SPECTOGRAM ASSIGNMENT

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CONTENTS

INTRODUCTION:

Epilepsy is a neurological disorder characterized by recurrent seizures caused by abnormal electrical activity in the brain. The analysis of electroencephalogram (EEG) data plays a crucial role in understanding and detecting epileptic seizures. This report focuses on constructing an analytical system using the **Short-Time Fourier Transform (STFT)** to generate spectrograms for visualizing the time-frequency characteristics of EEG signals.

The project utilizes EEG data from the CHB-MIT dataset, specifically targeting patient chb12, to analyze both seizure (ictal) and non-seizure (non-ictal) states. The tasks involved include preprocessing the EEG signals, generating spectrograms with varying parameters (e.g., window type, overlap ratio, and window length), and analyzing the effects of these parameters on the results. This report documents the results and discusses the impact of parameter tuning on the spectrogram outputs.

PRE-PROCESSING

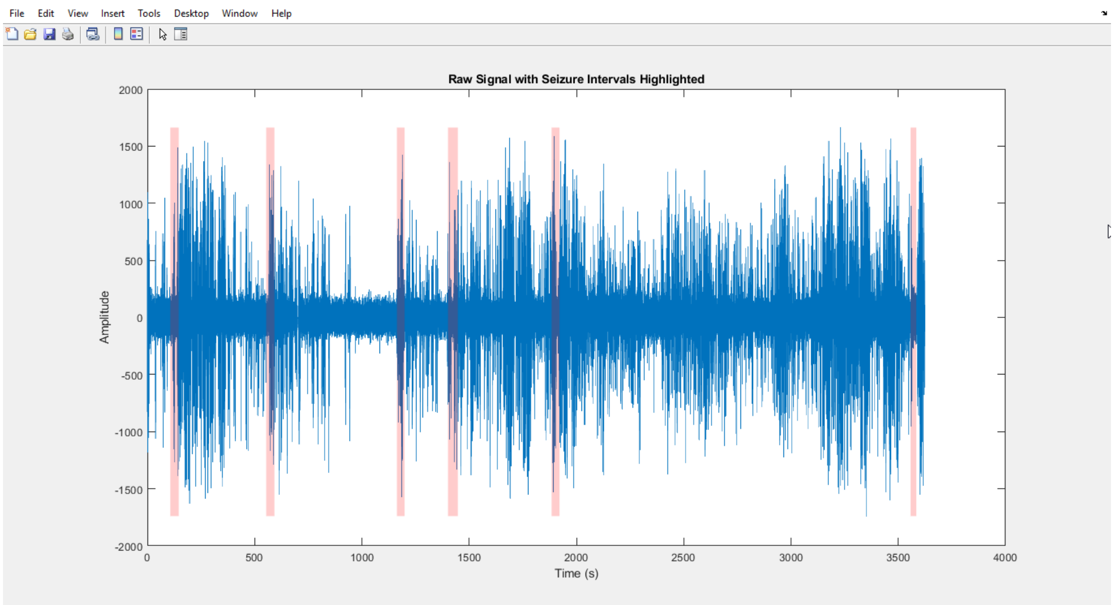

Figure 1 : Average Signal with Seizure Intervals Highlighted

- **Description**: This figure shows the average EEG signal across all valid channels, with seizure intervals highlighted in red.

- **Observations**:
    - The baseline activity is consistent, with distinct spikes in amplitude during seizure intervals.
    - The seizure regions clearly display increased activity, indicating abnormal electrical behavior.

- **implications**: This plot demonstrates the temporal localization of seizures and validates the accurate extraction of ictal states.

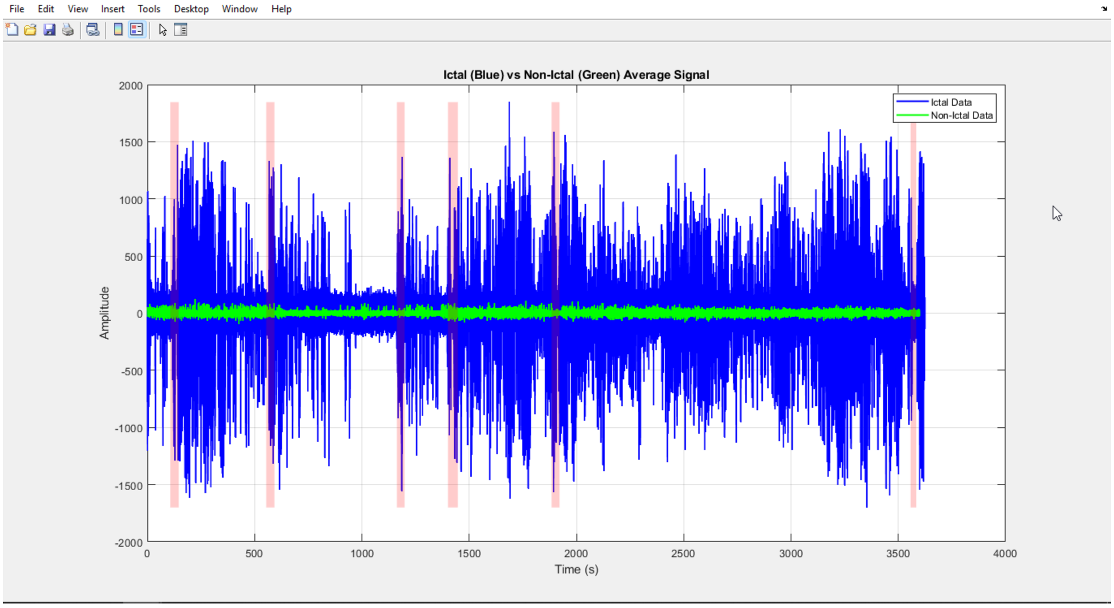

Figure 2: Ictal vs Non-Ictal Data with Seizure Intervals Highlighted

- **Description**: A comparative plot of ictal (seizure) and non-ictal (normal) data, with seizure intervals visually highlighted.
- **Observations:**
  - Ictal data (blue) exhibits higher amplitudes and more variability compared to non-ictal data (green).
  - Highlighted seizure intervals align with peaks in the ictal data, demonstrating the synchronization of brain activity during seizures.
- **Implications:** This graph effectively contrasts seizure and non-seizure states, emphasizing differences in signal amplitude and variability.

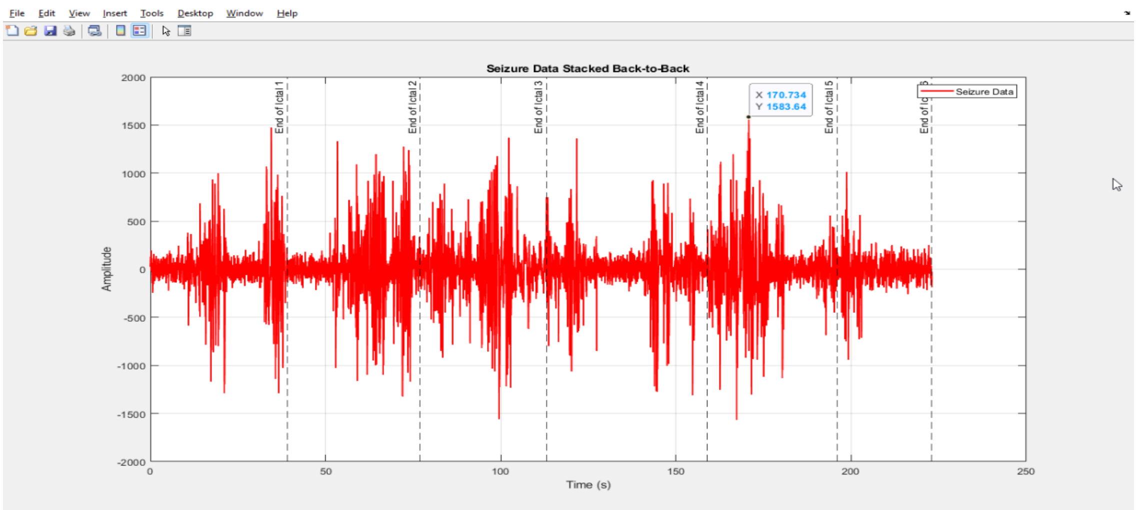

Figure 3: Seizure Data

- **Description** This plot displays seizure data stacked across multiple signal channels.
- **Observations**:
    - Significant signal amplitude variations during ictal periods are observed across channels.
    - The stacking highlights differences in seizure propagation or activity among the recorded channels, enabling a clearer understanding of temporal and spatial signal variations.
- **Implications**: This visualization is critical for assessing how signal characteristics differ among the channels during seizures.

