**EE 4142 – Sessional on Digital Signal Processing**

Department of Electrical and Electronic Engineering

Khulna University of Engineering & Technology

# Project Title (Experiment 5)

Bridging Signal and Intelligence: A DSP-Driven EEG Feature Pipeline for Neural Network Seizure Detection

## Submitted By


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# Abstract

This project presents a digital signal processing (DSP)-driven pipeline for preprocessing and feature extraction from electroencephalogram (EEG) data for seizure detection. Using the CHB-MIT Scalp EEG Database, the work demonstrates how classical DSP operations—such as filtering, convolution, correlation, and spectral analysis—can be systematically applied to real-world biosignals to produce features suitable for intelligent models such as neural networks. The preprocessing pipeline includes notch and bandpass filtering, segmentation, and normalization, followed by spectral and statistical feature computation. The results include comprehensive visualizations and extracted EEG band features that can serve as inputs to downstream machine learning models for automated seizure detection. This project bridges theoretical DSP concepts with practical biomedical applications, highlighting the role of digital signal processing in modern neural intelligence systems.

# Contents

# 1. Introduction

Electroencephalography (EEG) is a non-invasive method for measuring the electrical activity of the brain. Automated EEG analysis, particularly for seizure detection, is a critical application of biomedical signal processing. The complex, non-stationary nature of EEG data necessitates robust preprocessing and feature extraction methods to ensure meaningful interpretation and reliable classification.

Digital Signal Processing (DSP) provides a mathematical and algorithmic framework for analyzing signals in both time and frequency domains. This project integrates foundational DSP techniques learned during the EE 4135 course—including convolution, correlation, Discrete Fourier Transform (DFT), and digital filtering—into a practical EEG analysis pipeline implemented in Python using the MNE library.

The developed system preprocesses EEG data from the CHB-MIT dataset, extracts key temporal and spectral features, and prepares feature vectors ready for machine learning-based seizure classification.

# 2. Background

## 2.1 EEG and Seizure Activity

EEG signals capture electrical activity from multiple brain regions through scalp electrodes. Typical EEG signals have frequency components within 0.5–70 Hz, divided into standard bands:

- **Delta (0.5–4 Hz)** – Deep sleep and slow-wave activity
- **Theta (4–8 Hz)** – Drowsiness or meditation
- **Alpha (8–13 Hz)** – Relaxed wakefulness
- **Beta (13–30 Hz)** – Active thinking, concentration
- **Gamma (30–70 Hz)** – High-level cognitive processes

Seizures manifest as sudden, synchronized bursts of neuronal activity, often observable as sharp amplitude changes and altered spectral power in EEG recordings.

### 2.2 DSP in EEG Analysis

DSP techniques play a crucial role in EEG analysis:

- **Filtering** removes noise and artifacts (e.g., 60 Hz powerline interference).
- **Correlation and convolution** identify temporal relationships and apply smoothing.
- **Fourier Transform (FFT)** enables frequency-domain analysis, crucial for band-power estimation.
- **Digital filters (FIR, IIR)** ensure desired passband characteristics with linear or non-linear phase properties.

These tools form the foundation for constructing a preprocessing pipeline capable of isolating meaningful patterns in EEG signals.

# 3. Methodology

## 3.1 Data Acquisition

The CHB-MIT Scalp EEG Database was used, containing multi-channel EEG recordings from pediatric epilepsy patients. Data were stored in EDF format and loaded using the *mne.io.read_raw_edf()* function. Each recording contains both seizure and non-seizure intervals.

## 3.2 Preprocessing Pipeline

The preprocessing steps were designed to clean and standardize raw EEG data:

1. **Filtering:**

    - A 60 Hz notch filter was applied using an IIR notch design to remove powerline noise.
    - A bandpass FIR filter (0.5–70 Hz) was implemented using the window method to isolate the standard EEG frequency range.

2. **Segmentation:**

   The continuous EEG was divided into overlapping 10-second epochs for localized temporal analysis.

3. **Normalization:**

   Each epoch was normalized using z-score standardization (zero mean, unit variance) to ensure feature comparability across sessions.

## 3.3 DSP Operations

**Correlation Analysis:** Inter-channel Pearson correlation matrices were computed to measure spatial dependencies across EEG electrodes.

**Convolution Smoothing:** A moving average kernel was applied to demonstrate convolutional filtering effects and reduce short-term fluctuations.

**Spectral Analysis:** Fast Fourier Transform (FFT) and Welch Power Spectral Density (PSD) were used to estimate frequency content and compute power in standard EEG bands.

## 3.4 Feature Extraction

For each epoch, the following features were derived:

- **Band Power Features:** Mean, standard deviation, and median power in delta, theta, alpha, beta, and gamma bands.
- **Statistical Features:** Energy, variance, skewness, and kurtosis of time-domain signals.
- **Spectral Entropy:** Shannon entropy of normalized PSD to quantify signal complexity.
- **Inter-Channel Correlation Metrics:** Mean, standard deviation, and maximum correlation coefficients across channels.
- **Band Ratios:** Ratios such as $\alpha/\beta$ for cognitive state indication.

## 3.5 Implementation

The system was implemented in **Python (v3.10)** using **MNE, SciPy, NumPy, pandas, and Matplotlib**. The pipeline was run in a **Jupyter Notebook** for interactive visualization and stepwise validation.

All extracted features were aggregated into a structured DataFrame and exported as a CSV (chb_features.csv) for downstream neural network integration.

All the resources (data, code etc.) related to this project can be found under this repository: https://github.com/projectohid/4142-project

# 4. Results

The EEG preprocessing and feature extraction pipeline was successfully implemented and validated using visual and quantitative analyses. The results demonstrate the step-by-step transformation of raw EEG data into meaningful DSP-derived features ready for machine learning applications.

### 4.1 Spectrogram Analysis: Normal vs. Seizure Epochs

The spectrograms generated for the FP1–F7 electrode pair reveal distinct spectral signatures between normal and seizure segments:

- **Normal EEG segment:** In Fig. 1, the spectrogram displays distributed power across several frequency bands, with visible energy between 10–30 Hz corresponding to alpha and beta activity.

- **Seizure EEG segment:** In Fig. 2, the spectral power concentrates primarily below 10 Hz (delta and theta ranges), with an overall reduction in higher-frequency energy.

These contrasts confirm the successful differentiation of physiological and pathological EEG states. The results also validate the efficiency of the preprocessing steps—especially the notch and bandpass filters—which preserved core EEG content while attenuating noise and artifacts.

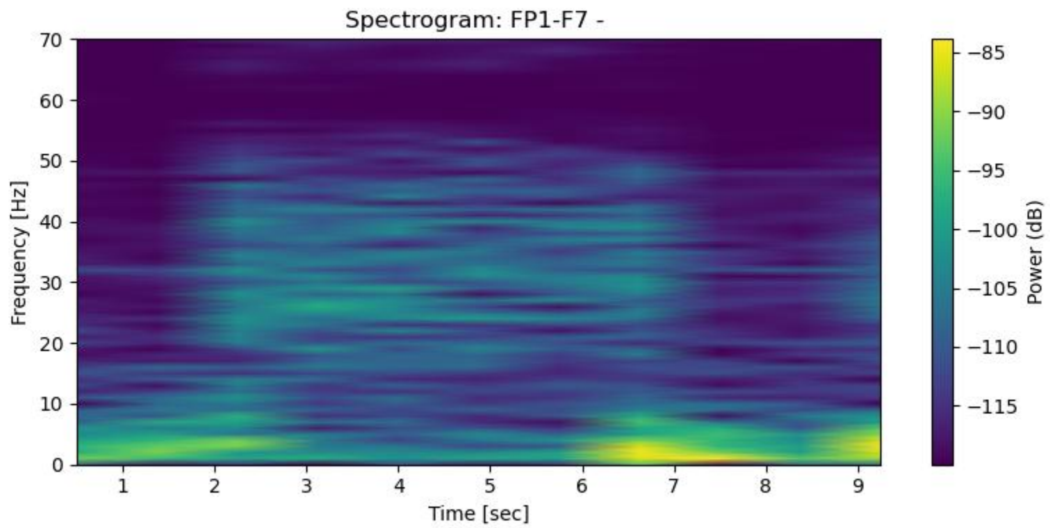



Fig. 1: Spectrogram for *Chb01_01.edf* (non-seizure).

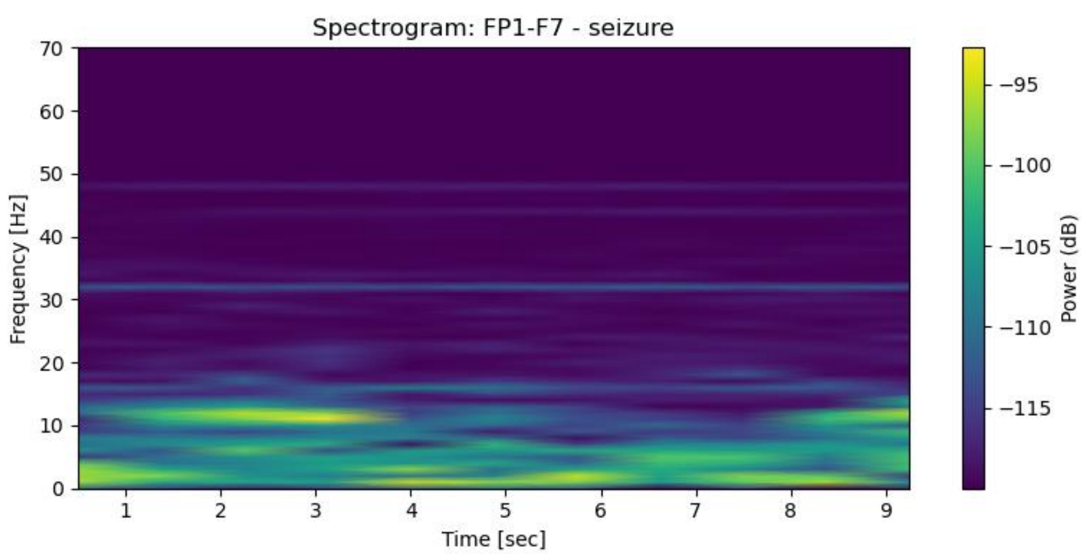



Fig. 2: Spectrogram for *Chb01_03.edf* (seizure).

