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Analysing and Investigating the Effect of Heroin Use Disorder for the Changes of Distinguishing Features in Brain Signal Processing

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ABSTRACT

Heroin use disorder alters brain function, leading to significant changes in EEG signals. This study proposes a novel approach to identify distinguishing EEG features in heroin addicts and healthy individuals by integrating frequency and non-frequency domain features. The methodology consists of four main stages: (1) Preprocessing, where EEG signals undergo a 50 Hz notch filter and a Butterworth low-pass filter (0.4–45 Hz) to remove noise and artefacts; (2) Feature Extraction, in which both frequency-domain features (power spectral density in alpha, beta, theta, and delta bands) and non-frequency-domain features (approximate entropy, permutation entropy, wavelet entropy, and fractal dimensions of Katz and Petrosian) are computed; (3) Feature Selection, where the Davies–Bouldin index is employed to determine the most discriminative features, independent of the number of clusters; and (4) Analysis and Interpretation, which highlights that approximate entropy in the Cz channel and power spectral density in the upper alpha band in the O1 channel provide the highest discriminative power. Compared to previous studies that primarily rely on frequency-domain features, this approach captures both linear and nonlinear dynamics of EEG signals, leading to improved differentiation between addicted and healthy individuals. While the method demonstrates high accuracy, its sensitivity to EEG preprocessing and the need for larger datasets remain key considerations. The findings suggest that this framework can contribute to more effective addiction diagnosis and monitoring, with potential integration into machine learning-based EEG classification models.

1 | Introduction

The effect of drug use on neurotransmitters in different areas of the brain, especially in the reward area, leads to the feeling of pleasure, which brings about changes in other parts and functions of the brain [1, 2]. Heroin or diamorphine is a highly addictive drug, derived from morphine, and is usually found as a white or brown powder. Over time, heroin use disorder affects people's lives widely, causing sexual and psychological disorders, digestive

problems, and damage to heart and brain health. Heroin and other powerful drugs have killed many people around the world [3, 4]. Heroin use significantly affects the user's brain, impairing their ability to properly interact with their surroundings [5, 6].

One of the effective ways to answer this challenge is to use brain signal processing to treat or diagnose drug addiction [7, 8]. Electroencephalography (EEG) has been widely used in investigating brain dysfunction for various samples in many researches [9, 10].

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Recording signals is considered as the first step in brain signal processing. Pre-processing is a critical step that is performed after recording and storage, because the signals are undoubtedly affected by noise and external interferences [11, 12]. When the brain signal is cleaned of hand-effects and interferences, feature extraction is performed due to the large volume of collected electroencephalogram (EEG) signal data [13, 14]. Feature extraction is used to reduce the amount of data by creating new features from the initial measurement data set. The extracted features contain information related to diagnosis or treatment [15, 16]. Feature extraction occurs in time domain, frequency domain or time-frequency domain and nonlinear [17, 18].

1.1 | Review of Related Studies

In the field of treatment or diagnosis of heroin use disorder using brain signal processing, many researches have been done to determine the distinguishing features and affected areas in the brain due to heroin consumption [19, 20]. In some researches, different statistical methods have been used to evaluate the power spectrum frequency differences between healthy people and people addicted to heroin [21, 22]. Nonlinear dynamic analysis, and source localization analysis, have been used in [23] to examine resting state EEG data for comparison between heroin addicts and healthy individuals. From the results of nonlinear features such as correlation dimension and Kolmogorov entropy, it has been significantly observed that the EEG signals are more irregular in the alpha band for people addicted to heroin compared to healthy people. In [24], three groups of 40 people have been tested, one group of which is heroin addicts and the other group of healthy people. The comparison results show that cognitive impairment with lower cognitive scores have significant differences in relation to abnormal EEG changes among the three study groups. In [25], the resting EEG spectrum of beta, alpha, theta, and delta rhythms in 32 patients undergoing chronic methadone maintenance treatment, 17 opioid users, and 25 healthy individuals were investigated using repeated measures analysis of variance. The results show a significant increase in the power of the beta and theta bands of the other two groups compared to healthy people. Also, there is an inverse correlation between the power of beta or theta bands and cognitive performance. In [26], the use of event-related potentials (ERPs) is proposed to investigate the processing of visual information related to heroin. Neutral and heroin-related pictures were presented to 33 men, including 19 heroin-dependent people and 14 healthy people. The results show that the processing of drug-related information is abnormal in heroin-dependent patients. Identifying the functional system abnormality of the brain of heroin addicts at rest, using brain source analysis and analysis of effective communication tools, is presented in [27]. The results in 15 male addicts and 14 male addicts show that chronic heroin abuse causes brain functional abnormalities. P300 is a positive deviation in a person's brain signal, which is created about 300 ms after the presentation of the target stimulus. This wave is an event-dependent potential, and it is extracted in the decision process. P600 is revealed in visual and auditory stimuli, and it will be observed in about 500 ms after applying the stimulus, and it will reach its peak in about 600 ms. The increase in beta and alpha two power activity, the delay of P300 and P600, as well as the reduction of the P300 and P600 amplitude are among the effects of chronic heroin use disorder

[28, 29]. In [30] P300 components among people addicted to several types of drugs and healthy people have been investigated and compared. The results show that the range and latency of P300 in people addicted to gamma-hydroxybutyrate (GHB) is significantly lower and longer than the methadone maintenance treatment (MMT) group and the healthy controls (HC) group. Also, for all three types of addiction, P300 amplitude in Fz, Cz, Pz, T5, and T6 channels has a negative correlation.

The spectral power of electroencephalography and the negative amplitudes and latencies of mismatch P300 and P600 components have been investigated in [31], where the test subjects include 19 heroin-addicted males and 19 healthy subjects. The results show higher beta power among heroin addicts, while showing a decrease in delta, theta and alpha powers compared to healthy subjects. Also, increasing attention to stimuli related to heroin can be concluded from the increase of P300 in response conditions among heroin addicts.

In [32], a statistical analysis for the relative frequency of wave bands from 30 EEGs recorded for three groups of addicts, under treatment and control (normal) has been done, each group of subjects is 10 people. The results show that the higher average range belongs to addiction subjects. Also compared to the signal source, the P300 channels presented a slightly higher average amplitude than the other channels in all subjects.

Changes of brain electrical activities using EEG spectral analysis and single-trial event-related potential measurements are presented in [33]. The results of examining the cognitive characteristics related to P300 show abnormal brain activities mainly in the beta band. They also confirm the decrease in the ability to process information among heroin addicts compared to healthy people.

The frequency domain features investigated in the above studies, such as the power spectrum or the P300 component alone, may omit some important information necessary to distinguish between healthy subjects and addicted subjects. Considering the dynamic nature of brain signals, it is also necessary to consider non-frequency characteristics. Research results show that the P300 component is different among heroin addicts, heroin quitters and healthy individuals during short-term memory tests. In [34], the P300 component was analysed in heroin addicts, former heroin users, and healthy individuals during a short-term memory test. The study involved 20 former heroin users (at least 6 months after quitting), 18 current heroin users, and 20 healthy controls matched in age, gender, and education level. The results indicated a significant reduction in the P300 amplitude in the fronto-central region among former heroin users compared to the other two groups. While this study considered demographic information and its impact on brain signals, it was limited to examining only the P300 component, whereas heroin use disorder affects multiple EEG components and sub-bands. In [35] investigated EEG signals in individuals undergoing heroin withdrawal. The study focused on P300 amplitude and found that the normalization of P300 was associated with prolonged abstinence from heroin use when comparing healthy individuals with former addicts. However, the analysis was performed only in the time domain, making it susceptible to EEG noise and artefacts, which

can significantly affect amplitude measurements. Although preprocessing techniques can mitigate these interferences, the results still remain influenced by them. In [36], EEG signals from ten heroin users and ten healthy individuals were analysed for P300 variations. The findings showed that P300 amplitude increased with heroin use, indicating that drug consumption directly affects cognitive processing. However, the study suggested that analysing additional EEG components and sub-bands could provide more comprehensive results. In [37] reported that relative power and central frequency of EEG sub-bands in heroin users showed statistically significant differences compared to healthy controls, particularly in the alpha and beta bands.