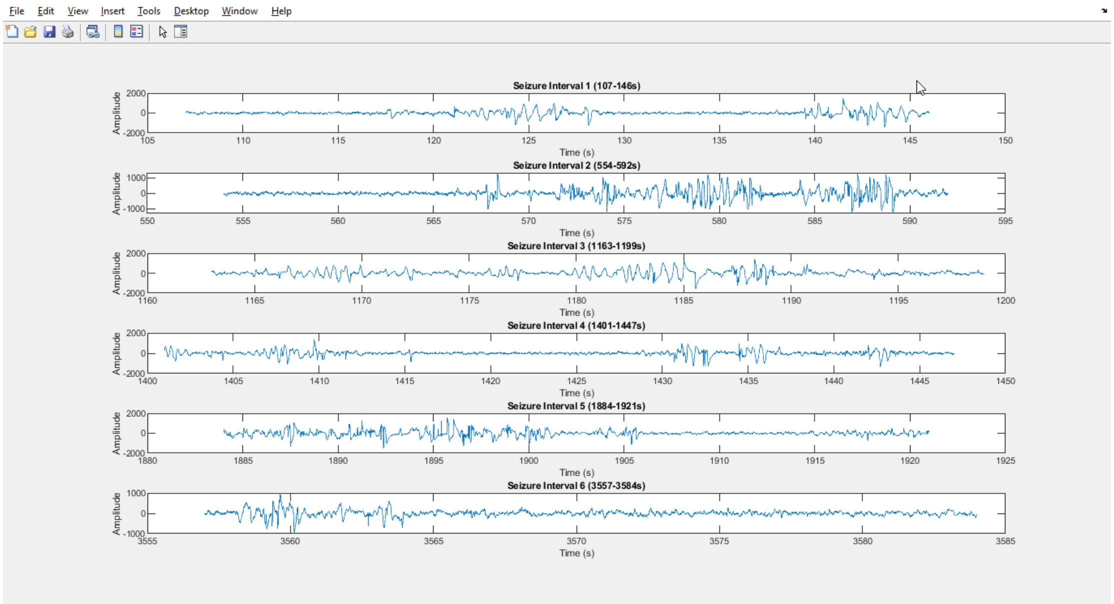

Figure 4 : Seizure Intervals Displayed for All Episodes

- **Description**: his figure shows individual seizure intervals as separate time segments, with each subplot representing a distinct interval. The time axis corresponds to the duration of each seizure episode.
- **Observations**:
    - The amplitude of the signal within each interval varies significantly, highlighting the distinct characteristics of seizure events.
    - Some intervals exhibit sharp spikes and rapid fluctuations, indicative of heightened activity during seizures.
    - Other intervals display milder signal variations, possibly corresponding to different phases of the seizures or varying severity.
- **Implications**:
    - This visualization allows for a focused analysis of the temporal structure of seizures, aiding in identifying specific patterns or features that may correlate with clinical observations.
    - Comparing these intervals can provide insights into the variability of seizure activity and its impact on the overall signal dynamics. Changing Window type

SPECTROGRAM ANALYSIS:

Window Types and Effects

To investigate the effect of different window types on the frequency representation of the EEG signal, various window functions were applied. These included:

- **Rectangular Window**: This type of window applies no smoothing, leading to high spectral leakage. Although it provides the simplest analysis, it is prone to distortion, especially for signals with sharp transitions. However, it provides the best **frequency resolution** because it retains the most energy of the signal.
- **Triangular Window**: This window reduces spectral leakage compared to the rectangular window by tapering the edges. However, it still allows for some leakage, making it more suitable for signals with moderate frequency content.
- **Hamming Window**: The Hamming window strikes a balance between time and frequency resolution. It reduces leakage more effectively than the rectangular and triangular windows, providing a clearer frequency response while still maintaining reasonable time resolution.
- **Blackman Window**: This window function provides minimal spectral leakage, making it ideal for minimizing distortion in the frequency domain. However, the trade-off is a reduced frequency resolution, which can make it less suitable for signals that require precise frequency information.

Figures illustrating the spectrograms for each of these window types are, showcasing the distinct effects of each window on the time-frequency representation of the EEG data.

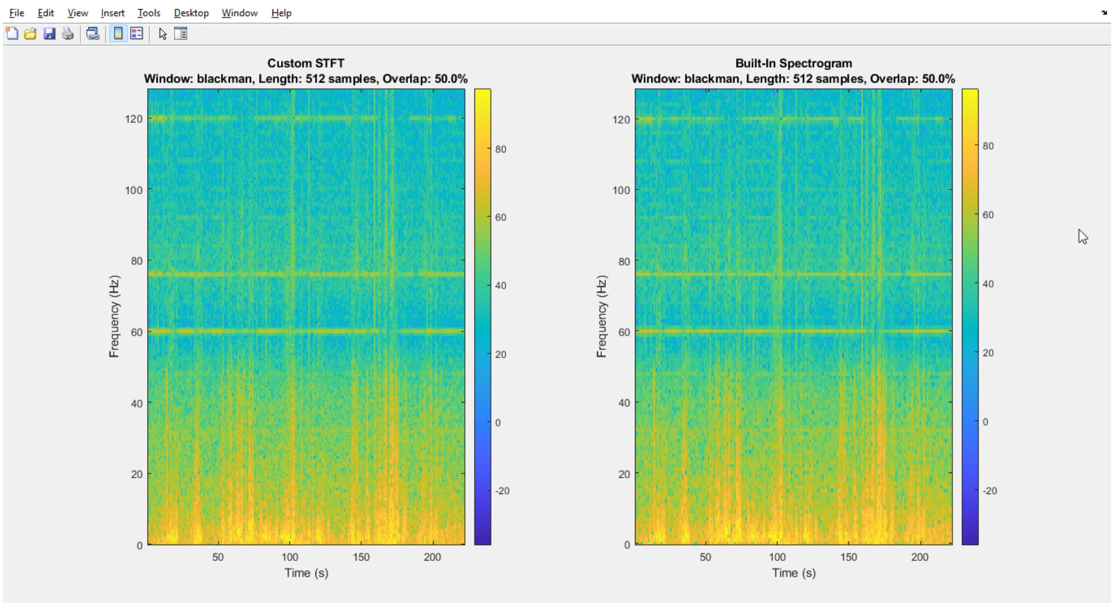

Figure 5 : Spectrogram with Blackman Window

- **Description**: This figure represents the spectrogram generated using a Blackman window.
- **Observations**:

- The Blackman window further minimizes spectral leakage compared to the Hamming window.
- Frequency resolution improves slightly at the expense of reduced time resolution.

- **Implications**:
    - The Blackman window is useful for tasks prioritizing frequency detail over time localization.

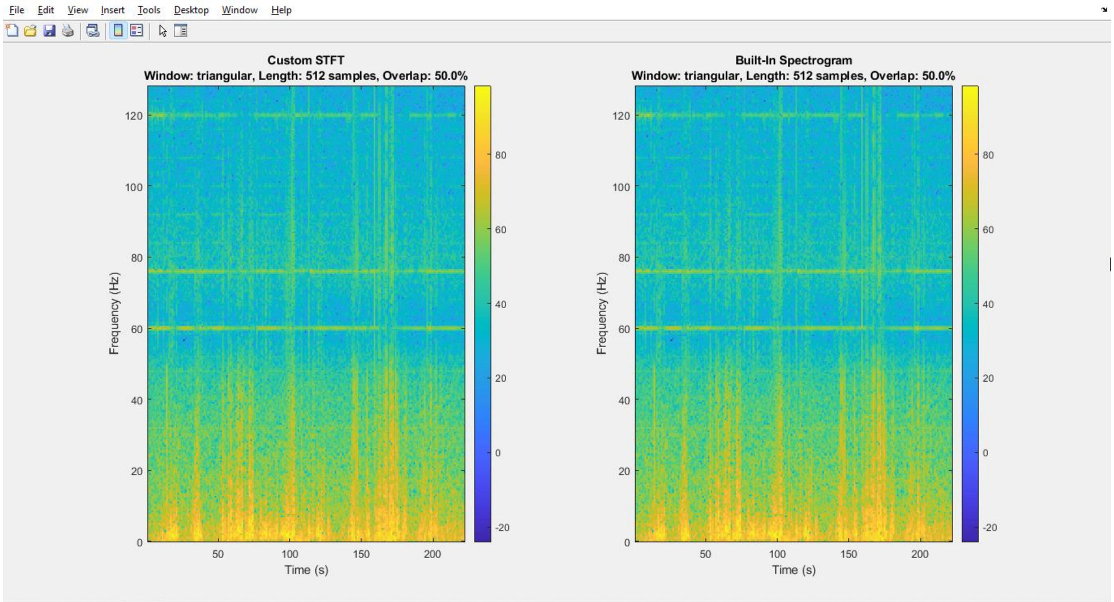

Figure 6 : Spectrogram with Triangular Window

- **Description**: Spectrogram using a triangular window.
- **Observations**:
    - Moderate tapering reduces leakage compared to the rectangular window.
    - Frequency resolution improves slightly, but some leakage remains.
- **Implications**: The triangular window is a middle ground between computational simplicity and reduced leakage.

