



Degree Project in Technology

Second cycle, 30 credits

Efficient and Generalizable Seizure Detection Algorithm

A subtitle in the language of the thesis

ZHEYUN SHOU

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Master's Programme, Systems, Control and Robotics, 120 credits

Date: May 20, 2025

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- Why was this problem worth a Bachelor's/Master's thesis project? (*i.e.*, why is the problem both significant and of a suitable degree of difficulty for a Bachelor's/Master's thesis project? Why has no one else solved it yet?)
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Acknowledgments

Författarnas tack

I would like to thank xxxx for having yyyy. Or in the case of two authors:
We would like to thank xxxx for having yyyy.

Stockholm, May 2025
Zheyun Shou

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Listings

If you have listings in your thesis. If not, then remove this preface page.

List of acronyms and abbreviations

LAN	Local Area Network
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network

The list of acronyms and abbreviations should be in alphabetical order based on the spelling of the acronym or abbreviation.

Chapter 1

Introduction

We use the *bibtex* package to handle our references. We, therefore, use the command `\cite{farshin_make_2019}`. For example, Farshin, *et al.*, described how to improve LLC cache performance in the context of links running at 200 Gbps.

Use the glossaries package to help yourself and your readers. Add the acronyms and abbreviations to `lib/acronyms.tex`. Some examples are shown below:

In this thesis, we will examine the use of **Local Area Networks (LANs)**. In this thesis, we will assume that **LANs** include **Wireless Local Area Networks (WLANs)**, such as **Wireless Fidelity (Wi-Fi)**.

1.1 Purpose

1.2 Research Question

1.3 Objectives

1.4 Research Methodology

Undersökningsmetod

1.5 Delimitations

Avgränsningar

1.6 Structure of the thesis

Chapter 2

Background

2.1 Epilepsy

A seizure represents a fundamental disruption of normal brain function, characterized by a transient surge of abnormal, excessive, or synchronous neuronal activity within the brain [1, 2]. These paroxysmal events can manifest through a wide spectrum of signs and symptoms, the nature of which is intrinsically linked to the specific cerebral networks involved in the ictal discharge and its subsequent propagation [3]. While an isolated seizure may be provoked by acute systemic insults or transient neurological stressors, the term epilepsy designates a more profound neurological condition: an enduring predisposition to generate unprovoked epileptic seizures, along with the associated neurobiological, cognitive, psychological, and social ramifications [4]. Clinically, epilepsy is typically diagnosed after at least one unprovoked seizure, especially when factors suggest a high likelihood of recurrence.

The global impact of seizures and epilepsy is considerable. Affecting an estimated 50 million individuals worldwide, epilepsy stands as one of the most prevalent serious neurological disorders [5]. Beyond the immediate risk of physical injury during an ictal event, seizures can precipitate or exacerbate cognitive difficulties, particularly in domains of memory and attention, and are frequently associated with psychological comorbidities such as anxiety and depression [6, 7]. The societal impact is also profound, with individuals often confronting stigma, discrimination, and limitations in education, employment, and personal autonomy [8]. The consequences of recurrent seizures permeate virtually every aspect of an individual's life.

The diagnostic process for seizures heavily relies on meticulous clinical

history-taking, including detailed eyewitness accounts, as the ictal events themselves are often brief and unpredictable, making direct observation by clinicians rare [9]. This dependence on subjective reporting, while indispensable, introduces potential inaccuracies and challenges in distinguishing seizures from other paroxysmal events [10]. Accurate seizure detection is not merely an academic exercise; it is critical for guiding appropriate therapeutic interventions, predicting long-term outcomes, and informing genetic counseling [11].

2.2 Electroencephalography for Brain Activity Monitoring

Electroencephalography (EEG) is a cornerstone neurophysiological technique used to record the electrical activity generated by the brain. It provides a non-invasive, direct measure of brain function by detecting voltage fluctuations resulting from ionic current flows within the neurons of the cerebral cortex [12, 13]. Specifically, EEG signals primarily reflect the summed postsynaptic potentials (both excitatory and inhibitory) of large populations of synchronously active pyramidal neurons oriented radially to the scalp [13, 14]. Due to its excellent temporal resolution, typically in the millisecond range, EEG is uniquely suited for capturing the rapidly changing dynamics of brain activity, making it an invaluable tool in both clinical neurology and neuroscience research, particularly for the assessment of conditions characterized by abnormal electrical discharges, such as epilepsy [15].

The acquisition of EEG data involves placing electrodes on the scalp, typically made of conductive materials like silver/silver-chloride (Ag/AgCl). These electrodes detect the minute electrical potentials (on the order of microvolts, μV) generated by the brain, which are then significantly amplified by differential amplifiers to make them suitable for digitization and subsequent analysis [16]. To ensure reproducibility and comparability of EEG recordings across different laboratories and individuals, standardized electrode placement systems are employed. The most widely adopted is the International 10-20 system and its extensions [17, 18]. This system positions electrodes at locations that are 10% or 20% of the total front-to-back or right-to-left distance of the skull, ensuring proportional spacing relative to cranial landmarks (nasion, inion, and preauricular points). Each electrode is labeled with a letter indicating the underlying brain lobe (e.g., F for frontal, P for parietal, T for temporal, O for occipital) and a number or another letter to denote its specific

position [17].

The resulting EEG waveforms are complex and are traditionally analyzed in terms of their frequency, amplitude, morphology, and topography. Clinically relevant information is often contained within specific frequency bands, such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (>30 Hz), each associated with different brain states or cognitive processes [13]. In the context of epilepsy, EEG is crucial for identifying interictal epileptiform discharges (IEDs) and for characterizing the electrographic signature of seizures themselves (ictal patterns) [19]. These patterns provide critical information for diagnosing epilepsy, classifying seizure types, localizing the seizure onset zone, and guiding treatment decisions.

