j = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{b_j} e^{\frac{-(t-\mu)^2}{2\sigma^2}} \, \mathrm{d}t, \tag{2}$$

where μ and σ denote the mean and standard deviation of time series $\mathbf{b}$, respectively. Subsequently, we linearly assign each x_i to an integer from 1 to c using $z_j^c = \mathrm{round}(c \cdot x_j + 0.5)$, where z_j^c denotes the j^{th} element of the classified time series [32], [34], [44].

Step 2) We define time series $z_i^{m,c}$ with respect to an embedding dimension $m-1$ and a time delay d according to $z_i^{m,c} = \{z_i^c, z_{i+d}^c, \ldots, z_{i+(m-1)d}^c\}$, $i = 1, 2, \ldots, N-(m-1)d$ [34], [44]. A fluctuation dispersion pattern $\pi_{v_0 v_1 \ldots v_{m-1}}$ is obtained by mapping each vector $z_i^{m,c}$, where $z_i^c = v_0$, $z_{i+d}^c = v_1, \ldots, z_{i+(m-1)d}^c = v_{m-1}$. The number of potential fluctuation-based dispersion patterns that can be assigned to each time series $z_i^{m,c}$ is determined by $(2c-1)^{(m-1)}$ [34].

Step 3) For each $(2c-1)^{m-1}$ possible dispersion patterns $\pi_{v_0 \ldots v_{m-1}}$, the relative frequency which is defined as:

$$p(\pi_{v_0 \ldots v_{m-1}}) = \frac{\#\{i \,\big|\, i \le N-(m-1)d, \mathbf{z}_i^{m,c} \text{ has type } \pi_{v_0 \ldots v_{m-1}}\}}{N-(m-1)d}, \tag{3}$$

where # represents cardinality. Considering m as an embedding dimension, $p(\pi_{v_0 \ldots v_{m-1}})$ denotes the number of dispersion patterns of $\pi_{v_0 \ldots v_{m-1}}$ that is assigned to $z_i^{m,c}$, divided by the total number of embedded series.

Step 4) Finally, based on Shannon entropy, the FDispEn value can be computed as follows:

$$\mathrm{FDispEn}(\mathbf{b}, m, c, d) = -\sum_{\pi=1}^{(2c-1)^{m-1}} p(\pi_{v_0 \ldots v_{m-1}}) \cdot \ln\left(p(\pi_{v_0 \ldots v_{m-1}})\right) \tag{4}$$

Notably, the mapping based on the NCDF used in the computation of FDispEn [44] for the initial temporal scale is consistently applied throughout all scales. Specifically, in MFDE, the standard deviation (σ) and mean value (μ) of the NCDF are set as the respective values of the principal data, and they remain unchanged for all time scales. This process resembles the maintenance of a constant value for r (usually 0.15 or 0.2 of the standard deviation of the principal time series) in the MSE based approaches [30].

D. OTHER MULTISCALE ENTROPIES

The MSE is a popular and powerful conditional entropy-based complexity metric based on sample entropy [26].

The MDE is a novel complexity measure for time series analysis that overcomes some of the limitations of MSE, such as undefined values for short signals and slow computation time [33]. This measure is based on dispersion entropy, which is a fast and robust entropy estimation method [33]. Matlab code for calculating MDE, MSE, and MFDE can be found at: https://github.com/HamedAzami.

Another newly developed entropy method, known as diversity entropy (DivE) [45], utilizes statistical probabilities of pattern similarities to depict the state distribution. This involves utilizing the distribution of cosine similarities between neighboring orbits to monitor internal pattern changes, consequently leading to more accurate complexity estimation. Simultaneously, the novel DivE approach is expanded into multiscale analysis, referred to as multiscale diversity entropy (MDivE) [45]. This extension aims to provide a comprehensive description of features by integrating it with a coarse-graining process.

E. STATISTICAL ANALYSIS

Given the data's normal distribution, a two-sample t-test (p-value < 0.05) was used to evaluate the significance of differences between the LS and HS groups. False discovery rate (FDR) correction was also used to adjust for the effects of multiple comparisons. To test for normality, a one-sample Kolmogorov-Smirnov test is utilized [46].

F. MACHINE LEARNING APPROACH

1) FEATURE EXTRACTION AND CLASSIFICATION

Features including MSE, MDE, MDivE, and MFDE have been extracted from each signal segment using a single scale factor of 25 in the occipital brain region corresponding to nonlinear EEG patterns in delta frequency band. Also, to compare the classification performance of linear and nonlinear features, PSD was used as a feature in the delta frequency band and the occipital lobe. It is worth mentioning that selection of the scale factor (frequency band) was based on the importance of delta frequency band in schizotypy. The occipital lobe is the region with the least effect of different kinds of artifacts originated from muscles, eye movement and blinking [47]. The results based on MFDE and power spectrum in this brain region and frequency band also led to most statistically significant differences between LS and HS.

