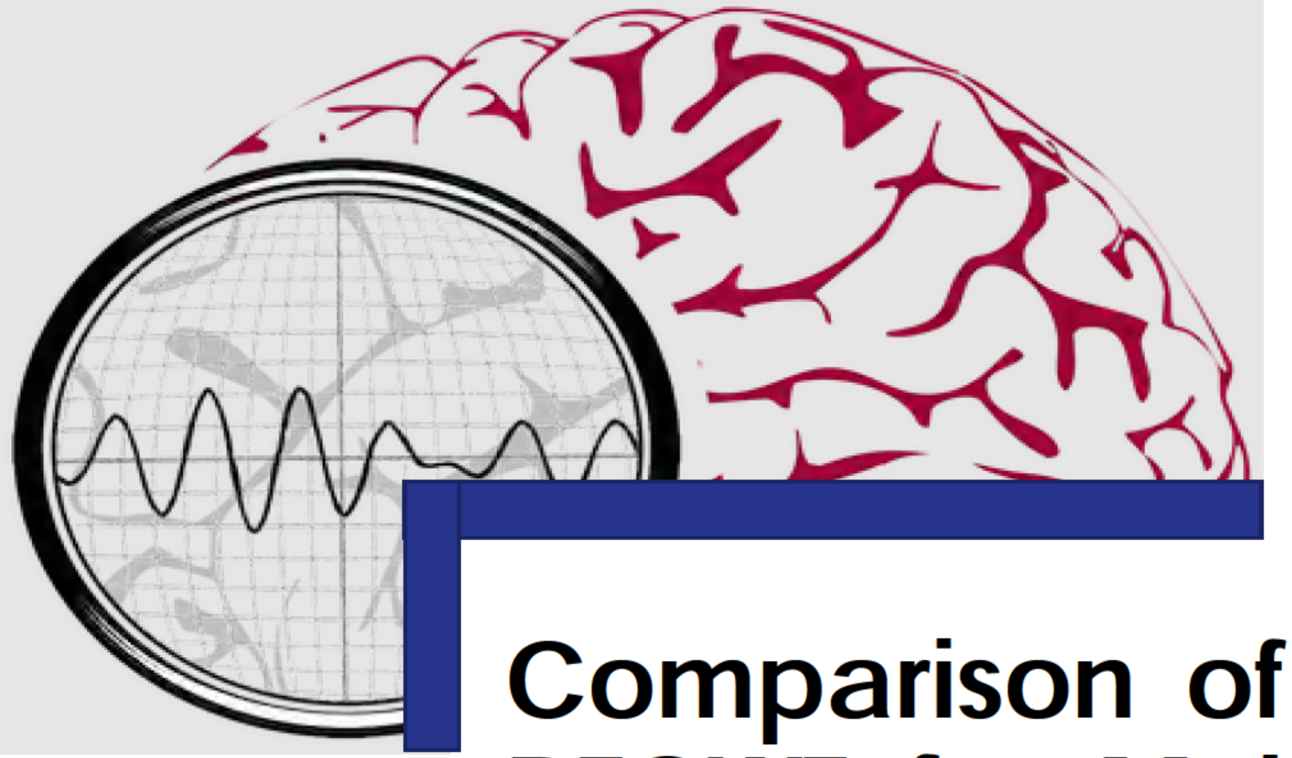
The 2021 IEEE Signal Processing in Medicine and Biology Symposium



Comparison of WPD DWT and DTCWT for Multi-Class Seizure Type classification

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Contents

Introduction

- Epilepsy is the second most common type of brain disease in human beings after stroke [1].

- It is defined as "a sudden and recurrent brain malfunction and is a disease that reflects an excessive and hypersynchronous activity of the neurons within the brain [1].

- Over 60 million of the world population has epilepsy; whose characterized feature is recurrent seizures [2].

Introduction

- According to the World Health Organization (WHO), eighty percent of epileptic patients live in underdeveloped or developing nations with insufficient medical services [3].

