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SPECTRAL ANALYSIS OF EEG SIGNALS FOR CHARACTERIZATION OF ADDICTION PATTERNS

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Abstract
Addiction is known to influence neural activity by altering the rhythmic patterns of brain signals. Electroencephalography (EEG), due to its non-invasive nature and high temporal resolution, provides an effective tool for studying such alterations. This paper presents a frequency-domain-based spectral analysis of EEG signals aimed at characterizing brain activity patterns related to addiction. EEG data were acquired under controlled conditions and subjected to preprocessing to remove noise and physiological artifacts using appropriate filtering techniques. The cleaned EEG signals were transformed into the frequency domain using Power Spectral Density (PSD) estimation based on Welch's method, which offers stable and noise-robust spectral representations. Spectral features were extracted by computing band power values from standard EEG frequency bands, namely Delta, Theta, Alpha, and Beta. Experimental analysis revealed distinct variations in spectral power distribution, with noticeable dominance of low-frequency components and suppression of higher-frequency rhythms in addiction-like patterns. The results demonstrate that frequency-domain EEG analysis provides meaningful insights into addiction-related neural dynamics. The proposed approach offers an interpretable and objective framework for characterizing addiction patterns and can serve as a foundational step for advanced EEG-based analytical and decision-support systems.
Keywords: Electroencephalogram (EEG), Spectral Analysis, Frequency-Domain Analysis, Power Spectral Density, EEG Band Power.

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Introduction
Addiction is a neurological condition that affects cognitive control, emotional regulation, and decision-making processes, leading to measurable changes in brain activity. Because altered neural oscillations frequently reflect these alterations, brain signal analysis is a crucial tool for comprehending mechanisms connected to addiction. Numerous neurological and psychological disorders have been successfully studied using electroencephalography (EEG), a popular non-invasive method for capturing brain activity with excellent temporal resolution [1], [2]. Time-domain properties are the backbone of traditional EEG analysis techniques; however, they might not fully capture the rhythmic brain activity linked to various mental and behavioural states. Frequency-domain analysis offers a more insightful representation of EEG signals since brain oscillations are fundamentally frequency-dependent. Spectral analysis enables the examination of power distribution across distinct frequency bands, each corresponding to specific brain functions and states [7]. EEG recordings are often contaminated by various noise sources and physiological

artifacts, including eye blinks, muscle movements, and power-line interference. Effective preprocessing is therefore essential to ensure reliable spectral analysis. Several signal processing techniques, including filtering and component-based artifact separation methods, have been reported to improve EEG signal quality prior to frequency-domain analysis [4]. A key method for frequency-domain EEG analysis is Power Spectral Density (PSD) estimation, which measures signal power across frequency components. Because of its ability to adapt to noise and capacity to provide consistent spectral estimates by signal segmentation and averaging, Welch's method is the most popular among the different PSD estimating techniques [3]. Because of this, it is especially useful for assessing biomedical data that are noisy, like EEG. According to earlier research, conditions connected to addiction are related to suppression of higher-frequency rhythms, particularly Alpha activity, and increased low-frequency EEG activity, such as Delta and Theta bands [5, 8]. Although a number of studies have examined EEG-based addiction analysis using machine learning and classification techniques, there aren't many focused investigations that highlight the interpretability and spectral characterisation of addiction-related brain activity. In order to describe addiction-related patterns using frequency-domain approaches, the current work conducts a systematic spectral analysis of EEG signals. The study uses EEG band power analysis and PSD calculation based on Welch's approach to find notable spectral fluctuations related to addiction-like brain activity. This work attempts to provide a strong foundation for future EEG-based analytical frameworks and offer a deeper understanding of addiction-related brain dynamics by concentrating on interpretable spectral components.