The reviewed studies indicate that heroin use disorder affects P300 amplitude, EEG spectral power, inter-band coherence, and brain asymmetry. However, most of these studies focus solely on either time-domain (e.g. P300) or frequency-domain features (e.g. spectral power analysis), without integrating both frequency and non-frequency features for a more comprehensive assessment. Furthermore, existing methods often rely on conventional feature selection approaches that lack robustness in distinguishing critical EEG patterns. Our study bridges these gaps by combining frequency-domain (power spectral density) and non-frequency-domain (entropy and fractal dimension) features to enhance heroin use disorder detection. Additionally, we employ the Davies–Bouldin index, a clustering-independent feature selection criterion, to systematically identify the most discriminative EEG channels. Our findings suggest that the Cz and O1 channels exhibit the highest distinguishing capability, providing a more refined framework for EEG-based addiction analysis.

1.2 | Research Highlights

This study presents a novel methodology for EEG-based heroin use disorder analysis, integrating both frequency-domain and non-frequency-domain features to enhance classification accuracy. While previous research primarily relied on power spectrum analysis, our approach extends feature selection by incorporating entropy-based measures (approximate and permutation entropy), fractal dimensions (Katz and Petrosian), and wavelet entropy, providing a more comprehensive characterization of brain signal complexity. A key advancement in this study is the application of the Davies–Bouldin index, which, unlike traditional methods such as Silhouette and Dunn indices, is independent of the number of clusters and provides a robust criterion for selecting the most discriminative EEG features. The results indicate that approximate entropy in the Cz channel (channel 11) and power spectral density in the upper alpha band in the O1 channel (channel 15) exhibit the highest discriminative power, highlighting the importance of nonlinear characteristics in addiction-related neural alterations. These findings not only contribute to improving EEG-based classification accuracy but also emphasize the necessity of integrating both frequency and non-frequency features for a more precise differentiation between addicted and healthy individuals. However, the proposed approach has certain limitations, including the need for larger datasets to ensure generalizability and its dependence on high-quality EEG preprocessing. By comparing our method with prior studies, we demonstrate that while many existing works focused solely on frequency-based features, our research bridges

the gap by incorporating both feature domains and employing an advanced feature selection criterion. These findings provide valuable insights into the neurological impact of heroin use disorder and pave the way for more effective diagnostic and monitoring techniques, including machine learning-driven EEG classification models. Based on existing research and their results, there is still no consensus on distinguishing features. For this reason, the purpose of this paper is to select appropriate and differentiating features to identify heroin addicts and healthy people based on individual features, which is done using the feature selection method. The innovation of this study can be briefly mentioned as follows:

- Identification of distinguishing features for detecting addiction in brain signals.
- Examination of time-domain and frequency-domain features for identifying distinguishing characteristics.
- Introduction of a new database for addiction detection based on brain signals.

1.3 | Structure of the Paper

The following is the structure of the paper. After stating the problem and the importance of the issue, the research database is mentioned in Section 2. In Section 3, the proposed method for selecting distinctive features in a healthy person and an addicted person is stated. Section 4 contains the evaluation and analysis of the results. Section 5 compares the results of this study with other researches. Finally, Section 6 provides conclusions and suggestions.

2 | Proposed Research Method

The method used in this research is shown in the block diagram of Figure 1. As can be seen, the proposed method includes three stages of pre-processing, feature extraction and feature evaluation. In this section, these three stages are briefly mentioned.

In this research, the database of EEG signals for addicted people and healthy people has been used [38]. This database contains EEG signals, recorded from 16 channels according to the international 10–20 system. The placement of the electrodes is shown in Figure 2. As can be seen, it includes the right ear reference and ground connection to the front channel (Fpz) with a sampling frequency of 256 Hz. It should also be noted that the EEG signals were recorded using the gUSBamp device manufactured by g.tec Medical Engineering GmbH.

2.1 | Dataset Under Study

The test samples in this study include 15 addicted people who are quitting heroin, and 15 healthy people with no history of drug or alcohol use or smoking, all of whom voluntarily and knowingly participated in the test. The participants are male and right-handed. First, an informed consent form was presented to the participants. Then, both groups completed the 28-question

EEG Signal Processing Workflow

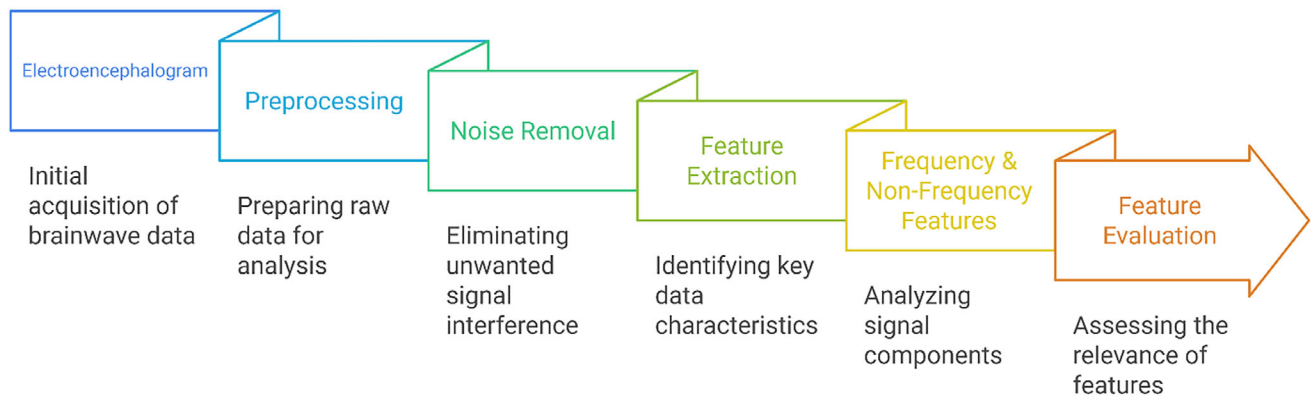


FIGURE 1 | Block diagram of the proposed research method.

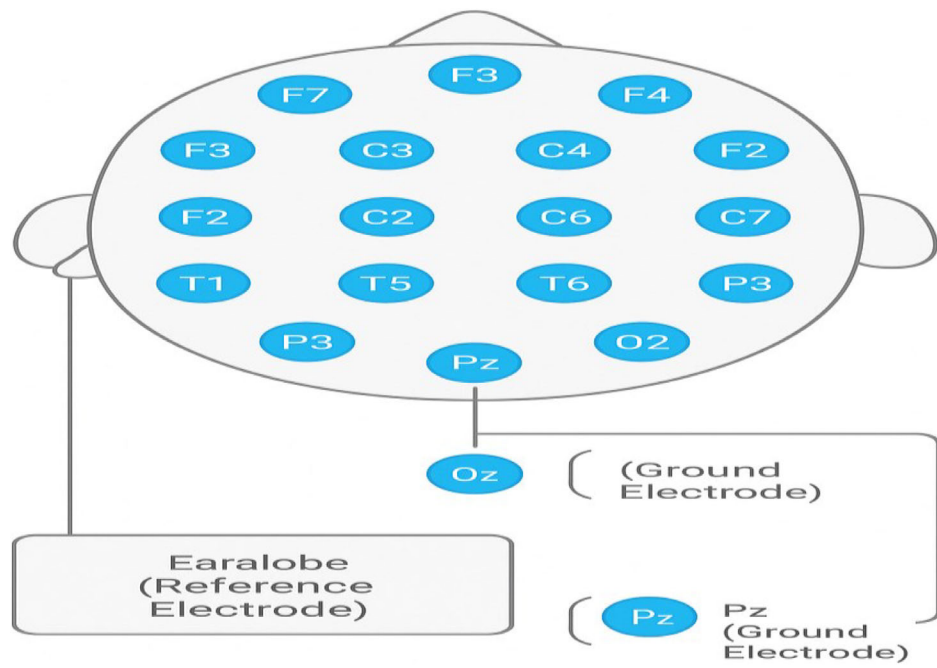


FIGURE 2 | Electrode placement.

general health questionnaire (GHQ-28). Also, addicts were asked to complete the 45-question Heroin Craving Questionnaire (HCQ-45), which was designed to evaluate their desire and willingness to become addicted to heroin. This questionnaire is used to evaluate the degree of dependence on drugs and confirm the state of addiction. In this questionnaire, physical symptoms, anxiety/insomnia, social dysfunction, severe depression, mood disorders, anxiety disorders, childhood disorders, and other related issues are considered. Participants who had psychiatric disorders or genetic or family history of neurological and related diseases were excluded from the trials. Other details of the participants are given in Table 1.