However, the utility of EEG is often challenged by the inherent low signal-to-noise ratio (SNR) and its susceptibility to various artifacts [16, 20]. EEG signals are frequently contaminated by physiological artifacts originating from non-cerebral sources, such as eye movements and blinks (electrooculogram, EOG), muscle activity (electromyogram, EMG) particularly from scalp and facial muscles, and cardiac activity (electrocardiogram, ECG) [20, 21]. Non-physiological artifacts also pose significant problems, including 50/60 Hz power line interference, electrode impedance issues (e.g., electrode pop or poor contact), and movement artifacts from patient motion or cable sway [21]. These artifacts can mimic or obscure true epileptiform activity, leading to potential misinterpretations if not properly addressed. Consequently, rigorous data preprocessing, encompassing techniques such as filtering, artifact detection, and artifact removal or suppression, is an indispensable yet often complex step before any meaningful analysis or automated interpretation of EEG data can be performed [21, 22]. The challenge of reliably distinguishing pathological neural signals from this pervasive noise, especially in long-term recordings or in ambulatory settings, underscores the need for robust and sophisticated signal processing and machine learning algorithms, forming a critical motivation for the research presented in this thesis.

2.3 Time-series classification

Time Series Classification (TSC) is a specialized area within machine learning concerned with assigning predefined categorical labels to unlabeled time series data [23]. A time series itself is a sequence of data points indexed in time order, commonly encountered in diverse domains such as finance, healthcare, environmental science, and industrial processes [24]. The primary

objective of TSC is to build a model that can learn discriminative patterns or features from a collection of labeled time series, enabling it to accurately predict the class of new, unseen time series instances, and providing a powerful framework for automated detection tasks [23, 25].

Early TSC methods often relied on distance-based measures, with Dynamic Time Warping (DTW) being a prominent example, which calculates similarity between two temporal sequences that may vary in time or speed [26]. Other approaches focused on extracting statistical or structural features from the time series (e.g., mean, variance, spectral properties, shapelets) and then applying standard static classification algorithms [25, 27]. While effective in certain contexts, these methods can sometimes struggle with the high dimensionality, inherent noise, and complex temporal dependencies often present in real-world time series data.

More recently, deep learning architectures have demonstrated state-of-the-art performance on many TSC benchmarks [28]. Prominent among these are variants of Convolutional Neural Networks (CNNs) and Residual Networks (ResNet), adapted for time series, and have achieved remarkable success by effectively capturing local and global patterns [29]. Methods like InceptionTime also utilizes modules with multiple convolutional filter sizes to capture features at different temporal scales [30]. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) units and Gated Recurrent Units (GRUs), are inherently suited for modeling temporal dependencies and have also been widely applied, though sometimes at a higher computational cost [31]. Furthermore, Transformer-based models, leveraging self-attention mechanisms, have shown significant promise in capturing long-range dependencies and complex relationships within time series data [32]. Other approaches also includes ensemble methods, which combine several heterogeneous classifiers into a large meta-ensemble [33, 34, 35]. However, training these models can be computationally intensive, require large datasets, which poses limits in a sparse data scenario.

Alongside the advancements in deep learning, a distinct and highly competitive paradigm has gained prominence, focusing on transform-based feature engineering coupled with efficient classification. This approach decouples the often complex task of feature extraction from the subsequent classification step, allowing for specialized, powerful feature generation techniques to be paired with simpler, faster classifiers. Early and comprehensive exemplars of this philosophy include toolkits like `hctsa` (Highly Comparative Time-Series Analysis) [36] and `catch22` [37]. `hctsa` facilitates the extraction of thousands of diverse time-series features derived

from a wide array of scientific literature, enabling extensive data-driven exploration and the potential discovery of novel discriminative patterns [36]. In contrast, catch22 offers a more concise, curated set of 22 canonical time-series characteristics selected for their broad applicability and high discriminative power in general-purpose TSC tasks, aiming for robust performance with minimal redundancy [37]. Both these methodologies transform raw time series into a rich feature space, thereby empowering relatively simple classifiers to perform effectively.

Another highly influential branch within this “transform-then-classify” paradigm emerged with ROCKET (RandOm Convolutional KErnel Transform) [38]. ROCKET demonstrated that convolving time series with a large number of randomly generated, diverse convolutional kernels and extracting simple summary statistics (typically the maximum value and proportion of positive values) could yield highly discriminative features. These features then enable robust linear classifiers, such as ridge regression, to achieve state-of-the-art accuracy with exceptional speed, bypassing the need for complex backpropagation and extensive hyperparameter tuning associated with many deep learning models [38, 39]. The success of ROCKET spurred further innovations: MiniROCKET significantly reduced computational overhead by optimizing kernel parameters and focusing primarily on the proportion of positive values feature [40], while MultiROCKET enhanced performance by incorporating a richer set of summary statistics from the convolved outputs and an improved kernel generation strategy [41]. Building upon this lineage, Detach-ROCKET further reinforces the modular nature of the approach by separating, or “detaching” the redundant random kernels from the classifier training stage [42]. This design preserves computational efficiency and enhances the flexibility of feature generation, thereby readily supporting ensemble methods such as Detach Ensemble [43], where diverse feature sets can be strategically combined. The collective strength of these methods lies in their computational efficiency, reduced reliance on massive datasets, and potential for greater interpretability, making them particularly well-suited for challenging biomedical signal analysis tasks.

2.4 Related works

The automated detection of epileptic seizures from EEG signals has been an active area of research for several decades, driven by the need to alleviate the laborious and subjective process of manual EEG review by neurologists, and enable timely clinical intervention [44, 45].

Early approaches predominantly relied on extracting salient features from EEG segments in various domains: time, frequency, and time-frequency—followed by classification using conventional machine learning algorithms [46, 47]. Common features include statistical measures (e.g., variance, kurtosis), spectral power in different EEG bands (delta, theta, alpha, beta, gamma), wavelet coefficients, and entropy measures [48, 49]. Classifiers such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), Random Forests (RF), and Artificial Neural Networks (ANNs) were then trained on these extracted features to distinguish ictal (seizure) from interictal (non-seizure) or normal EEG patterns [50, 49]. While these methods have shown success, their performance heavily depends on the quality and relevance of the handcrafted features, which often require domain expertise and may not generalize well across diverse patient populations or recording conditions [44, 45].