Background

A non-invasive method for capturing brain electrical activity with great temporal precision, electroencephalography (EEG) has been used extensively to investigate neurological disorders and cognitive processes [1], [7]. Frequency-domain analysis is a useful method for investigating underlying brain dynamics because EEG signals are composed of rhythmic oscillations produced by synchronized neural activity. The usual frequency bands for EEG oscillations are Delta, Theta, Alpha, and Beta, each of which is linked to different physiological and mental states. Human brain activities are classified into specific frequency rhythm categories, as shown in Table 1. Changes in how power is distributed throughout these frequency bands are frequently a sign of aberrant or changed brain activity [9]. Specifically, disrupted neural regulation and poor cognitive control have been connected to changes in low- and mid-frequency EEG oscillations. EEG frequency properties can be systematically evaluated through frequency-domain analysis utilizing Power Spectral Density (PSD) estimates. Because Welch's approach is flexible to noise and can produce stable spectral representations through signal segmentation and averaging, it is frequently used for PSD estimation [3]. Effective preprocessing is necessary for reliable spectral analysis because EEG recordings are subject to variations including muscle activity, eye blinks, and power-line interference, which, if left unchecked, can greatly alter spectral properties [4], [10]. According to earlier neurophysiological research, addiction-related disorders are linked to decreased Alpha-band power and elevated low-frequency EEG activity, which reflects compromised brain control mechanisms [5], [8], and [11].

Table I Frequency Ranges

Wave Type	Frequency	Activity
Delta	Less than 4 Hz	Occur during sleep, coma
Theta	4- 8 Hz	Emotional Stress
Alpha	8 - 13 Hz	Sensory stimulation
Beta	14 - 20 Hz	Mental activity
Gamma	20 – 60Hz	Visual attention

Methodology

A. EEG Data Acquisition

A Super Sonic 32-channel EEG recording equipment was used to obtain the electroencephalography (EEG) signals used in this research. Because of its great temporal resolution, EEG is a non-invasive method that is frequently used to monitor brain electrical activity and analyze neural oscillations linked to cognitive and behavioral states [1], [7]. To ensure reliable signal acquisition during the recording procedure, scalp electrodes were placed according to a conventional electrode placement configuration. A thorough understanding of neural dynamics was made possible by the multi-channel arrangement, which allowed for the simultaneous recording of brain activity from many brain regions. To achieve steady and high-quality EEG signals, the electrode–skin impedance was reduced before recording. To minimize motion-related artifacts and outside disruptions, the individual maintained a relaxed condition during the recording session. The EEG signals were digitally stored and exported using the EEG recording software for further signal processing and analysis. Since raw EEG recordings often contain physiological artifacts and environmental noise, the collected signals were subsequently processed using appropriate preprocessing techniques before performing frequency-domain spectral analysis.

B. Preprocessing of EEG Signals

The reliability of spectrum analysis can be affected by a variety of noise sources and physiological variations in raw EEG recordings. Eye blinks, muscular movement, baseline drift, and electrical noise from power-line sources are common sources of interference. Therefore, before doing frequency-domain analysis, preprocessing is a crucial step to improve data quality and isolate significant neuronal activity [4], [10]. In order to minimize unnecessary frequency components and environmental interference, preprocessing in this work was carried out utilizing a combination of band-pass and notch filtering. Band-pass filtering was used to eliminate both high-frequency noise and low-frequency drift while maintaining the frequency range essential to EEG activity. This filtering step preserves neural oscillations corresponding to the standard EEG frequency bands such as Delta, Theta, Alpha, and Beta, which are commonly analyzed in neurophysiological studies [1], [9]. A notch filter was used in addition to band-pass filtering to remove power-line interference that is frequently seen in EEG recordings. Spectral analysis may be significantly affected by narrow-band disturbances around the power-line frequency triggered by electrical noise produced by nearby electronic devices. Without changing the fundamental components of the brain signal, the notch filter precisely reduces this interference [10]. Band-pass and notch filtering together increase signal quality and guarantee that brain function is accurately reflected in the EEG data required for spectral analysis. In order to determine EEG spectral features linked to addiction-related brain activity, the preprocessed signals are then utilized for frequency domain analysis using Power Spectral Density (PSD) estimates. The difference between the raw EEG signal and the filtered signal is illustrated in Figure 1.