## 4.2 Raw vs. Filtered Signal Comparison

In Fig. 3, the **time-domain plot**, the filtered EEG signal appears smoother and less noisy compared to the raw signal, demonstrating effective removal of baseline drift and 60 Hz interference.

The **frequency-domain comparison** (via FFT spectra in Fig. 3) shows a clear suppression of peaks around 60 Hz, confirming the notch filter's success. The FIR bandpass filter further confined the spectrum within the 0.5–70 Hz physiological window, ensuring that only meaningful neural activity was retained.

Overall, both the time and frequency representations validate the designed filters' effectiveness and stability.

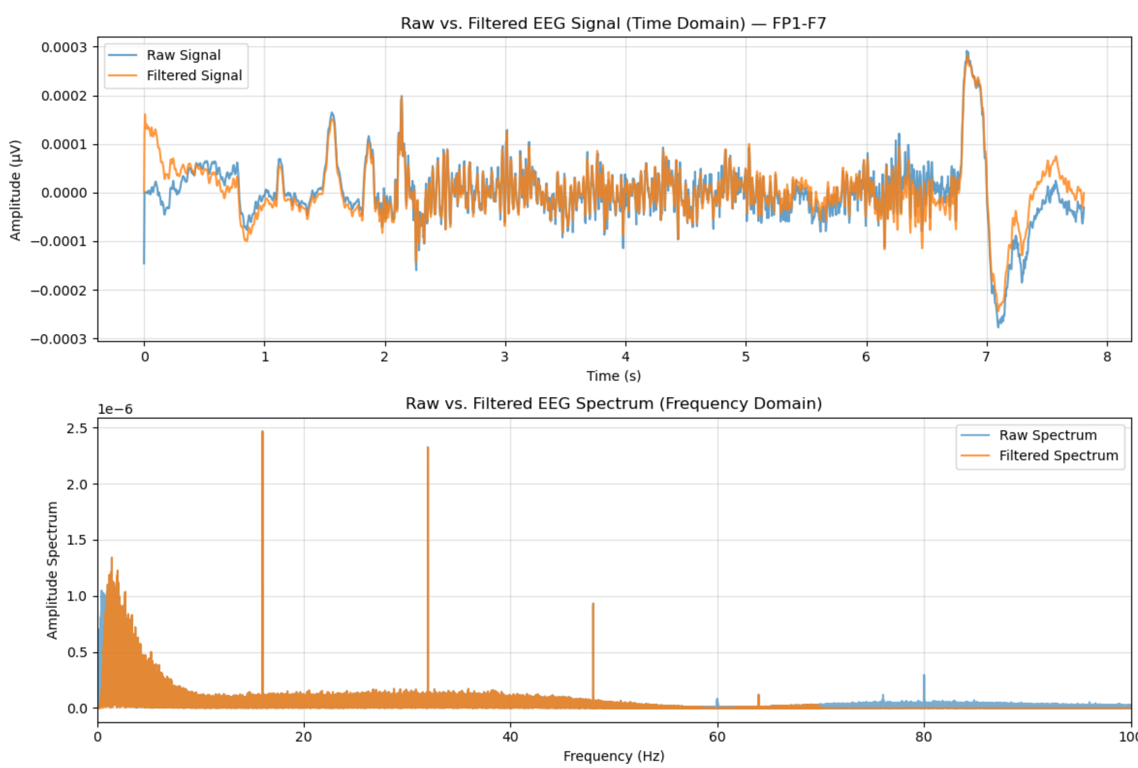



Fig. 3: Raw and filtered Signals and their Spectrums for *Chb01_01.edf* .

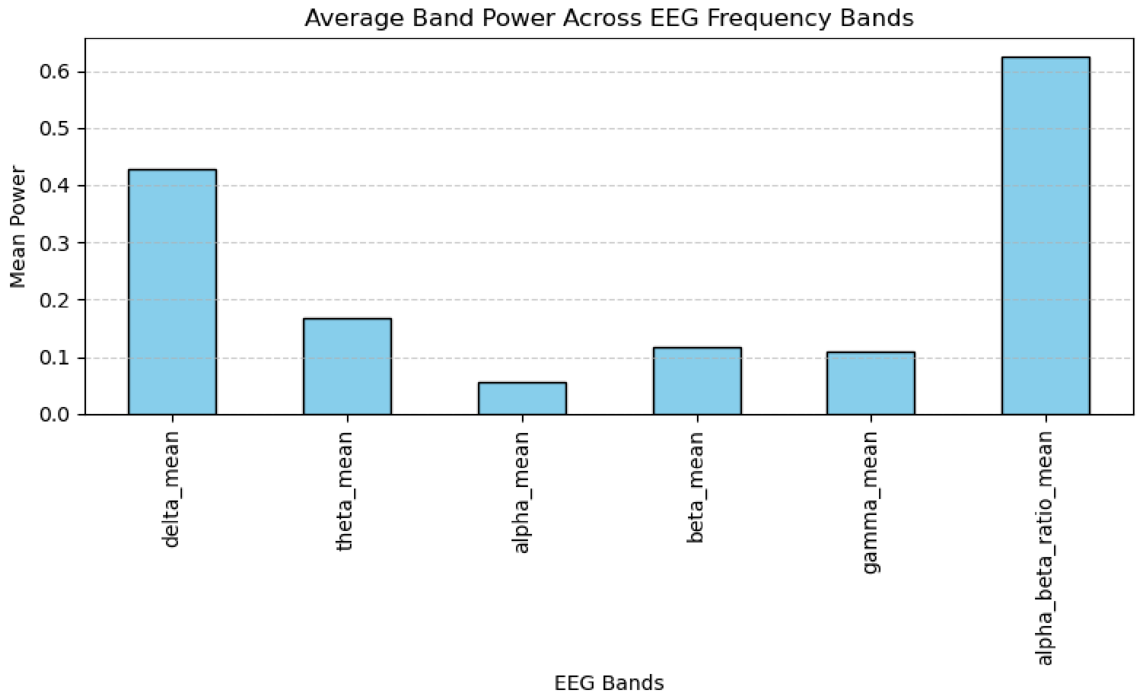



Fig. 4: Average Band Power Across EEG Frequency Bands for *Chb01_01.edf* .

## 4.3 EEG Band Power Distribution

In Fig. 4, bar plots of **mean power across standard EEG bands (Δ, θ, α, β, γ)** exhibit the following hierarchy:

**Δ (delta) > θ (theta) > β (beta) > γ (gamma) > α (alpha)**

This distribution confirms that low-frequency activity dominates the recordings, consistent with typical seizure EEG patterns. The inclusion of the **α/β ratio** further emphasizes a strong slow-wave prevalence, which serves as an indicator of seizure onset or drowsiness.

This result quantitatively supports the spectral observations seen in the spectrograms.

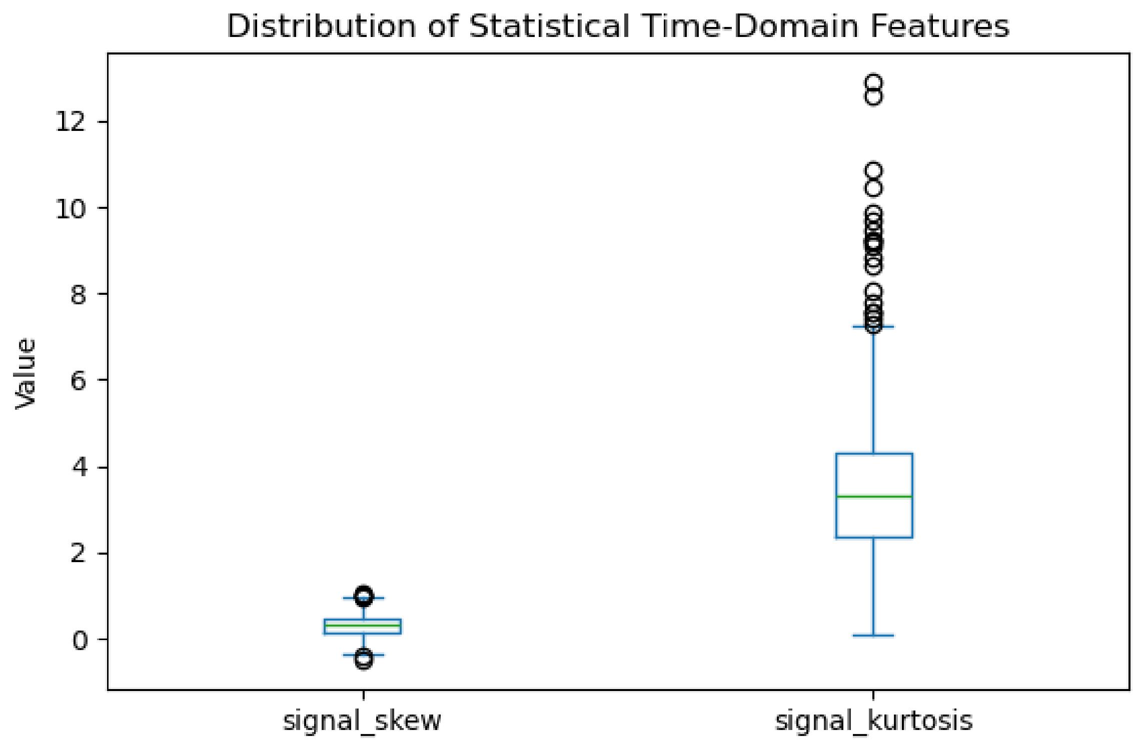



Fig. 5: Distribution of Statistical Time-Domain Features for *Chb01_01.edf* .

### 4.4 Time-Domain Statistical Features

In Fig. 5, Box plots of **signal skewness** and **kurtosis** highlight clear temporal-domain statistical characteristics of EEG signals:

- **High kurtosis** values indicate the presence of sharp transient peaks typical of epileptiform discharges.
- **Low skewness** suggests a relatively symmetric amplitude distribution but with frequent outliers.