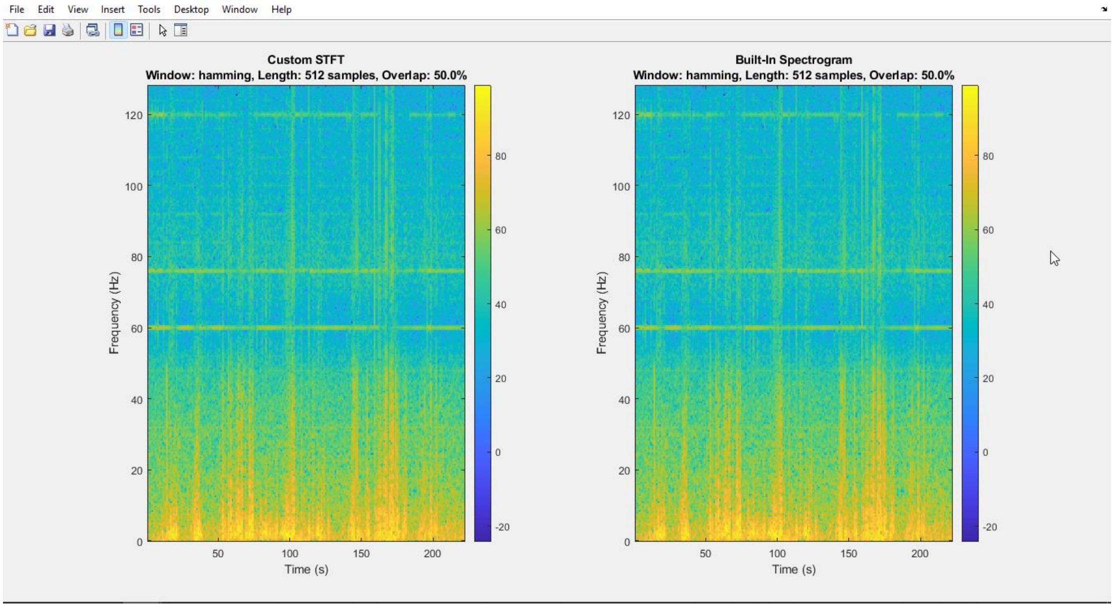

Figure 7 : Spectrogram with Hamming Window

- **Description**: This figure represents the spectrogram generated using a Hamming window.
- **Observations**:
    - The Hamming window significantly reduces spectral leakage, offering clearer frequency bands.
    - There is a good balance between time and frequency resolution.
- **Implications**:
    - The Hamming window is ideal for applications requiring moderate resolution and minimal leakage.

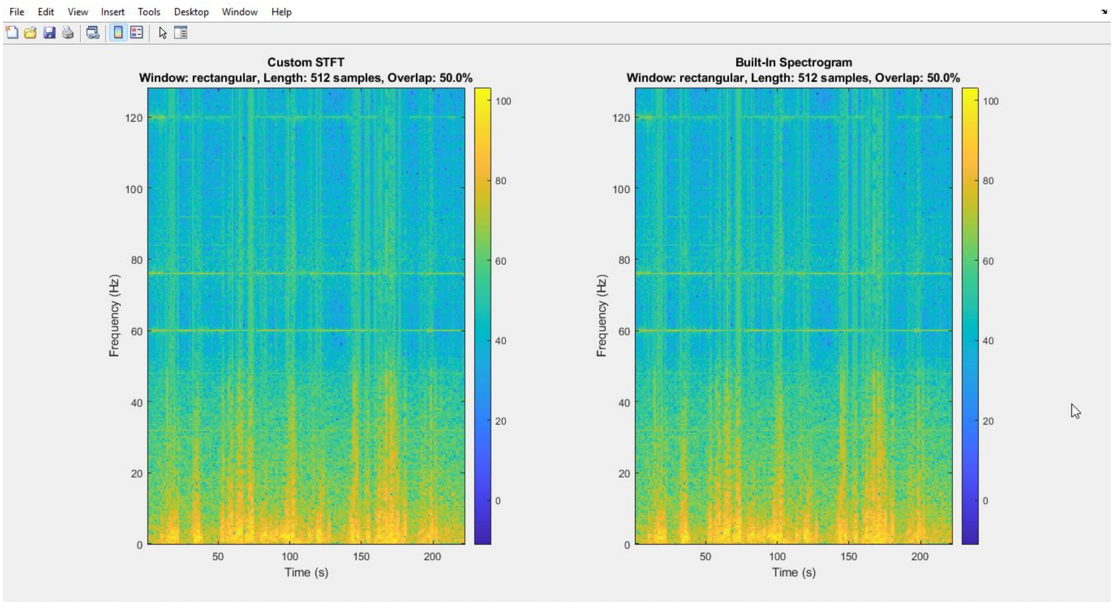

Figure 8 : Spectrogram with Rectangular Window

- **Description**: This figure represents the spectrogram generated using a rectangular window.
- **Observations**:
  - The rectangular window exhibits significant spectral leakage due to abrupt signal truncation.
  - Frequency boundaries are blurred, making it challenging to identify specific frequency components accurately.
- **Implications**:
  - The use of a rectangular window results in poor frequency resolution and smearing in the spectrogram.

Overlapping Ratio

The overlap between successive windows also plays a crucial role in the smoothness of the resulting spectrogram. When using a **low overlap**, the spectrogram may appear disjointed, with noticeable gaps between frames. This can result in a less accurate representation of the signal's evolution over time.

In contrast, a **high overlap** results in smoother transitions between windows, producing a more continuous spectrogram that offers a better representation of the signal's time-frequency content. A typical approach is to use a 50% overlap between consecutive windows, but higher overlaps, such as 85%, may provide even smoother transitions without significant computational cost. For this report, an overlap ratio of 85% was used to ensure a detailed and continuous representation of the signal.

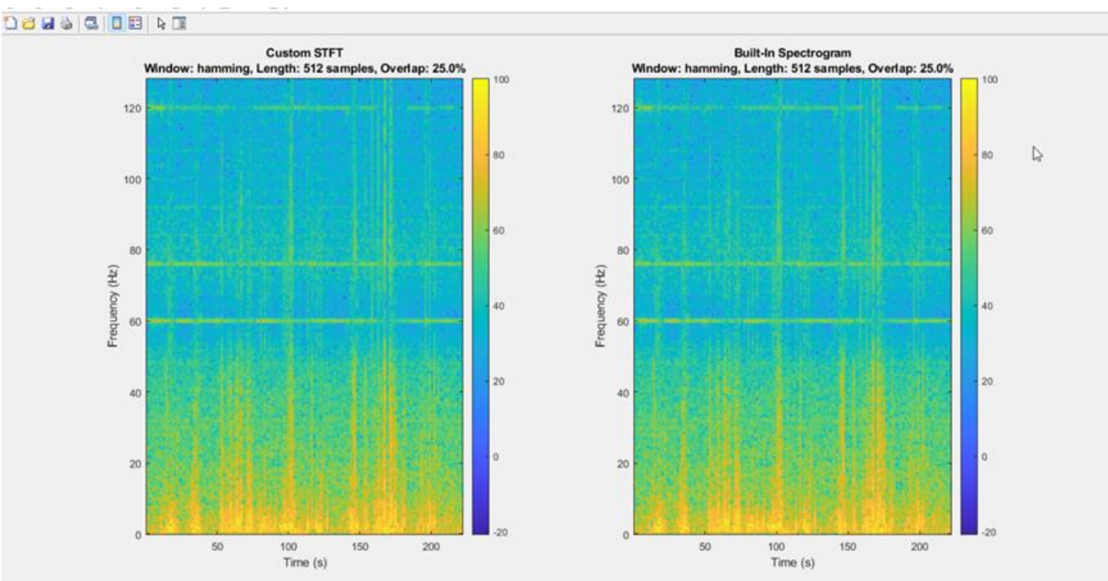

Figure 9 : Spectrogram with 25% Overlap

- **Description**: This figure shows the spectrogram generated with a 25% overlap between frames.
- **Observations**:
  - There are visible discontinuities between consecutive frames, resulting in blocky artifacts.
  - Time resolution is limited due to insufficient overlap.

- **Implications**:
  - A low overlap ratio reduces computational cost but sacrifices time resolution and introduces artifacts.