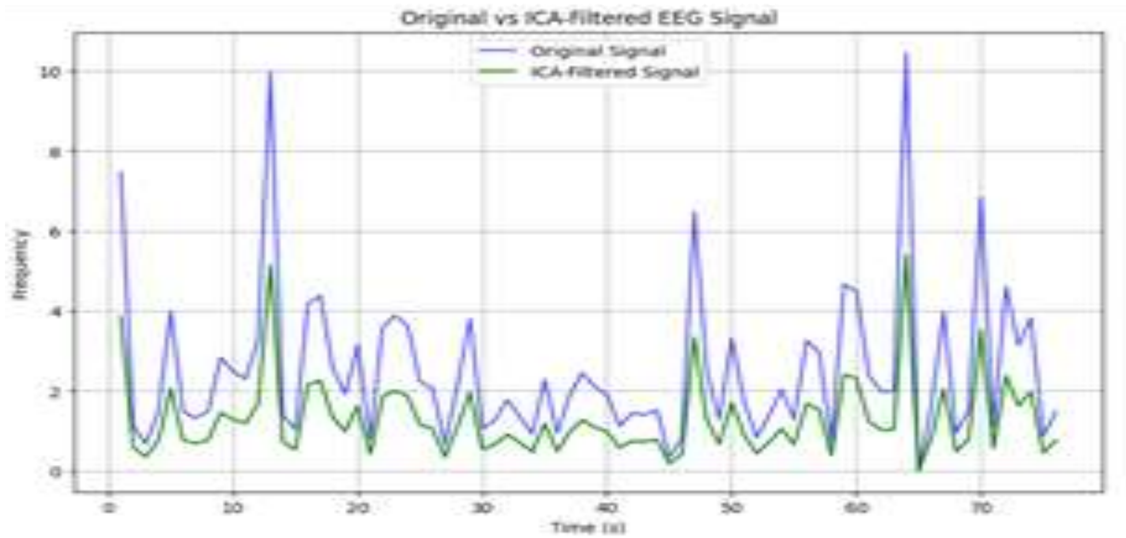

Figure 1. Comparison between raw EEG signal and filtered EEG signal after preprocessing

C. Spectral Analysis Method

An important instrument for analyzing the rhythmic properties of EEG signals is frequency-domain analysis. Compared to time-domain analysis, which tracks changes in the signal over time, frequency-domain analysis looks at the distribution of signal power among various frequency components. Because brain activity is naturally represented by oscillations that occur in different frequency bands, this method is very helpful for EEG analysis [2], [7].In this study, Power Spectral Density (PSD) was calculated to examine the spectral properties of the EEG signals. PSD gives quantitative information about the energy contained in various frequency ranges and displays the distribution of signal power across frequency components. Dominant frequency components related to particular neural activity and brain states can be found by analyzing the PSD of EEG data [2]. Welch's method is one of the most popular PSD estimation techniques in biomedical signal processing because it provides robust and reliable spectral projections. By splitting the signal into overlapping segments, applying a window function to each segment, calculating the duration of each segment, and then averaging the results, Welch's method enhances spectral estimation. This averaging procedure is very useful for evaluating EEG signals because it lowers variance in the spectral estimate and increases robustness against noise [3]. In this research, Welch's method-based PSD estimation was used to convert the preprocessed EEG signals into the frequency domain. Analysis of power distribution across various EEG frequency bands is made possible by the resulting spectral representation, which is important for spotting differences in patterns of neural activity. The EEG band power features corresponding to the Delta, Theta, Alpha, and Beta frequency ranges are then extracted using the calculated PSD values.
Mathematically, the Power Spectral Density of a discrete signal can be expressed as:

$$P_{xx}(f) = \frac{1}{N} \left| \sum_{n=0}^{N-1} x(n) e^{-j2\pi f n} \right|^2$$

where x(n) represents the discrete EEG signal, N is the number of samples, and f denotes the frequency component. The PSD provides a measure of signal power corresponding to each frequency value.