2.2 | Data Preprocessing

MATLAB software was used to process and analyse the recorded data. In the initial stage of preprocessing, a notch filter centred

at 50 Hz was applied to eliminate power line interference, which is commonly present in industrial and laboratory environments in Iran. This filter effectively suppressed strong and disruptive components at 50 Hz, thereby improving the signal-to-noise ratio and enhancing the accuracy of subsequent EEG feature extraction. Next, a sixth-order Butterworth low-pass filter with a passband of 0.4 to 45 Hz was used to attenuate frequency components outside the typical range of brain activity. This filtering step aimed to reduce both high-frequency noise (such as muscular and electronic artefacts) and low-frequency noise (originating from movement artefacts, electrode drifts, and environmental fluctuations). The Butterworth filter was chosen for its flat frequency response in the passband and minimal ripples in the transition region, making it particularly suitable for EEG signal analysis. The selected frequency range preserves all major EEG bands—including delta, theta, alpha, and beta—while effectively attenuating unwanted low-frequency components (such as eye blinks and slow movements) and high-frequency artefacts.

TABLE 1 | Characteristics of participants in the study.

Attribute	Addicts	Healthy controls
Number of participants	15 men	15 men
Age (mean)	32.27 years	38.34 years
Education (years–mean)	8.67 years	15 years
Marital status	8 married, 7 single	4 married, 11 single
Duration of heroin use (years–mean)	11.2 years	–
Daily dose of heroin (grams–mean)	1.2 g	–
Duration of abstinence (days–mean)	10.07 days	–

This ensures a cleaner signal for robust and reliable feature extraction.

The removal of ocular artefacts such as eye blinks is typically not performed using simple high-pass or low-pass filters, since these can also remove important neural information [39, 40]. In this study, the application of the sixth-order Butterworth low-pass filter was primarily intended to improve the overall signal-to-noise ratio and to reduce general movement-related and environmental noise, rather than to specifically remove eye blink artefacts. Additionally, because our data were recorded in both eyes-open and eyes-closed states—and eye blinks are typically very limited in the eyes-closed condition—we did not apply dedicated advanced methods such as ICA for ocular artefact removal in this study. However, it is absolutely important to use more accurate methods such as ICA or wavelet-based approaches to remove artefacts, and they are considered in future studies to further enhance data quality and analytical accuracy.

Furthermore, the removal of artefacts caused by eye movements, such as eye blinks, was not directly performed using this method in this study. The data were recorded in both eyes-open and eyes-closed states, and eye blinks are typically very limited in the eyes-closed state. In this study, the main goal of preprocessing was to improve the overall signal-to-noise ratio and to reduce movement and environmental artefacts.

2.3 | Extracted Features

In this study, both frequency-domain and non-frequency-domain features were extracted to identify the most distinguishing characteristics of EEG signals in heroin use disorder. The motivation behind selecting these features lies in the complex and dynamic nature of brain activity, which is influenced by substance abuse [41]. Frequency-domain features, such as power spectral density, allow for the examination of energy distribution across different EEG bands, providing insights into changes in brain rhythms. On the other hand, non-frequency features, including various entropy and fractal-based measures, capture signal complexity, irregularities, and underlying neural dynamics that may not be

evident through traditional spectral analysis alone. Among the non-frequency features, approximate entropy (ApEn) [42], and permutation entropy (PE) [43] are particularly useful in analysing EEG signals, as they measure the degree of randomness and predictability in neural activity. ApEn assesses the regularity of EEG time series, where lower values indicate highly structured neural patterns and higher values reflect greater disorder and instability. This characteristic is especially relevant for studying addiction-related neural changes, as heroin consumption has been associated with increased disorganization in cognitive and neural processing. Similarly, PE evaluates the randomness of signal patterns, offering another perspective on how heroin use disorder affects the complexity of neural oscillations. Increased entropy values in heroin users suggest a loss of structured brain activity, which may be linked to cognitive deficits and impaired decision-making abilities. Additionally, fractal-based measures, including Katz fractal dimension [44], Petrosian fractal [45], dimension, and box-counting fractal dimension [46], provide further insight into the self-similarity and complexity of EEG signals. These methods help quantify the degree of irregularity in the brain's electrical activity, which may be altered in addiction due to changes in neural connectivity and network efficiency. The advantage of using these fractal dimensions is their ability to capture hidden patterns within EEG signals that may not be visible through conventional statistical analyses. Meanwhile, wavelet entropy [47], which analyses the distribution of signal energy across different time scales, may contribute to understanding alterations in brain wave organization that could be associated with heroin use disorder. By integrating these non-frequency features with power spectral analysis, this study offers a comprehensive approach to characterizing the altered brain activity in heroin addicts, which can lead to improved classification and diagnostic methods.

This dual approach combining frequency-based power spectrum analysis with non-frequency entropy and fractal measures—enables a more thorough understanding of addiction-related EEG changes. While traditional power spectrum analysis can detect shifts in specific EEG bands such as alpha, beta, and theta, the inclusion of entropy and fractal measures allows for a deeper investigation into the dynamic and nonlinear properties of brain signals. This holistic perspective ensures that subtle but significant differences between heroin-addicted individuals and healthy controls are captured, paving the way for more accurate and effective EEG-based diagnostic tools for substance use disorders. A one-dimensional vector of length m extracted by a sliding window over the signal is defined as follows:

$$u[i] = [x[i] \ x[i+1] \ \dots \ x[i+m-1]]^T \quad (1)$$

where $x[i]$ is the output after windowing, $x[i]$ is the input signal, m is the window length, and i is the sample index within the defined window. The self-similarity of the vector generated from the signal is defined by $C_{i,m}$ self-similarity based on the window applied to the signal is given by:

$$C_{i,m} = \frac{1}{N-m+1} \sum_{j=1}^{N-1} \theta(r - \|u(i) - u(j)\|_{\infty}) \quad (2)$$

where $\theta(x)$ is the step function, which is defined by Equation (3).

$$\theta(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (3)$$

When X has the highest self-similarity, $u(j)$ and $u(i)$ are very close to each other, and the value of C_i will be maximized. Based on the calculated parameters, ApEn computes the internal similarity index across all possible transitions in the sample vectors, indicating the length and resistance to changes. The approximate entropy ApEn is computed using Equation (4) [48, 49]:

$$\text{ApEn}(X, m, r) = \frac{1}{N - m + 1} \sum_{i=0}^{N-m} \log C_{i,m}(r) - \frac{1}{N - m} \sum_{i=0}^{N-m-1} \log C_{i,m-1}(r) \quad (4)$$

where $C_{i,m}$ represents the self-similarity, m is the window length, N is the total number of signal samples, and r is the overlap value in the window. Permutation entropy (PE) is a measure of the complexity of a signal. For a sample vector $u[i]$ after windowing and a permutation π_k with order m , which includes $m!$ patterns, the probability of a permutation pattern for all $k = 1, 2, \dots, m!$ is defined as the probability of occurrence of a sample vector with similar patterns. Permutation entropy calculates the likelihood that the sample vector has a pattern similar to the permutation pattern. Permutation entropy is defined as follows [50, 51].

$$P(\pi_k) = \frac{1}{N - m + 1} \sum_{i=0}^{N-m} f(u[i], \pi_k) \quad (5)$$

where N is the total number of samples. The following relation applies when $u[i]$ and π_k have similar patterns; otherwise, the value is zero.

$$f(u[i], \pi_k) = 1 \quad (6)$$

In this case, a pattern with order $u[i]$ is defined according to the elements of the original signal. Therefore, PE is defined by Equation (7) [52].

$$\text{PE} = - \sum_{k=1}^{m!} p(\pi_k) \log(\pi_k) \quad (7)$$

Wavelet entropy expresses the uncertainty of a process by calculating its wavelet transform [53].

$$\text{WEn}(X, m, B) = \frac{1}{\log(B)} \sum_{i=1}^B W(p_i) \log(W(p_i)) \quad (8)$$

where W is the discrete wavelet transform applied to the probability distribution function, X is the signal, m is the wavelet transform level, and B are the wavelet transform components. The Katz fractal dimension is a mathematical index that can measure the complexity of a signal [54]. It is a fast algorithm for calculating fractal dimensions and is used to measure signal complexity

[55, 56].

$$Lm(T) = \frac{1}{T} \left[\sum_{i=1}^{N-m} |x[m + iT] - x[(i-1)T]| \right] \left[\frac{N-a}{\left[\frac{N-m}{T} \right] T} \right] \quad (9)$$

where x is the brain signal, the partial time series over the time interval T , and the start time m for $m = 0, 1, 2, \dots$ are calculated. N is the total number of samples in a signal. The fractal dimension method, similar to a box-counting method, acts as a perimeter measurement method, where the signal is covered by a grid. The line length, sometimes considered the curve length, is the overall vertical length of the signal used to calculate the fractal dimension of the signal [57].