- Worryingly, the vast majority of those people remain undiagnosed and hence do not receive adequate treatment and care. Furthermore, those with epilepsy have three times more risk of premature death comparatively [4].

- Electroencephalography (EEG) is the most commonly used tool to diagnose seizures [5].

- Roughly 66% of seizures can be controlled by medication, whereas about 8% only can be controlled by surgical intervention. While for the rest, no medical treatment exist [6].

Motivation

- The Accurate seizure type classification will support the epileptologist to provide the appropriate medication.

- Correct classification is necessary as some seizure medications and equipment are only for the treatment of certain seizure types [10].

- Seizure type classification may also be beneficial also for researchers in establishing a link between certain syndromes or etiologies [10].

- **Many variables complicate the diagnosis of seizure classification :**
  - Overlapping symptoms
  - Inter-subject variability

Related Work

- For the last two decades, most of the research has concentrated on automatic detection and predication of epileptic seizures using scalp EEG.

- However, seizure type classification received little attention due to:
  - Nonavailability of large clinical EEG data,
  - The difficulties inherent in this task.

- *The Temple University Hospital EEG Seizure Corpus (TUSZ) [13].*

Related Work

Method	No. of seizure classes	Classes considered	Features	Performance (%)
Transfer learning Inceptionv3[11]	8*	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, NORM+	SFFT	88.3 Accuracy
AlexNet[12]	8*	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, NORM+	SFFT	84.06 Accuracy
CNN+LSTM+MLP[8]	8	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, MYSZ	SFFT	97.40 F1-score
SeizureNet Ensemble CNNs[14]	7	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	FFT	95 F1-score
Plastic NMN[15]	7	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	FFT	94.5 F1-score
K-NN[16]	7	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	FFT	90.1 F1
XGBoost[17]	7	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	FFT	85.1 F1-score
SVM [18]	4*	GNSZ, FNSZ, TCSZ, NORM+	MFCC+HD+ICA	91.4 Accuracy
FPGA-based ANN[19]	3*	GNSZ, FNSZ, NORM+	CWT	95.14 Accuracy
SVM[20]	4	GNSZ, FNSZ, SPSZ, TNSZ	EMD	95 Accuracy

*Including non-seizure EEG class.

+Normal EEGs.

In this Work

- We compare three important signal decomposition techniques:

  - Discrete Wavelet Decomposition (DWT),
  - Wavelet Packet Decomposition (WPD),
  - Dual-Tree Wavelet Decomposition (DTCWT).

- Three different combination of features.

- Evaluation across different Patient

Table 1. Seizure Type Statistics in the TUSZ v1.5.2

Seizure Type	No. of seizure events	Duration (Seconds)	No. of patients
FNSZ	1836	121139	150
GNSZ	583	59717	81
CPSZ	367	36321	41
ABSZ	99	852	12
TNSZ	62	1204	3
TCSZ	48	5548	12
SPSZ	52	2146	3
MYSZ	3	1312	2

Temple University Hospital

Temple University Health System

The Temple University Hospital EEG Seizure Corpus (TUSZ v1.5.2)

Seizures > 3000

Patients > 300

The largest publicly available EEG dataset

Seizure Types*

Focal Seizures (FNSZ)

- Simple Partial (SPSZ)
- Complex Partial (CPSZ)

Generalized Seizures (GNSZ)

- Absence (ABSZ)
- Myoclonic (MYSZ)
- Tonic (TNSZ)
- Tonic Colonic (TCSZ)

*Cdc.gov. 2021. Types of Seizures | Epilepsy | CDC. [online] Available at: <https://www.cdc.gov/epilepsy/about/types-of-seizures.htm> [Accessed 25 November 2021].