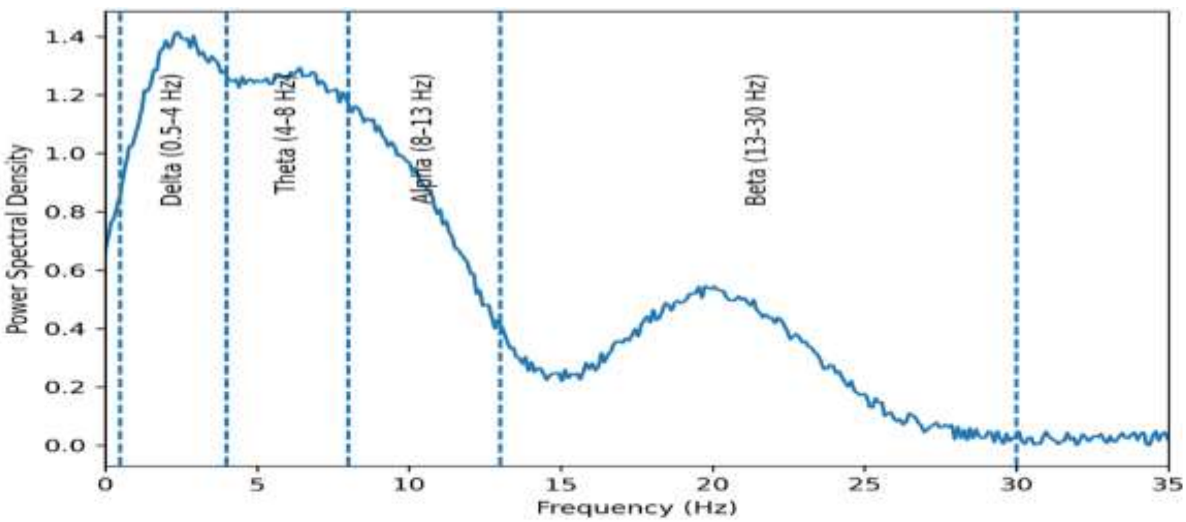

Figure 2.PSD with EEG bands

D. EEG Band Power Extraction

The next step is to extract the power associated with particular EEG frequency bands after getting the Power Spectral Density (PSD) representation of the EEG signals. Standard frequency bands that represent various physiological and cognitive states of brain activity are frequently used in the analysis of EEG signals. Delta, Theta, Alpha, and Beta are the most extensively researched bands; each occupies a different frequency range [7], [9], and While the Theta band (4–8 Hz) is frequently linked to tiredness and decreased alertness, the Delta band (0.5–4 Hz) is typically connected with profound sleep and slow-wave brain activity. While the Beta band (13–30 Hz) is linked to active thinking, focus, and alertness, the Alpha band (8–13 Hz) usually represents calm and relaxed mental states [7], [9], [12]. Variations in the spectral power of these frequency bands provide valuable insights into neural dynamics and cognitive states. In this work, the spectral power within the appropriate frequency ranges for each EEG band was integrated to get band power values from the PSD. Band power features are commonly used in biomedical signal processing and neuroscience to analyze brain activity patterns and neurological disorders because they offer a simplified and understandable representation of EEG spectral properties [2], [12]. The derived band power values in this work allow the characterisation of spectral variations linked to brain activity connected to addiction.

Results

Power Spectral Density (PSD) estimation based on Welch's approach was used to convert the pre-processed EEG signals into the frequency domain. The distribution of signal power among the various frequency components of the EEG signals is shown by the spectral representation. Within the typical EEG frequency ranges, significant brain waves are present, according to PSD analysis. The distribution of signal power among the Delta, Theta, Alpha, and Beta bands, which represent various functional states of brain activity, is highlighted by the spectral distribution. By integrating the PSD within the corresponding frequency ranges of each EEG band, band power values were calculated. These band power measurements enable comparison of power distribution across various frequency components and offer a quantitative presentation of the spectrum features of the EEG signals. The spectral patterns show significantly less power levels in the Alpha band and comparatively more activity in lower-frequency bands like Delta and Theta. These spectral power variations show fundamental patterns of brain activity and represent variations in neural oscillatory action. The observed spectral features show that frequency-domain analysis can produce interpretable indicators of brain activity and successfully capture significant fluctuations in EEG signals.

