BM4152 Biosignal Processing
Paper Implementation

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Contents

1. Introduction and Background

1.1 Introduction and Background

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Often biological signals are non-stationary and traditional frequency domain analysis is incapable of handling time varying properties of the signal, thus wavelets provide a time frequency analysis that is crucial in analysis of EEG signals. A Mother wavelet is scaled and translated, that scale (which corresponds to matching frequency) would emphasize the matching frequency ranges while translating in time axis. (Because Area Under Curve maximizes when the wavelet matches the signal).

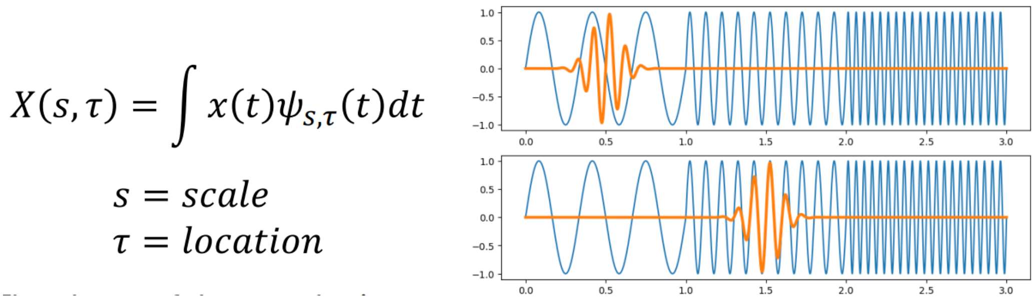

Figure 1.1: Wavelet Transform, src - BM4152 Lecture slides

EEG signal being resultant scalp potential resulting from extra cellular current flow generated by post synaptic potentials in cerebral cortex could be used to diagnosed a wide range of neurological anomalies. Seizures being among one of widely affected anomalies, underlying pathology of the seizure is due sudden excitatory spikes due various reasons starting from to ion channel dysfunctions, network level dynamics of brain cortex, structural abnormalities in the brain cortex which could be detected using EEG.

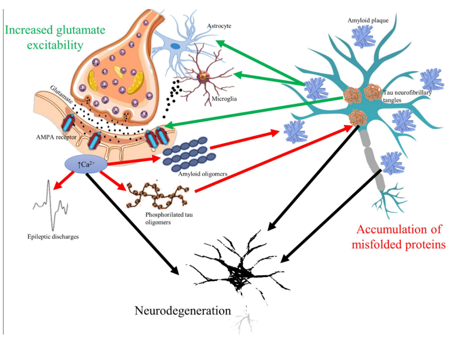

Figure 1.2: Glutamate mediated hyperexcitability, src Andras et. al. Inhibiting Epileptiform Activity in Cognitive Disorders [3]

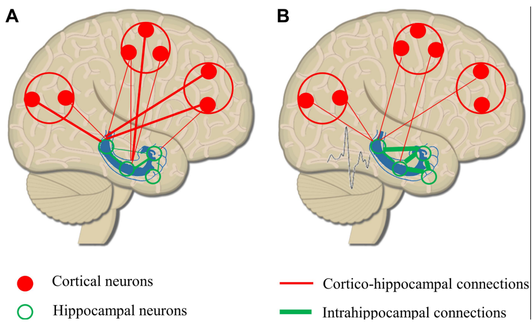

Figure 1.3: Remodeling circuitry due to epilepsy src Andras et. al. Inhibiting Epileptiform Activity in Cognitive Disorders [3]

However, computationally detecting epileptic seizures is challenging due to being nonstationary signals with varying morphologies with spikes, slow waves etc. As the wavelets rely on maximizing area under curve of matching portions shape of the wavelet plays a crucial part, selecting the most suitable wavelet for epilepsy detection is a crucial point.

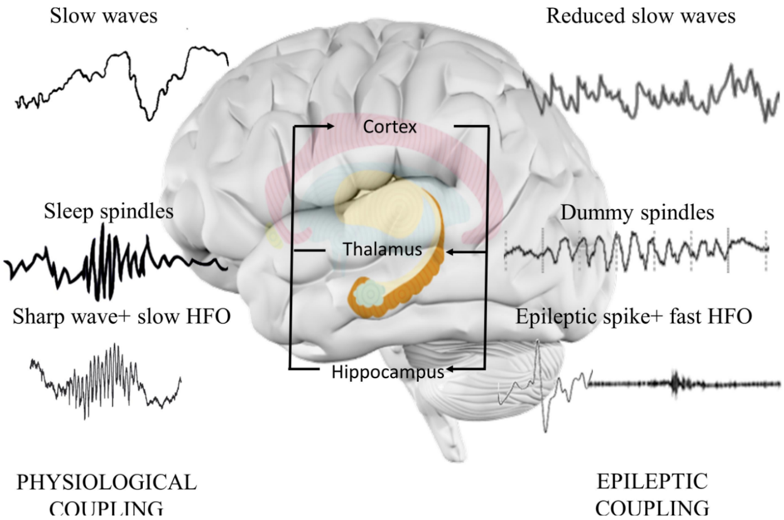

Figure 1.4: Epileptic EEG Morphologies, src Andras et. al. Inhibiting Epileptiform Activity in Cognitive Disorders [3]