The Petrosian fractal dimension is a fast algorithm for calculating the fractal dimension, which is faster than the Katz fractal dimension. This fractal dimension is calculated from a binary sequence, so the first step is to convert the input signal to a binary sequence, for which there are several methods. The difference between consecutive samples is considered to calculate the fractal dimension of Petrosian, and based on the calculated value relative to the standard deviation of the window, a value of one is assigned for more, and a value of zero is assigned to it [58, 59]. Fractal dimension analysis is a powerful tool for assessing the complexity and self-similarity of EEG signals, providing valuable insights into neural irregularities caused by heroin use disorder. Unlike traditional frequency-based analysis, which examines energy distribution across specific bands, fractal dimension methods capture the dynamic, nonlinear characteristics of brain activity. In this study, three fractal-based measures were used: Katz fractal dimension, Petrosian fractal dimension, and box-counting fractal dimension. Katz's method estimates the structural complexity of EEG waveforms, while Petrosian's approach quantifies rapid signal fluctuations, making it particularly useful for detecting neural instability. The box-counting method evaluates how EEG signals scale across different resolutions, revealing changes in self-similarity patterns associated with addiction-related brain alterations. Higher fractal dimension values typically indicate greater irregularity and disrupted connectivity in neural networks, which are common in substance use disorders. By integrating these fractal features with spectral and entropy-based measures, this study enhances the ability to distinguish between heroin-addicted individuals and healthy controls, providing a more comprehensive approach to EEG-based addiction analysis. Finally, the fractal dimension is calculated from the binary sequence as follows

$$D = \frac{\log_{10}(n)}{\log_{10}(n) + \log_{10}\left(\frac{n}{n+0.4N_D}\right)} \quad (10)$$

where n is the length of the signal (number of points) and N_D represents the number of sign changes (number of dissimilar pairs) in the generated binary sequence. The box-counting method is used to estimate the fractal dimension of EEG signals by analysing their self-similarity and complexity at different scales. The EEG signal is segmented and covered with a grid of boxes of varying sizes, and the number of occupied boxes is counted at each scale. The fractal dimension is then derived by observing how the number of occupied boxes changes as the box size decreases.

This method helps capture hidden structural patterns in EEG signals, which are altered in heroin addicts due to disrupted neural connectivity and irregular brain activity. The computed box-counting fractal dimension values serve as features that enhance the discrimination between heroin-addicted individuals and healthy controls, making it a valuable addition to the feature extraction process [60, 61].

In the frequency domain, the power spectrum feature in each sub-band can be used. EEG signals are typically identified and examined in four frequency bands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (15–30 Hz), along with the sensory-motor rhythm (12–15 Hz). EEG is unique for each individual. Therefore, calculating the individual alpha frequency (IAF) and transition frequency (TF) can be used for more precise analysis.

In physiological studies, the EEG power spectrum reflects the number of neurons firing simultaneously. The power spectrum of the signal is obtained from the Fourier transform of the brain signal. Based on the overlap and Welch's method, the power spectral density is calculated using the following relation [62, 63]:

$$P_{xx}^{(i)}(f) = \frac{1}{LU} \left| \sum_{n=0}^{L-1} W(n) X_i(n) e^{-j2\pi f n} \right|^2 \quad (11)$$

where $W(n)$ is the window, L is the window length, and x is the segment of the signal within the window. U is the window normalization factor and is calculated as follows:

$$U = \frac{1}{L} \sum_{n=0}^{L-1} W^2(n) \quad (12)$$

The signal power using Welch's method is calculated by the following formula:

$$P_{xx}^i(f) = \frac{1}{K} \sum_{i=0}^{K-1} P_{xx}^{(i)}(f) \quad (13)$$

The amplitude of the EEG signal depends on various factors such as the anatomical and physiological characteristics of the brain, the surrounding tissues and the impedance of the electrode for each person, which is different for each person. These factors cause significant changes in the absolute power spectrum of the EEG signal. To compensate for these variations, the relative power spectrum is calculated as follows:

$$P_r(f) = \frac{P_a(f)}{\sum P_a(f_i)} \quad (14)$$

where $P_r(f)$ is the relative power spectrum at frequency f , and $P_a(f)$ is the absolute power spectral density at the same frequency. Research has shown that the frequency sub-band ranges of brain signals are unique to each individual and vary from person to person; therefore, the frequency range of each sub-band should be calculated separately for each individual [64]. In most individuals, after closing their eyes and being in a state of alertness, the alpha rhythm becomes dominant. When a person opens their eyes and does not engage in any specific mental activity, the alpha rhythm is blocked, and no dominant spectrum is observed in the brain signal. By obtaining the baseline brain signal of

an individual in both the eyes-closed and eyes-open states, the frequency range where the power spectrum of the eyes-closed state diverges from that of the eyes-open state can be identified. With this identified frequency range, the individual alpha peak (IAP) for each person can be calculated as follows:

$$IAP = \frac{\sum_{f=f_1}^{f=f_2} P_r(f) \times f}{P_r(f)} \quad (15)$$

where $P_r(f)$ represents the power spectrum of the signal, f is the frequency in hertz, and f_1 and f_2 are the lower and upper frequencies of the extracted alpha range for each person. After calculating the IAP and TF for each individual, the range from $TF-2$ Hz to TF Hz is considered the theta sub-band, TF to $IAP-2$ Hz as the individual's lower alpha sub-band, $IAP-2$ to IAP Hz as the second lower alpha sub-band, and IAP to $IAP+2$ Hz as the upper alpha sub-band.

In this study, a diverse set of features including frequency-domain features (power spectral density) and non-frequency features (entropy-based and fractal measures) was utilized to provide a comprehensive representation of EEG signals in the analysis of heroin use disorder. Traditional methods that rely solely on spectral power analysis often fail to capture the complexity and irregularities present in neural activities, which are critical indicators of brain changes associated with addiction. By employing entropy measures (approximate entropy and permutation entropy) to assess signal unpredictability and fractal dimensions (Katz, Petrosian, and box-counting) to evaluate self-similarity and complexity, a more holistic approach is presented that can effectively identify distinguishing features in the EEG of addicted versus healthy individuals. The results of this study offer a more robust framework for EEG-based addiction diagnosis and pave the way for advanced clinical applications, such as neurofeedback, in the analysis of addiction-related disorders.

3 | Davies–Bouldin Index

In this paper, the Davies–Bouldin index is used to evaluate the extracted features. In this index, the similarity between two features R_{ij} is defined based on the dispersion of features S_i and S_j . The similarity between two features is defined as follows [65]:

1. $R_{ij} \geq 0$
2. $R_{ij} = R_{ji}$
3. If S_i and S_j are both zero, then R_{ij} is also zero.
4. If $S_j > S_K$ and $d_{ij} = d_{ik}$ then $R_{ij} > R_{ik}$
5. If $S_j = S_K$ and $d_{ij} < d_{ik}$ then $R_{ij} > R_{ik}$.