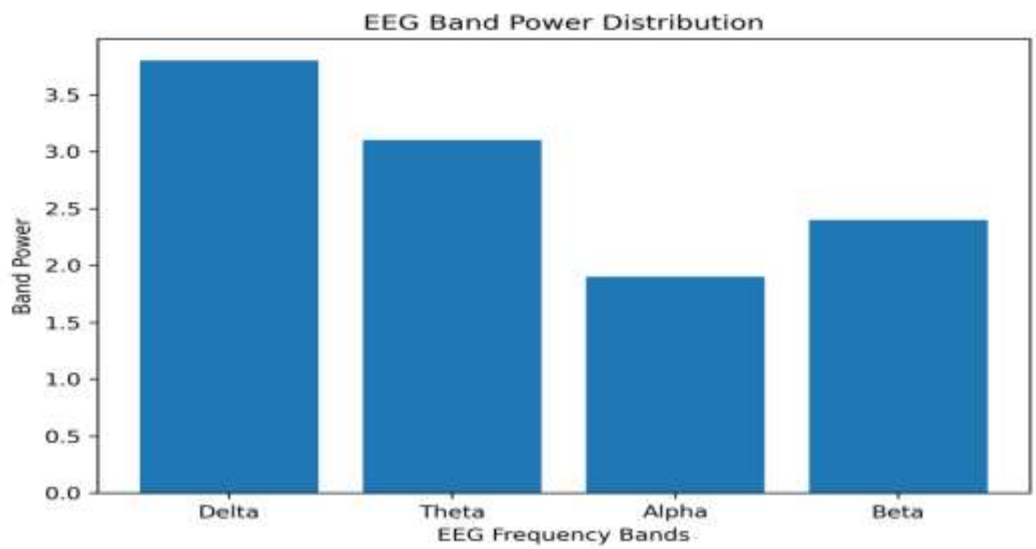

Figure 3. Band power distribution across the standard EEG frequency bands

Discussion

The EEG signals' spectral analysis shows clear differences in the power distribution across various frequency bands. The retrieved band power features enable the analysis of brain activity patterns from a frequency-domain view and provide insight into the underlying neurological oscillatory behavior. The research shows that the Alpha band has considerably less spectral power, while the lower-frequency bands, especially Delta and Theta, have substantially higher activity. Changes in neural dynamics and states of cognitive processing may be reflected in such variations in spectral power. According to earlier research, altered brain regulation mechanisms and poor cognitive control are frequently linked to elevated slow-wave activity and decreased Alpha-band power [5], [8], and [11]. The results of the spectral analysis are in line with findings from previous EEG-based research examining changed patterns of brain activity. By measuring the distribution of signal energy across various EEG bands, frequency-domain analysis makes it possible to clearly identify these changes. A reliable framework for investigating such neural oscillatory features is provided by the application of Power Spectral Density estimates and band power extraction. The findings indicate the value of spectral EEG analysis in analyzing differences in brain activity patterns and detecting significant alterations in neural oscillations. The method allows for understanding EEG-based patterns linked to changed brain states and offers an understandable representation of neural dynamics by concentrating on interpretable spectral components.