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As the area under the curve maximizes when the signal component matches the wavelet shape, it is crucial to to detect the best wavelet shape as the mother wavelet optimized for EEG signals that would match the underlying physiological signals. Here we try to find the best mother wavelet shape from already existing wavelet shapes that are derived from different mathematical equations (such as mexican hat as the second derivative of the gaussian).

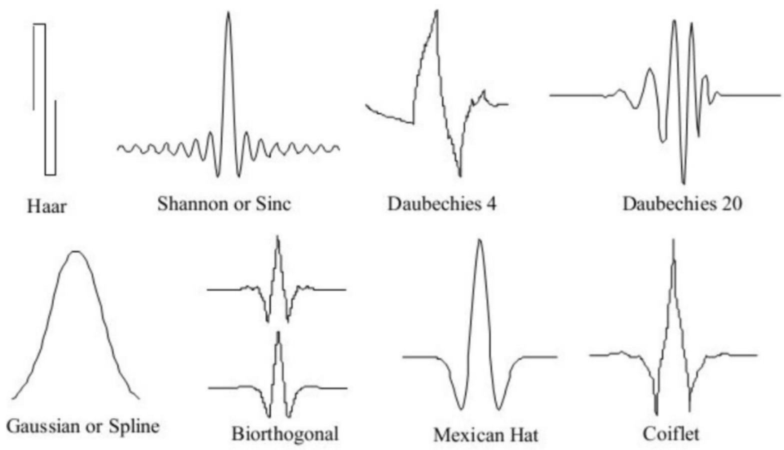

Figure 1.5: Wavelet Shapes, src - BM4152 Lecture slides

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And also due to computational complexity discrete wavelet transform is favored than the continuous counterpart and minimum number of decomposition levels required in the DWT plays a considerable role as well. Finally, the success of the detection of seizure would depend on the features considered as well as the classification method. Addressing these issues “Gandhi et. al. (2011). A comparative study of wavelet families for EEG signal classification” studies the optimum method of applying DWT for EEG classification.

2. Overview of Selected Paper and Dataset

2.1 Selected Paper

The selected paper [1] is focused on evaluating different wavelet families based on their performance on classifying epileptic seizures. The paper uses Discrete Wavelet Transform to perform a time-frequency analysis and extract features from the wavelet transformation. This paper benchmarks different wavelet families, such as Daubechies, Haar, Coiflets and Bi-orthogonal, and compares their performance in accurately classifying EEG signals.

Key contributions of the paper include:

- **Wavelet Transform Application:** The paper empasizes the necessity of wavelet transformation because the traditional frequency domain transformations would fail in non stationary EEG signals that exhibits extremly complex morphologies.
- **Comparative Analysis:** This paper benchmarks the performance of different wavelet families in the performance of classifying epileptic seizures. As well as benchmark for different features as well.

2.2 Selected Dataset: Andrzejak EEG Dataset

The Andrzejak EEG dataset is a well-known benchmark for seizure detection studies [2]. It contains five distinct sets of EEG signals (denoted A–E), each comprising 100 single-channel EEG segments of 23.6 seconds duration. These segments were carefully selected and processed to meet stationarity criteria, ensuring reliable analyses.

Key features of the dataset include:

- **Data Composition:**
  - Sets A and B consist of surface EEG recordings from healthy individuals, taken with eyes open and closed, respectively.
  - Sets C, D, and E are intracranial EEG recordings from epilepsy patients. Sets C and D were recorded during seizure-free intervals, with set D focusing on the epileptogenic zone, and set E captures seizure activity.
- **Recording Details:**
  - EEG signals were recorded with a 128-channel amplifier, sampled at 173.61 Hz, and filtered within the 0.53–40 Hz range.
  - Strict artifact removal (e.g., eye movement, muscle activity) and segmentation processes ensured high-quality data for nonlinear time-series analysis.
- **Purpose and Usage:** This dataset has been extensively used for analyzing nonlinear deterministic and stochastic properties of EEG signals, especially in the context of epilepsy. It provides a robust framework for testing classification algorithms under various physiological and pathological conditions.