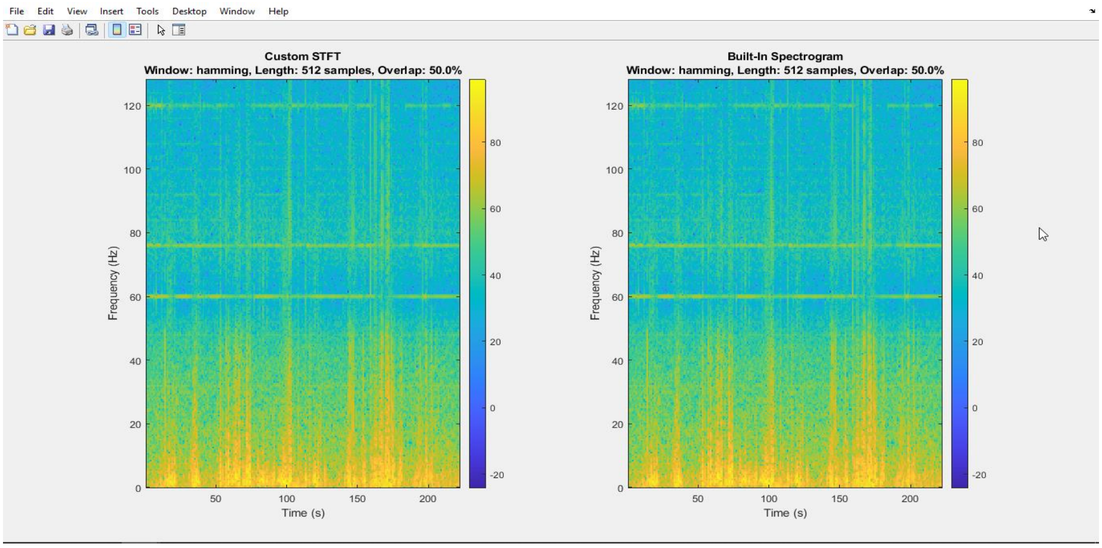

Figure 10 : Spectrogram with 50% Overlap

- **Description**: This figure shows the spectrogram generated with a 50% overlap between frames.
- **Observations**:
  - A balance is achieved between time continuity and computational efficiency.
  - Frequency and time resolutions are both acceptable for practical analysis.
- **Implications**:
  - A 50% overlap is a good compromise for EEG spectrogram analysis.

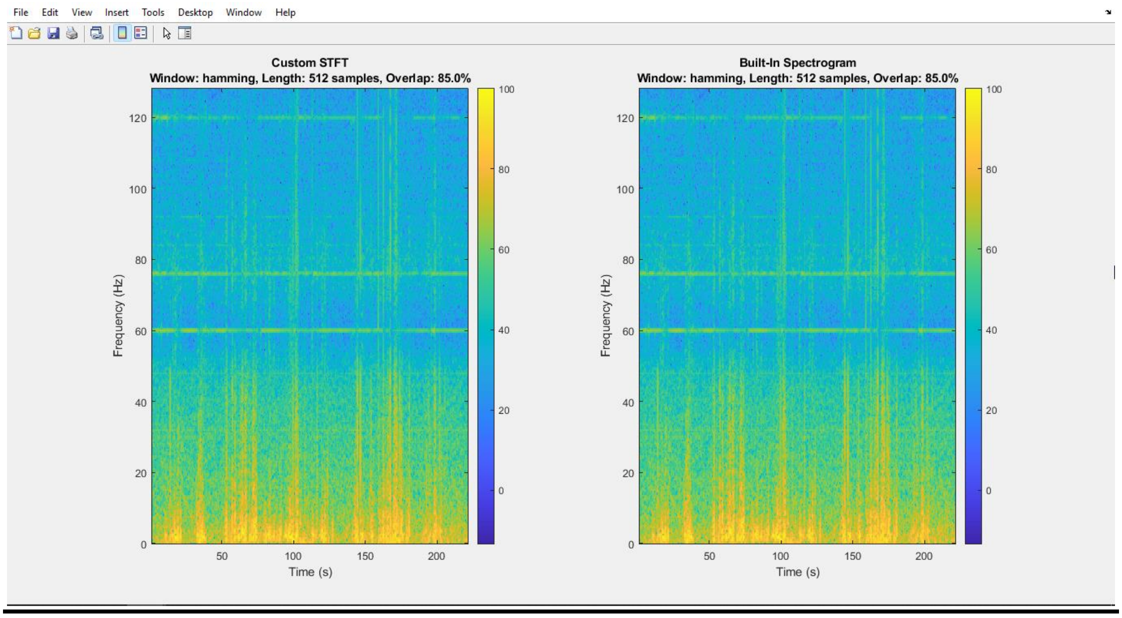

Figure 11 :Spectrogram with 85% Overlap

- **Description**: Spectrogram with a high overlap ratio.
- **Observations**:
    - Time continuity is significantly improved, capturing finer temporal changes.
    - Computational complexity increases due to overlapping data points.
- **Implications**: High overlap is suitable for applications requiring high time resolution.

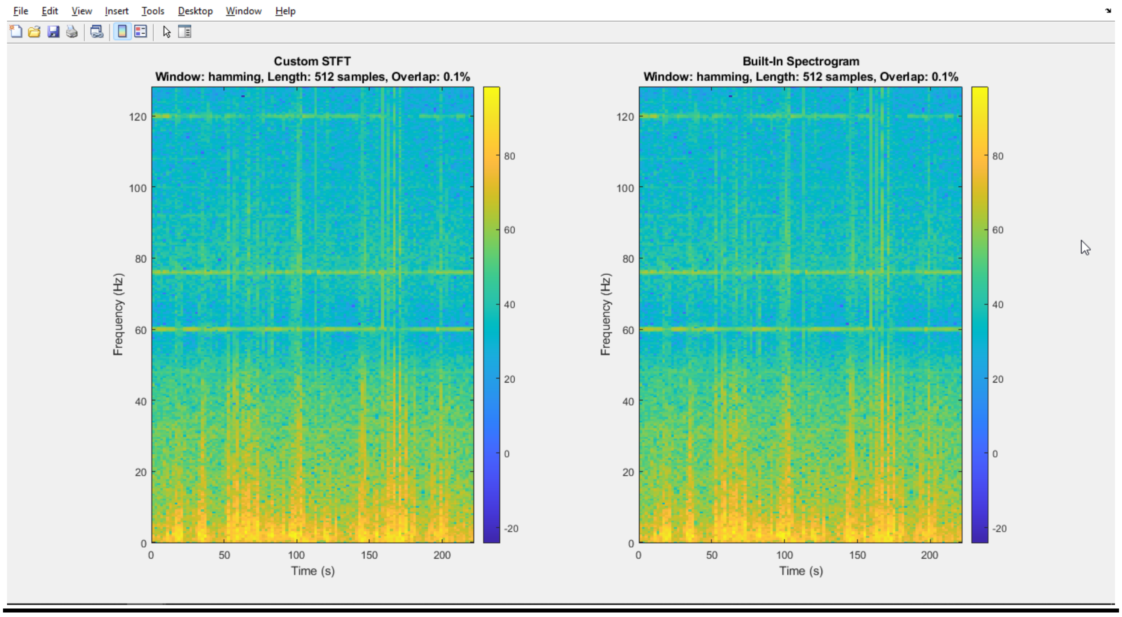

Figure 12 : Spectrogram with 0.1% Overlap

- **Description**: Spectrogram with minimal overlap between frames.
- **Observations**:

- Severe discontinuities between frames lead to blocky artifacts in the spectrogram.
  - Time resolution is poor due to insufficient frame continuity.
- **Implications**: Low overlap is computationally efficient but unsuitable for EEG analysis due to poor quality.

Window Length and Resolution Trade-offs

The choice of window length significantly impacts the balance between time and frequency resolution in the spectrogram. A short window results in high time resolution, meaning that rapid changes in the signal can be captured more accurately. However, this comes at the cost of reduced frequency resolution, making it harder to distinguish between closely spaced frequencies.
On the other hand, a longer window length improves the frequency resolution, allowing for better separation of frequency components. However, this compromises time resolution, which can make it difficult to identify rapid changes in the signal over time. Thus, a trade-off must be made based on the specific analysis requirements.