Classification problems

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7-class problem

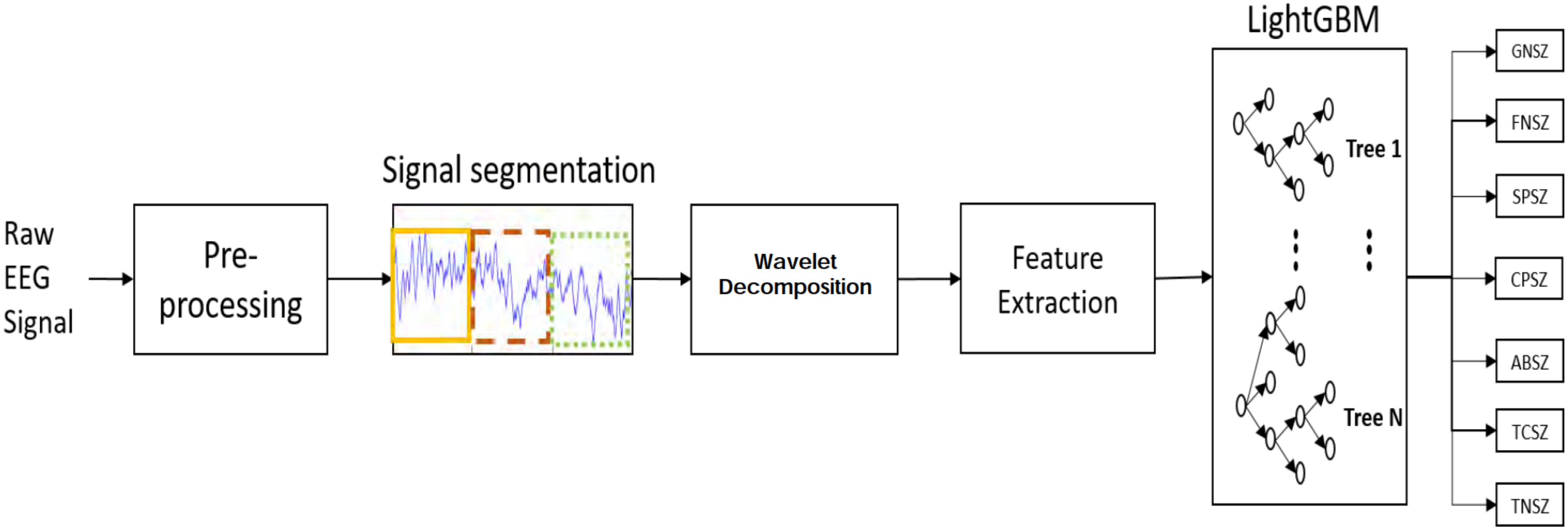
- Specific and non specific

5-class problem

- Only specific types

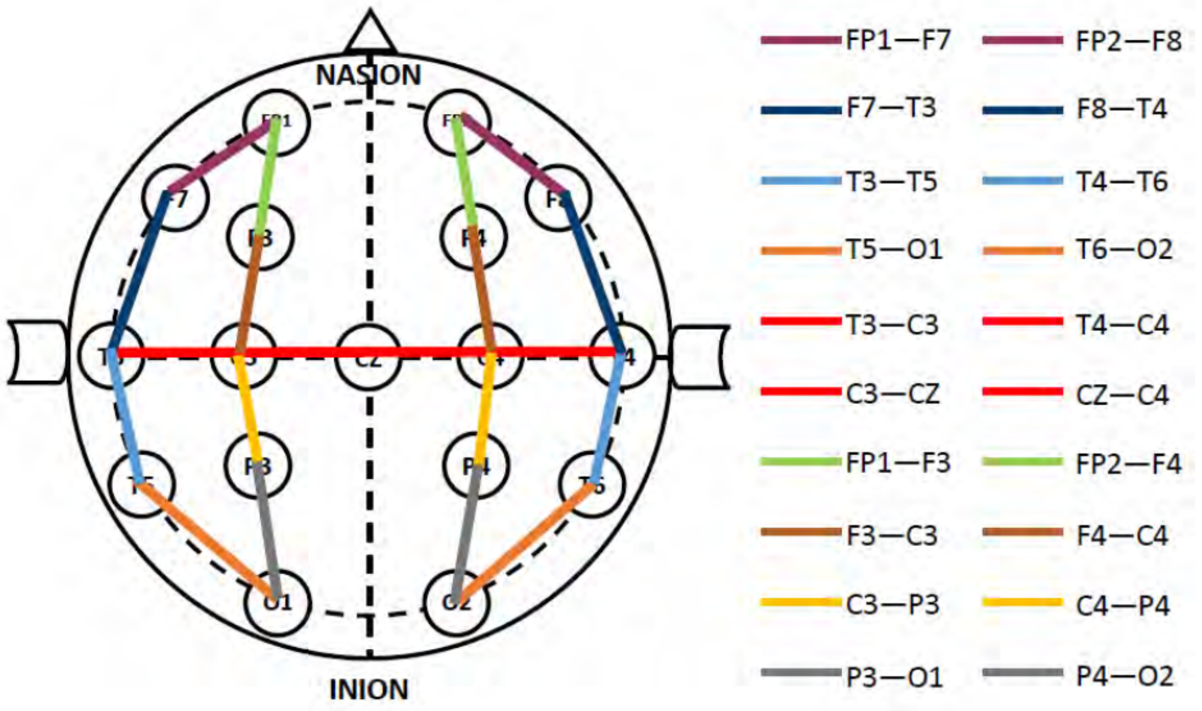