3. Methods Description

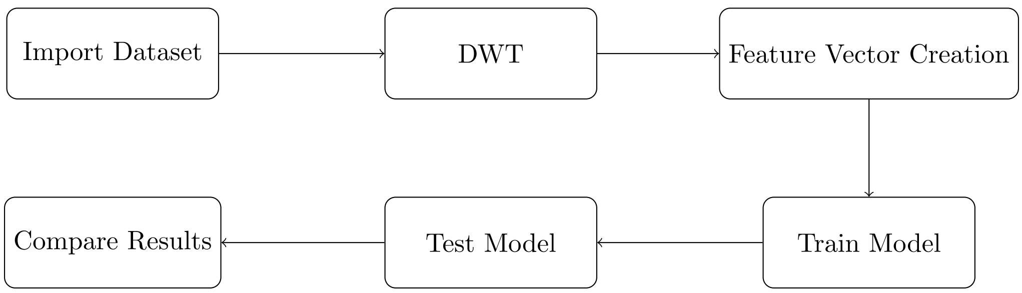
3.1 Main Experiments

Firstly, we investigated whether the feature vectors constructed from Discrete Wavelet Transform (DWT) are clearly separable by using different mother wavelets. This is essential because, if the features are visually distinct, sophisticated classification models or algorithms may not be necessary, and the performance of all wavelet families would likely converge. For this, we extracted features using DWT coefficients and visualized them through basic plots to assess their separability.

Secondly, we examined how the number of decomposition levels affect the seizure classification. This is another independent variable that would significantly influences classification performance. In order to understand its effect, we decomposed the EEG signals into several levels and evaluate their impact on the precision of the classification by plotting the precision against the level of decomposition. By doing so, we can identify an optimal decomposition level that balances accuracy and computational efficiency.

Finally, we experimented to select the best mother wavelet to classify epileptic seizures. Thus, we decomposed the EEG signals using different mother wavelets to be tested and extracted the corresponding features. Used classification methods to classify the features extracted and benchmarked to test the most suitable mother wavelet. Other than the major goal of selecting the best mother wavelet we were able to select the most suitable feature as well as expriment with different classification techniques.

3.2 Flow Diagram



The general methodology for this study involves several key steps, as depicted in the flow diagram. Each step contributes to identifying the best wavelet family and the most effective features for EEG signal classification.

3.2.1 Import Dataset and Signal Preprocessing

We imported dataset using standard python I/O operations, preprocessed the data (especially removed noise) to make the upcoming steps more robust .

3.2.2 Discrete Wavelet Transform (DWT)

Here we decomposed the EEG signal using the Discrete Wavelet Transform (DWT). As EEG signals are non-stationary time frequency analysis is necessary for any feature learning. Inorder to find the best mother wavelet different mother wavelets have been tested out.

3.2.3 Feature Vector Construction

Here we extracted features from Discrete Wavelet Transform (DWT) coefficients to construct feature vectors for classification. The energy of the detailed coefficients ((3.1)) quantifies the high-frequency content, while the energy of the approximation coefficients ((3.2)) captures the low-frequency components. Entropy ((3.3)) reflects the complexity or randomness of the detailed coefficients. Standard deviation ((3.4)) measures the variability of the coefficients, and the mean ((3.5)) represents their average value. Together, these features—energy, entropy, standard deviation, and mean—form the feature vectors, enabling effective classification of signal characteristics.

$$\mathrm{ED}_i = \sum_{j=1}^{N} |D_{ij}|^2 \tag{3.1}$$

$$\mathrm{EA}_i = \sum_{j=1}^{N} |A_{ij}|^2 \tag{3.2}$$

$$\mathrm{ENT}_i = -\sum_{j=1}^{N} D_{ij}^2 \log(D_{ij}^2) \tag{3.3}$$

$$\sigma_i = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(D_{ij}-\mu_i)^2} \tag{3.4}$$

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} D_{ij} \tag{3.5}$$

3.2.4 Train Model

After constructing the feature vectors, we trained a classifier model using these feature vectors. Commonly used classifiers such as Support Vector Machines (SVM) or Probabilistic Neural Networks (PNN) were used in the paper and we used them for reproducing the results. We also further improved using Gaussian Naive Bayes classifiers and Convolutional Neural Networks.

3.2.5 Test Model and Evaluate Results

Then we tested the model using unseen data. We used the classification accuracy and computational time as performance indexes which is same as the paper. Testing was carried out using different mother wavelets as well as for different features to select the best.

4. Implementation Details

4.1 Implementation

Data Preprocessing After importing the dataset, the raw signals were visualized to understand their characteristics and detect any apparent abnormalities. Filtering was performed as a preprocessing step to enhance the signal quality. However, the results were primarily derived from the raw data, as the original methodology did not specify preprocessing.