To mitigate the impact of noisy segments, the median value across all signal segments was calculated for each subject. This median value was then used as a feature in subsequent analysis steps. After extracting mentioned features, three widely used classifiers, namely K-nearest neighbor (KNN), linear discriminant analysis (LDA) and support vector machines (SVMs), have been selected to differentiate between the schizotypy groups. Additionally, two ensemble classifiers (Bagged Trees and RUSBoost) were employed to evaluate and enhance the classification performance. Bagged Trees, also known as bootstrap aggregating, is an ensemble learning method that involves constructing multiple decision tree models using different bootstrapped samples from the training data. Each model is trained on a slightly different subset of the data, and the final prediction is obtained by averaging the predictions of all the trees in the ensemble. By combining the outputs of multiple models, Bagged Trees can help to reduce overfitting and improve the overall accuracy and robustness of a classifier [48], [49]. The literature highly recommends RUSBoost as a fast and effective hybrid boosting classification algorithm for evaluating imbalanced data [50]. This algorithm integrates two techniques, namely, random under-sampling (RUS) and AdaBoostM1. This algorithm performs resampling based on the weights of the samples in the training dataset. Specifically, RUS randomly removes samples from the majority class until a desired balance is achieved between the class distributions. Furthermore, RUSBoost has been shown to outperform AdaBoostM1 [51], a popular boosting algorithm that uses an ensemble method with decision trees as learners. This approach sequentially trains the next learner model on samples that were misclassified by previous learners to improve classification accuracy. This approach ensures that the algorithm focuses on difficult-to-classify examples, which can significantly enhance the overall performance of the model [51].

2) PERFORMANCE EVALUATION

In this study, leave-one-out cross-validation (LOOCV) was used to assess the performance of the classification model. This method involves using data from $N - 1$ participants for training and the remaining one for testing. By repeating this process N times, with each participant's data being held out once for testing, LOOCV can provide a more accurate estimate of the model's overall performance. The performance of the model was assessed using several measures, including accuracy, sensitivity, specificity, and F1-score.

III. RESULTS

Figure 1 shows the mean and standard deviation of MFDE for LS and HS individuals as a function of scale factor for each brain region separately. It is worth mentioning that certain scale factors, such as 4, 10, 18, and 25, have a specific association with different frequency bands in EEG signals. In particular, scales 4, 10, 18, and 25 correspond to the beta (12–30 Hz), alpha (8–12 Hz), theta (4–8 Hz), and delta (1–4 Hz) frequency bands, respectively. So, the violin plot of MFDE for LS and HS individuals for the mentioned scale factors for each brain region is shown in Figure 2.

Table 1 presents the statistical outcomes of MFDE for the LS vs. HS individuals across various brain regions for the specified scale factors. Significant group differences were observed in all regions–frontal, central, parietal, temporal, and occipital– at the same scale factor (25). Significant differences were also observed in the parietal and occipital regions in the scale factor 18 which corresponds to the alpha frequency band. Finally, the occipital region at scale factor 25 (associated with the delta frequency band) stands out as displaying the most pronounced differences between the two schizotypy groups.

TABLE 1. Scale factor and statistical differences between the LS and HS groups for MFDE in five brain regions. The most significant difference is highlighted in bold. ES represents effect size. The symbol * denotes that the FDR corrected *p*-value is less than 0.05.

Brain Region	Scale factor (ES value)	*p*-value (corrected)	*t*-value
Frontal	4 (0.146)	0.702	-0.386
	10 (0.288)	0.477	-0.759
	18 (0.738)	0.138	1.943
	25 (1.176)	0.021*	3.098
Central	4 (0.37)	0.397	-0.975
	10 (0.571)	0.222	-1.505
	18 (0.8)	0.111	2.106
	25 (1.147)	0.021*	3.022
Temporal	4 (0.398)	0.378	-1.049
	10 (0.541)	0.235	-1.427
	18 (0.609)	0.218	1.604
	25 (1.079)	0.028*	2.843
Parietal	4 (0.327)	0.439	-0.862
	10 (0.621)	0.218	-1.637
	18 (0.969)	0.047*	2.553
	25 (1.499)	0.005*	3.949
Occipital	4 (0.459)	0.315	-1.21
	10 (0.570)	0.222	-1.503
	18 (1.322)	0.011*	3.483
	25 (1.958)	**0.0003***	**5.158**

TABLE 2. The statistical differences between the LS and HS groups for MFDE, MDE, MSE, and MDivE of the brain occipital lobe signal at scale factor 25, as well its PSD in the delta frequency band. The most significant difference is highlighted in bold. ES represents effect size. The symbol * denotes that the FDR corrected *p*-value is less than 0.05.