More recently, deep learning techniques have demonstrated the ability to automatically learn hierarchical feature representations directly from raw or minimally processed EEG data [51, 52, 53]. Convolutional Neural Networks (CNNs) have been widely adopted for their proficiency in capturing spatial and temporal patterns from EEG signals, often treating multichannel EEG as an image or a set of parallel time series [54, 55, 56]. Recurrent Neural Networks (RNNs), particularly LSTMs and GRUs, are well-suited for modeling the temporal dynamics and long-range dependencies in EEG sequences [57, 58]. Hybrid models combining CNNs for feature extraction and RNNs for sequence modeling (CNN-LSTM) have also shown promising results [59, 60]. Furthermore, Transformer models, with their self-attention mechanisms, are increasingly being explored for EEG analysis, including seizure detection, due to their capability to capture global dependencies in long sequences [53, 61, 62, 63, 64, 65, 66]. These deep learning approaches often achieve good performance but typically require substantial amounts of labeled data for training and can be computationally intensive [51, 52].

Some recent works also explore the application of ROCKET-based methodologies for EEG feature learning in seizure detection, aiming to combine the speed of random convolutional kernel transforms with effective classification [67, 68]. These approaches seek to provide a balance between high accuracy and computational efficiency, which is crucial for practical clinical applications, especially in resource-constrained environments or for real-time monitoring systems [69, 70].

Chapter 3

Method

3.1 Data Processing

3.1.1 Data

In this project, two datasets are employed for model training and evaluation. The first dataset is the TUH EEG Seizure Corpus [71] (TUSZ), which comprises recordings from a total of 459 subjects. Within this corpus, a subset of the EEG recordings contains annotated seizure events, while the remainder consists of background (BCKG) recordings included to balance the dataset and to better assess the system's false alarm performance. Here BCKG recordings are defined as those that do not exhibit any of the following patterns: spike and/or sharp waves, periodic lateralized epileptiform discharges, generalized periodic epileptiform discharges, eye movements, or artifacts. Each EEG recording consists of 19 channels corresponding to the standard 10–20 system scalp electrode montage (see Figure 3.1), with a sampling rate of 256 Hz. See the publication of Obeid et al. [72] for further details on data collection.

Another dataset we used is the Siena Scalp EEG Database [73]. This database contains EEG recordings from 14 patients, collected at the Unit of Neurology and Neurophysiology at the University of Siena. The participants include 9 males (ages 25–71) and 5 females (ages 20–58). Each subject was monitored using Video-EEG at a sampling rate of 256 Hz. The recordings include 19 EEG channels, based on the standard 10–20 system scalp electrode montage (see Figure 3.1). See the publication of Detti et al. [74] for further details on data collection.

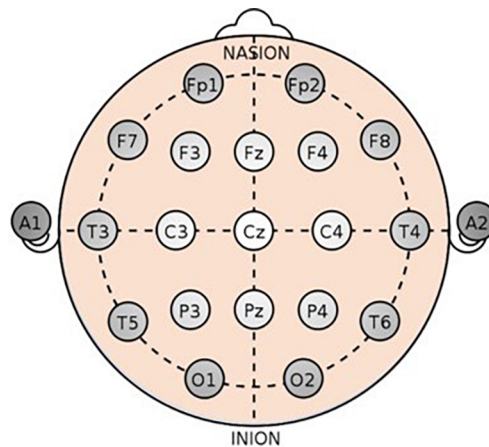


Figure 3.1: Electrode locations for EEG signals. From Shah, V. et al [71]

3.1.2 Data preprocessing

To support model training across multiple datasets, we convert each dataset to the Seizure Community Open-Source Research Evaluation (SzCORE) standardized format [75] for data and seizure annotations. This format is compatible with the Brain Imaging Data Structure (BIDS).

The model is trained on the large Temple University Seizure Corpus (TUSZ) dataset, which includes 1,134 recordings with seizures and 4,585 background recordings. All recordings are downsampled to 128 Hz. Each recording is segmented into non-overlapping 10-second epochs. These epochs are then categorized as seizure, interictal, or background (bckg). Seizure epochs are sampled from periods annotated as seizures. Interictal epochs are sampled from intervals between annotated seizure events. Background epochs are sampled exclusively from recordings labeled as BCKG. Seizure epochs are assigned the label 1 (seizure), while interictal and background epochs are assigned the label 0 (non-seizure).

3.2 Model

3.2.1 ROCKET and MINIROCKET

ROCKET (**R**and**O**m **C**onvolutional **K**ernel **T**ransform) achieves state-of-the-art classification accuracy for time series classification while requiring only a

Do you have any text to describe your own adaptations of this to make it run? You want to help a student to be able to replicate

fraction of the computational resources used by most existing methods [38]. It transforms time series using random convolutional kernels and uses the transformed features to train a linear classifier. The method was later reformulated as MINIROCKET (**MINI**mally **RandOm** **C**onvolutional **K**ernel **T**ransform), which is up to 75 times faster than ROCKET on large datasets and is almost deterministic, while maintaining nearly the same accuracy [40]. MINIROCKET is significantly faster than other methods with similar accuracy and provides significantly better accuracy than methods with comparable computational efficiency.

3.2.2 Detach-ROCKET

Although ROCKET and MINIROCKET are efficient and computationally lightweight, many of the randomly generated features are redundant or non-informative, increasing the computational burden and may reduce the model's generalizability. Detach-ROCKET addresses this issue by introducing Sequential Feature Detachment (SFD), a method designed to identify and prune the non-essential features from ROCKET-based models [42]. In SFD, the transformed features are ranked according to their contribution to the model's decisions. At each iteration, a fixed proportion of the least informative features is discarded. Let \mathbb{F} denote the complete set of features generated by ROCKET's random convolutional kernels. The subset of currently active features is represented by $\mathbb{S} \subseteq \mathbb{F}$, which is initially set to \mathbb{F} .