Typically, the similarity between two features is defined as follows:

$$R_{ij} = \frac{S_i + S_j}{d_{ij}} \quad (16)$$

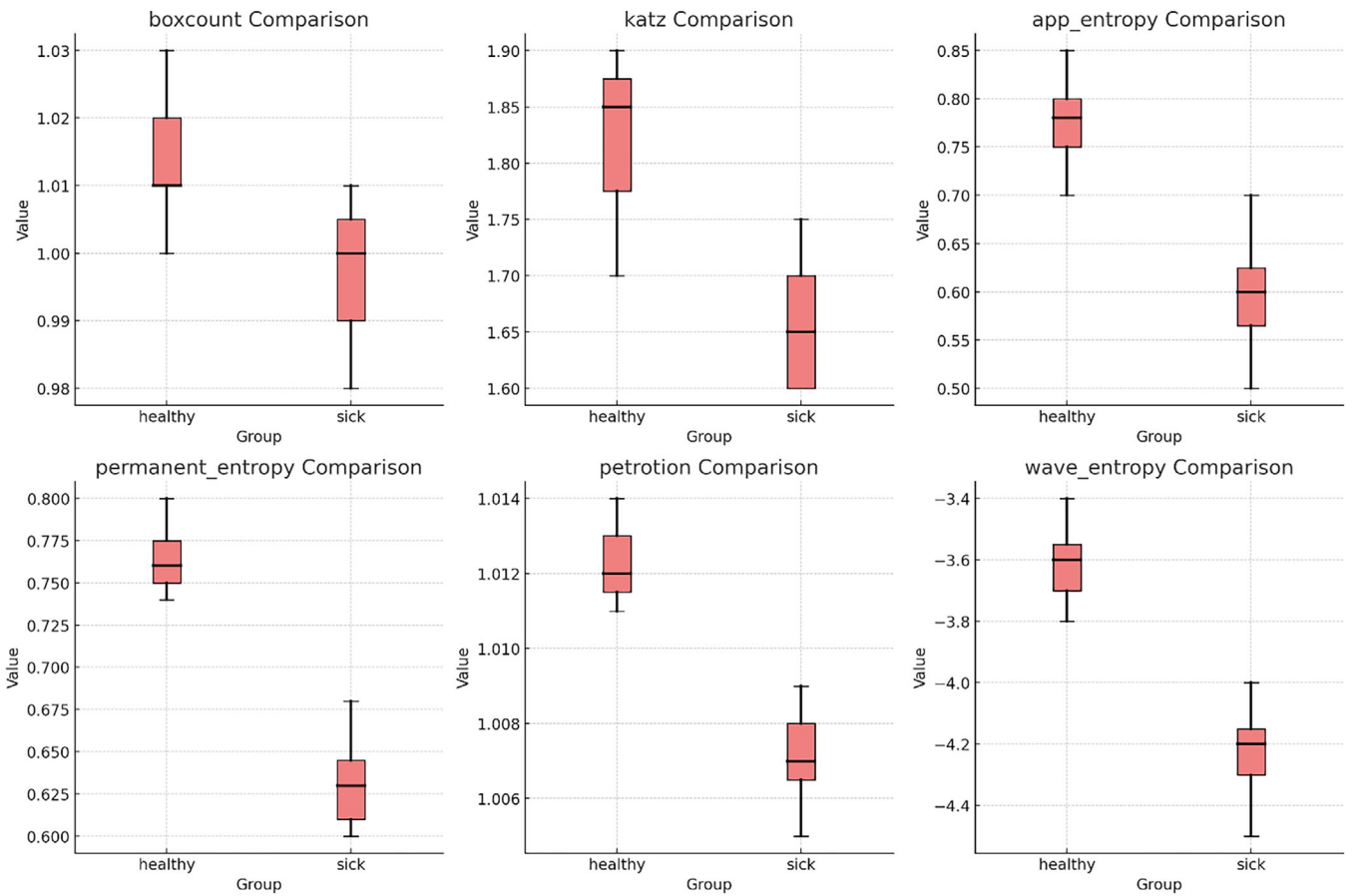


FIGURE 3 | Comparison of non-frequency features across all channels.

where S_i and S_j represent the dispersion matrices of the i -th and j -th features, respectively, which are calculated using the following equations.

$$d_{ij} = d(V_i, V_j) \quad (17)$$

$$S_i = \frac{1}{\|C_i\|} \sum_{x \in C_i} d(X, V_i) \quad (18)$$

Based on the aforementioned information and the definition of similarity between two features, the Davies–Bouldin index is defined as follows:

$$DB = \frac{1}{n_c} \sum_{i=1}^{n_c} R_i \quad (19)$$

where R_i is calculated as follows:

$$R_i = \max (R_{ij}), i = 1, \dots, n_c, j = 1, \dots, n_c \quad (20)$$

This index essentially calculates the average similarity between each feature and the most similar feature to it. In fact, the higher the value of this index, the better the feature produced.

4 | Simulation Results and Discussion

To analyse EEG signals, non-frequency features such as approximate entropy, wavelet entropy, permutation entropy, Katz fractal

dimension, Petrosian fractal dimension and box counting dimension have been extracted from different channels. Also, frequency characteristics such as relative power spectrum in different subbands in all channels were also extracted and used to differentiate between groups.

For all the participants in the test, the evaluation characteristics are compared using the graph. Figure 3 shows the difference of non-frequency characteristics for all channels in different subbands.

In addition to approximate entropy, other non-frequency features were also analysed to assess their potential in differentiating between heroin use disorder and healthy individuals. Although these features did not reach the same level of discriminative power, several of them demonstrated consistent trends. For instance, permutation entropy and wavelet entropy both showed lower values in the addicted group, suggesting a reduction in temporal complexity and energy distribution across time scales. Furthermore, the fractal dimension metrics—including Katz, Petrosian, and box-counting—were also lower in the heroin use disorder group, indicating a simplification in the structural complexity of EEG signals. These findings, while not all statistically significant at the same threshold, support the broader pattern of reduced neural complexity and signal irregularity in heroin-affected individuals, and complement the core results based on approximate entropy and spectral features. The comparison is based on the Davies–Bouldin index with a significance level

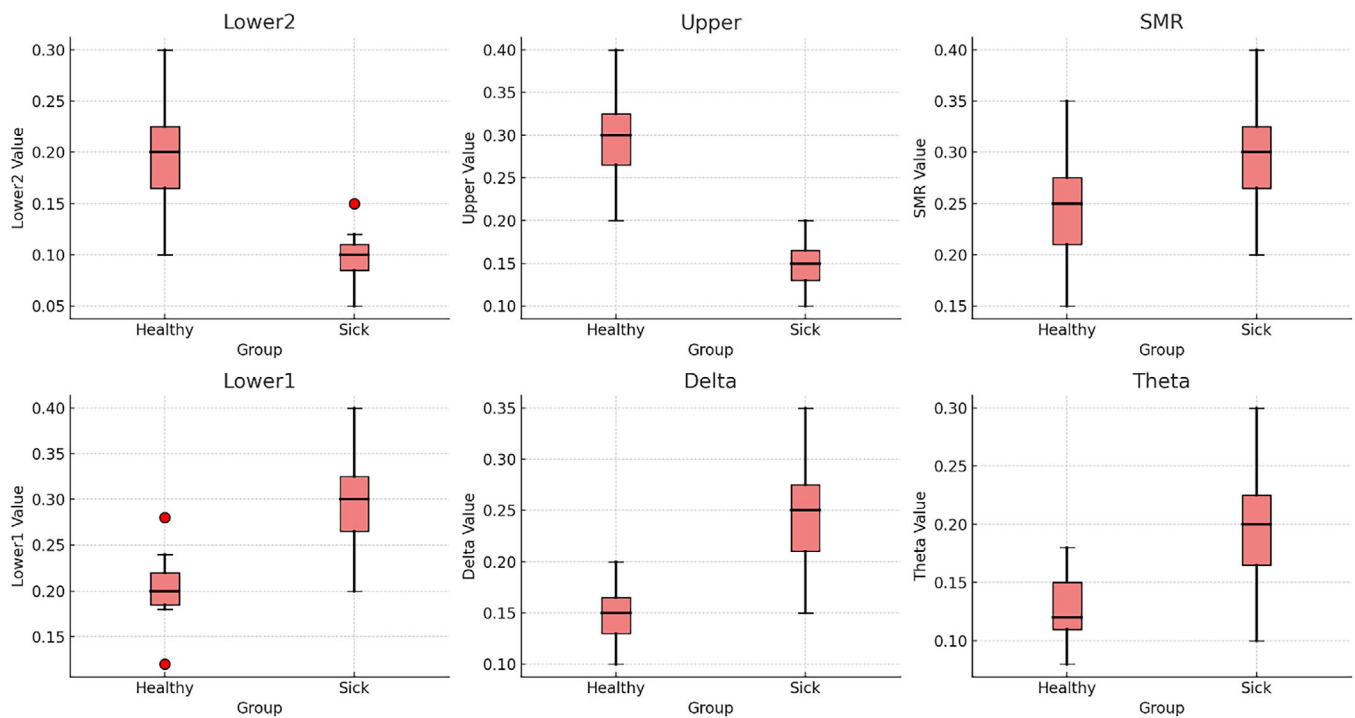


FIGURE 4 | Comparison of power spectrum across different subbands.

of 0.005. No significant difference was observed in channels 10, 14, 15 and 9, while the increase of Davies–Bouldin index is significant among addicted people. The most distinctive non-frequency feature, based on the Davies–Bouldin index, was the approximate entropy in the Cz channel (No. 11) with a value of 5.22. The evaluation of the frequency characteristics is shown in Figure 4, as it can be seen that the reduction of this characteristic is among the addicted people. A significant difference has been observed in the upper alpha subband in channel O1 (No. 15).