Feature	Scale factor (ES value)	*p*-value (corrected)	*t*-value
PSD	Delta (0.822)	0.091	-2.167
MDivE	25 (0.322)	0.782	0.849
MSE	25 (1.14)	0.018*	3.004
MDE	25 (1.274)	0.015*	3.356
MFDE	**25 (1.958)**	**0.0003***	**5.158**

To demonstrate the superiority of our nonlinear approach over the linear power spectrum method, we present the relative power for the occipital brain region with a focus on four main canonical EEG frequency bands, including delta, theta, alpha, and beta bands (Figure 3). The performance of the proposed nonlinear approach (MFDE) has been compared with other commonly used nonlinear approaches, including MDE, MSE and MDivE. To facilitate this, Figure 4 illustrates a comparison between the LS and HS individuals in the occipital region at scale factor 25 for MFDE, MDE, MSE and MDivE. In addition, Figure 4 includes a comparison of the relative power in delta frequency bands between two groups of schizotypy. Table 2 displays the statistical results of the comparison between the LS and HS groups for MFDE, MDE, MSE and MDivE of the occipital lobe at a scale

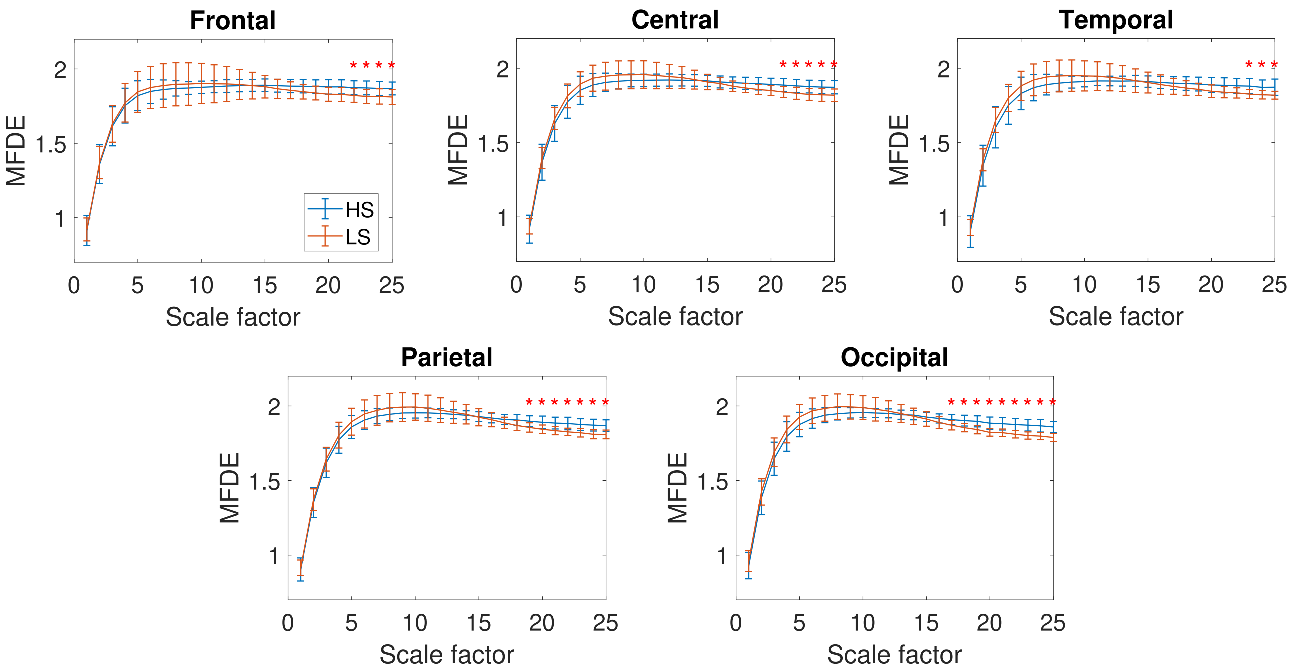

FIGURE 1. The mean and standard deviation of MFDE for the LS and HS individuals as a function of scale factor for each brain region. * represents the scale factor with significant differences ($p < 0.05$) between the LS and HS individuals.