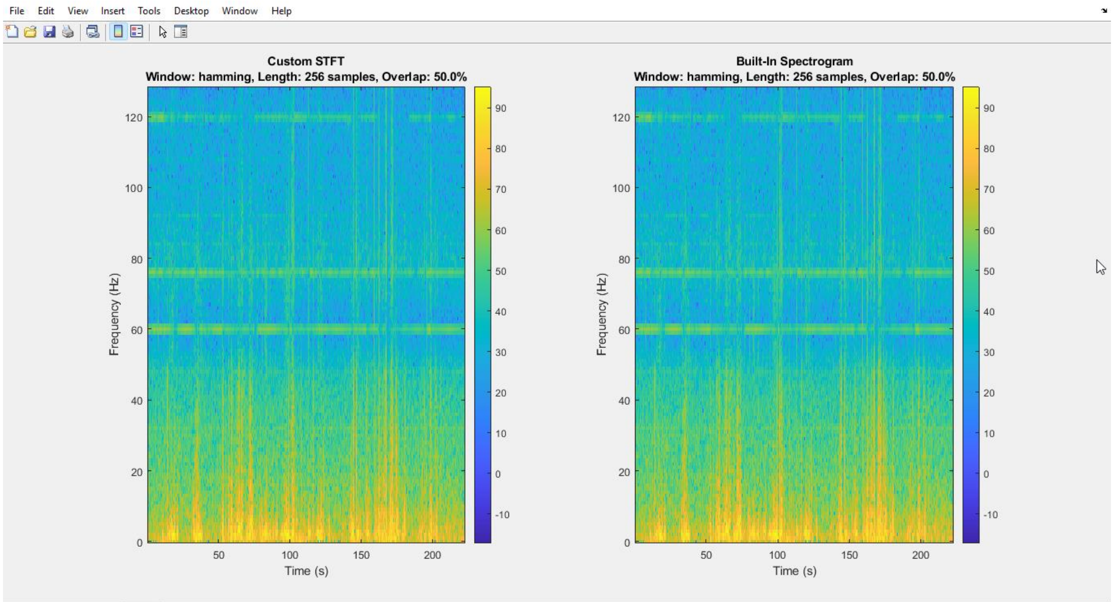

Figure 13 : Spectrogram with 256 Samples Window Length

- **Description**: Spectrogram with a short window length of 256 samples.
- **Observations**:
  - High time resolution captures rapid changes in the signal.
  - Poor frequency resolution results in wide-spread frequency components.
- **Implications**: Short windows are useful for detecting transient events.

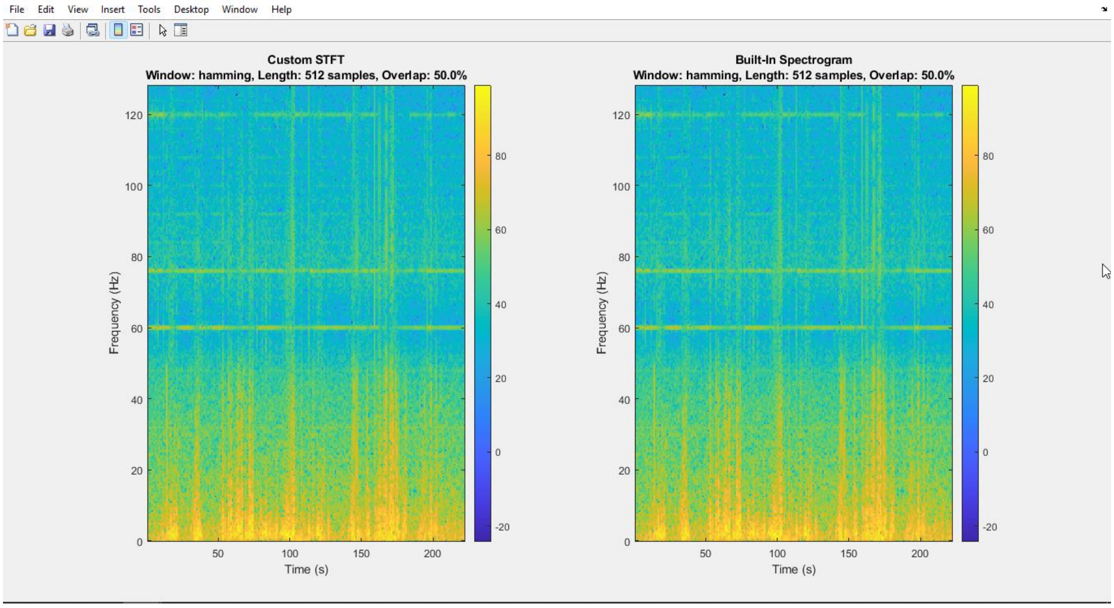

Figure 14 :Spectrogram with 512 Samples Window Length

- **Description**: Spectrogram with a medium window length of 512 samples.
- **Observations**:
  - Balanced time and frequency resolution.
  - Both transient and steady-state signal features are represented.
- **Implications**:
  - Medium-length windows are optimal for EEG analysis requiring balanced resolution.

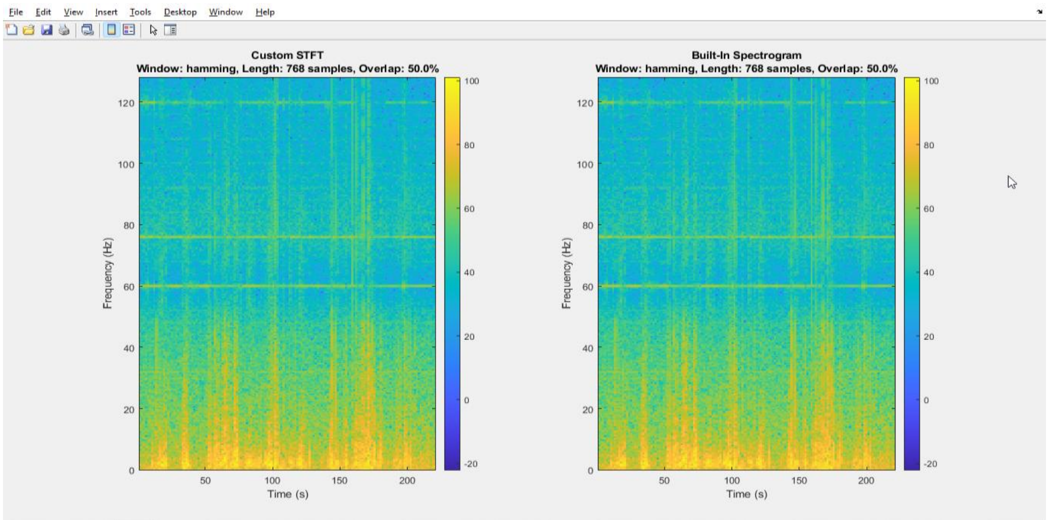

Figure 15 : Spectrogram with 768 Samples Window Length

- **Description**: Spectrogram generated with a medium window length of 768 samples.
- **Observations**:
  - A good balance is achieved between time and frequency resolution.
  - Both transient and steady-state features of the EEG signal are well-represented.

- **Implications**: Medium window lengths are optimal for analyzing EEG signals with a mix of steady and rapidly changing patterns.

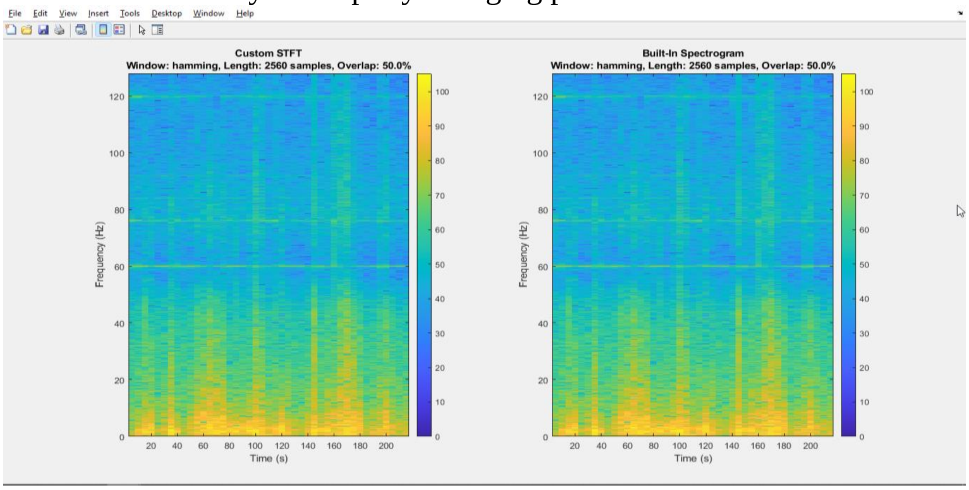

Figure 16 : Spectrogram with 2560 Samples Window Length

- **Description**: Spectrogram generated with a long window length of 2560 samples.
- **Observations**:
  - High frequency resolution results in narrow and well-defined frequency bands.
  - Poor time resolution causes rapid changes in the EEG signal to be smoothed out.
- **Implications**: Long windows are ideal for applications requiring detailed frequency analysis but are less effective for capturing transient events.