These observations confirm that seizure-related EEG activity is impulsive and non-Gaussian in nature, aligning with theoretical expectations.

## 4.5 Spectral Entropy vs. Delta Band Power

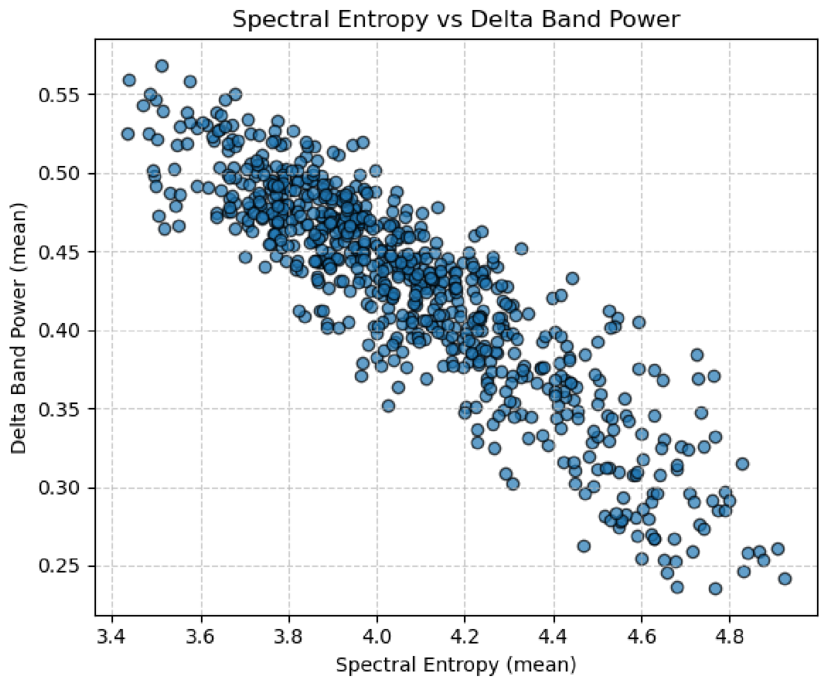



Fig. 6: Spectral Entropy vs. Delta Band Power for *Chb01_01.edf* .

In Fig. 6, a scatter plot between **spectral entropy** and **delta band power** shows a pronounced **negative correlation**. As delta power increases, spectral entropy decreases, reflecting a reduction in signal complexity and variability during seizure events.

This demonstrates that entropy serves as a robust nonlinear indicator of brain state regularity and complements power-based metrics for seizure characterization.

## 4.6 Inter-Channel Correlation Analysis

In Fig. 7, the box plot of **inter-channel correlation metrics** (mean, standard deviation, maximum) reveals that:

- **Maximum correlation values** approach 1.0, showing strong synchronization across channels during seizure periods.
- **Mean correlation** values remain moderately high with small variance, suggesting consistent phase coupling.

This spatial coherence corroborates the known property of seizures producing large-scale, synchronous neural oscillations across cortical regions.

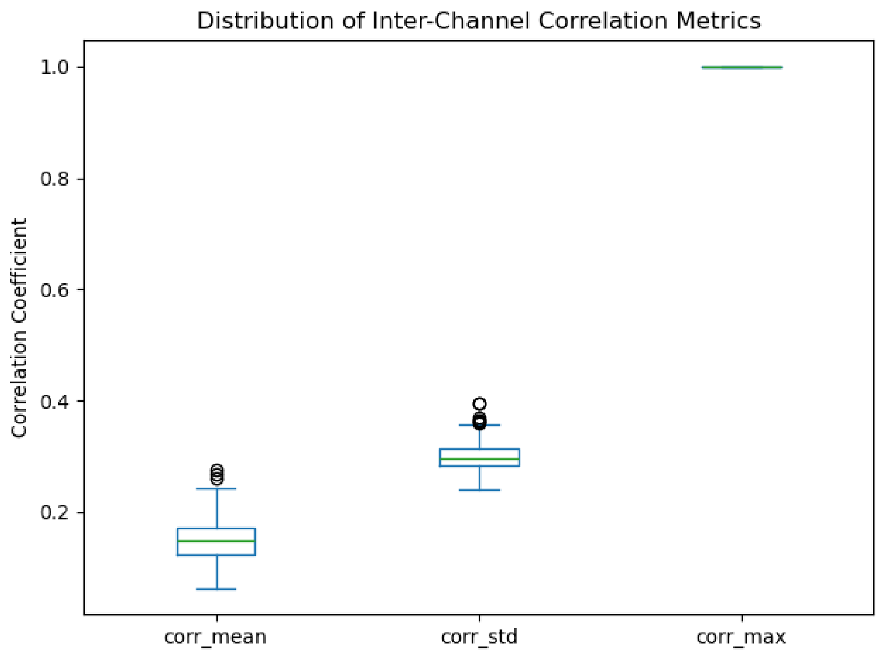



Fig. 7: Distribution of Inter-Channel Correlation Metrics for *Chb01_01.edf* .

## 4.7 Feature Matrix and Neural Network Readiness

| | delta_mean | delta_std | delta_max | delta_median | theta_mean | theta_std | theta_max | theta_median | alpha_mean | alpha_std |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.439917 | 0.122878 | 0.680715 | 0.425868 | 0.134942 | 0.048450 | 0.229849 | 0.132495 | 0.046567 | 0.029513 |
| 1 | 0.491996 | 0.147472 | 0.753315 | 0.489125 | 0.157016 | 0.071678 | 0.355560 | 0.139707 | 0.052553 | 0.036122 |
| 2 | 0.375810 | 0.082527 | 0.485999 | 0.389008 | 0.155521 | 0.067377 | 0.320863 | 0.145871 | 0.055865 | 0.031640 |
| 3 | 0.328070 | 0.089442 | 0.475458 | 0.338504 | 0.164152 | 0.065626 | 0.293830 | 0.164945 | 0.056487 | 0.021148 |
| 4 | 0.467772 | 0.085527 | 0.657703 | 0.458547 | 0.173338 | 0.052196 | 0.284436 | 0.168564 | 0.054683 | 0.029469 |

5 rows × 34 columns

Table I: Part of the extracted Feature Matrix for *Chb01_01.edf* .

The extracted features (in **Table I**) - including band powers, statistical metrics, entropy, and correlation values - were compiled into a structured **DataFrame**. Each 10-second EEG epoch produced a 30+ dimensional feature vector suitable for machine learning.

Preliminary inspection confirmed that seizure and non-seizure epochs occupy distinct regions in feature space. This confirms that the DSP-based pipeline effectively converts raw EEG signals into interpretable, discriminative representations suitable for downstream neural network classification.

## 4.8 Summary of Results

| **Analysis Domain** | **Key Observation** | **DSP Technique Used** |
|---|---|---|
| **Spectrograms** | Low-frequency dominance in seizure epochs | STFT / Spectrogram |
| **Filtering** | Removal of 60 Hz noise and high-frequency artifacts | Notch & FIR Bandpass |
| **Band Power** | High $\Delta$ and $\theta$ power; reduced $\alpha$, $\beta$, $\gamma$ | FFT + Welch PSD |
| **Statistical Features** | High kurtosis, low skewness | Time-domain analysis |
| **Spectral Entropy** | Negatively correlated with $\Delta$ power | Entropy computation |
| **Correlation Features** | High inter-channel synchronization | Pearson correlation |
| **Feature Set** | Distinct seizure/non-seizure separation | DSP-based feature extraction |

Table II: Summary of Results for *Chb01_01.edf* .

The summary of results in **Table II** comprehensively demonstrate how classical DSP techniques—filtering, spectral analysis, correlation, and statistical quantification—enable the transformation of raw EEG data into reliable, interpretable feature vectors for intelligent seizure detection systems.

# 5. Discussion

The comprehensive analysis of the EEG signals through multiple DSP techniques provides strong validation of the designed processing pipeline. The graphical outputs demonstrate how each stage of filtering, transformation, and feature extraction contributes to isolating seizure-related dynamics from normal brain activity.

## 5.1 Spectral Characteristics and Signal Transformation

The **spectrogram analysis (Fig. 1 and Fig. 2)** clearly distinguished normal and seizure EEG segments. In normal states, spectral power was distributed across a broad range (10–30 Hz), while during seizures, energy concentrated predominantly below 10 Hz, corresponding to delta and theta rhythms. This confirms the transition from desynchronized (normal) to synchronized (seizure) neuronal activity, which is a hallmark of epileptic EEG patterns.

The **raw versus filtered signal plots (Fig. 3)** further demonstrate the effectiveness of the notch and bandpass filters. The removal of 60 Hz interference and baseline drift produced cleaner waveforms, while preserving critical low-frequency components. The corresponding FFT plots confirmed that the filter design successfully confined the EEG energy within the physiologically meaningful 0.5–70 Hz band, validating both time- and frequency-domain integrity.

## 5.2 Band Power and Frequency-Domain Trends

The **EEG band power distributions in Fig. 4** revealed a dominance of low-frequency components (delta > theta > beta > gamma > alpha), with a particularly high alpha/beta ratio during seizure activity. This quantitative observation reinforces the spectrogram findings, indicating strong low-frequency synchronization typical of epileptic discharges. The gradual attenuation of higher-frequency bands also suggests a reduction in cortical information processing during seizure episodes, consistent with neurophysiological expectations.

## 5.3 Time-Domain Statistical Behavior

Time-domain statistical analysis, including **skewness** and **kurtosis (in Fig. 5)**, provided further insight into EEG morphology. High kurtosis values indicate the frequent occurrence of transient, high-amplitude spikes, representing sharp epileptic waveforms. Low skewness values confirm that amplitude distributions remain roughly symmetric but are characterized by heavy tails. This implies that seizure signals exhibit impulsive, non-Gaussian behavior, validating the statistical distinctiveness of pathological EEG activity.