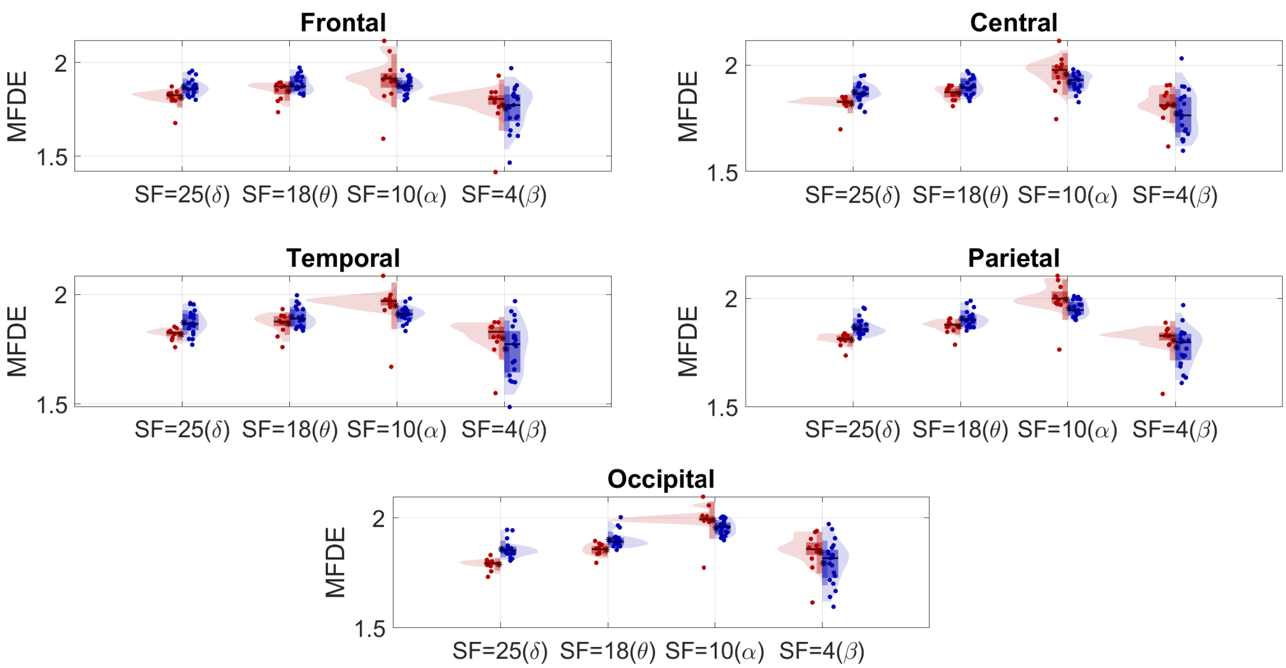

FIGURE 2. The violin plot of MFDE for LS and HS individuals using four scale factors (4, 10, 18, and 25) for each brain region. The violin plots in blue and red correspond to HS and LS groups, respectively.

factor of 25, as well as the PSD of the occipital lobe in the delta frequency band. As shown in Table 2, MFDE in the occipital brain region at scale factor 25 exhibits the most significant differences between the two groups of schizotypy (p = 0.0003, ES = 1.958). It is worth noting that among all the nonlinear measures, there is no significant difference (with the lowest ES) between the two schizotypy groups when using MDivE. Therefore, we will exclude this measure from the classification step.

A. SCHIZOTYPY CLASSIFICATION

To assess the proposed method and the reliability of linear and non-linear features for schizotypy classification, we utilized the MFDE at scale 25 corresponding to nonlinear fluctuation