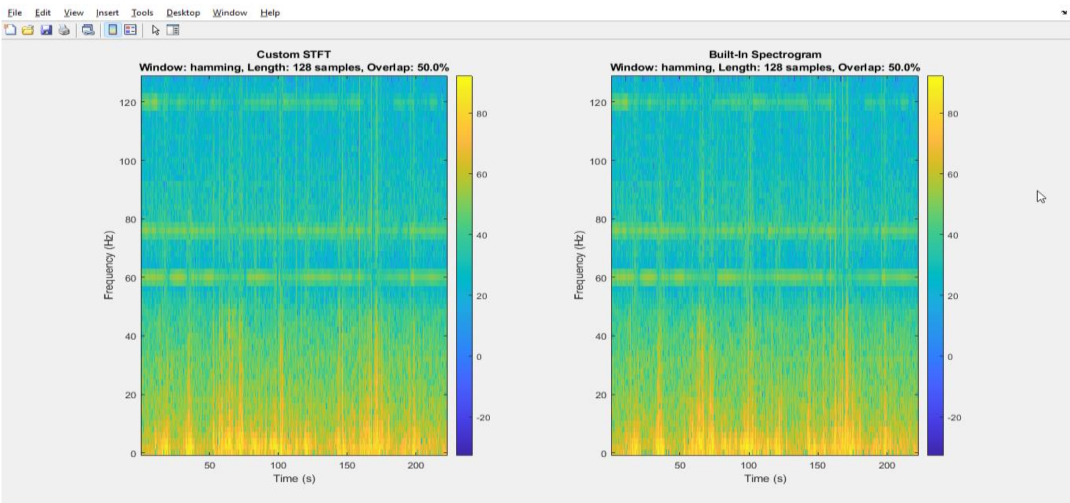

Figure 17 : pectrogram with 128 Samples Window Length

- **Description**: Spectrogram generated with a short window length of 128 samples.
- **Observations**:
  - High time resolution captures rapid changes in the EEG signal effectively.

    - Poor frequency resolution leads to wide and overlapping frequency components.
- **Implications**: Short windows are suited for detecting transient events, such as quick changes in seizure activity.

NORMAL DATA

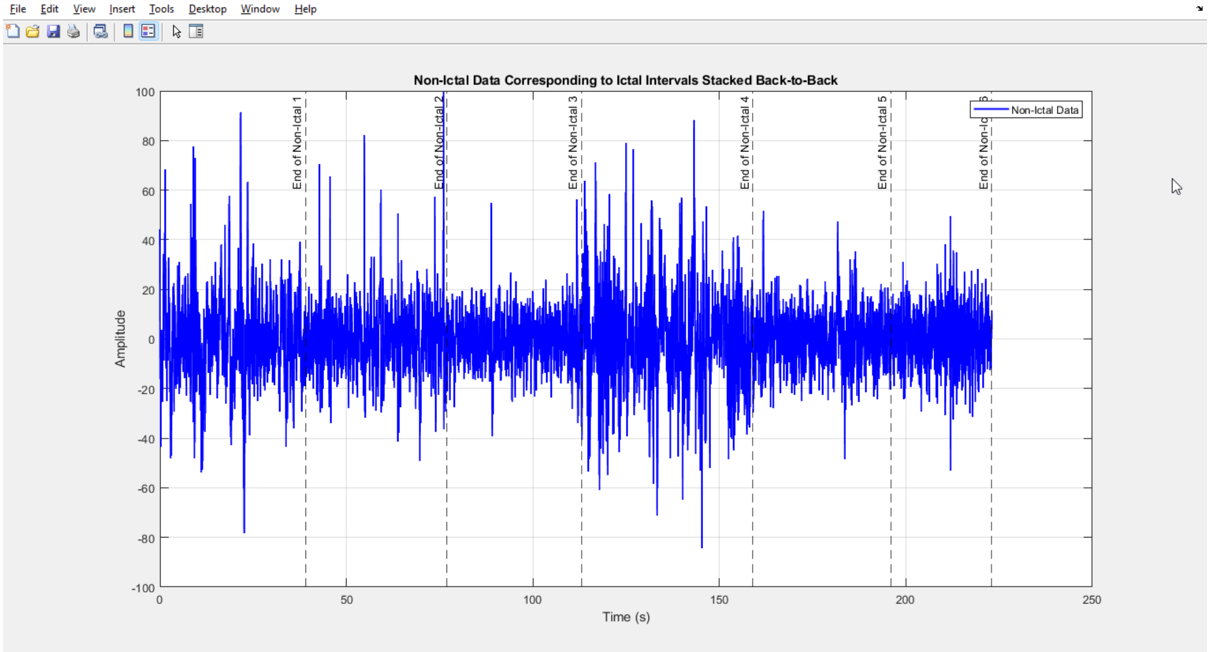

Figure 18 Non-Ictal Data Corresponding to Ictal Intervals Stacked Back-to-Back

Description:
The non-ictal data segments corresponding to the same ictal intervals were extracted and stacked back-to-back for analysis.

Observations:
Smooth transitions between intervals with no abrupt changes, as expected in non-ictal data. The amplitude variations are relatively uniform.

Implications:
Non-ictal data shows a lack of distinct seizure-like patterns, validating the data extraction process. Provides a baseline for spectrogram analysis.

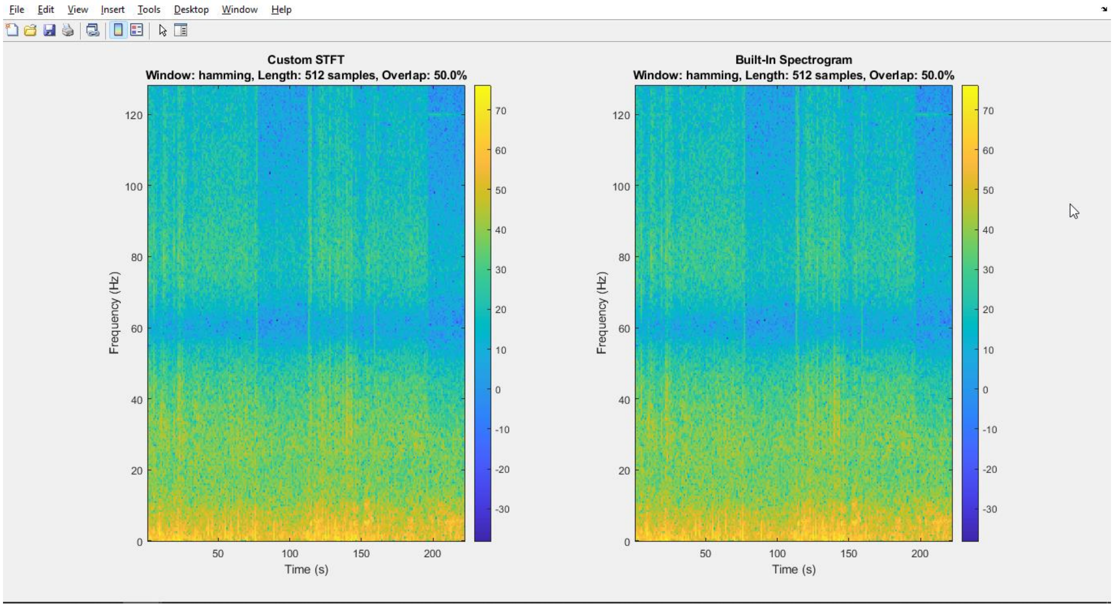

Figure 19 Custom Spectrogram (STFT) with Hamming Window vs Built-in for Normal Data

Description:
Spectrogram generated using the Hamming window in a custom STFT function compared to MATLAB's built-in spectrogram.

Observations:

- The Hamming window results in sharp frequency peaks with minimal leakage.
- The custom STFT aligns closely with the built-in spectrogram but has slight differences in frequency resolution.

Implications:
The Hamming window balances time and frequency resolution well, producing clear spectral components. The custom implementation is consistent but may have minor deviations due to computational or parameter differences.

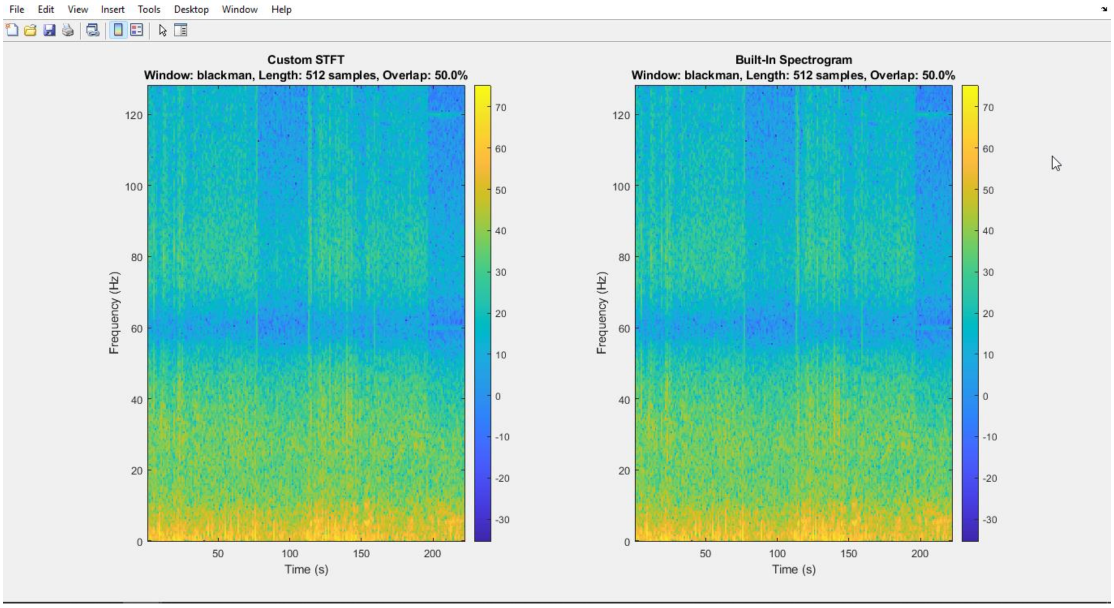

Figure 20 Custom Spectrogram (STFT) with Blackman Window vs Built-in for Normal Data

Description:
Spectrogram generated using the Blackman window compared to MATLAB's built-in spectrogram.