## 5.4 Entropy and Signal Complexity

The **spectral entropy versus delta power** scatter plot **in Fig. 6** demonstrated a strong **negative correlation**—as delta power increased, entropy decreased. This relationship captures a key neurodynamic feature: during seizure onset, the brain's electrical activity becomes more synchronized and predictable, resulting in a loss of complexity.

Entropy thus acts as a nonlinear descriptor of neural regularity, complementing traditional power-based features.

## 5.5 Inter-Channel Correlation and Spatial Coherence

The **correlation feature box plots in Fig. 7** revealed consistently high inter-channel synchronization, with maximum correlation values nearing 1.0 during seizures. This reflects strong spatial coherence between cortical regions, an expected outcome of the widespread neuronal coupling that occurs during epileptic episodes. Such correlation-based metrics not only confirm the physiological basis of seizures but also provide spatially rich descriptors that enhance the separability of seizure and non-seizure states in feature space.

## 5.6 Integrated DSP Insights

Overall, the results demonstrate that classical DSP operations—filtering, spectral decomposition, convolution, and correlation—when applied systematically, can effectively reveal the underlying physiological and pathological signatures in EEG data. Each transformation stage contributes uniquely:

- Filtering ensures clean signal integrity.

- FFT and PSD analyses expose frequency-domain behavior.
- Statistical and entropy measures quantify waveform shape and complexity.
- Correlation metrics capture inter-regional neural coherence.

Together, these findings confirm that the DSP-based approach not only improves EEG interpretability but also provides robust, explainable inputs for intelligent seizure detection models.

# 6. Conclusion and Future Work

This study demonstrates the successful application of **Digital Signal Processing (DSP)** techniques for the analysis and feature extraction of EEG signals related to epileptic seizure detection.

Through systematic filtering, spectral analysis, and statistical quantification, the pipeline achieved a complete transformation of noisy, raw EEG recordings into interpretable and discriminative feature sets.

The key conclusions are as follows:

1. **Effective Preprocessing:** The designed notch and FIR bandpass filters efficiently removed powerline interference and baseline drift while preserving essential EEG components.
2. **Distinct Spectral Patterns:** Spectrograms and PSD plots revealed clear separation between normal and seizure states, characterized by low-frequency dominance during seizures.
3. **Meaningful Statistical and Nonlinear Features:** High kurtosis and low entropy highlighted the impulsive, synchronized nature of seizure EEG signals.

4. **Spatial Correlation Evidence:** Correlation analyses confirmed strong inter-channel coupling, providing spatial context for the observed frequency-domain effects.

5. **Feature Set Readiness for Machine Learning:** The extracted features (band power, entropy, correlation, skewness, kurtosis, etc.) form a well-structured, interpretable dataset suitable for neural network–based classification or real-time seizure prediction.

In essence, the DSP-driven framework successfully bridges **theoretical signal processing principles** and **practical biomedical interpretation**, demonstrating that traditional DSP tools can form the analytical backbone for modern intelligent EEG analysis systems.

**Future work may include:**

- Integration of **adaptive and wavelet-based filters** for dynamic noise suppression,
- Implementation of **Independent Component Analysis (ICA)** for artifact rejection, and
- Development of **deep learning models** trained on the DSP-derived features for automated, real-time seizure detection.

# References

[1] L. Tan and J. Jiang, *Digital Signal Processing: Fundamentals and Applications*, 3rd ed. Elsevier Science, 2018.

[2] M. Teplan, "Fundamentals of EEG measurement," *Measurement Science Review*, vol. 2, no. 2, pp. 1–11, 2002.

[3] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," *Journal of Neuroscience Methods*, vol. 123, no. 1, pp. 69–87, 2003.

[4] U. R. Acharya, S. V. Sree, G. Swapna, R. J. Martis, and J. S. Suri, "Automated EEG analysis of epilepsy: A review," *Knowledge-Based Systems*, vol. 45, pp. 147–165, 2013.

[5] A. Aarabi, R. Fazel-Rezai, and Y. Aghakhani, "EEG seizure prediction: Measures and challenges," *Computers in Biology and Medicine*, vol. 42, no. 4, pp. 376–390, 2012.

# Appendix: Python Code Used in This Project

# project

November 2, 2025

## 1 Required Tools

[1]:
```
# !pip install mne scipy numpy pandas scikit-learn matplotlib tqdm
```

## 2 B. Imports & config

[2]:
```
import os
import glob
import numpy as np
import pandas as pd
import mne
from scipy import signal
from scipy.stats import skew, kurtosis
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, confusion_matrix
from tqdm import tqdm
import matplotlib.pyplot as plt
import warnings

# For reproducibility
RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)

# Ignoring all warnings
warnings.filterwarnings('ignore')

# Config
DATA_DIR = "data"        # folder containing subject folders or EDF files
SUBJECT = "chb01"                     # optional, for iterating per-subject
EDF_GLOB = os.path.join(DATA_DIR, "*.edf")    # or glob on subject subfolder
OUTPUT_FEATURE_CSV = "data/chb_features.csv"
```

# 3 C. Utility: load EDF

[3]:
```python
def load_edf(edf_path, preload=True, verbose=False):
    """
    Loads an EDF file using mne.io.read_raw_edf
    Returns Raw object
    """
    raw = mne.io.read_raw_edf(edf_path, preload=preload, verbose=verbose)
    # CHB-MIT has annotation channel sometimes; drop if present
    # Keep only EEG channels
    picks = mne.pick_types(raw.info, eeg=True, meg=False, eog=False)
    if len(picks) == 0:
        raise RuntimeError("No EEG channels found in EDF: " + edf_path)
    raw.pick(picks)
    return raw
```

## 3.1 Example:

[4]:
```python
raw = load_edf("data/chb01_01.edf")
raw.info, raw.ch_names[:10]
```

[4]:
```
(<Info | 8 non-empty values
  bads: []
  ch_names: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, …
  chs: 23 EEG
  custom_ref_applied: False
  highpass: 0.0 Hz
  lowpass: 128.0 Hz
  meas_date: 2076-11-06 11:42:54 UTC
  nchan: 23
  projs: []
  sfreq: 256.0 Hz
  subject_info: <subject_info | his_id: Surrogate>
 >,
 ['FP1-F7',
  'F7-T7',
  'T7-P7',
  'P7-O1',
  'FP1-F3',
  'F3-C3',
  'C3-P3',
  'P3-O1',
  'FP2-F4',
  'F4-C4'])
```

## 4 D. Filters - design & apply

[5]:
```
def design_notch(freq, sfreq, quality=30.0):
    """IIR notch via iirnotch (scipy). freq in Hz (e.g., 60)."""
    w0 = freq / (sfreq / 2.)
    b, a = signal.iirnotch(w0, quality)
    return b, a
```

[6]:
```
def design_bandpass_fir(lowcut, highcut, sfreq, numtaps=801, window='hamming'):
    """
    FIR bandpass design with window method. numtaps should be odd for linear␣
↪phase.
    Returns filter coefficients b (FIR) and a=1.
    """
    nyq = 0.5 * sfreq
    low = lowcut / nyq
    high = highcut / nyq
    b = signal.firwin(numtaps, [low, high], pass_zero=False, window=window)
    a = np.array([1.0])
    return b, a
```

[7]:
```
def design_bandpass_iir(lowcut, highcut, sfreq, order=4, btype='band'):
    """Butterworth IIR design (bi-directional recommended for zero-phase)."""
    nyq = 0.5 * sfreq
    low = lowcut / nyq
    high = highcut / nyq
    b, a = signal.butter(order, [low, high], btype=btype)
    return b, a
```

[8]:
```
def apply_filter_raw(raw, b, a, method='sos', use_sos=True):
    """
    Apply filter to an mne Raw object data (zero-phase by filtfilt).
    If b,a are IIR or FIR, use filtfilt on numpy data.
    """
    data = raw.get_data()  # shape (n_channels, n_samples)
    sfreq = int(raw.info['sfreq'])
    #filtfilt for zero-phase
    try:
        filtered = signal.filtfilt(b, a, data, axis=1, padtype='odd',␣
↪padlen=3*(max(len(a), len(b))))
    except Exception as e:
        # fallback using lfilter (non-zero-phase)
        filtered = signal.lfilter(b, a, data, axis=1)
    new_raw = mne.io.RawArray(filtered, raw.info, verbose=False)
    return new_raw
```

### 4.1 Example usage:

[9]:
```
raw = load_edf('data/chb01_01.edf')
b_notch, a_notch = design_notch(60, raw.info['sfreq'])
print("Notch Filter Parameters: ")
print(f"b: {b_notch}, \na: {a_notch}")
raw_notched = apply_filter_raw(raw, b_notch, a_notch)

b_bp, a_bp = design_bandpass_fir(0.5, 70, raw.info['sfreq'], numtaps=801)
raw_bp = apply_filter_raw(raw_notched, b_bp, a_bp)
print("Bandpass Filter Parameters: ")
print(f"b: {b_bp[:4]}, \na: {a_bp}")
```

```
Notch Filter Parameters:
b: [ 0.97603957 -0.19133722  0.97603957],
a: [ 1.         -0.19133722  0.95207915]
Bandpass Filter Parameters:
b: [1.07434505e-04 1.00760813e-04 6.61639283e-06 4.17781736e-05],
a: [1.]
```

## 5 E. Segmentation (epoching) & normalization

[10]:
```
def segment_raw(raw, epoch_length_sec=10.0, overlap=0.0):
    """
    Splits raw data into fixed-length epochs.
    Returns list of numpy arrays shape (n_channels, epoch_samples)
    """
    sfreq = raw.info['sfreq']
    epoch_samples = int(epoch_length_sec * sfreq)
    step = int(epoch_samples * (1 - overlap))
    data = raw.get_data()
    total_samples = data.shape[1]
    epochs = []
    starts = range(0, total_samples - epoch_samples + 1, step)
    for s in starts:
        ep = data[:, s:s+epoch_samples].copy()
        epochs.append(ep)
    return np.array(epochs)  # shape (n_epochs, n_channels, n_samples)
```