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Wavelet Transform Discrete wavelet transform was carried out using pywavelet library for the EEG signals. The function takes the signal, wavelet and number of decomposition levels as input arguments and performs dyadic discrete wavelet transform to return the coefficients.

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Feature Extraction Manual functions were written to extract the given features from the coefficients for the base implemented features (such as entropy) using the equations and for more advanced features used built in functions as well.

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Classification Used the built in sklearn SVM classifier for the support vector machine based classification data was randomly split in to train and test sets and the model trained on the train test was tested on the test set. For PNN built in frameworks were not supported anymore and required older versions of base libraries thus implemented our own custom implementation. AS the paper emphasizes on the gaussian based models we also went further to test Gaussian Naive Bayes classifier as well and finally used a CNN with modern techniques to achive perfect result as well.

4.2 Challenges Faced

Implementation Challanges -We faced few challenges during the implementation , mainly because the original paper didn't provide enough details. One major issue was the lack of information about preprocessing and other steps in the data processing pipeline. For example, the paper didn't clearly mention which subdataset (A, B, C, or D) was used as seizure free signals, except for the first experiment. So, we had to assume they based their results on the "eyes closed" subdataset (B). Another challenge was implementing the Probabilistic Neural Network (PNN), as there weren't any readily available libraries for it thus we used a custom version of our own. These gaps made the process more difficult and required extra effort to fill in the missing details.

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Extension Challenges- The classifications models were achiving very high accuracies even with just re-implementing thus there was a small room to improve upon accuracy, thus we went to improvements that would be crucial in bio-signal processing such as reducing computational complexities and decomposition levels which are crucial in edge monitoring devices. And also the CNN with attention achieved near perfect performance and there was no room to further improvements.)

5. Implementation Results

The results we got in our implementation are closely similar to those reported in the original paper. In the following, we present our findings and compare them directly with the results of the paper to highlight similarities and differences.

Firstly, we visualize the clustering of feature vectors based on the energy values of D2 and D3. As shown in Figure 5.1, our results closely resemble the clustering trends observed in the original paper's results. Both images display distinct groupings for "eyes closed" and epileptic signals, with some major differences in the spread of the points. These variations could be attributed to differences in preprocessing assumptions and dataset handling. Despite these discrepancies, our plot supports the observation made by the original researchers: the feature vectors are not clearly separable. This highlights the necessity for more sophisticated classification algorithms to effectively distinguish between the two classes.

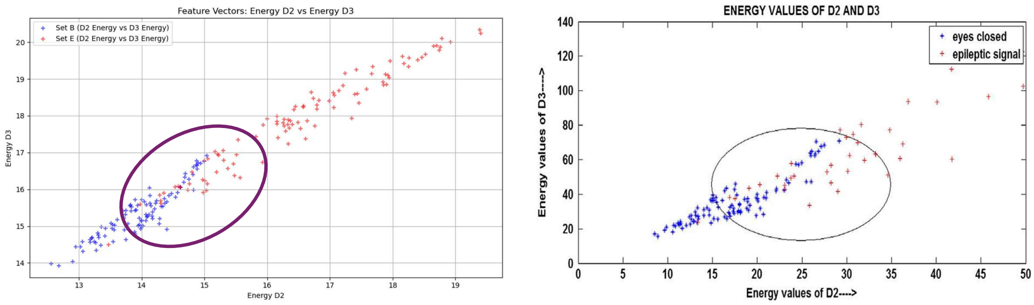


Figure 5.1: Comparison of feature vectors (energy values of D2 and D3) between our implementation (left) and the original paper's results (right). Both images show clustering in D2 vs. D3 energy space for "eyes-closed" and epileptic signals, with minor differences in clustering spread.

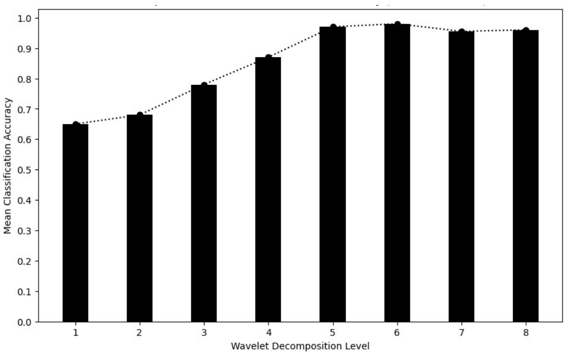
Next, we analyzed the impact of wavelet decomposition levels on classification accuracy for Coif1 and Db2 wavelets. Figure 5.2 compares our results with those from the original paper. Our results as well as the original result show a clear increase in accuracy as the decomposition level increases, stabilizing after a certain point. However, we observed both minor and major differences at specific number of decomposition levels, that is likely caused due to preprocessing variations or dataset assumptions.