As it is clear from the results, significant differences in non-frequency features have been observed only in approximate entropy. Other non-frequency features such as permutation entropy, wavelet entropy, Petrosian fractal dimension, Katz fractal dimension and box count dimension have not shown significant differences or are not significant enough to be used as distinctive features. To analyse the distinguishing features in EEG signals between heroin addicts and healthy individuals, the Davies–Bouldin index was employed to evaluate the reparability of the extracted features. Figure 5 illustrates the Davies–Bouldin index values for approximate entropy across different EEG channels. As observed, the value of this index is highest in channel Cz (channel 11), indicating the greatest discriminative ability. This finding suggests that approximate entropy in the Cz region exhibits a significant difference between the two experimental groups. As can be seen, the Davies–Bouldin index shows a significant difference in three channels, while the remaining 13 channels show significant differences, with channel 11 (Cz) showing the most significant difference. Similarly, Figure 6 presents the Davies–Bouldin index for power spectral density in the alpha subband, showing that channel O1 (channel 15) has the lowest Davies–Bouldin index value, which indicates the highest discriminative capability in this frequency domain feature. These

results highlight the importance of combining frequency-domain and non-frequency-domain features to improve the classification of addicted and healthy individuals through EEG signal processing.

To further evaluate the effectiveness of the proposed method across different EEG channels, we conducted a comparative analysis using the Davies–Bouldin index for both approximate entropy and power spectral density in the alpha subband across all available channels. Figure 5 illustrates the Davies–Bouldin index values for approximate entropy, where channels 9 and 10 exhibited significantly higher values, indicating their strong discriminative capability in distinguishing between heroin addicts and healthy individuals. This suggests that non-frequency features tend to show high specificity in particular EEG channels.

Similarly, Figure 6 presents the Davies–Bouldin index values for power spectral density in the alpha subband across different EEG channels. Unlike approximate entropy, the discriminative power for frequency-based features is more evenly distributed, with channels 4, 5, and 8 showing higher Davies–Bouldin index values. This finding suggests that frequency-domain features provide broader spatial representation across multiple EEG channels, whereas non-frequency features highlight specific localized differences.

These results confirm that certain EEG channels exhibit significantly higher discriminative power, supporting the effectiveness of the Davies–Bouldin index for feature selection. The observed differences between frequency and non-frequency features also emphasize the importance of integrating both feature types to achieve a more comprehensive analysis of heroin use disorder's impact on brain activity.

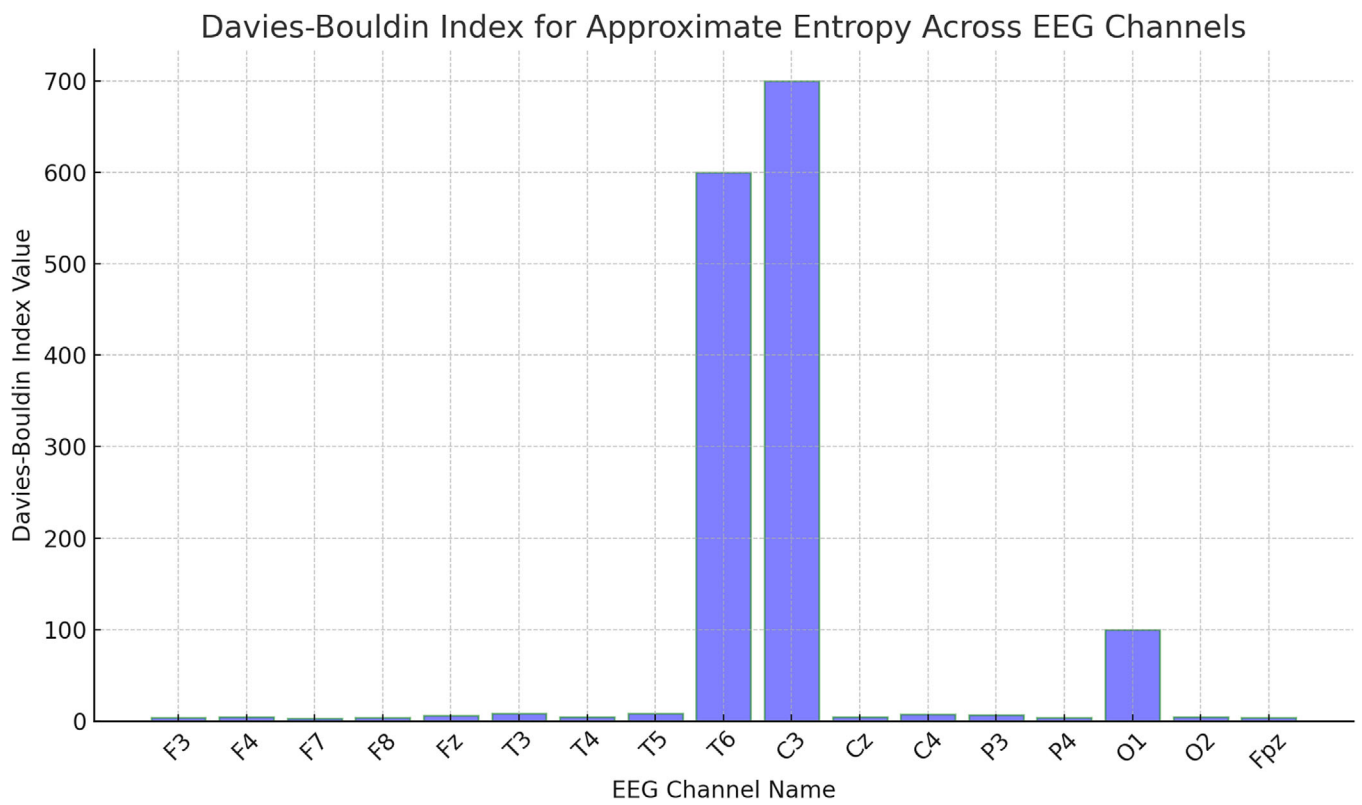


FIGURE 5 | Comparison of Davies–Bouldin index values across all channels for approximate entropy feature.