At each step t , a ridge classifier is trained on the active feature set \mathbb{S}_t by solving the following optimization problem:

$$\hat{\theta}_t^{\text{ridge}} = \underset{\theta}{\operatorname{argmin}} \left\{ \sum_{i=1}^N \left(y_i - \theta_0 - \sum_{k \in \mathbb{S}_t} x_{ik} \theta_k \right)^2 + \lambda \sum_{k \in \mathbb{S}_t} \theta_k^2 \right\} \quad (3.1)$$

The training process produces a set of optimal coefficients $\hat{\theta}_t^{\text{ridge}} = \{\hat{\theta}_k\}$, where each coefficient is proportional to the contribution of a corresponding feature on the classifier's decision. The features are then ranked according to the absolute values of their coefficients. Let p denote the proportion of features to be removed. At each step, the lowest $100 \cdot p\%$ of ranked features discarded, and the remaining $100 \cdot (1 - p)\%$ are retained to form the updated feature set \mathbb{S}_{t+1} . Since p controls the trade-off between computational cost and model accuracy, it is set to 0.05 to ensure a conservative yet computationally affordable pruning procedure, meaning that 5% of the features are removed at

each step.

To determine the optimal number of features to finally retain in our dataset, we solve the following optimization problem:

$$Q_c = \underset{q}{\operatorname{argmax}} f_c(q) = \underset{q}{\operatorname{argmax}} \{ \alpha(q) + c \cdot q \}. \quad (3.2)$$

In this equation, Q_c represents the accuracy curve obtained by evaluating the model at each pruning step, q represents the proportion of pruned features, and $\alpha(q)$ the accuracy of the pruned model on the validation set. The hyperparameter c is the weighting factor between accuracy and data size, in which a smaller c value favors accuracy and larger c value favors data size. We set $c = 0.1$, as this achieves the optimal performance according to Fig.4 in [42].

3.2.3 Detach Ensemble

Given the high dimensionality of multivariate time series such as the 19-channel EEG data in this project, relying on a single set of randomly generated kernels may inadequately capture the complex spatio-temporal patterns and inter-channel relationships critical for seizure detection. To address this limitation and improve model generalization and robustness, an ensemble approach based on Detach-ROCKET is employed. The Detach Ensemble involves training N independent Detach-ROCKET models. For each model, a subset of the training data is used to determine the optimal pruning size, and the model is then pruned using SFD. Each pruned model is then assigned a weight based on its performance on the training set [43].

For classifying a given input instance, predictions from each individual model are aggregated via a weighted average, using the predetermined model weights, to yield a final ensemble probability score. This probability is then thresholded (commonly at 0.5) to produce the definitive classification label (seizure or non-seizure).

In our implementation, we use an ensemble of $N = 10$ Detach-MiniROCKET models. This number was chosen as a balance between seeking improved performance through ensemble diversity and managing computational resources, as training significantly more models becomes resource-intensive. Each of the 10 model is trained independently using the procedure described in Section 3.2.2, including the application of SFD with $p = 0.05$ and the feature selection criterion $c = 0.1$.

3.3 Evaluation of Models

The performance of the trained Detach-ROCKET and Detach Ensemble model are assessed through two complementary evaluation frameworks: epoch-wise and event-wise analysis.

Firstly, an epoch-wise evaluation is conducted based on the 10-second non-overlapping segments described in Section 3.1.2. Standard classification metrics including accuracy, sensitivity, precision, and the F1-score are computed on the test set. The confusion matrix is also examined to understand the distribution of classification errors. This epoch-based assessment provides views of the model's ability to correctly classify individual epochs.

However, recognizing that clinical assessment of epilepsy monitoring often focuses on the detection of seizure episodes (events) rather than isolated time epochs, an event-wise evaluation is performed. During the evaluation procedure, event-based sensitivity, precision, and F1-score are calculated based on the open-source `timescoring` library [76].

3.3.1 Evaluation metrics

To evaluate the performance both epoch-wise and event-wise, we first define and explain the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) in this study: True Positive (TP): An instance correctly identified as belonging to the positive class (seizure); True Negative (TN): An instance correctly identified as belonging to the negative class (non-seizure); False Positive (FP): An instance incorrectly identified as belonging to the positive class when it belongs to the negative class (a non-seizure instance classified as seizure); False Negative (FN): An instance incorrectly identified as belonging to the negative class when it belongs to the positive class (a seizure instance classified as non-seizure).

For epoch-wise evaluation, a TP is a correctly classified seizure epoch, an FP is a non-seizure epoch classified as seizure, etc. For event-wise evaluation, the following parameters were configured to combine the epochs to seizure events, as suggested by the 2025 Seizure Detection Challenge:

- **Minimum Overlap:** Any temporal overlap, however brief, between a reference event and a hypothesis event is sufficient to consider it a potential match. This setting maximizes sensitivity to detecting any part of a seizure.
- **Pre-ictal Tolerance:** A hypothesis event starting up to 30 seconds before

the onset of a reference event can still be considered a detection of that event.

- **Post-ictal Tolerance:** A hypothesis event ending up to 60 seconds after the end of a reference event can still be considered part of the detection of that event.
- **Minimum Duration:** Reference or hypothesis events separated by less than 90 seconds are merged into a single, longer event before scoring. This duration corresponds to the sum of the pre- and post-ictal tolerances, preventing closely spaced detections from being penalized multiple times.

In this configuration, a reference event refers to a labeled seizure event, a hypothesis event refers to a model predicted event. Based on these criteria, an event-based TP occurs when a reference seizure event is correctly matched with one or more hypothesis seizure events according to the overlap and tolerance rules. An event-based FP corresponds to a hypothesis seizure event that does not match any reference event. An event-based FN represents a reference seizure event that is not matched by any hypothesis event. For the specific application of seizure detection, event-wise metrics are considered more clinically meaningful than epoch-wise metrics. Consequently, while both will be reported, event-wise performance will be the primary focus for evaluating the model's practical utility.