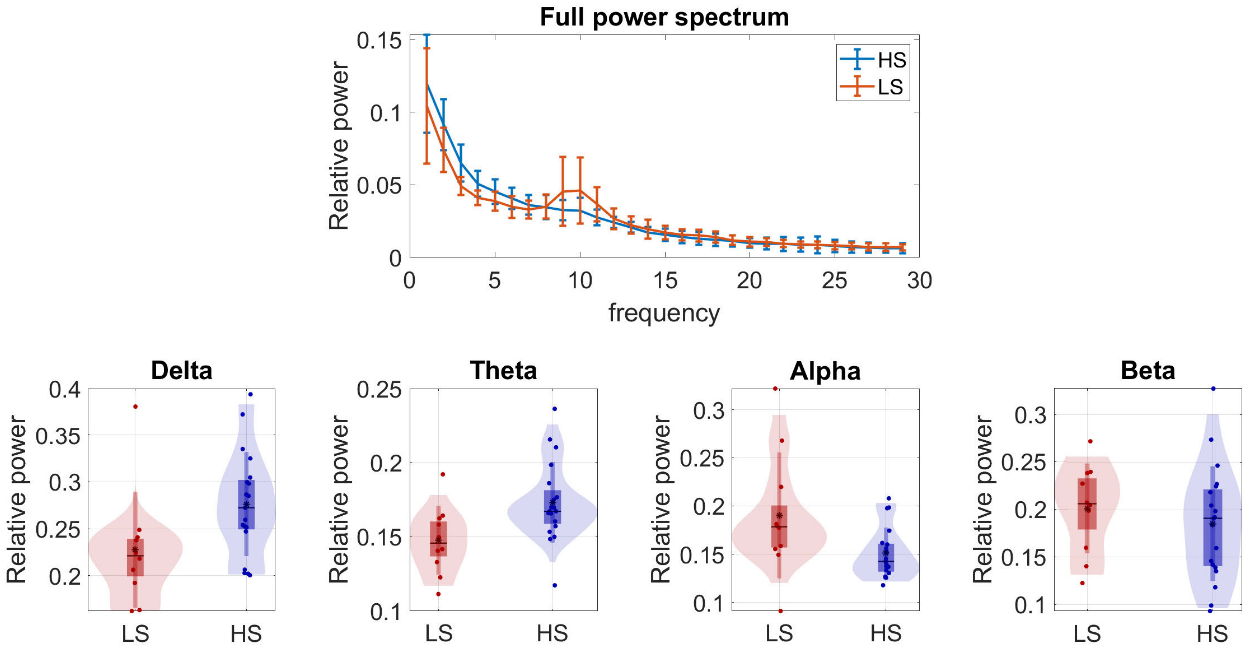

FIGURE 3. The relative power for the occipital brain region with a focus on four canonical EEG frequency bands.

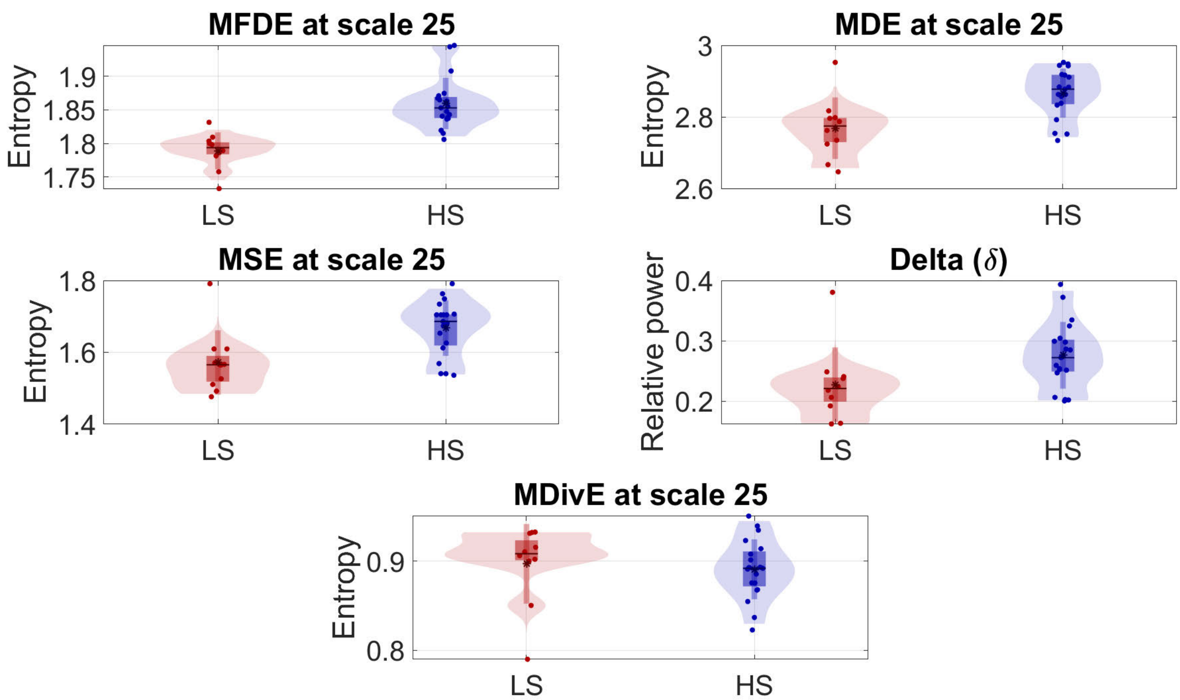

FIGURE 4. The violin plot of MFDE, MDE, MSE, MDivE and relative power for LS and HS individuals for the occipital region. All nonlinear analyses were conducted at scale factor 25, and the relative power was measured in the delta frequency band.

patterns in delta and the relative delta power for all the 29 participants, consisting of 19 HS and 10 LS. After testing was completed on all participants, the confusion matrix was calculated based on the results. As previously mentioned, one participant was reserved for use as a test set, while the remaining 28 participants were included in the training set. The results of the proposed method are shown in Table 3, which presents various metrics used to evaluate the method's classification performance. These metrics include accuracy, sensitivity, specificity, and F1-score. The results indicate that

TABLE 3. The classification performance of various EEG features using different classifiers for the occipital lobe electrodes.