One of the observations in our result is that accuracy begins to decrease after peaking at level 6 decomposition. This could be due to an insufficient number of samples in the signals to calculate higher decomposition levels, such as 9 or 10. Consequently, we limited our plots to decomposition levels up to 8. Performing higher decompositions without enough samples may result in the loss of important information residing in lower frequency components. This highlights the importance of considering signal characteristics when choosing decomposition levels.

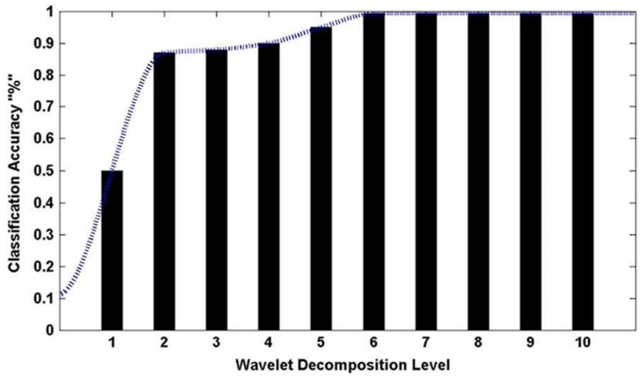
We compared the classification accuracy and computation time for various wavelet features using PNN and SVM. Tables 5.1 and 5.2 present our implementation results, while the paper's results are shown in Tables 2 and 3. Below, we discuss the performance trends and identify the best wavelet and feature for classification based on these comparisons.

For PNN, both our implementation (Table 5.1) and the paper's results (Table 2) highlight **Coif1** as the best-performing wavelet. Specifically, the **Energy** and **STD (Standard Deviation)** features achieved the highest classification accuracy for both seizure-free and epileptic signals. In our results, Coif1 with Energy achieved 100% accuracy for seizure-free signals and 97% for epileptic signals, with a computation time (CT) of 0.022 seconds. The paper's results show Coif1 with Energy achieving slightly lower accuracy: 99.29% for seizure-free signals and 99.31% for epileptic signals, with a CT of 0.024 seconds. These findings indicate that our implementation effectively replicated and, in some cases, exceeded the accuracy reported in the paper.

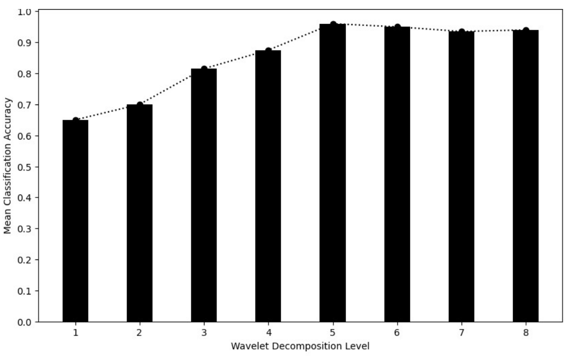
For SVM, our results (Table 5.2) also highlight **Coif1** as the best-performing wavelet, consistent with the paper's findings (Table 3). Our implementation achieved a classification accuracy of 100% for seizure-free signals and 96% for epileptic signals using Coif1 with Energy and Energy+STD features. The paper's results reported slightly lower accuracy for Coif1 with Energy, achieving 95.50% for seizure-free signals and 96.11% for epileptic signals. Additionally, our implementation showed a decrease in accuracy for higher decomposition levels, which



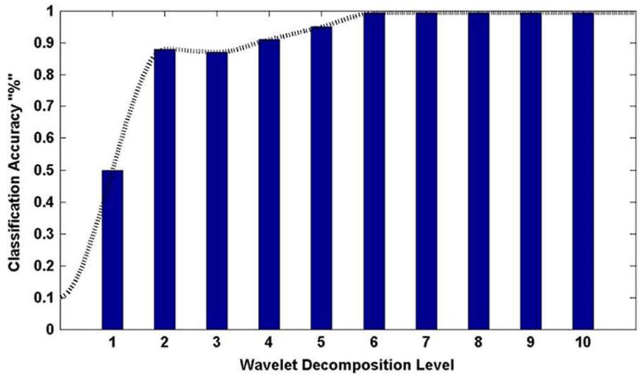
Classification accuracy of various decomposition levels for Coif1.



Classification accuracy of various decomposition levels for Coif1.



Classification accuracy of various decomposition levels for Db2.



Classification accuracy of various decomposition levels for Db2.