[11]:
```
def normalize_epoch(epoch, method='zscore'):
    """
    epoch: (n_channels, n_samples)
    method: 'zscore' or 'minmax' or 'per_channel_mean'
    """
    if method == 'zscore':
        mean = epoch.mean(axis=1, keepdims=True)
        std = epoch.std(axis=1, keepdims=True)
```

```
        std[std == 0] = 1.0
        return (epoch - mean) / std
    elif method == 'minmax':
        mn = epoch.min(axis=1, keepdims=True)
        mx = epoch.max(axis=1, keepdims=True)
        denom = (mx - mn)
        denom[denom == 0] = 1
        return (epoch - mn) / denom
    else:
        return epoch - epoch.mean(axis=1, keepdims=True)
```

### 5.1 Example:

[12]:
```
epochs = segment_raw(raw_bp, epoch_length_sec=10.0, overlap=0.5)
norm_epoch = normalize_epoch(epochs[0], 'zscore')

print(f"epochs shape: {epochs.shape}")
print(f"normamized epoch shape: {norm_epoch.shape}")
```

```
epochs shape: (719, 23, 2560)
normamized epoch shape: (23, 2560)
```

## 6 F. DSP demonstrations - correlation, convolution (smoothing), FFT

[13]:
```
def channel_correlation_matrix(epoch):
    """Compute Pearson correlation matrix between channels for an epoch."""
    return np.corrcoef(epoch)
```

[14]:
```
def smooth_epoch(epoch, kernel_len=5):
    """Convolve each channel with a moving average kernel (simple smoothing)."""
    kernel = np.ones(kernel_len) / kernel_len
    smoothed = signal.convolve(epoch, kernel[None, :], mode='same')
    return smoothed
```

[15]:
```
def compute_fft(epoch, sfreq):
    """
    Compute FFT magnitudes per channel for an epoch.
    Returns freqs and mags shape (n_channels, n_freqs)
    """
    n = epoch.shape[1]
    freqs = np.fft.rfftfreq(n, 1.0/sfreq)
    fft_vals = np.fft.rfft(epoch, axis=1)
    mags = np.abs(fft_vals) / n
    return freqs, mags
```

```python
[16]: def plot_time_and_spectrum(epoch, sfreq, channel_idx=0, title=None):
    t = np.arange(epoch.shape[1]) / sfreq
    freqs, mags = compute_fft(epoch[[channel_idx]], sfreq)
    plt.figure(figsize=(12,4))
    plt.subplot(1,2,1)
    plt.plot(t, epoch[channel_idx])
    plt.xlabel("Time (s)"); plt.title("Time domain" + (": "+title if title else␣
↪""))
    plt.subplot(1,2,2)
    plt.semilogy(freqs, mags[channel_idx])
    plt.xlabel("Frequency (Hz)"); plt.title("Magnitude spectrum")
    plt.tight_layout()
    plt.show()
```

### 6.1 Example usage:

```python
[17]: corr = channel_correlation_matrix(norm_epoch)
sm = smooth_epoch(norm_epoch, kernel_len=11)
```

# 7 G. Spectral analysis helpers (Welch, band powers, spectral entropy)

```python
[18]: def bandpower_psd(epoch_channel, sfreq, band, nperseg=None):
    """Compute band power using Welch PSD (absolute power)."""
    if nperseg is None:
        nperseg = min(256, epoch_channel.size)
    freqs, psd = signal.welch(epoch_channel, fs=sfreq, nperseg=nperseg)
    freq_res = freqs[1] - freqs[0]
    low, high = band
    idx_band = np.logical_and(freqs >= low, freqs <= high)
    power = np.trapz(psd[idx_band], freqs[idx_band])
    return power
```

```python
[19]: def compute_all_band_powers(epoch, sfreq, bands=None):
    """
    epoch: (n_channels, n_samples)
    bands: dict of band_name -> (low, high)
    Returns dict band_name -> array(n_channels,)
    """
    if bands is None:
        bands = {
            'delta': (0.5, 4),
            'theta': (4, 8),
            'alpha': (8, 13),
            'beta' : (13, 30),
            'gamma': (30, 70)
```

```
        }
    res = {}
    for name, band in bands.items():
        res[name] = np.array([bandpower_psd(epoch[ch], sfreq, band) for ch in␣
 ↪range(epoch.shape[0])])
    return res
```

[20]:
```
def spectral_entropy(epoch_channel, sfreq, nperseg=None):
    """Spectral entropy via normalized PSD (Shannon entropy)."""
    if nperseg is None:
        nperseg = min(256, epoch_channel.size)
    freqs, psd = signal.welch(epoch_channel, fs=sfreq, nperseg=nperseg)
    psd_norm = psd / np.sum(psd)
    psd_norm = psd_norm + 1e-12  # avoid log(0)
    ent = -np.sum(psd_norm * np.log2(psd_norm))
    return ent
```

# 8 H. Feature extraction for one epoch

[21]:
```
def extract_features_for_epoch(epoch, sfreq):
    """
    epoch: (n_channels, n_samples)
    Returns a dictionary of aggregated features for the epoch (flattened across␣
 ↪channels).
    Strategy: for each channel compute bandpowers, energy, mean, var, skew,␣
 ↪kurtosis, spectral entropy.
    Also compute pairwise correlation stats (mean, std of upper-triangular␣
 ↪entries).
    """
    feats = {}
    n_ch = epoch.shape[0]
    # band powers per channel
    bands = {
        'delta': (0.5, 4),
        'theta': (4, 8),
        'alpha': (8, 13),
        'beta' : (13, 30),
        'gamma': (30, 70)
    }
    bp = compute_all_band_powers(epoch, sfreq, bands=bands)
    for band_name, arr in bp.items():
        feats[f'{band_name}_mean'] = arr.mean()
        feats[f'{band_name}_std']  = arr.std()
        feats[f'{band_name}_max']  = arr.max()
        feats[f'{band_name}_median'] = np.median(arr)
```

```
    # Time-domain stats per channel aggregated
    energies = np.sum(epoch**2, axis=1)
    feats['energy_mean'] = energies.mean()
    feats['energy_std']  = energies.std()
    feats['signal_mean'] = epoch.mean()
    feats['signal_std']  = epoch.std()
    feats['signal_skew'] = skew(epoch.reshape(-1))
    feats['signal_kurtosis'] = kurtosis(epoch.reshape(-1))

    # spectral entropy aggregated
    entropies = np.array([spectral_entropy(epoch[ch], sfreq) for ch in␣
 ↪range(n_ch)])
    feats['spec_ent_mean'] = entropies.mean()
    feats['spec_ent_std']  = entropies.std()

    # Correlation matrix summary
    corr = channel_correlation_matrix(epoch)
    # take upper triangle without diagonal
    iu = np.triu_indices_from(corr, k=1)
    if len(iu[0]) > 0:
        corr_vals = corr[iu]
        feats['corr_mean'] = np.nanmean(corr_vals)
        feats['corr_std']  = np.nanstd(corr_vals)
        feats['corr_max']  = np.nanmax(corr_vals)
    else:
        feats['corr_mean'] = 0
        feats['corr_std'] = 0
        feats['corr_max'] = 0

    # Additional: relative bandpower ratios (e.g., alpha/beta)
    total_power_per_ch = np.sum([bp[b][...] for b in bp], axis=0) + 1e-12
    alpha = bp['alpha']
    beta  = bp['beta']
    feats['alpha_beta_ratio_mean'] = np.mean(alpha / (beta + 1e-12))

    return feats
```

## 8.1 Example:

[22]:
```
feats = extract_features_for_epoch(norm_epoch, raw.info['sfreq'])
pd.Series(feats)
```

[22]:
```
delta_mean                4.399167e-01
delta_std                 1.228783e-01
delta_max                 6.807148e-01
delta_median              4.258677e-01
theta_mean                1.349422e-01
```

```
theta_std                  4.845031e-02
theta_max                  2.298486e-01
theta_median               1.324952e-01
alpha_mean                 4.656732e-02
alpha_std                  2.951320e-02
alpha_max                  1.199470e-01
alpha_median               4.241738e-02
beta_mean                  8.853269e-02
beta_std                   4.415512e-02
beta_max                   1.917555e-01
beta_median                7.905160e-02
gamma_mean                 8.281448e-02
gamma_std                  7.025587e-02
gamma_max                  2.544092e-01
gamma_median               5.518275e-02
energy_mean                2.560000e+03
energy_std                 3.547891e-13
signal_mean               -3.861645e-18
signal_std                 1.000000e+00
signal_skew                2.563691e-01
signal_kurtosis            2.943603e+00
spec_ent_mean              3.894096e+00
spec_ent_std               6.048319e-01
corr_mean                  9.407926e-02
corr_std                   3.192047e-01
corr_max                   1.000000e+00
alpha_beta_ratio_mean      5.907506e-01
dtype: float64
```

# 9 I. Build feature matrix from a file (with optional label annotations)

[23]:
```
def build_feature_matrix_from_edf(edf_path, epoch_length_sec=10.0, overlap=0.5,
                                  apply_notch=True, notch_freq=60.0,
                                  bp_filter=('fir', 0.5, 70),␣
 ↪normalize_method='zscore',
                                  label=None, verbose=False):
    """
    Processes one EDF file end-to-end and returns a DataFrame with per-epoch␣
 ↪features and labels.
    bp_filter: ('fir'|'iir', lowcut, highcut)
    label: optional (e.g., 1 for seizure, 0 for non-seizure) - to build a label␣
 ↪mapping externally using annotations
    """
    raw = load_edf(edf_path, preload=True)
    sfreq = raw.info['sfreq']
```

```
    # notch
    if apply_notch:
        b_n, a_n = design_notch(notch_freq, sfreq, quality=30.0)
        raw = apply_filter_raw(raw, b_n, a_n)

    # bandpass
    ftype, lowcut, highcut = bp_filter
    if ftype == 'fir':
        b_bp, a_bp = design_bandpass_fir(lowcut, highcut, sfreq, numtaps=801)
    else:
        b_bp, a_bp = design_bandpass_iir(lowcut, highcut, sfreq, order=4)
    raw = apply_filter_raw(raw, b_bp, a_bp)

    # segmentation
    epochs = segment_raw(raw, epoch_length_sec=epoch_length_sec,␣
↪overlap=overlap)

    features_list = []
    for epoch in epochs:
        epoch_norm = normalize_epoch(epoch, method=normalize_method)
        feats = extract_features_for_epoch(epoch_norm, sfreq)
        feats['edf_file'] = os.path.basename(edf_path)
        # optionally adding epoch start time (samples) or any annotation-based␣
↪label
        feats['label'] = label
        features_list.append(feats)

    df = pd.DataFrame(features_list)
    return df
```

