Introduction

1. **Definition of the topic plus background**
   Seizure detection from EEG signals is a crucial task to detect abnormal brain activity. EEG signals are often noisy and vary significantly between patients in uncontrolled environments. Automatic systems must handle real-world data to support accurate seizure diagnosis and monitoring.

2. **Accepted state of the art plus problem to be resolved**
   Current models extract spatial, temporal, or frequency features but usually fail to capture all three types simultaneously. They reduce false detections and increase accuracy under controlled environments with limited variability. These models still struggle in real-world cases with high inter-patient variability and noise reducing classification accuracy and increasing overfitting.

3. **Authors' objectives**
   This work proposes a seizure detection model combining EEGNet, Transformer, STFT, and cGANs.
   The objective is to improve accuracy and generalization in uncontrolled real-world EEG scenarios.

4. **Introduction to the literature**
   Recent works extract spatial, temporal, or frequency features from EEG signals to classify seizure types and improve prediction accuracy.

   Other approaches generate synthetic EEG data to enhance model robustness and generalization across patients.

5. **Survey of pertinent literature**
   EEGNet + Transformer [Zhu and Wang, 2023] extracts spatial-temporal features but presents overfitting

   MBMD captures frequency features using wavelet branches but fails when there is too much noise [Peng et al., 2024].

   EfficientNet-B0 + SVM combines deep and spectral features but performs worse without inter-subject normalization [Saadoon et al., 2023].

   STFT + MMD-AAE aligns domains across patients but shows lower sensitivity than attention-based or transformer architectures [Peng et al., 2022].

6. **Authors' contribution**
   We introduce a model that uses synthetic data from cGANs and frequency features from STFT.
   The model improves robustness against noise and variability in EEG signals.

7. **Aim of the present work**
   The goal is to reduce overfitting in seizure detection using a hybrid adversarial deep learning model.
   We use STFT to extract time-frequency features and cGANs to augment training data.

8. **Main results of the present work**
   The proposed model outperformed EEGNet + Transformer by 2.72% in accuracy, 11.14% in precision, and 24.97% in F1-score. It also reduced the generalization gap from 0.6964 to 0.1474.

9. **Future implications of the work**
   The model will be able to detect seizures accurately in uncontrolled scenarios improving treatment options for patients.

10. **Outline of structure**
    Chapter 2 presents theoretical concepts related to EEGs, deep learning models, STFT, and conditional adversarial learning.

    Chapter 3 reviews state-of-the-art seizure detection approaches using machine learning and adversarial strategies.

    Chapters 4 to 6 describe the proposed model, experimental results, and conclusions.