Figure 5.2: Comparison of classification accuracy at various wavelet decomposition levels for Coif1 (top) and Db2 (bottom) wavelets. Left: our results. Right: original paper results. Both show increasing accuracy with higher decomposition levels, stabilizing after a certain point.

was also reflected in the paper's results. This is likely due to the limited number of samples available to compute meaningful features at deeper levels of decomposition.

Based on these comparisons, **Coif1** consistently emerged as the best-performing wavelet for both PNN and SVM classifiers across seizure-free and epileptic classifications. Among the features, **Energy** and **Energy+STD** provided the highest classification accuracy in both our implementation and the paper's results.

While our implementation results align closely with those in the paper, there are a few key differences. Our implementation achieved slightly higher accuracy for certain wavelet-feature combinations, particularly with SVM. This could be attributed to differences in preprocessing, dataset assumptions, or hardware/software optimizations. Additionally, the computation times in our implementation were generally lower compared to the paper, likely due to more efficient coding practices or hardware differences.

Overall, our results validate the findings from the paper while demonstrating the robustness of the implemented methods. The consistency in identifying Coif1 and Energy as the best wavelet-feature combination highlights the reliability of our implementation.

Table 5.1: Wavelet Feature Classification Accuracy and Computation Time - PNN

Wavelet	**Feature**	**Seizure-Free CA (%)**	**Epileptic CA (%)**	**CT (s)**
db2	energy	100.0	96.0	0.022 755
db2	std	99.0	96.0	0.022 401
db2	entropy	95.0	93.0	0.022 820
db2	energy_std	100.0	96.0	0.024 049
haar	energy	100.0	95.0	0.022 497
haar	std	99.0	95.0	0.022 490
haar	entropy	97.0	94.0	0.022 393
haar	energy_std	100.0	95.0	0.023 468
coif1	energy	100.0	97.0	0.022 414
coif1	std	100.0	97.0	0.022 316
coif1	entropy	98.0	95.0	0.022 542
coif1	energy_std	100.0	97.0	0.024 299
bior1.1	energy	100.0	95.0	0.025 277
bior1.1	std	99.0	95.0	0.023 129
bior1.1	entropy	97.0	94.0	0.021 883
bior1.1	energy_std	100.0	95.0	0.021 977

Table 5.2: Wavelet Feature Classification Accuracy and Computation Time - SVM

Wavelet	**Feature**	**Seizure-Free CA (%)**	**Epileptic CA (%)**	**CT (s)**
db2	energy	99.0	96.0	0.001 965
db2	std	99.0	96.0	0.002 267
db2	entropy	91.0	96.0	0.001 377
db2	energy + std	99.0	96.0	0.001 861
haar	energy	100.0	96.0	0.001 533
haar	std	98.0	96.0	0.001 254
haar	entropy	91.0	97.0	0.001 820
haar	energy + std	100.0	95.0	0.001 014
coif1	energy	100.0	96.0	0.001 922
coif1	std	99.0	94.0	0.001 244
coif1	entropy	90.0	95.0	0.001 726
coif1	energy + std	100.0	96.0	0.001 533
bior1.1	energy	100.0	96.0	0.001 362
bior1.1	std	98.0	96.0	0.001 847
bior1.1	entropy	91.0	97.0	0.001 859
bior1.1	energy + std	100.0	95.0	0.002 045

6. Conclusion and Possible Improvements

6.1 Conclusion and Possible Improvements

Summary

The paper investigates about the effect of the wavelet type, features used, number of decomposition, classification method on detection of epileptic seizures. Discrete Wavelet Transform was implemented for given number of levels using different wavelets and different statistical features were extracted and classified to bench-marked to select the best.Re implemented results are on par with the paper and coeif1 showed the best performance.

Improvements

Effect of the Kernel

For further improvements we started by investigating the effect of the kernel used in the support vector machine. Linear kernel seemed to be out performing other kernels which could be expectable looking at the shape of the margin of the data-points of the two classes.