2-class problem

- Only non-specific



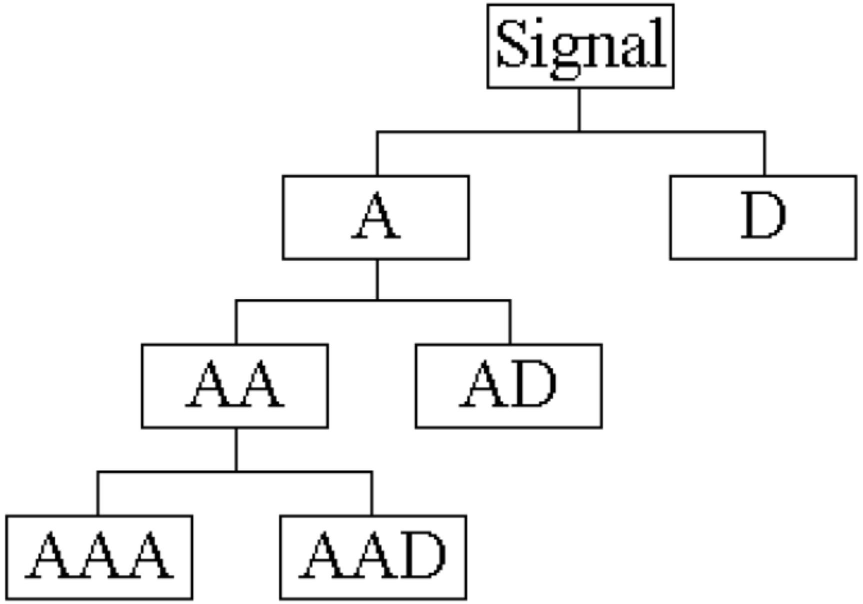
Raw
EEG
Signal
Pre-
processing
Signal segmentation
Wavelet
Decomposition
Feature
Extraction
LightGBM
Tree 1
Tree N
GNSZ
FNSZ
SPSZ
CPSZ
ABSZ
TCSZ
TNSZ