## 9.1 Example (no labels):

[24]:
```
df = build_feature_matrix_from_edf("data/chb01_01.edf", epoch_length_sec=10,␣
↪overlap=0.5)
df.head()
```

[24]:
```
   delta_mean  delta_std  delta_max  delta_median  theta_mean  theta_std  \
0    0.439917   0.122878   0.680715      0.425868    0.134942   0.048450
1    0.491996   0.147472   0.753315      0.489125    0.157016   0.071678
2    0.375810   0.082527   0.485999      0.389008    0.155521   0.067377
3    0.328070   0.089442   0.475458      0.338504    0.164152   0.065626
4    0.467772   0.085527   0.657703      0.458547    0.173338   0.052196

   theta_max  theta_median  alpha_mean  alpha_std  …  signal_skew  \
0   0.229849      0.132495    0.046567   0.029513  …     0.256369
1   0.355560      0.139707    0.052553   0.036122  …     0.163628
```

```
2   0.320863      0.145871     0.055865    0.031640  …     0.083959
3   0.293830      0.164945     0.056487    0.021148  …     0.441731
4   0.284436      0.168564     0.054683    0.029469  …     0.309528

   signal_kurtosis  spec_ent_mean  spec_ent_std  corr_mean  corr_std  \
0         2.943603       3.894096      0.604832   0.094079  0.319205
1         3.781029       3.952233      0.678081   0.089288  0.290171
2         3.887230       4.371788      0.646738   0.092746  0.248896
3         3.293229       4.486092      0.552320   0.147066  0.260859
4         2.573853       3.889251      0.465952   0.148925  0.287578

   corr_max  alpha_beta_ratio_mean      edf_file  label
0       1.0               0.590751  chb01_01.edf   None
1       1.0               0.548683  chb01_01.edf   None
2       1.0               0.484118  chb01_01.edf   None
3       1.0               0.531328  chb01_01.edf   None
4       1.0               0.694480  chb01_01.edf   None

[5 rows x 34 columns]
```

# 10 J. Batch process EDF files & save features

## 10.1 Example: process all EDF files found in EDF_GLOB and save features

[25]:
```python
edf_files = sorted(glob.glob(EDF_GLOB))
print(f"Found {len(edf_files)} EDF files. Processing a sample or all...")
```

```
Found 2 EDF files. Processing a sample or all…
```

### 10.1.1 For demo, we process first N files or all; adjust N or provide list of seizure/non-seizure labels externally.

[26]:
```python
N = len(edf_files)  # smaller number for quick run, e.g., 3
all_dfs = []
for edf in tqdm(edf_files[:N]):
    # NOTE: For CHB-MIT, seizure annotations are in separate files; here we set␣
↪label=None.
    # Later to parse the .seizure files or the dataset readme to get epoch␣
↪labels.
    try:
        df_temp = build_feature_matrix_from_edf(edf, epoch_length_sec=10.0,␣
↪overlap=0.5,
                                                apply_notch=True, notch_freq=60.
↪0,
                                                bp_filter=('fir', 0.5, 70),
                                                normalize_method='zscore')
        all_dfs.append(df_temp)
```

```
    except Exception as e:
        print("Error processing", edf, ":", e)

if len(all_dfs) > 0:
    features_df = pd.concat(all_dfs, ignore_index=True)
    features_df.to_csv(OUTPUT_FEATURE_CSV, index=False)
    print("Saved features to", OUTPUT_FEATURE_CSV)
else:
    features_df = pd.DataFrame()
    print("No features created.")
```

```
100%|      | 2/2 [04:03<00:00, 121.67s/it]

Saved features to data/chb_features.csv
```

- Combine features from seizure and non-seizure EDFs
- Assuming features already extracted into 'features_df' or similar variable
- If not, make sure earlier cells create 'features_df' containing at least ['edf_file', ]

[27]:
```
# Drop any completely empty columns (safe cleanup)
features_df = features_df.dropna(axis=1, how='all')

# --- Add label column manually ---
# Label seizure vs. non-seizure based on filename
features_df['label'] = features_df['edf_file'].apply(
    lambda f: 1 if 'seizure' in f.lower() or '03' in f.lower() else 0
)

# Now separate features (X) and labels (y)
# Keep only numerical feature columns
exclude_cols = ['edf_file', 'label']
X = features_df.drop(columns=[col for col in exclude_cols if col in features_df.
 ↪columns], errors='ignore')
y = features_df['label']

print("Feature matrix shape:", X.shape)
print("Labels shape:", y.shape)
print("Class balance (0=non-seizure, 1=seizure):")
print(y.value_counts())
```

```
Feature matrix shape: (1438, 32)
Labels shape: (1438,)
Class balance (0=non-seizure, 1=seizure):
label
0    719
1    719
Name: count, dtype: int64
```

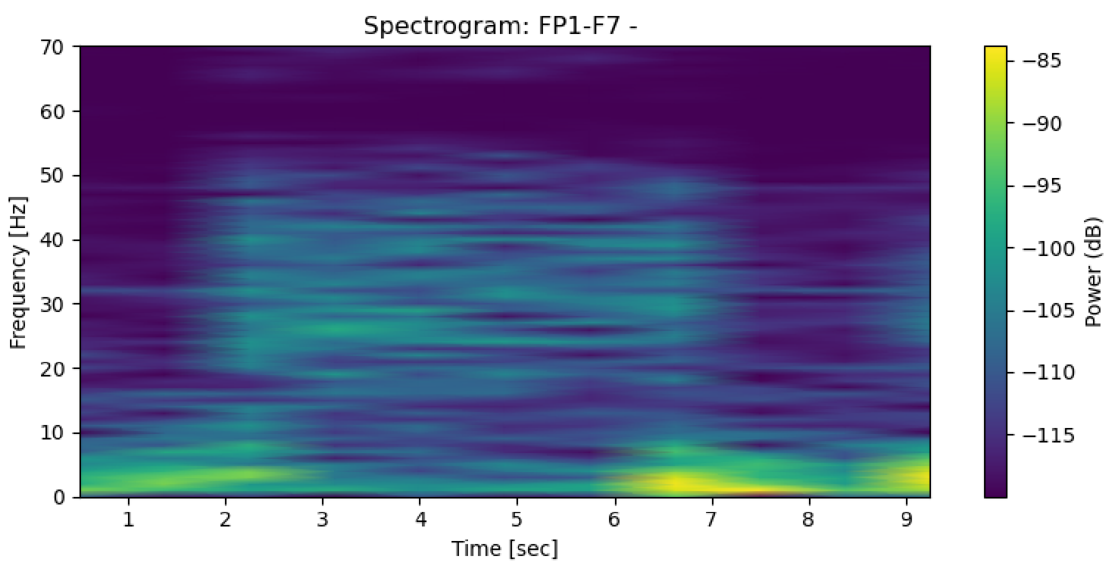
# 11 K. Visualizations

[28]:
```
# Plotting example spectrogram for first epoch of first file
def plot_spectrogram(epoch_channel, sfreq, channel_name='ch0', nperseg=256,␣
↪seizure=False):
    f, t, Sxx = signal.spectrogram(epoch_channel, fs=sfreq, nperseg=nperseg)
    plt.figure(figsize=(8,4))
    plt.pcolormesh(t, f, 10*np.log10(Sxx + 1e-12), shading='gouraud')
    plt.ylabel('Frequency [Hz]')
    plt.xlabel('Time [sec]')
    plt.title(f"Spectrogram: {channel_name} - {"seizure" if seizure else ""}")
    plt.colorbar(label='Power (dB)')
    plt.ylim(0, 70)
    plt.tight_layout()
    plt.show()
```

## 11.1 Fig. 1: Spectrogram for Chb01_01.edf (non-seizure).

[29]:
```
raw_example = load_edf(edf_files[0])
print(raw_example.info['sfreq'])
raw_example = apply_filter_raw(raw_example, *design_notch(60, raw_example.
↪info['sfreq']))
epochs = segment_raw(raw_example, epoch_length_sec=10.0, overlap=0.0)
plot_spectrogram(epochs[0][0], raw_example.info['sfreq'],␣
↪channel_name=raw_example.ch_names[0])
```

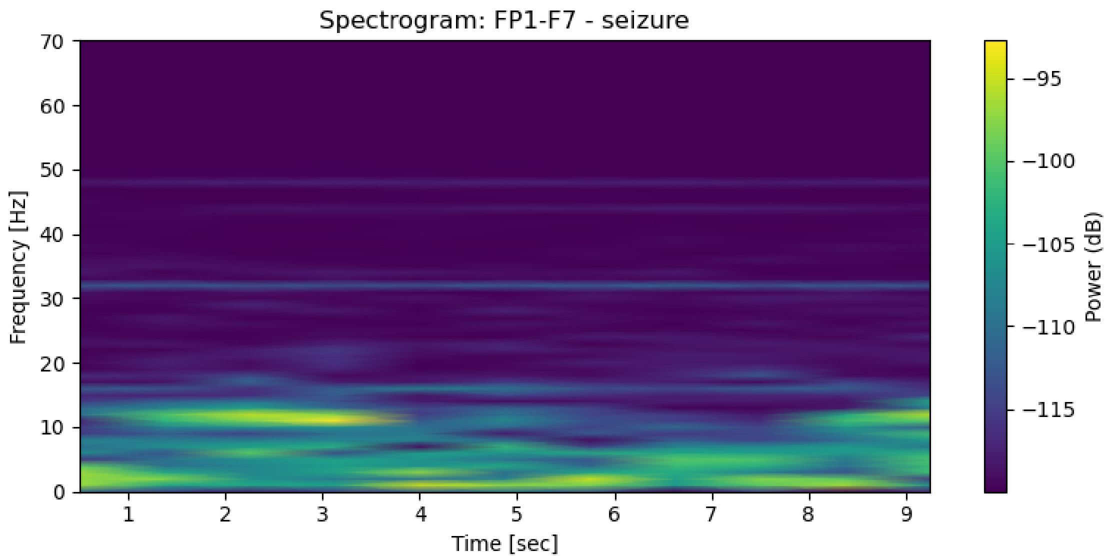
```
256.0
```



## 11.2 Fig. 2: Spectrogram for Chb01_03.edf (seizure).

[30]:
```
raw_example = load_edf(edf_files[1])
print(raw_example.info['sfreq'])
raw_example = apply_filter_raw(raw_example, *design_notch(60, raw_example.
 ↪info['sfreq']))
epochs = segment_raw(raw_example, epoch_length_sec=10.0, overlap=0.0)
plot_spectrogram(epochs[0][0], raw_example.info['sfreq'],␣
 ↪channel_name=raw_example.ch_names[0], seizure=True)
```