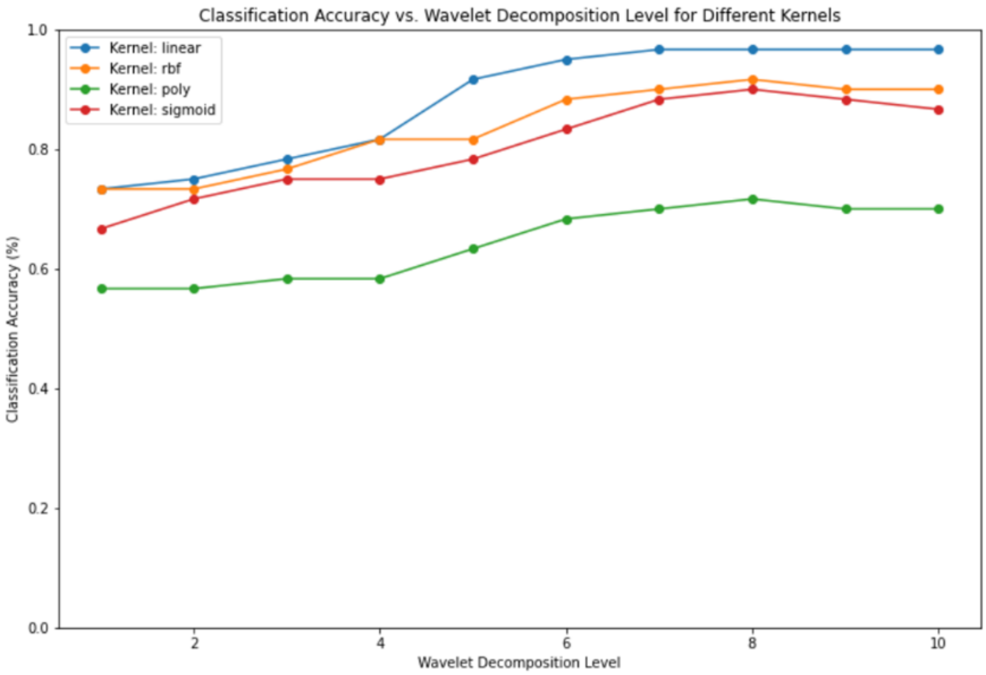


Figure 6.1: Effect of the Kernel

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Exploring more Features

Then we tried on exploring more features such as RMS, Kurtosis, Skewness etc. In the implementation of the original paper energy was the best performing feature and it showed near perfect result when using six decomposition levels upwards. But upon further investigations we found out that Kurtosis by its own would perform better even with just two decomposition levels. The importance of less decomposition levels come in edge devices which are constricted on computing power and power consumption. It is also revealed that using both energy and kurtosis further improved the performance.