Preprocessing

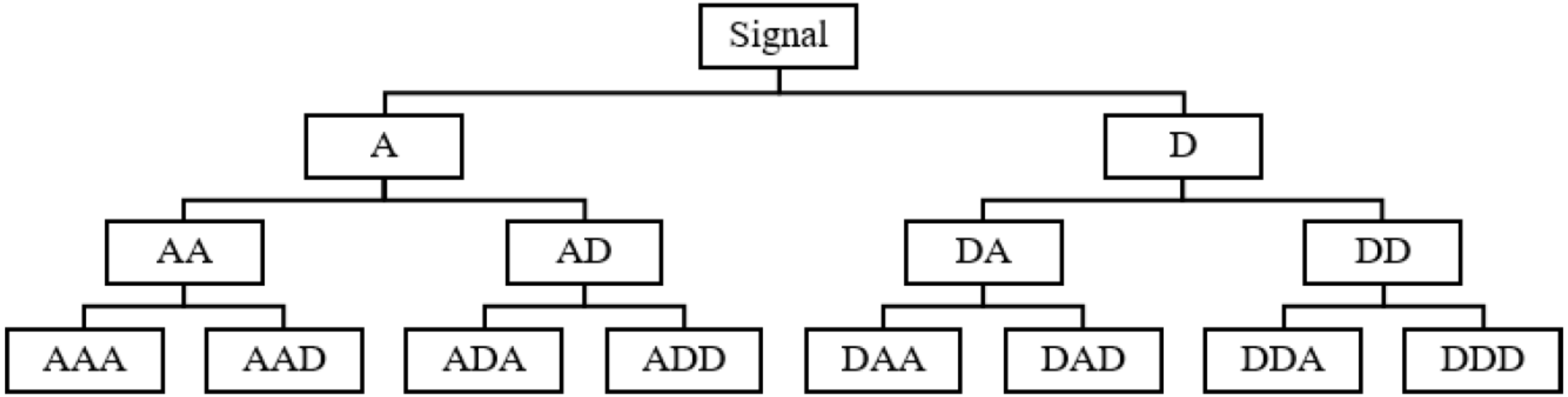


- 250HZ,
- Butterworth filter a passband filter in the range of 0.4 to 49.5 Hz is applied to the signals to filter our the noise,
- Segmentation 2 seconds,

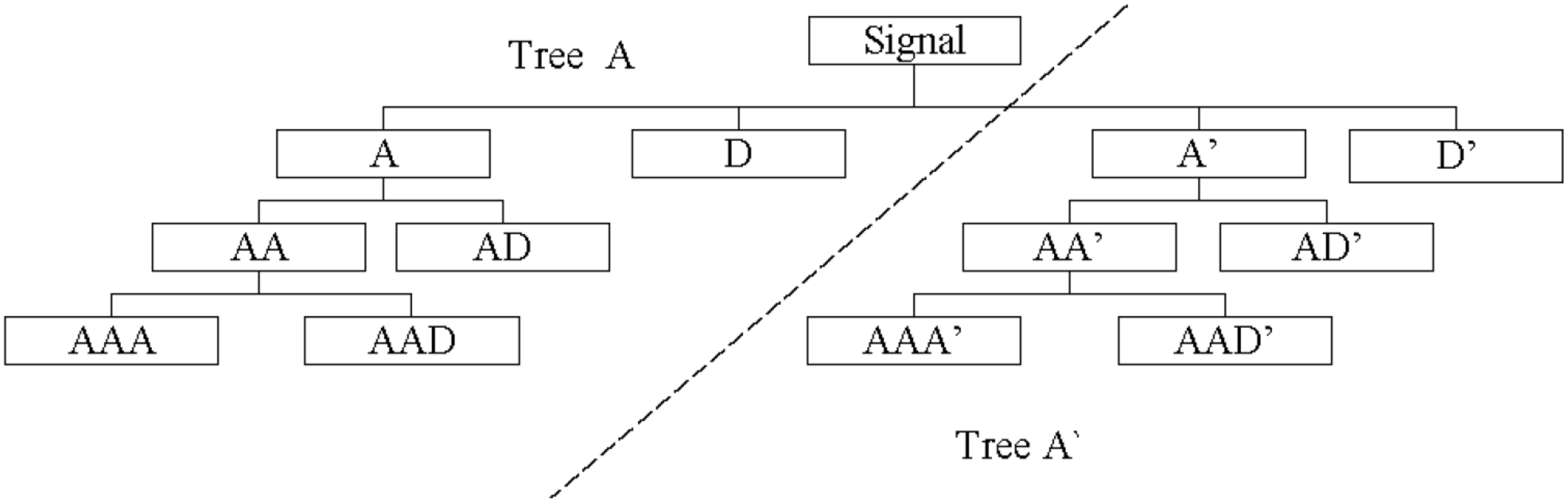
DWT



WPD



DTCWT



Feature Extraction

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Computed Features

1. Mean absolute values **F1**,
2. Average power **F2**,
3. Standard deviation **F3**,
4. Ratio of the absolute mean values of adjacent coefficients **F4**,
5. Skewness **F5**,
6. Kurtosis **F6**.