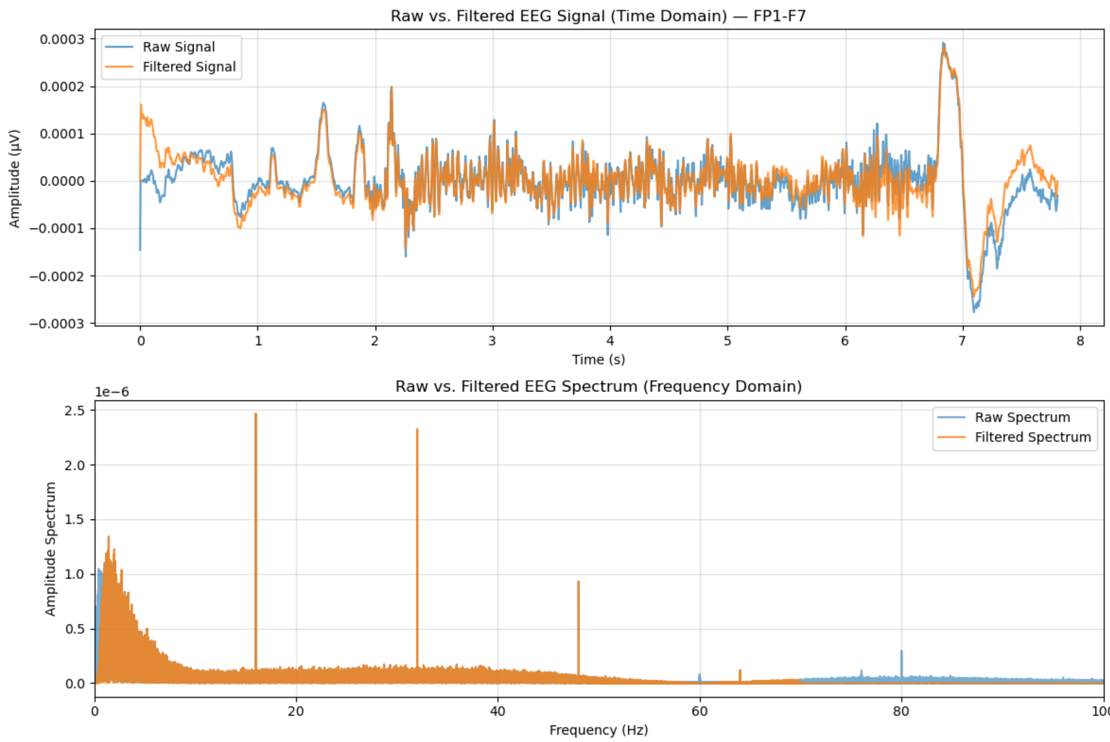
```
256.0
```




## 11.3 Fig. 3: Raw and filtered Signals and their Spectrums for Chb01_01.edf .

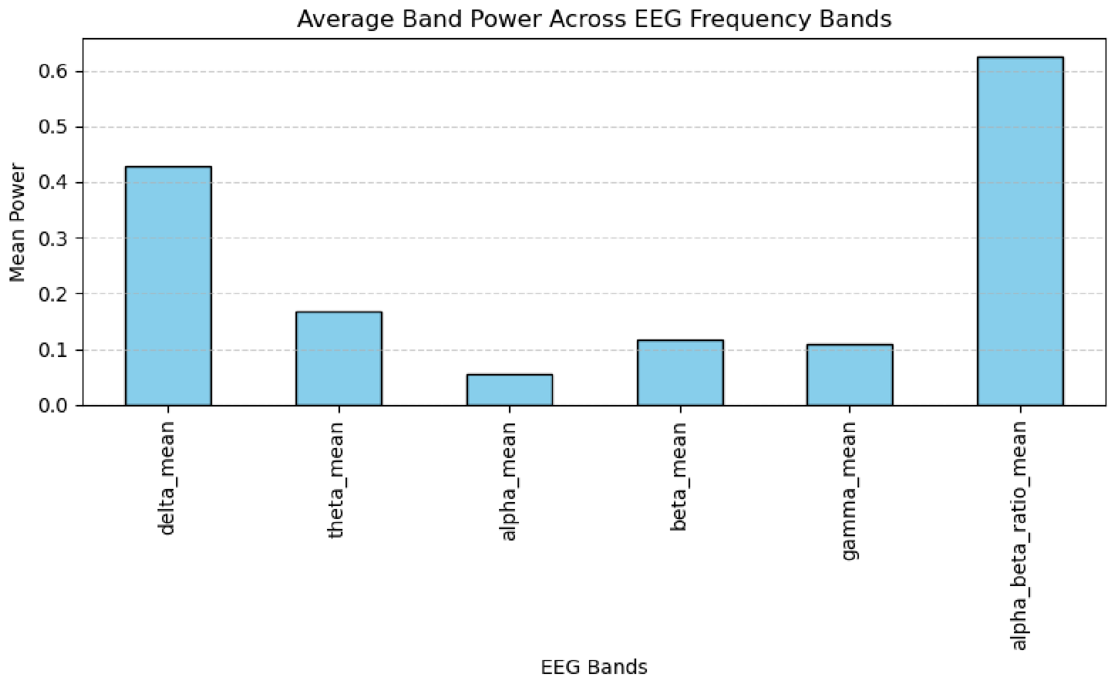
[31]:
```
edf_path = edf_files[0]
raw_original = load_edf(edf_path)
sfreq = raw_original.info['sfreq']

# Applying notch and bandpass filtering
b_notch, a_notch = design_notch(60, sfreq)
raw_notched = apply_filter_raw(raw_original, b_notch, a_notch)
b_bp, a_bp = design_bandpass_fir(0.5, 70, sfreq, numtaps=801)
raw_filtered = apply_filter_raw(raw_notched, b_bp, a_bp)

# Picking one electrode and extract data
channel = raw_filtered.ch_names[0]  # e.g., 'FP1-F7'
raw_data, times = raw_original[channel, :]
filt_data, _ = raw_filtered[channel, :]
```

```python
# Computing FFT for frequency-domain comparison
def compute_fft(signal, fs):
    N = len(signal)
    freqs = np.fft.rfftfreq(N, d=1/fs)
    spectrum = np.abs(np.fft.rfft(signal)) / N
    return freqs, spectrum

freqs_raw, spec_raw = compute_fft(raw_data[0], sfreq)
freqs_filt, spec_filt = compute_fft(filt_data[0], sfreq)

# Plotting time and frequency domain together
plt.figure(figsize=(12, 8))

# --- Time Domain ---
plt.subplot(2, 1, 1)
plt.plot(times[:2000], raw_data[0][:2000], label='Raw Signal', alpha=0.7)
plt.plot(times[:2000], filt_data[0][:2000], label='Filtered Signal', alpha=0.8)
plt.title(f"Raw vs. Filtered EEG Signal (Time Domain) - {channel}")
plt.xlabel("Time (s)")
plt.ylabel("Amplitude (µV)")
plt.legend()
plt.grid(alpha=0.4)

# --- Frequency Domain ---
plt.subplot(2, 1, 2)
plt.plot(freqs_raw, spec_raw, label='Raw Spectrum', alpha=0.6)
plt.plot(freqs_filt, spec_filt, label='Filtered Spectrum', alpha=0.8)
plt.xlim(0, 100)  # Focus on EEG band range
plt.title("Raw vs. Filtered EEG Spectrum (Frequency Domain)")
plt.xlabel("Frequency (Hz)")
plt.ylabel("Amplitude Spectrum")
plt.legend()
plt.grid(alpha=0.4)

plt.tight_layout()
plt.show()
```




## 11.4 Fig. 4: Average Band Power Across EEG Frequency Bands for Chb01_01.edf .

[32]:
```
band_features = [col for col in df.columns if col.startswith(('delta', 'theta', 'alpha', 'beta', 'gamma')) and col.endswith('_mean')]
if band_features:
    plt.figure(figsize=(8, 5))
    df[band_features].mean().plot(kind='bar', color='skyblue', edgecolor='black')
    plt.title("Average Band Power Across EEG Frequency Bands")
    plt.ylabel("Mean Power")
    plt.xlabel("EEG Bands")
    plt.grid(axis='y', linestyle='--', alpha=0.6)
    plt.tight_layout()
    plt.show()
else:
    print("No band power features found.")
```




## 11.5 Fig. 5: Distribution of Statistical Time-Domain Features for Chb01_01.edf .

[33]:
```
stat_features = ['signal_skew', 'signal_kurtosis']
available = [f for f in stat_features if f in df.columns]

if available:
    df[available].plot(kind='box', figsize=(6, 4))
    plt.title("Distribution of Statistical Time-Domain Features")
    plt.ylabel("Value")
    plt.tight_layout()
    plt.show()
else:
    print("No statistical time-domain features found.")
```