Observations:

- Broader frequency peaks compared to Hamming.
- Minimal side lobes, resulting in smooth and clean spectral representation.

Implications:
The Blackman window is ideal for reducing spectral leakage, but its wide main lobe sacrifices frequency resolution. Suitable for noise suppression in low-noise environments.

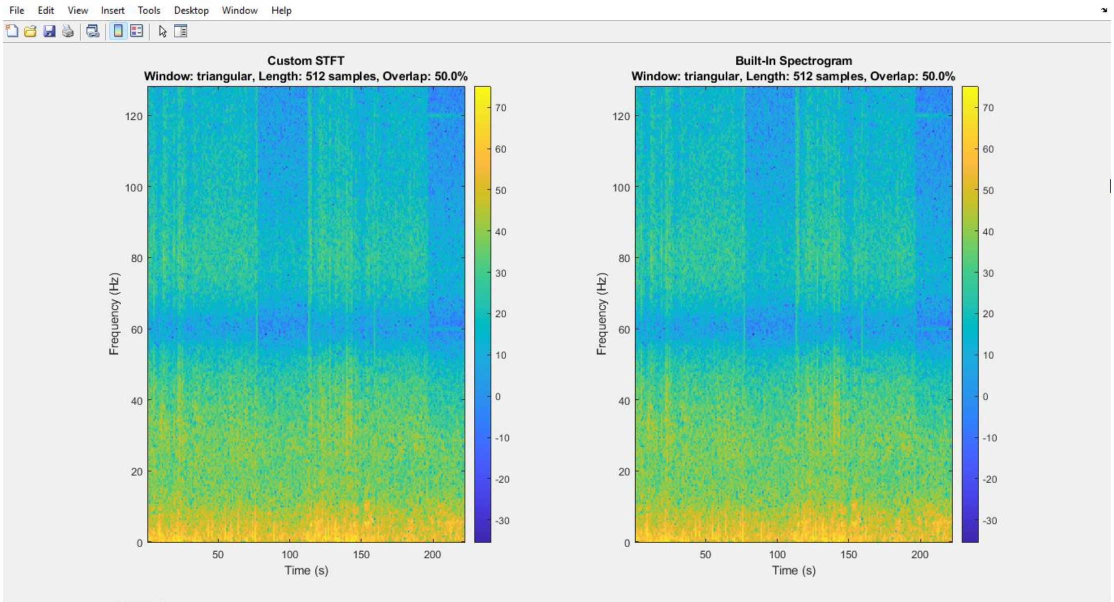

Figure 21 Custom Spectrogram (STFT) with Triangular Window vs Built-in for Normal Data

Description:
Spectrogram using a triangular window compared to the built-in spectrogram.

Observations:

- Sharper frequency peaks than Blackman but more leakage than Hamming.
- Balanced time-frequency representation.

Implications:
The triangular window provides moderate spectral leakage and resolution, making it a good middle ground for general-purpose analysis.

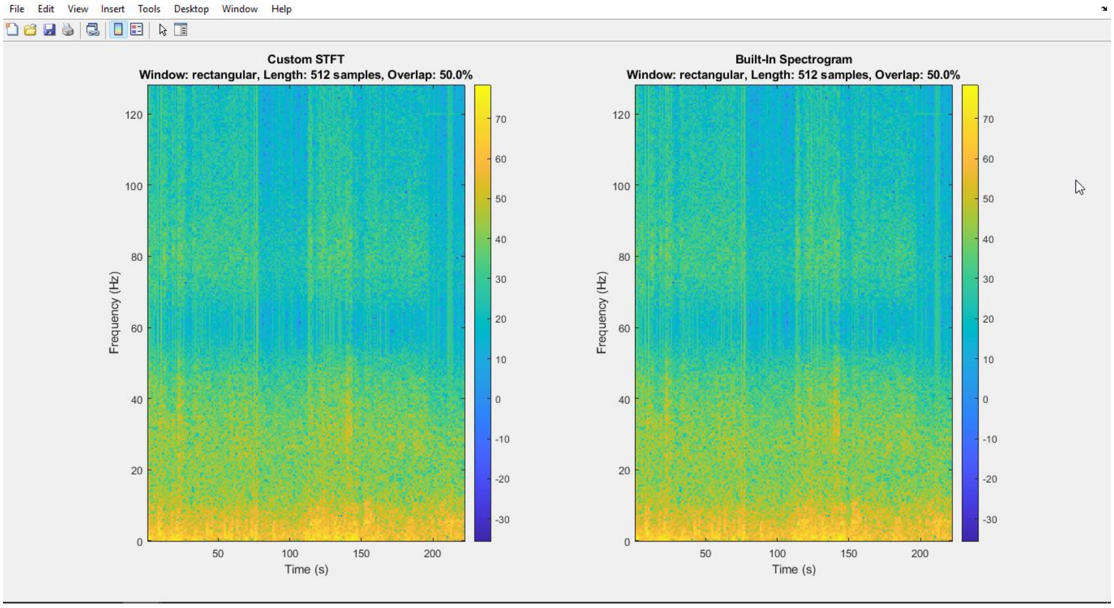

Figure 22 Custom Spectrogram (STFT) with Rectangular Window vs Built-in for Normal Data

Description:
Spectrogram generated using the rectangular window compared to the built-in spectrogram.

Observations:

- High spectral leakage and broad frequency peaks.
- Prominent artifacts and smearing across the spectrogram.

Implications:
The rectangular window is unsuitable for precise spectrogram analysis due to

excessive leakage but may highlight broad trends in frequency.

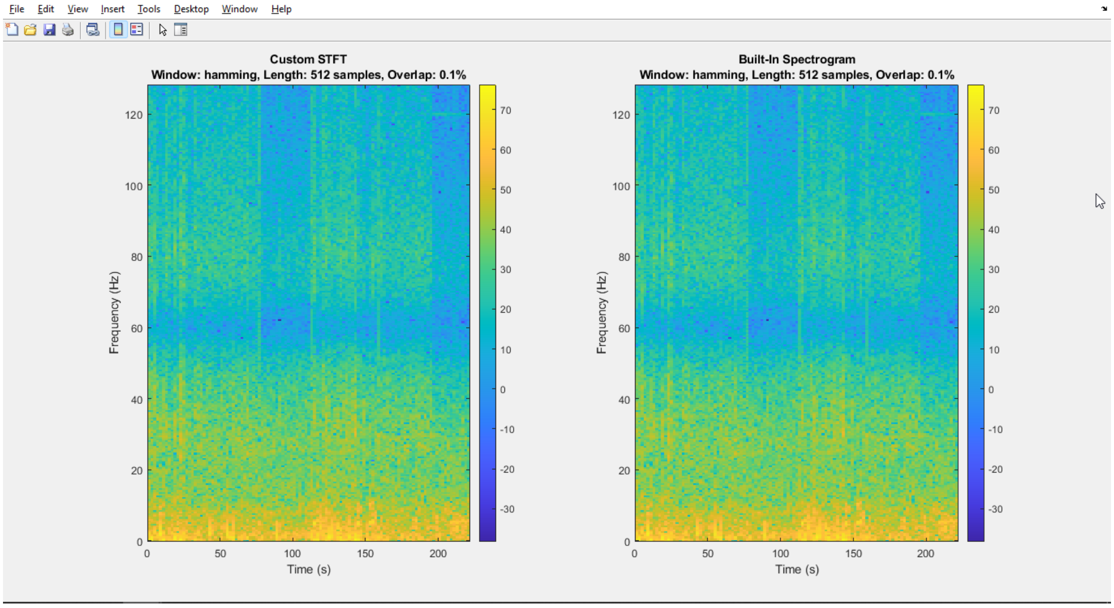

Figure 23 Custom Spectrogram (STFT) with Overlap Ratio = 0.1% vs Built-in Spectrogram

Description:
Spectrogram generated with minimal overlap between consecutive segments compared to the built-in spectrogram.