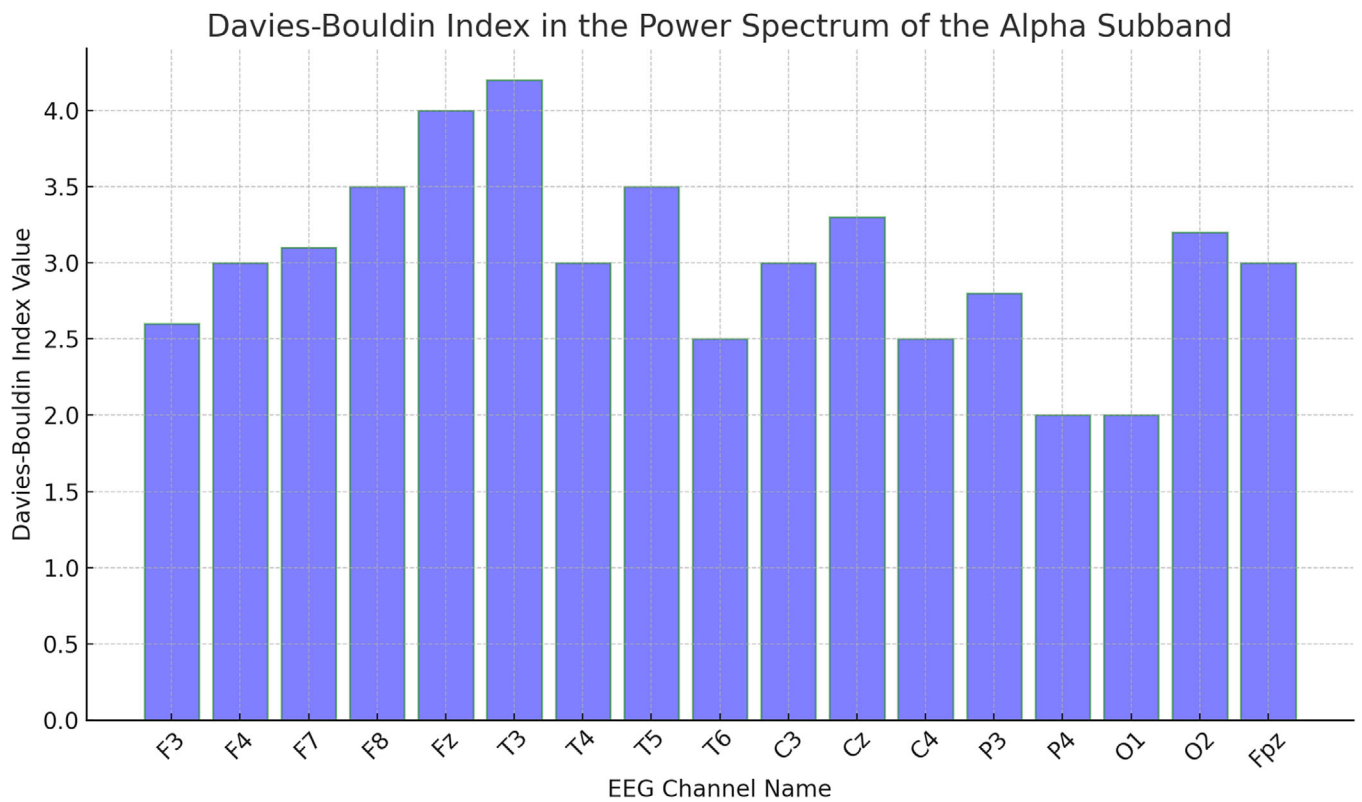


FIGURE 6 | Comparison of Davies–Bouldin index values across all channels for alpha band power spectrum.

5 | Discussion and Comparison of Results

The studies reviewed in this section show the significant effect of heroin consumption on the brain. The studies conducted so far show that the use of drugs is accompanied by changes in brain function. Few studies have been conducted in the field of brain disorders related to heroin use.

In [66], 33 heroin addicts and 12 healthy people were evaluated with 14 neuropsychological and electroencephalography tests. The relative power and central frequency of the alpha and beta sub-bands have been checked in all test subjects. The results show the independence of the relationships between the cognitive variables and the average frequencies of alpha 2 in the left hemisphere from the chronic effects of heroin, and also the increase in the frequency of alpha 2 in the right hemisphere by the length of chronic heroin use is predicted by the results.

In [67], EEG power and coherence measures for 18 heroin-dependent subjects were compared with 12 healthy subjects, which the results show an increase in the relative power of beta-2 and gamma coherence in the left hemisphere of heroin-dependent people compared to healthy people.

The amplitude of low-frequency fluctuation reveals changes in the power of spontaneous neural activity inherent in the brain [68]. Heroin use disorder is influenced by the abnormal amplitude of low frequency fluctuation (LFF). In [69], 91 people including 40 healthy people and 51 people dependent on heroin were studied. The results show an increase in the amplitude of low-frequency fluctuation in people addicted to heroin compared to healthy people. Also, the more heroin addicts use heroin for a longer period of time, the amplitude of low-frequency fluctuation in the areas related to the brain increases less.

The cumulative effects of heroin on brain function have been investigated in [70], where the relationships between EEG spectral power, average frequency and duration of heroin use have been considered. The required data were collected from 19 monopolar electrode locations in 13 healthy individuals and 33 heroin addicts. The results show that the frequency changes in the alpha 2 subband are more prominent in the frontal and central regions, and are related to the duration of heroin use per day. The decrease in the average frequency of alpha one subband was more prominent in the central, temporal and axial regions, which was mainly observed in heroin addicts who used a high dose of the drug. The power spectrum of brain electrical activity in sick people corresponds to the duration of addiction withdrawal. The results show that high consumption of heroin causes changes in the frequency of neural oscillations.

Both frequency and non-frequency characteristics have been evaluated using Davies–Bouldin index in this research. The power spectrum in the upper alpha band in channel O1 (channel 15) had the lowest Davies–Bouldin index value of 1.94. To select distinctive features, the lowest value of the Davies–Bouldin index is more effective. Therefore, in this study, the O1 channel with a Davies–Bouldin value of 1.94 is proposed as the most distinctive frequency feature. Based on the authors' studies, no comprehensive research has been conducted on non-frequency characteristics. This research identifies the most distinctive fea-

ture as approximate entropy in channel Cz (channel 11) with a Davies–Bouldin value of 5.22.

Table 2 summarizes the comparison of studies on the effects of EEG signal changes. Although various features for linear and nonlinear frequency characteristics have been considered, the main challenge remains the Fourier transform's inefficiency for dynamic signals. To overcome this challenge, these studies divided EEG signals into short, overlapping time intervals. However, it appears that non-frequency features might provide a more effective analysis.

One of the primary strengths of the proposed method is its holistic approach to EEG signal analysis, integrating both frequency-domain and non-frequency-domain features to enhance the detection of neural alterations associated with heroin use disorder. Unlike conventional studies that predominantly rely on power spectral analysis, our methodology incorporates entropy-based measures (approximate entropy, permutation entropy) and fractal dimensions (Katz and Petrosian), which capture the intrinsic complexity and self-similarity of brain signals. This dual-feature extraction strategy enables a more refined differentiation between addicted and healthy individuals, offering a richer representation of brain activity patterns that would otherwise remain undetected through frequency-based methods alone.

To ensure optimal feature selection and classification performance, we employ the Davies–Bouldin index, a clustering-independent metric that effectively ranks EEG features based on their discriminative power. This selection mechanism eliminates the dependency on a predefined number of clusters, making it adaptive and robust across different datasets. While computational efficiency is a crucial aspect of EEG-based diagnostics, we acknowledge that certain non-frequency features, such as approximate entropy, introduce additional processing overhead. However, this trade-off is justified as it significantly improves classification accuracy by capturing subtle signal irregularities indicative of addiction-related neural disruptions.

A key finding in our study is that EEG channels Cz and O1 exhibit the highest discriminative power, reinforcing the role of the central and occipital regions in addiction-related neurophysiological changes. This insight holds practical significance for optimizing EEG-based diagnostic models, as it suggests the potential for dimensionality reduction strategies that retain only the most informative channels, thereby improving computational efficiency while maintaining high classification performance. Although our model demonstrates robust accuracy, further validation on larger and more diverse datasets is necessary to enhance its generalizability. Future research will focus on leveraging transfer learning techniques and domain adaptation approaches to assess the adaptability of our framework across different EEG datasets and addiction-related neurological conditions.

In order to more accurately evaluate the diagnostic capability of features extracted from EEG signals, the support vector machine (SVM) learning algorithm was used as one of the effective and reliable methods in the field of pattern recognition. In this analysis, selected features, including nonlinear indices in the time domain such as approximate entropy and spectral features in

TABLE 2 | Differences in EEG signals between healthy individuals and addicts.

Reference	Method	Results	Method limitation
[65]	Examination of relative power and central frequency of alpha and beta subbands	Examined two features simultaneously in the frequency domain	Differences were examined in only two subbands between healthy and addicted individuals
[66]	Examination of the coherence of the power spectral density of brain signals to determine differences between hemispheres	Examined all subbands to determine differences between healthy and addicted individuals in the hemispheres	Only the coherence of power signal was examined (one feature is not sufficient)
[67]	Dynamics and frequency characteristics of EEG signals	Examined differences in time and frequency domain characteristics across all head points and brain area Examined the impact of drug use on addicts and healthy individuals	Did not determine the amount of methadone used for treatment
[68]	Examination of the relationship between power spectrum and mean frequency of EEG and duration of heroin use	- Examined drug-related disorders in treatment process- Examined all subbands to determine the relationship	Only one feature was considered for the relationship analysis
This study	Determination of distinguishing features in the time and frequency domain	- Investigating all subbands and channels in both frequency and non-frequency features- Determined the heroin in brain effected—applied an appropriate method for determining distinguishing features	Did not determine the relationship between brain regions in the examined frequency and non-frequency features