Based on these setting, we define the accuracy, sensitivity, precision, f1-score and false alarm rate as following:

- **Accuracy:** the proportion of total instances that were correctly classified.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.3)$$

- **Sensitivity:** the proportion of true positive instances that were correctly identified by the model.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (3.4)$$

- **Precision:** the proportion of instances predicted as positive that were actually positive.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3.5)$$

- F1 Score: the harmonic mean of Precision and Sensitivity, providing a single metric that balances both concerns.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (3.6)$$

- False positive rate (FPR): the number of false positives per 24 hours. A low FPR is crucial for clinical usability, as frequent false alarms can reduce clinician trust in the system.

$$\text{FPR} = \frac{FP}{FP + TN} \quad (3.7)$$

3.4 Channel Relevance Estimation

To estimate the relevance of individual EEG channels within our Detach-ROCKET Ensemble, we adopt the methodology proposed by Solana et al. [43]. This process first assesses channel relevance on each Detach-MINIROCKET model:

1. **Kernel Selection:** Sequential Feature Detachment (SFD) identifies and selects the most relevant kernels within the MiniROCKET model.
2. **Channel Retrieval:** For each kernel selected by SFD, the specific EEG channels it processed are retrieved.
3. **Importance Weighting:** Each retrieved channel receives an importance score proportional to its kernel's weight (θ_i). It is then divided by the number of channels in that same kernel.
4. **Relevance Aggregation:** The weighted importance scores for all channels are summed across the selected kernels. These sums are then normalized to create a relative channel relevance histogram.

The final ensemble relevance for each channel is then determined by taking the median of relevancies from base models and normalizing across all channels.

Chapter 4

Results and Analysis

4.1 Experiments on TUSZ Corpus

4.1.1 Training and test with Detach-MINIROCKET and Ensemble

In this project, we trained two models, Detach-ROCKET and Detach Ensemble, on the TUSZ dataset.

Due to hardware constraints and the large size of the dataset, we randomly select 50% of the available subjects to construct the working dataset. This subset is then divided into training and test sets based on subject identifiers to ensure that the evaluation reflects the model's generalizability across individuals. We allocate 80% of the subjects to the training set and the remaining 20% to the test set. Each subject includes multiple sessions and runs, with each run containing several recordings labeled as either seizure or background (BCKG). See . Notably, a portion of the subjects in the dataset contribute exclusively BCKG recordings, without any associated seizure activity.

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To accommodate memory limitations and promote a balanced and diverse training set, after segmenting the recordings in the training set into non-overlapping 10-second epochs, we include all available seizure epochs, randomly select an equal number of interictal epochs, and randomly sample half that number of background epochs for model training. For the evaluation of epoch-wise accuracy, this methodology resulted in an average of approximately 20,000 epochs being used for model training, with an average of about 5,000 epochs allocated for testing. The models' performances were initially assessed using epoch-wise accuracy. Table 4.1 shows the accuracy of

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both models, averaged over three trials.

The models are then evaluated on a dataset comprising the same subjects included in the test set during model training, while using all the epochs produced by these subjects without selecting a subset of them. Note that the evaluation dataset, though comprising the same subjects as test set, is however unbalanced with more non-seizure epochs than seizure epochs. Performance was evaluated using sensitivity, precision, F1-score, and False Positive Rate (FPR), computed at the recording level for both epoch-wise and event-wise analyses. Table 4.2 shows the performance metrics for the single Detach-MINIROCKET model using 10,000 features and 10-model Detach-MINIROCKET ensemble, each of the base models using 10,000 features. These reported values are averaged first across all evaluation recordings and then across the three random data partitions. The high event-wise F1-score of both models demonstrates the model’s strong generalization capabilities across different individuals. Figure 4.1 provides examples of the models’ output on representative recordings containing either seizure or background EEG patterns.

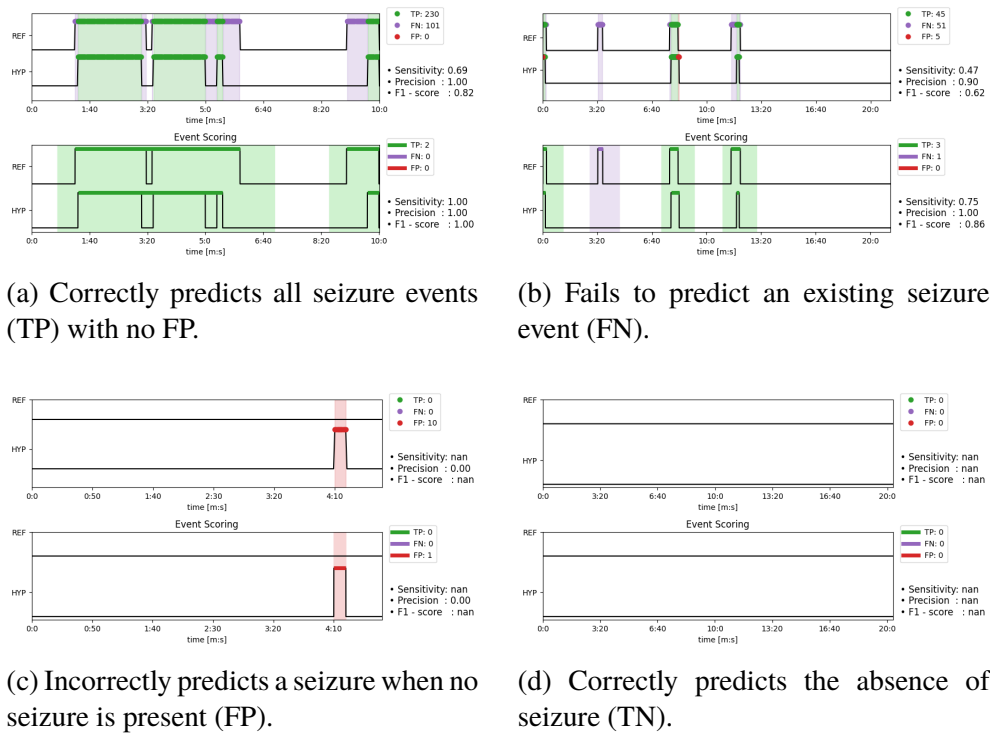
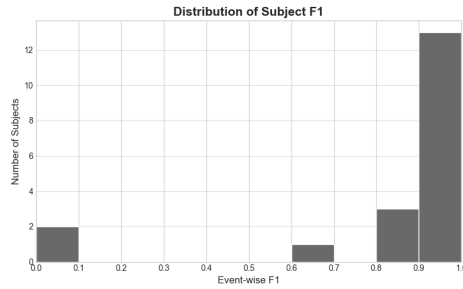