Feature	Classifier	Accuracy (%)	Sensitivity(%)	Specificity (%)	F1-score
PSD	KNN ($K = 9$)	68.96	78.94	50	0.76
	LDA	62.06	78.94	30	0.73
	Linear-SVM	62.06	78.94	30	0.73
	Bagged Trees	72.41	78.94	60	0.78
	RUSBoost	79.31	89.47	60	0.85
MSE	KNN ($K = 9$)	68.96	73.68	60	0.75
	LDA	68.96	78.94	50	0.76
	Linear-SVM	75.86	78.94	70	0.81
	Bagged Trees	72.41	68.42	80	0.76
	RUSBoost	79.31	89.47	60	0.85
MDE	KNN ($K = 9$)	68.96	78.94	50	0.76
	LDA	72.41	84.21	50	0.8
	Linear-SVM	68.96	78.94	50	0.76
	Bagged Trees	79.31	78.94	80	0.83
	RUSBoost	75.86	89.47	50	0.82
MFDE	KNN ($K = 9$)	89.65	89.47	90	0.91
	LDA	89.65	89.47	90	0.91
	Linear-SVM	93.1	94.73	90	0.94
	Bagged Trees	75.86	84.21	60	0.82
	RUSBoost	**96.55**	**100**	**90**	**0.97**

the MFDE feature with a scale factor of 25, which is related to the delta frequency band, in the occipital lobe is highly effective in identifying individuals with high schizotypal traits through classification performance. It is evident that using just one feature, the RUSBoost classifier correctly identified most of the participants (28 out of 29).

B. CORRELATION ANALYSIS

Figure 5 illustrates the correlation between MFDE at scale factor 25 and several SPQ scores, namely total SPQ score and the cognitive perceptual, interpersonal, and disorganization subscales of the SPQ in the occipital brain region. As can be observed, the correlations between the MFDE complexity measure at scale 25 and schizotypal traits were stronger compared to those between relative power and schizotypal traits. From the correlation analysis results, it is evident that the brain complexity correlated positively with all the SPQ scores. Additionally, the highest correlation was observed between MFDE and SPQ disorganization scores. It is worth noting that a higher total SPQ score indicates a greater likelihood of having schizotypal personality traits. The Disorganization subscale assesses disordered thinking, speech, and behavior, including eccentricity, constricted affect, and odd speech patterns [40]. The Cognitive-Perceptual subscale, which measures an individual's tendency to experience unusual perceptions, thoughts, and beliefs, includes items related to magical thinking, ideas of reference, perceptual aberrations, and odd beliefs. The Interpersonal subscale measures an individual's ability to form and maintain close relationships, including the degree of social anxiety, discomfort in social situations, and lack of close friends.

C. COMPUTATIONAL TIME

This study was conducted on a Windows PC equipped with a 2.50GHz Intel (R) Core (TM) i5-10300H processor and 16GB RAM by utilizing MATLAB 2019a. We set the embedding dimension ($m = 2$), the number of classes ($c = 6$), and the time lag ($tau = 1$) for both MFDE and MDE [23], [32]. Additionally, we employed $m = 2$ and $r = 0.2$ times the standard deviation of the signal for the calculation of MSE [52]. For MDivE, we set $m = 2$ and intervals ($e = 10$) [45]. To assess the computational time of both the complexity methods, a single four-second segment containing 1024 samples was used. The computational times are as follows: MFDE: 0.011 ms; MDE: 0.011 ms; MSE: 0.013 ms; and MDivE: 0.014 ms, demonstrating that all the complexity approaches exhibit efficient computational speed.

IV. DISCUSSION

Schizotypy represents an important vulnerability-state in healthcare systems worldwide as it serves as a potential precursor to various mental disorders [53]. It has been reported that 75% of the British population has had one or more paranormal experiences [9]. Six percent of Australian adolescents aged 11 to 12 years old have high levels of the core schizotypal traits, namely cognitive disorganization, impulsive non-conformity, introversion, and self-other disturbance [8]. It has been found to be ten times more prevalent in families of individuals with schizophrenia compared to those with depression [38]. Early identification of these tendencies through schizotypy diagnosis can facilitate prompt preventive intervention of emerging mental disorders [54]. Conversely, delayed diagnosis and treatment of psychosis-like symptoms are associated with worse outcomes in patients with psychosis [39]. Advances in signal processing and machine learning technologies present promising opportunities for the early detection and efficient monitoring of such disorders. Considering the convergence of empirical and computational advances, it is essential to study the brain complexity of this personality trait to improve its diagnosis and treatment efficiency.