Experiments

- Experiment 1: feature set (F1,F2,F3,F4.)
- Experiment 2: feature set (F1,F2,F5,F6.)
- Experiment 3: features set (F1–F6.)

Table 2. Number of features in each decomposition technique

Method	No. of sub-bnds	No. of features		
		EXP1	EXP2	EXP3
DWT	5	20	20	30
WPD	16	64	64	96
DTCWT	9	36	36	54

- The number of features will increase by:
  - Number of segments
  - Number of Channels

Feature Aggregation

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- We computed a large set of features.

$$M_i \in \mathbb{R}^{(Si \times F)}$$

- Median of all segments' features.

$$M_{aggregate} \in \mathbb{R}^{(I \times F)}$$

Classification problems

7-class problem

- Specific and non specific

5-class problem

- Only specific types

2-class problem

- Only non-specific

$$\text{Weighted F1} = \sum_{n=1}^{7} \frac{\alpha_n \times F1_n}{7} \quad [16]$$

$$\alpha_n = \frac{Number\ of\ Seizure\ Type\ n}{Total\ Seizure\ Number} \quad [16]$$

Cross validation Scheme

5 folds seizure wise cross validation[8]

We used a stratified 5-fold cross-validation which is inspired by state-of the art technique [8] in which the proportional distribution of classes in the entire dataset is randomly allocated to five-folds. This will also ensure a fair performance comparison with existing state-of-the-art research studies.

3 folds patient-wise cross validation[16]

We adopted the validation technique of Asif et al. [14,16] in which they applied 3-fold cross-validation across patients. In this scenario, the data presented in Table II is split into three-folds. The selected classes of seizures include data from minimum of three patients. Therefore, this ensures that data used for testing is always from distinct patients whose data has never been used in the training phase.

Table 3. Performance comparison of F1-score (%) for different feature extraction methods at the seizure level and patient level.

		WPD			DTCWT			DWT		
	Validation	EXP1	EXP2	EXP3	EXP1	EXP2	EXP3	EXP1	EXP2	EXP3
7 classes	Seizure-wise	89.6	87.6	89.2	**89.9**	86.7	89.8	88.4	86.0	89.2
	Patient-wise	63.1	63.4	**64**	63.2	59.44	63.9	58.6	59.7	63.3
5 classes	Seizure-wise	95.1	94.5	94.9	**95.8**	93.3	95.3	95.1	91.9	94.3
	Patient-wise	62.3	**66.6**	65.9	65.4	60.9	65.7	61.4	62.2	63.4
2 classes	Seizure-wise	92.73	92.123	93.06	**93.29**	91.64	93.24	92.54	91.72	93.04
	Patient-wise	82.61	80.19	**83.97**	81.26	75.98	80.23	77.47	77.089	81.52

Table 4. Performance comparison of previous works with proposed method for multi-type seizure classification

Method	No. of seizure classes	Performance Evaluation(%)	
		Seizure_wise	Patient_wise
Inceptionv3[11]	8*	88.3 Accuracy	–
AlexNet[12]	8*	84.06 Accuracy	–
CNN+LSTM+MLP[8]	8	97.40 F1-score	–
SeizureNet[14]	7	95 F1-score	62 F1-score
NMN[15]	7	94.5 F1-score	–
K-NN[16]	7	90.1 F1-score	40 F1-score
XGBoost[16]	7	85.1 F1-score	54.2 F1-score
Proposed method using WPD	7	89.6 F1-score	**64 F1-score**
Proposed method using DTCWT	7	89.9 F1-score	**63.9 F1-score**
Proposed method using DWT	7	89.2 F1-score	**63.3 F1-score**

*Including non-seizure EEG class.

Future Work

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- In future, we plan to employ deep learning techniques to learn from the wavelet-based extracted features for better comparison and classifications.

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Thank You!

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