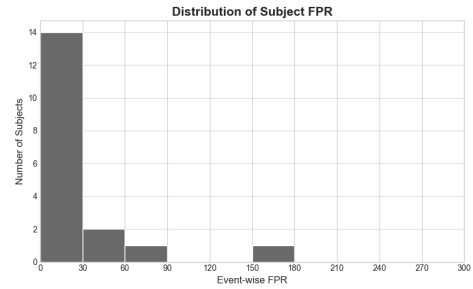
Figure 4.1: Examples of model evaluation outcomes.

To further assess the model’s generalization capabilities across individual

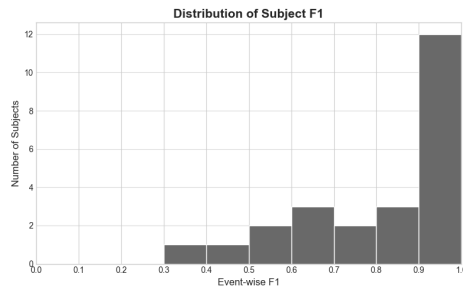
subjects, subject-wise performance metrics were computed on the test set. Figure 4.2 illustrates the distribution of event-wise F1 scores and False Positive Rates(FPR per 24h) across individual subjects from a representative evaluation, revealing considerable inter-subject variability. For both models, a significant proportion of subjects obtained F1 scores in the highest bin of 0.9-1.0. FPR values also showed considerable variation across subjects, with a significant proportion of subjects demonstrating low false alarm rates(below 30). Despite this observed inter-subject performance variation, these distributions suggest that both models generalize effectively for a majority of individuals. It is important to note that the F1 score distribution presented in Figure 4.2 excludes subjects who contributed exclusively background (BCKG) recordings to the test set (i.e., had no annotated seizure events). For these subjects, True Positives (TP) and False Negatives (FN) are inherently zero, so the F1 score cannot be calculated.



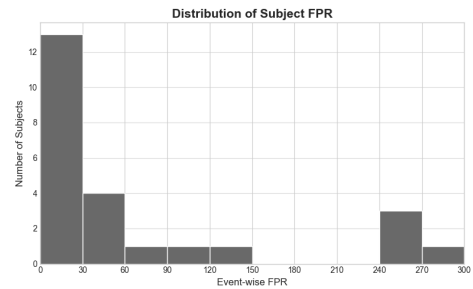
(a) Subject-wise event F1 score distribution for the Detach-MINIROCKET model on the TUSZ test set.



(b) Subject-wise event FPR distribution for the Detach-MINIROCKET model on the TUSZ test set.



(c) Subject-wise event F1 score distribution for the Detach-MINIROCKET Ensemble on the TUSZ test set.



(d) Subject-wise event FPR distribution for the Detach-MINIROCKET Ensemble on the TUSZ test set.

Figure 4.2: Distribution of subject-wise performance metrics on the TUSZ test set for different model configurations.

While both models demonstrate good event-wise F1 scores and generalization across subjects, the Detach-MINIROCKET model exhibits lower epoch-wise performance. This suggests that, compared to the Detach Ensemble model, it's difficult for a single Detach-ROCKET model with 10,000 features to sufficiently sample the feature space and encode meaningful multichannel information. Despite this limitation, the single Detach-MINIROCKET model is significantly more computationally efficient, as it requires training only one model. On the other hand, although the Detach Ensemble model introduces higher computational costs, it offers enhanced model interpretability by providing a built-in way to generate label probabilities and estimate channel relevance, which is particularly valuable in the context of seizure detection.

4.1.2 Benchmark

To establish a robust, interpretable, and accessible baseline for our models, we selected catch22 [37] as our benchmark. catch22 offers a concise set of 22 highly discriminative and computationally inexpensive time-series features, distilled from the much larger hctsa feature set [36]. Its design emphasizes generalizability and interpretability across diverse time series domains [23, 37]. Furthermore, the widespread availability and easy implementation of catch22 contribute to its utility as a practical and reproducible benchmark for evaluating the performance and computational costs of more complex or specialized algorithms in TSC tasks.

Our models and catch22 are evaluated on the TUSZ dataset. Table 4.1 and Table 4.2 summarize a comparative performance with the benchmark model, averaged over three distinct random splits, each using 50% of the total available subjects. Our results indicate that the Detach Ensemble model outperforms the other models in overall test accuracy, as well as in both epoch-wise and event-wise F1 scores. Specifically, Detach Ensemble achieved a test accuracy approximately 10% higher than Detach-MINIROCKET and 2% higher than catch22. For event-wise F1 scores, Detach Ensemble outperforms catch22 by 4% and Detach-MINIROCKET by 1%. For epoch-wise F1 scores, Detach Ensemble substantially outperforms both catch22 and Detach-MINIROCKET by 6%. Notably, both Detach-MINIROCKET and the Detach Ensemble achieved higher event-wise F1 scores than catch22, while requiring significantly lower computational resources, as detailed in Section 4.5. Furthermore, Detach-MINIROCKET exhibited the lowest False Positive Rate (FPR) among the evaluated models.

Table 4.1: Comparison of epoch-wise training and test accuracies for the single Detach-MINIROCKET (D-MINIROCKET) model, Detach-MINIROCKET Ensemble (D-MINIROCKET Ens.) and catch22.

	Train Acc.	Test Acc.
D-MINIROCKET	0.95	0.71
D-MINIROCKET Ens.	0.97	0.81
catch22	1.00	0.79

Table 4.2: Comparison of model performance for single Detach-MINIROCKET (D-MINI), 10-model Detach-MINIROCKET ensembles (D-MINI Ens.) and catch22, using 50% of the dataset.