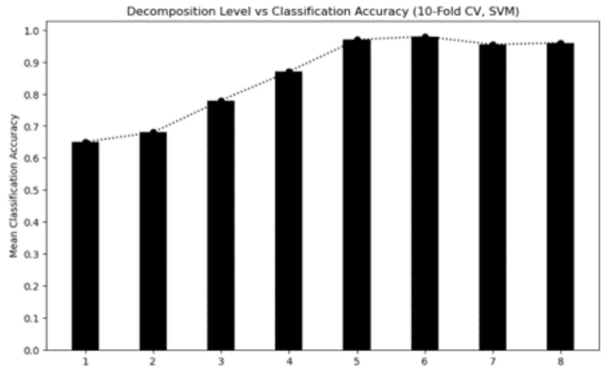

Figure 6.2: Base Result

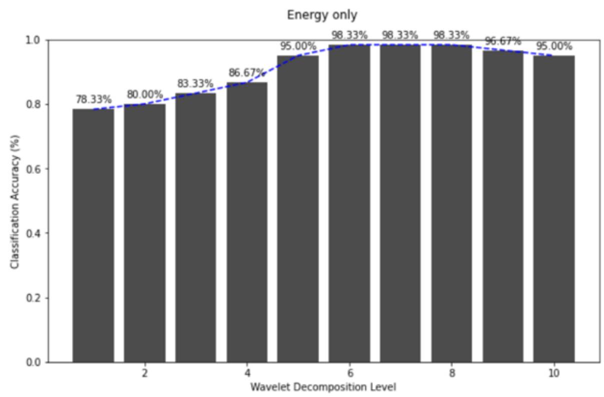

Figure 6.3: Energy Only

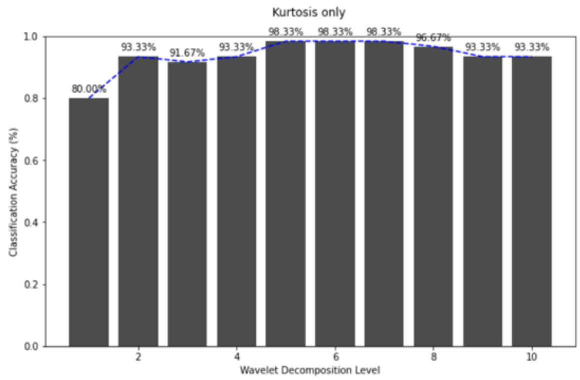

Figure 6.4: Kurtosis Only

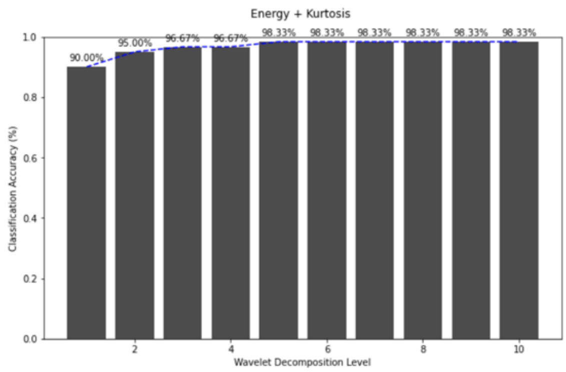

Figure 6.5: Energy and Kurtosis

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Best Classifier

Other than the Support Vector Machine and Probabilistic Neural Network Implementation of the paper we tried out few other classification techniques.

Gaussian Naive Bayes classifier seems to be better performing the PNN and SVM even using less number of decomposition levels.

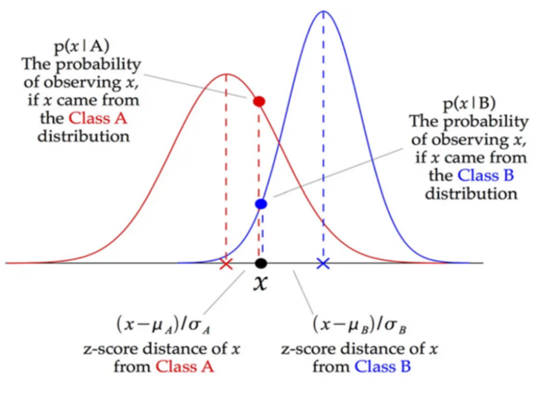

Figure 6.6: Gaussian Naive Bayes

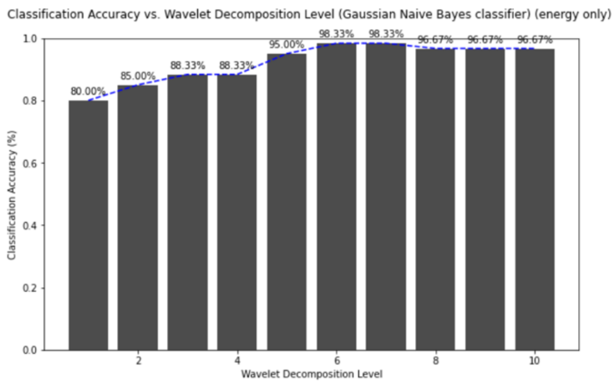

Figure 6.7: Gaussian Naive Bayes Classifier Result

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Convolution Neural Networks with few adjustments seemed to achieve a perfect performance even for the seizure class which was not possible in other methods even though they achieved perfect performance for the seizure free class.

Few block compromising of 1D convolution followed by Batch Normalization, Dropout to reduce over-fitting and Relu activation was used as the CNN architecture. Further improvements also included in-cooperating attention mechanisms and an experimental augmentation technique.

```
x = Conv1D(64, 3, dilation_rate=1, activation='relu', kernel_regularizer=l2(0.001))(input_layer)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)

x = Conv1D(128, 3, dilation_rate=2, activation='relu', kernel_regularizer=l2(0.001))(x)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)

x = Conv1D(256, 3, dilation_rate=4, activation='relu', kernel_regularizer=l2(0.001))(x)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)

# Attention layer setup
query_value_attention_seq = Attention()([x, x])

x = Flatten()(query_value_attention_seq)
x = Dense(64, activation='relu', kernel_regularizer=l2(0.002))(x)
x = Dropout(0.5)(x)
output_layer = Dense(1, activation='sigmoid')(x)
```

Figure 6.8: CNN

```
11/11 [==============================] - 0s 16ms/step - loss: 0.1308 - accuracy: 1.0000 - val_loss: 0.1330 - val_accuracy: 1.
0000
6/6 [==============================] - 0s 4ms/step - loss: 0.1338 - accuracy: 1.0000
Test Accuracy: 100.00%
```

Figure 6.9: CNN Result

Bibliography

[1] Gandhi, T., Panigrahi, B. K., Anand, S. (2011). A comparative study of wavelet families for EEG signal classification. *Neurocomputing, 74* (17), 3051–3057. `https://doi.org/10.1016/j.neucom.2011.04.`

[2] Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review. E, Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics, 64* (6). `https://doi.org/10.1103/physreve.64.061907`

[3] Horvath, A. A., Csernus, E. A., Lality, S., Kaminski, R. M., Kamondi, A. (2020). Inhibiting epileptiform activity in cognitive disorders: possibilities for a novel therapeutic approach. Frontiers in Neuroscience, 14, 557416