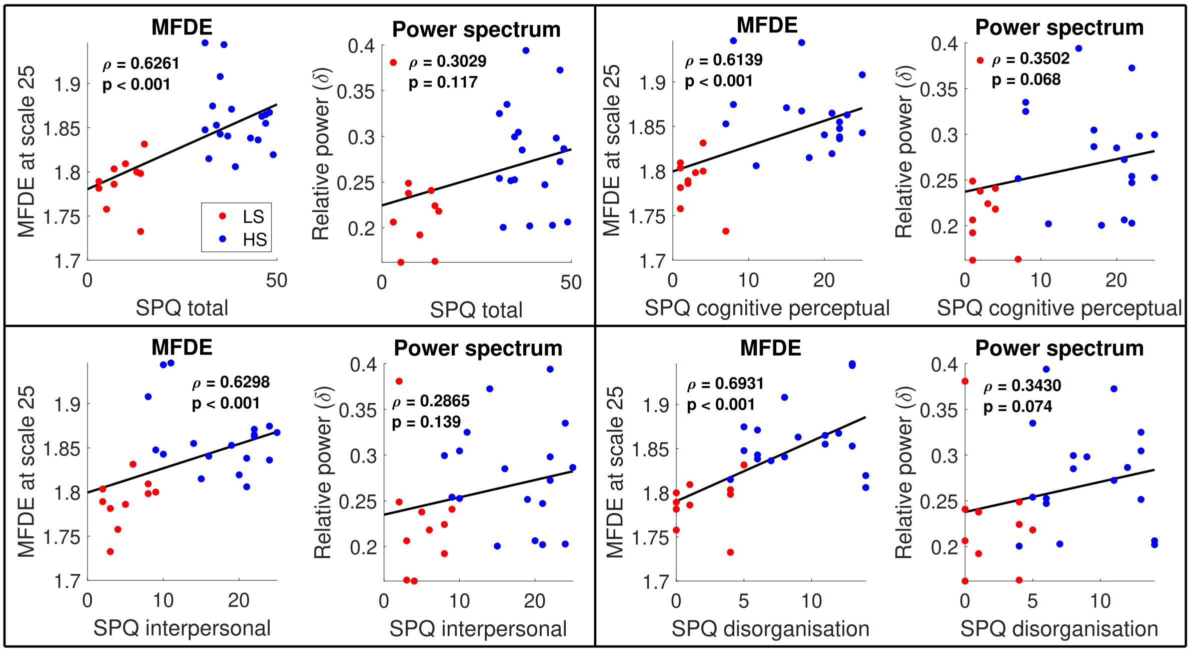

FIGURE 5. **Correlation between both MFDE (with a scale factor of 25) and relative power in the delta frequency band, and several SPQ scores including total SPQ score, cognitive perceptual, interpersonal, and disorganisation in the occipital brain region. ρ = Spearman's rho.**

To the best of our knowledge, this is the first time a study investigates the relationship between MFDE as a fluctuation-based complexity metric and the level of schizotypy. Our results indicated that brain electrical activity in the occipital lobe of individuals with HS, as measured by the MFDE at scale factor 25 (related to the delta frequency band; scale factor τ corresponds to fs/(2*τ) [43]), exhibits the most significant differences when compared to those with LS. Although there are no group differences when employing MDivE as a nonlinear method, the other nonlinear measures of EEG dynamics in the occipital lobe, i.e. MSE and MDE, yielded analogous results when using the same scale factor as MFDE and demonstrate significant differences between the two groups.

Our results showed that the entropy and the relative power of HS participants' EEGs are higher than those of LS participants in the delta frequency band. Dimitriadis et al. [55] found that an increase in delta band power was associated with an improved performance of mental calculation tasks, suggesting that this frequency range may play a main role in cognitive processes. Specifically, delta band activity reflects the engagement of attentional resources necessary for solving complex cognitive tasks. Overall, delta frequency appears to play an crucial role in regulating various aspects of cognitive functioning, particularly those related to attention and memory [56]. Furthermore, our findings are consistent with the studies of schizophrenia suggesting an increase in low-frequency power specifically at delta and theta frequencies as observed through EEG analysis [57], [58], [59], [60]. On the other hand, studies conducted using EEG on both schizophrenia patients and their relatives [58], [61] have revealed higher levels of low-frequency power exclusively in patients. This implies that increased power in the low-frequency range, such as delta frequency, may be linked to psychotic symptoms [57]. In other words, these results could indicate the effect of schizotypal traits, not its cause. Thus, further investigation is required to elucidate how these modifications may heighten vulnerability for psychosis.