Observations:

- Poor time resolution with noticeable gaps between segments.
- Frequency resolution is clear, but transitions are discontinuous.

Implications:
Minimal overlap is inadequate for capturing smooth temporal changes. It is only suitable when computational efficiency is prioritized over accuracy.

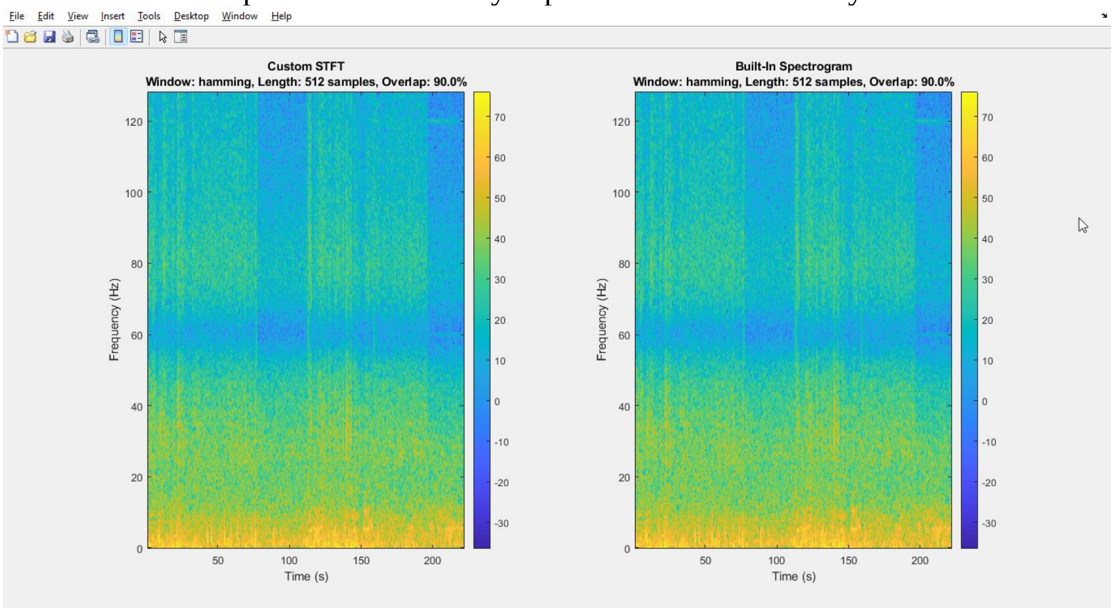

Figure 24 Custom Spectrogram (STFT) with Overlap Ratio = 90% vs Built-in Spectrogram

Description:
Spectrogram generated with a high overlap ratio compared to the built-in spectrogram.

Observations:

- Smooth transitions with high temporal resolution.
- Slight smearing in frequency components due to the overlap.

Implications:
A high overlap ratio improves time resolution but increases redundancy in the data. Suitable for applications requiring fine temporal details, albeit at a computational cost.

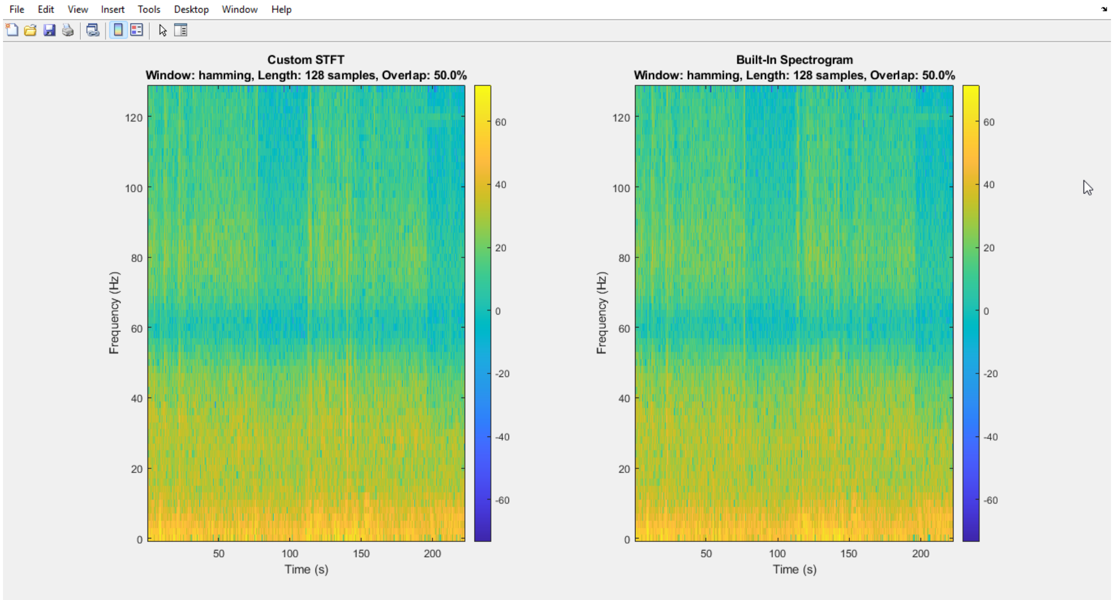

Figure 25 Custom Spectrogram (STFT) with Window Length = 128 Samples vs Built-in Spectrogram

Description:
Spectrogram generated with a short window length compared to the built-in spectrogram.

Observations:

- Excellent time resolution but poor frequency resolution.
- Frequency components appear broader and less distinct.

Implications:
Short windows are ideal for capturing rapid temporal changes but compromise the

ability to resolve fine frequency details.

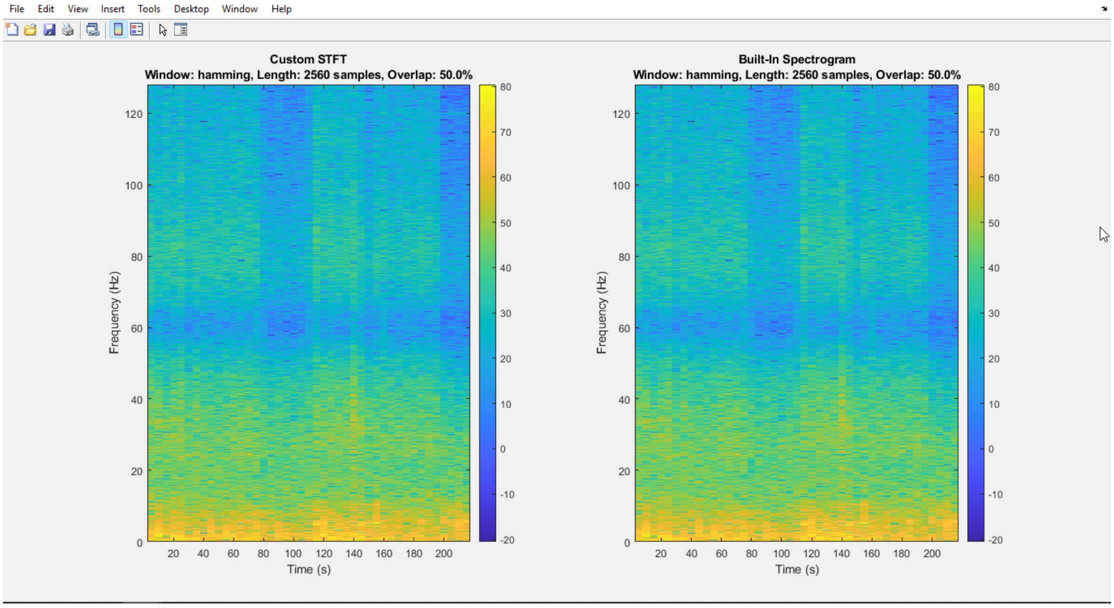

Figure 26 Custom Spectrogram (STFT) with Window Length = 2560 Samples vs Built-in Spectrogram

Description:
Spectrogram generated with a long window length compared to the built-in spectrogram.

Observations:

- Excellent frequency resolution but poor time resolution.
- Temporal details are lost, and transitions appear smeared.

Implications:
Long windows are suitable for steady-state or low-frequency signals, but they fail to capture transient events accurately.

CONCLUSION

This report focused on EEG signal analysis using the Short-Time Fourier Transform (STFT). We tested different window types—Rectangular, Triangular, Hamming, and Blackman—finding that the Hamming and Blackman windows minimized spectral leakage while maintaining good frequency resolution. The window length affected time and frequency resolution, with shorter windows offering better time resolution, and longer ones providing better frequency resolution. Additionally, higher overlap ratios (85%) improved the smoothness and continuity of the spectrogram. The choice of window and overlap ratio is crucial for accurate EEG signal analysis.