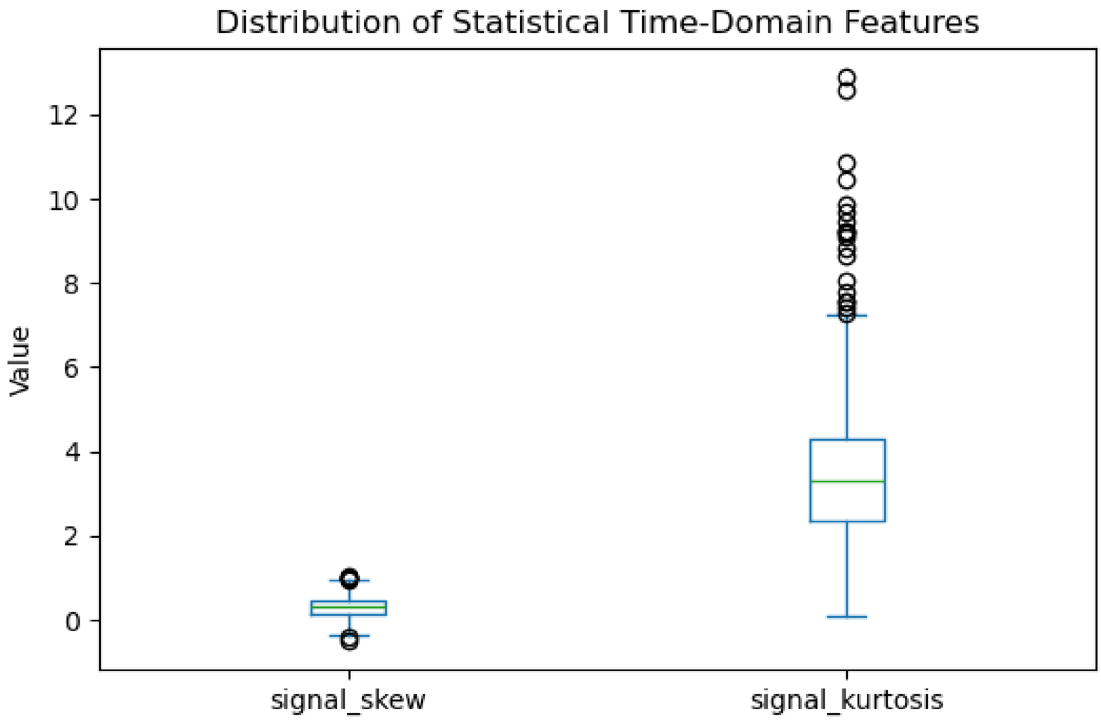
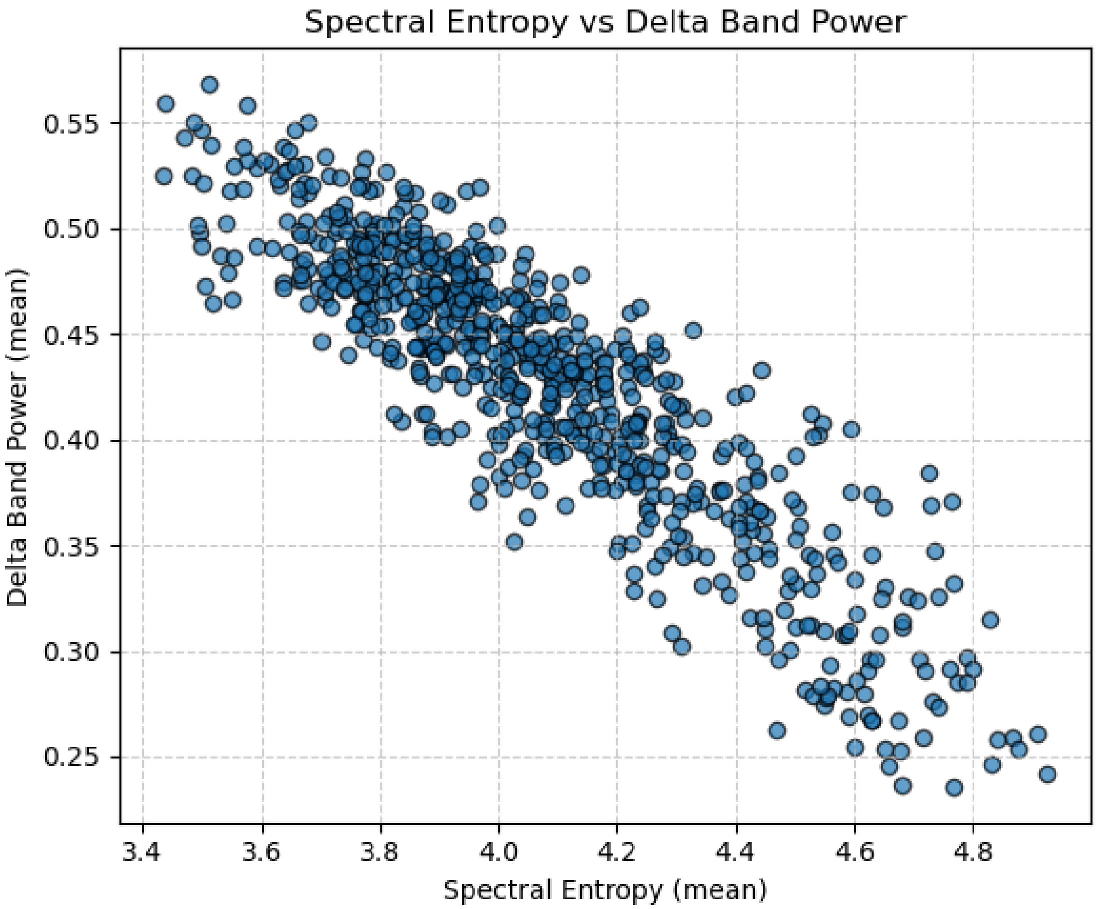



Fig. 6: Spectral Entropy vs. Delta Band Power for Chb01_01.edf .

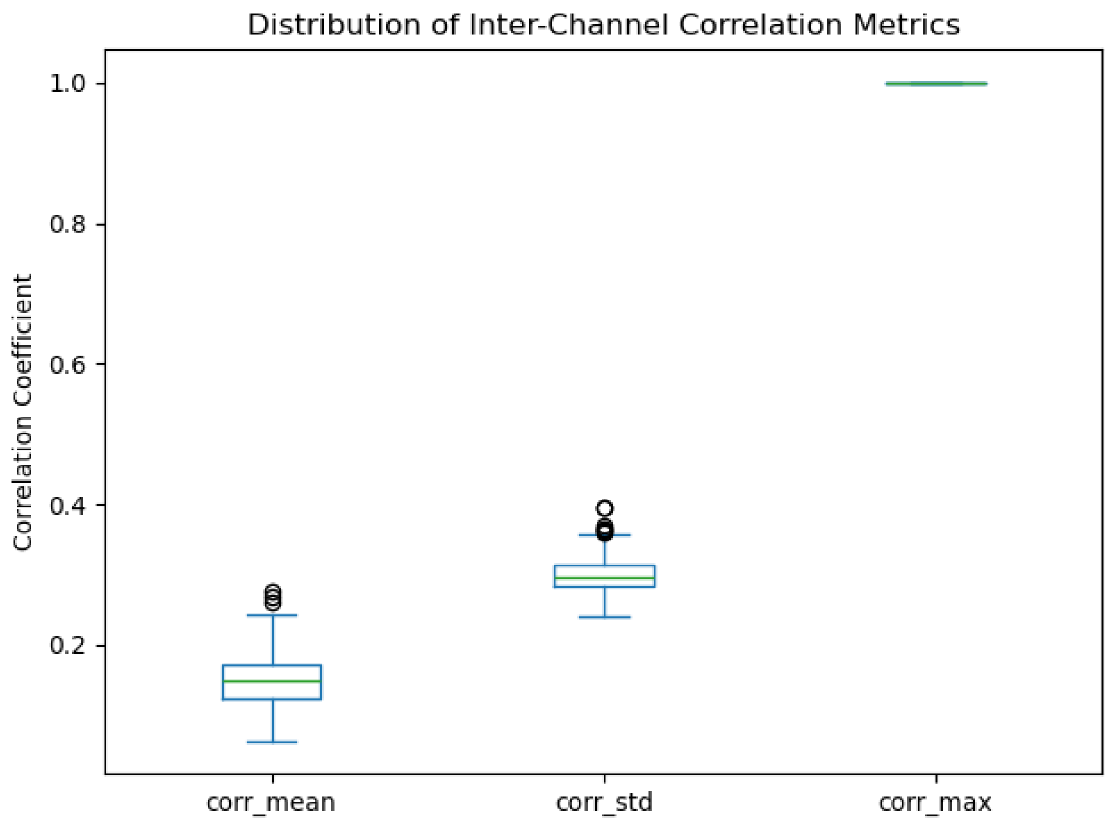
[34]:
```
if {'spec_ent_mean', 'delta_mean'}.issubset(df.columns):
    plt.figure(figsize=(6, 5))
    plt.scatter(df['spec_ent_mean'], df['delta_mean'], alpha=0.7, edgecolor='k')
    plt.xlabel("Spectral Entropy (mean)")
    plt.ylabel("Delta Band Power (mean)")
    plt.title("Spectral Entropy vs Delta Band Power")
    plt.grid(True, linestyle='--', alpha=0.6)
    plt.tight_layout()
    plt.show()
else:
    print("Required columns not found for entropy-power correlation.")
```




## 11.6 Fig. 7: Distribution of Inter-Channel Correlation Metrics for Chb01_01.edf .

[35]:
```
corr_cols = [c for c in ['corr_mean', 'corr_std', 'corr_max'] if c in df.
  ↪columns]
if corr_cols:
    plt.figure(figsize=(7, 4))
    df[corr_cols].plot(kind='box')
    plt.title("Distribution of Inter-Channel Correlation Metrics")
    plt.ylabel("Correlation Coefficient")
    plt.tight_layout()
    plt.show()
else:
    print("Correlation feature columns not found.")
```

```
<Figure size 700x400 with 0 Axes>
```


Distribution of Inter-Channel Correlation Metrics
Correlation Coefficient
1.0
0.8
0.6
0.4
0.2
corr_mean
corr_std
corr_max