Conclusion

The an efficient method for analyzing neural rhythmic patterns and interpreting fluctuations in brain activity is spectral analysis of EEG recordings. Analyzing the distribution of signal power across various frequency components linked to neurological activities is made possible by converting EEG signals from the time domain to the frequency domain. The study analyzed the spectrum properties of the preprocessed EEG signals using the Power Spectral Density estimate based on Welch's approach. In order to quantitatively assess the spectral power distribution, band power values were derived for the standard EEG frequency bands, which are Delta, Theta, Alpha, and Beta. The observed fluctuations in band power demonstrate the value of frequency-domain methods for EEG signal processing and offer insights into underlying brain processes. The findings demonstrate that spectral analysis can effectively capture meaningful characteristics of EEG signals and provide interpretable indicators of brain activity patterns. The methodology presented in this study offers a systematic framework for analyzing EEG signals using spectral features and contributes to ongoing research in EEG-based analysis of neural activity.

Future Scope

Future research can further extend the present work by incorporating larger EEG datasets obtained from multiple subjects and recording sessions to improve the reliability and generalization of the spectral analysis. An expanded dataset would allow a more comprehensive investigation of variations in neural oscillatory patterns across different individuals. Further studies may also explore additional EEG frequency bands and advanced spectral features to obtain deeper insights into brain activity patterns. Incorporating higher resolution spectral analysis techniques could provide a more detailed characterization of neural oscillations. Another potential direction involves integrating machine learning and statistical analysis methods with the extracted EEG spectral features. Such approaches may enable automated identification and classification of brain activity patterns based on frequency-domain characteristics. In addition, future work can investigate real-time EEG signal analysis systems that utilize spectral features for continuous monitoring of brain activity. This may support the development of practical EEG-based analytical frameworks for studying neural dynamics and behavioral conditions.

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References

1. S. Sanei and J. A. Chambers, *EEG Signal Processing*. Chichester, U.K.: Wiley, 2007.

2. N. V. Thakor and S. Tong, "Advances in quantitative electroencephalogram analysis methods," *Annu. Rev. Biomed. Eng.*, vol. 6, pp. 453–495, 2004.
3. P. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Trans. Audio Electroacoust.*, vol. 15, no. 2, pp. 70–73, Jun. 1967.
4. S. Makeig, T.-P. Jung, A. J. Bell, D. Ghahremani, and T. J. Sejnowski, "Blind separation of auditory event-related brain responses into independent components," *Proc. Natl. Acad. Sci. USA*, vol. 94, no. 20, pp. 10979–10984, 1997.
5. C. Chen, G. Porjesz, H. Rangaswamy, K. Kamarajan, B. J. Jones, and H. Begleiter, "Reduced frontal lobe activity in subjects with alcohol dependence: Evidence from EEG spectral analysis," *Biol. Psychiatry*, vol. 62, no. 7, pp. 647–655, 2007.
6. S. S. Kumar and P. S. Kumar, "EEG spectral analysis for detection of neurological disorders," *Int. J. Biomed. Eng. Technol.*, vol. 11, no. 2, pp. 153–165, 2013.
7. D. L. Schomer and F. H. Lopes da Silva, *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, 6th ed. Philadelphia, PA, USA: Lippincott Williams & Wilkins, 2011.
8. J. D. Rangaswamy and G. Porjesz, "Understanding alcohol use disorders with neuroelectrophysiology," *Handbook of Clinical Neurology*, vol. 125, pp. 383–414, 2014.
9. W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis," Brain Research Reviews, vol. 29, no. 2–3, pp. 169–195, 1999.
10. S. Fatourechi, R. K. Ward, K. Najarian, and A. Birch, "EMG and EOG artifacts in brain computer interface systems: A survey," Clinical Neurophysiology, vol. 118, no. 3, pp. 480–494, 2007.
11. H. Rangaswamy and G. Porjesz, "Uncovering neurophysiological correlates of alcohol dependence using EEG," Clinical EEG and Neuroscience, vol. 39, no. 1, pp. 35–41, 2008.
12. R. Nunez and R. Srinivasan, *Electric Fields of the Brain: The Neurophysics of EEG*, 2nd ed. Oxford, U.K.: Oxford University Press, 2006.
13. M. Teplan, "Fundamentals of EEG measurement," *Measurement Science Review*, vol. 2, no. 2, pp. 1–11, 2002.