Config.	Level	Sens.	Prec.	F1	FPR
D-MINI	Epoch	0.52	0.68	0.51	7 915
	<i>Range</i>	<i>(0.50, 0.53)</i>	<i>(0.66, 0.69)</i>	<i>(0.49, 0.55)</i>	<i>(6798, 9035)</i>
	Event	0.90	0.86	0.86	27
	<i>Range</i>	<i>(0.87, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(xxxx, xxxx)</i>
D-MINI Ens.	Epoch	0.72	0.60	0.57	14 543
	<i>Range</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(xx, xx)</i>
	Event	0.95	0.85	0.87	37
	<i>Range</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(xxxx, xxxx)</i>
catch22	Epoch	0.60	0.63	0.51	9 603
	<i>Range</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(xxxx, xxxx)</i>
	Event	0.88	0.84	0.83	36
	<i>Range</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(0.50, 0.53)</i>	<i>(xxxx, xxxx)</i>

4.2 Sensitivity Analysis

The performance of a single Detach-MINIROCKET model, and consequently its sensitivity to hyperparameter changes, can be significantly influenced by the stochastic nature of its random convolutional kernel generation [38, 77]. While this inherent randomness is integral to the efficiency of the ROCKET family, it makes it more difficult to isolate the specific impact of individual hyperparameter adjustments in limited model instances, as it can have a large variation due to randomness rather than solely the hyperparameter change. In contrast, Detach-Ensemble, by aggregating multiple Detach-MINIROCKET instances, reduces such stochastic effects, leading to more stable and representative performance characteristics. Given

the foundational homogeneity between Detach Ensemble and its constituent Detach-MINIROCKET models (as the ensemble is built from them), our detailed sensitivity analysis was primarily focused on the Detach-Ensemble configuration.

We therefore explored the effect of key parameter choices on the Detach-Ensemble’s test accuracy, epoch-wise and event-wise F1 score. The key parameters investigated were:

1. number of models (N)
2. epoch duration
3. training data size

Table 4.3: Performance evaluation of the Detach-Ensemble model under varying hyperparameter configurations.

N	Epoch Duration	Test Acc.	Epoch F1	Event F1
10	10	0.86	0.64	0.89
10	5	0.86	0.45	0.86
10	20	0.68	0.66	0.89
5	10	0.73	0.46	0.85
20	10	0.84	0.69	0.92

The impact of training data size on model performance is shown in Figure 4.3. A notable deterioration in performance is observed when the proportion of training data used falls below 30% of the total dataset. Beyond this point, the model achieves a relatively stable and high level of performance. This finding supports our decision to use 50% of the available data for training, as it offers a conservative, resource-efficient approach while ensuring robust model performance. The result also suggests model’s ability for effective generalization even when trained on limited dataset sizes.

4.3 Cross-Dataset Evaluation

To evaluate the models’ generalization capabilities on unseen data, we assess model performance on the Siena Scalp EEG Database. This independent dataset provides an opportunity to test the model’s robustness to variations in patient populations, recording equipment, and potential differences in EEG

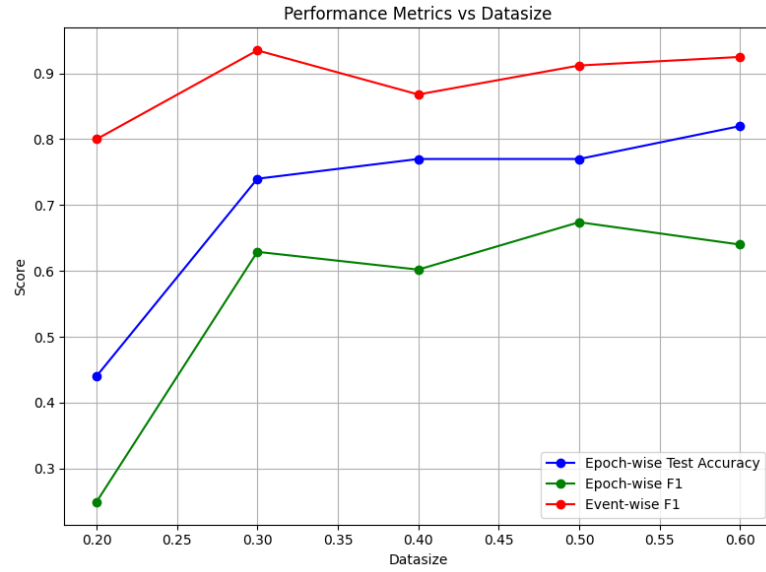


Figure 4.3: Performance of the Detach-Ensemble model on varying training datasize proportions

characteristics. Table 4.4 presents the averaged performance of our models when evaluated on the entire Siena dataset, compared with catch22. The results demonstrate that both Detach-MINIROCKET and Detach-Ensemble models achieve better F1 scores (both epoch-wise and event-wise) and lower event-wise False Positive Rates (FPR) compared to catch22 on this cross-dataset validation task.

To further understand models' cross-dataset generalization capabilities, we refer to the publicly reported outcomes of the Seizure Detection Challenge 2025.

In this challenge, proposed algorithms were trained on publicly available datasets and then evaluated on a private EEG dataset (Dianalund Scalp EEG dataset), with rankings primarily determined by their event-wise F1 score. Adhering to the same epoch-to-event aggregation rules employed in the challenge, our Detach-MINIROCKET and Detach-Ensemble model achieved an event-wise F1 score of 0.41 and 0.42 on the Siena dataset, respectively. This performance is highly competitive with the top-ranked algorithms in the challenge, which reported event-wise F1 scores of 0.43, 0.36, and 0.34. Given that the Siena dataset represents an entirely different data distribution from the training set (TUSZ), the performance of our models indicates a strong capacity for generalization and robust seizure detection across diverse datasets.

Table 4.4: Cross-dataset performance comparison of Detach-MINIROCKET, Detach-MINIROCKET Ensemble, and catch22 on the Siena dataset.