the frequency domain such as Upper Alpha band power, were evaluated independently in different channels. In this study, EEG data were collected from 15 healthy individuals and 15 individuals with heroin use disorder, resulting in a total of 30 participants. Each participant's EEG was recorded from 16 channels, with approximately 14,000 samples per channel. To ensure robust and reliable feature extraction, the continuous signals from each channel were divided into 14 non-overlapping segments. This segmentation approach resulted in 224 segments per participant (16 channels $\times$ 14 segments) and a total of 6720 segments for the entire dataset (30 $\times$ 224). From each segment, a single feature vector was extracted corresponding to either the approximate entropy or the upper alpha power feature. These feature vectors served as inputs to the SVM classifier for training and testing, creating a sufficiently large and diverse dataset to enable precise classification of EEG data associated with heroin use disorder. For model training and testing, 70% of the data were used for training and 30% were used for testing. In order to examine the performance of the classifier, two important criteria, accuracy and precision, recall and F1 score, were used. Equation (21) computes the accuracy, Equation (22) displays the accuracy value, recall in Equation (23) and F1score in Equation (24) [71, 72]:

$$\text{Precision} = \frac{TP}{TP + FP} \times 100 \quad (21)$$

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP} \times 100 \quad (22)$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100 \quad (23)$$

$$F1\text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (24)$$

Figure 7 presents the classification performance of the SVM model for the approximate entropy feature across all EEG channels. The results indicate that Channel 15 (O1) exhibited the highest performance (F1-score), identifying it as the most effective channel for this feature. The superiority of this channel can be attributed to its sensitivity to the complexity and irregularity of EEG signals, which are particularly pronounced in individuals with substance use disorders. As highlighted in the article, approximate entropy serves as a nonlinear measure that captures the increased disorder and instability in brain activity due to heroin use. The occipital region, where channel O1 is located, is particularly responsive to such dynamic alterations. Importantly, these findings are consistent with the Davies–Bouldin index analysis, which showed that channel O1 had the lowest Davies–Bouldin value for approximate entropy, indicating its highest discriminative power. This alignment between the machine learning results and the statistical analysis reinforces the robustness and validity of the proposed framework for analysing addiction-related brain activity.

Figure 8 illustrates the performance metrics of the SVM model for the upper alpha power feature across the EEG channels. In this figure, Channel 11 (Cz) demonstrated the highest performance (F1-score), confirming its role as the most discriminative channel for this feature. The article explains that upper alpha power is closely linked to cognitive processes

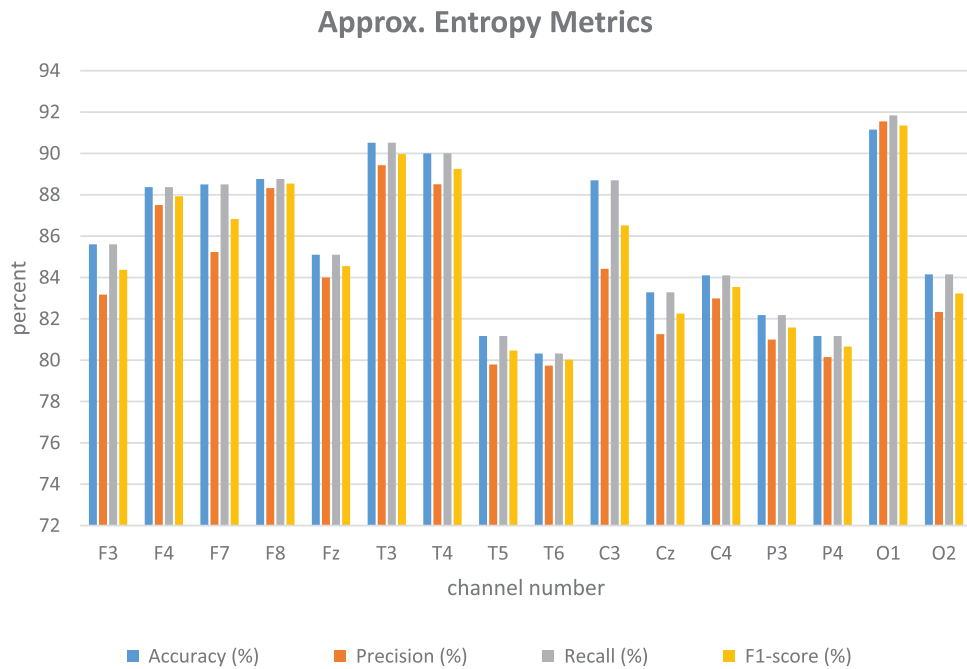


FIGURE 7 | The performance metrics (accuracy, precision, recall, and F1-score) of the SVM classifier for the approximate entropy feature across all EEG channels.

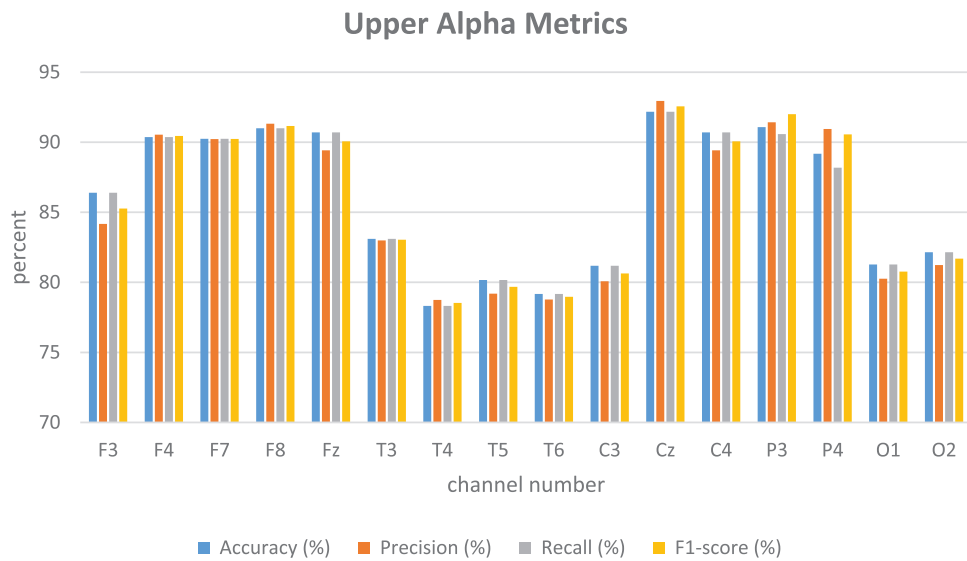


FIGURE 8 | The performance metrics (accuracy, precision, recall, and F1-score) of the SVM classifier for the upper alpha power feature across all EEG channels.

and memory functions, which are significantly affected by heroin use disorder. The central location of the Cz channel makes it particularly effective in capturing changes in alpha power across different brain regions. Furthermore, the Davies–Bouldin index analysis corroborates these findings, as channel Cz exhibited the lowest Davies–Bouldin index value for the upper alpha feature, indicating its superior ability to distinguish between healthy and addicted individuals. This consistency between the statistical and machine learning analyses underscores the effectiveness of the comprehensive approach used in this study for reliable EEG-based analysis of heroin use disorder.

6 | Conclusion

A comprehensive set of frequency and non-frequency features from different sub-bands and electrodes is extracted in this paper in order to determine the distinctive features in the EEG signals of healthy people and people addicted to heroin. The results show clear differences in these characteristics, underscoring the potential of EEG analysis in identifying the neurological effects of heroin use disorder. In the upper alpha band, a significant decrease in the power spectrum in the O1 channel was observed for addicted subjects, indicating potential changes in brain activity associated with addiction. Also, the approximate entropy

in the Cz channel shows a significant increase among addicts, which indicates a higher level of complexity and disorder in the brain signals of addicts. These two characteristics of reduced power spectrum in the upper alpha band in the O1 channel, and high approximate entropy in the Cz channel, emerged as important indicators, which effectively differentiate between the neurological symptoms of healthy subjects and heroin addicts. The implications of these findings are profound, and offer new ways to use EEG in the diagnosis and understanding of heroin use disorder. By using these specific EEG features, the researcher's ability to identify and monitor the neurological effects of heroin use can be increased, thereby contributing to more targeted and effective interventions. This study not only improves the understanding of the brain's response to heroin use disorder, but also emphasizes the potential of EEG as a test tool in the field of neuropsychological assessment and addiction research.

Author Contributions

Atefeh Tobieha: conceptualization, data curation, formal analysis, investigation, software, writing – original draft preparation. **Neda Behzadfar:** formal analysis, investigation, writing – original draft preparation. **Mohammadreza Yousefi:** formal analysis, investigation, writing – original draft preparation. **Homayoun Mahdavi-Nasab:** project administration, supervision, validation, visualization, writing – review & editing. **Ghazanfar Shahgholian:** project administration, supervision, validation, visualization, writing – review & editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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