Previous research has suggested that the occipital region plays a main role in a certain cognitive processes, including visual processing and attentional control, which may be disrupted in individuals with schizotypal traits [62]. Apart from that, this region plays a vital role in examining the disconnection hypothesis in individuals with schizotypal traits. Hu et al. [15] demonstrated that the positive schizotypy group exhibited smaller regional differences in the strength of alpha connectivity compared to the control group. This diffuse pattern was observed between frontal and occipital regions as well as between central and occipital regions. This effect suggests a more widespread pattern of connectivity in the positive schizotypy group, indicating a reduction in local computational processing or a lack of synchrony between brain regions. On the other hand, individuals with higher levels of negative schizotypy showed a greater difference between the occipital region and other regions in terms of the number of significant connections arising from each node, as compared to the control group. This observed effect implies an inhibition of information flow from the occipital region in individuals with negative schizotypy.

Recent research suggests that MFDE holds promise as a valuable tool for neurological conditions like Alzheimer's disease (AD) and this method has potential to assess neurodegenerative diseases [23], [24] besides schizotypal traits. The potential of EEG entropy during resting-state EEG and Rapid Eye Movement (REM) sleep to distinguish subjects with AD and healthy controls was evaluated [23], [24]. The findings revealed significant differences in EEG entropy based on MFDE during resting-state and REM sleep between individuals with AD and healthy controls. Thus, it is plausible to hypothesize that alterations in MFDE may be associated with schizotypy due to such cognitive alterations in learning and memory arising from disorganisation.

The correlation analysis between MFDE and certain schizotypy scores further demonstrated its superiority over the PSD-based approach. The results related to MFDE in the delta frequency band exhibited a significant and positive correlation with all schizotypal traits. This greater delta activity denoting aspects of cognitive functioning, namely attention and memory, may complement the disrupted concentration characterized by disorganization. Furthermore, the relative power of the delta frequency band did not exhibit such a significant correlation. This finding suggests that MFDE may be a more powerful tool for evaluating the relationship between the nonlinear patterns of EEG and schizotypy scores than the popular relative PSD-based metrics. All the classifiers achieved high levels of accuracy in evaluating schizotypy using only one feature, indicating that the MFDE is a highly informative and powerful metric for this purpose. Overall, the results suggest that the MFDE of EEG may have a potential to be considered as a biomarker for assessing schizotypy.

V. LIMITATIONS OF THE STUDY

In spite of the interesting findings based on MFDE to extract meaningful nonlinear features of EEG (having a high classification accuracy and significant correlation with SPQ scores), the analysis was based on a small sample. The empirical evidence underscores the pivotal role of convolutional neural networks (CNN) in EEG analysis [63]. Hence, in instances where the sampling size is sufficiently substantial, it is recommended to integrate a diverse array of features encompassing both linear and nonlinear elements, alongside metrics for brain connectivity. Employing this approach holds the potential to create engender the creation of a robust diagnostic tool for the early identification of this particular personality trait. Therefore, future studies should examine a larger number of participants. Additionally, it is recommended that future studies aim for more balanced data in terms of factors such as sex, age, and group sample sizes to ensure that the results accurately and robustly reflect the broader population. Also, future studies may gain advantages by including other significant demographic factors, such as diverse ethnic, as these factors could enhance the system's reliability and robustness for clinical diagnosis and possibly for use in some advanced denoising algorithms, such as multiscale principal component analysis (MSPCA) [64], [65], [66], known to yield valuable and robust outcomes in certain EEG studies. This can be achieved by employing larger and more diverse cohort datasets, ultimately leading to improved accuracy and robustness. Graphical features play a substantial role in enhancing the interpretability and readability of EEG signals [67]. Therefore, we are adopting graphical features as our research direction to further enhance the interpretability of results.

VI. CONCLUSION

This study is the first attempt to use MFDE, a measure of nonlinear complexity, to characterize EEG fluctuations in schizotypy. We found significant differences in MFDE values between the LS and HS groups at scale factor 25 (time scale 100 ms), which corresponds to the nonlinear EEG fluctuations associated with the delta frequency band. The HS individuals exhibited increased complexity, particularly in the occipital region. Moreover, machine learning techniques provided evidence to support this claim. These features led to a high classification accuracy (96.55%) in discriminating the HS from LS groups. Overall, these findings suggest that MFDE has the potential to be a valuable tool for researchers investigating the neural basis of complex psychological constructs in schizotypy. However, further research on a larger schizotypal sample is needed to better understand the properties of the MFDE in the delta frequency band before it can be considered as a biomarker of schizophrenia given the predictive status of schizotypy towards schizophrenia.

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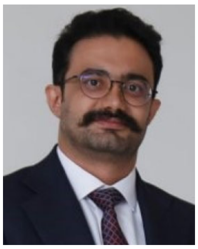

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