	Epoch F1	Event F1	Event FPR
D-ROCKET	0.36	0.41	55
D-ROCKET Ens.	0.34	0.42	58
catch22	0.28	0.37	82

4.4 Channel Relevance

To investigate the relative importance of different EEG channels for seizure detection within our framework, we employed the channel relevance estimation method proposed by Solana et al. [43]. This method was applied to each of the well-performing Detach-MINIROCKET Ensemble models developed during our training phase. Figure 4.4 illustrates the mean and standard deviation of the estimated channel relevance values, aggregated across these selected ensemble models.

Observations from Figure 4.4 indicate that channels Fp1 and C4 exhibit notably high mean relevance values compared to other channels. However, these channels also display relatively large standard deviations. Conversely, channel F8 presents with a significantly low mean relevance value and a comparatively small standard deviation, indicating its consistently minor role in seizure detection for our models on the TUSZ dataset.

Further analysis involved ranking channels from most to least relevant within each individual ensemble model. This ranking revealed that channels Fp1, C4, and O1 were frequently identified among the top four most relevant channels (appearing 4 out of 7 times for each of these channels across the evaluated models). In contrast, channel F8 was most frequently found among the top four least relevant channels (6 out of 7 model instances), with channel T3 also appearing frequently in this less relevant group (4 out of 7 model instances).

The consistent findings combining these two analytical approaches suggest that channels Fp1 and C4 are likely more critical for our seizure detection task on the TUSZ dataset, while channel F8 appears to be consistently less informative. In practical scenarios where computational resources are constrained, or where feature selection is desired to emphasize inter-channel relationships or reduce model complexity, these findings suggest that prioritizing channels such as Fp1, C4, and potentially O1, while deprioritizing

F8 and possibly T3, could be a viable strategy.

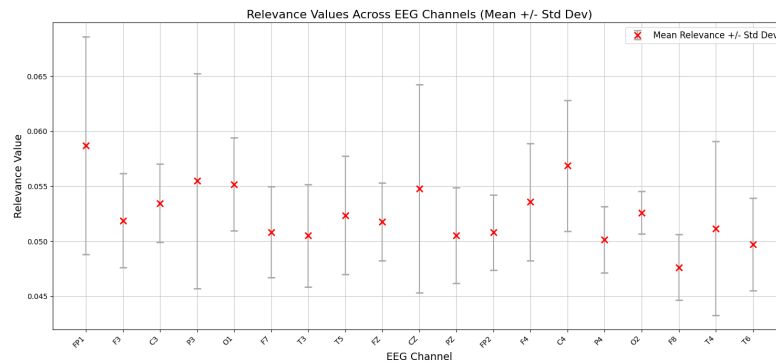


Figure 4.4: Mean and standard deviation of estimated channel relevance values across selected Detach-MINIROCKET Ensemble models. Higher mean values suggest greater overall importance, while standard deviation indicates variability across models.

4.5 Model Efficiency

The computational efficiency of the models, particularly their prediction speed, is a critical factor for practical deployment, especially in real-time seizure detection scenarios. To evaluate this, prediction times were measured on an Intel(R) Xeon(R) Platinum 8480C processor for a representative EEG recording of 1208 seconds in duration. The results are summarized in Table 4.5.

As indicated in Table 4.5, the single Detach-MINIROCKET model processed the entire recording in just 0.74 seconds, which is approximately 17.1 times faster than the catch22 benchmark. The Detach-MINIROCKET Ensemble, while inherently introducing a higher computational cost due to the aggregation of multiple individual models, still completed the prediction in 6.88 seconds. This remains notably faster than catch22, by a factor of approximately 1.8. These findings highlight the significant computational advantages of the ROCKET-based feature transformation approach employed by our models. In particular, the rapid inference capability of the single Detach-MINIROCKET model demonstrates strong potential for applications requiring near real-time processing and decision-making. While the ensemble model requires increased prediction time, it provides enhanced predictive performance and is therefore still a competitive choice.

Table 4.5: Model prediction time (seconds) on a 1208s EEG recording.

D-MINIROCKET	D-MINIROCKET Ens.	Catch22
0.74s	6.88s	12.68s

Chapter 5

Discussion

5.1 Limitations

5.2 Ethics and Sustainability

Chapter 6

Conclusions and Future work

6.1 Conclusions

6.2 Future work

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Appendix A

Supporting materials

Here is a place to add supporting material that can help others build upon your work. You can include files as attachments to the PDF file or indirectly via URLs. Alternatively, consider adding supporting material uploaded as separate files in DiVA.

The BibTeX references used in this thesis are attached. 

Some source code relevant to this project can be found at <https://github.com/ggmaquirejr/E-learning> and <https://github.com/ggmaquirejr/Canvas-tools>.

Your reader can access the attached (embedded) files using a PDF tool such as Adobe Acrobat Reader using the paperclip icon in the left menu, as shown in ?? or by right-clicking on the push-pin icon in the PDF file and then using the menu to save the embedded file as shown in ??.

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  \item Results/Conclusions/Impact: What are your key results/\linebreak[4]conclusions? What will others do based on your results? What can be done now that you have finished - that could not be done before your thesis project was completed?
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% The form of the entries in this file is \newacronym{label}{acronym}{phrase}
%                                     or \newacronym[options]{label}{acronym}{phrase}
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\newacronym[longplural={Debugging Information Entities}]{DIE}{DIE}{Debugging Information Entity}
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\newacronym[shortplural={OSes}, firstplural={operating systems (OSes)}]{OS}{OS}{operating system}

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\newacronym{IQL}{IQL}{Independent -QLearning}

% example of putting in a trademark on first expansion
\newacronym[first={NVIDIA OpenSHMEM Library (NVSHMEM\texttrademark)}]{NVSHMEM}{NVSHMEM}{NVIDIA OpenSHMEM Library}

\newacronym{KTH}{KTH}{KTH Royal Institute of Technology}

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\newacronym{VM}{VM}{virtual machine}
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\newacronym{WLAN}{WLAN}{Wireless Local Area Network}
\newacronym{UN}{UN}{United Nations}
\newacronym{SDG}{SDG}{Sustainable Development Goal}
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