Comparison of Handcrafted Features and Autoencoders for Epileptic Seizure Detection

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University of Osnabrück, Neurodynamics SoSe 2022

Abstract

Epilepsy is a common neurological disease that more than 50 million people worldwide suffer from. Here, Machine Learning (ML) approaches may help detect seizures based on EEG recordings. In recent years, the interest in automated classification grew bigger and consequently, the methods used to detect seizures are numerous. Many ML techniques, for example end-to-end approaches like autoencoder and feature-based approaches like using handcrafted feature extraction together with Principle Component Analysis (PCA), proved that they are able to identify epilepsy. This variety of possible approaches begs the question: Which of them performs best in regards to accuracy? To answer this question, we compared these two methods given the same dataset (UBonn) and classifier. Since the data set provided more EEG sequences of healthy participants than of seizures, we calculated the balanced accuracy. Our results indicate that the PCA performs better than the autoencoder. The former was performing best for eight features with a balanced accuracy of 99.27%, while the latter only reached an accuracy of 95.05% for 32 features.

Introduction

Epilepsy is one of the most common neurological disorders typically characterized by recurrent and uncontrollable seizures, which seriously affects the quality of life of epilepsy patients. Therefore, finding accurate diagnostic methods is a crucial issue [10]. Machine learning methods have the potential to automate clinical diagnostics based on the EEG. These methods can be categorized into feature-based (handcrafted features), and end-to-end approaches (automatic feature learning from signals) [3,9]. In this study, we want to compare these two approaches. Therefore, we have chosen to implement two different simple pipelines that are representative of one of the approaches. As a feature-based approach we are extracting statistical features on wavelet subbands and further reduce the dimensionality of the feature subspace using Principal Component Analysis (PCA), a statistical procedure to explore distinctive features using orthogonal transformation. As an end-to-end approach, we are applying a stacked sparse autoencoder that automatically learns the important features of the EEG pattern. To compare the two approaches, both systems were trained on the same data set and their balanced accuracy was tested for 2, 4, 8, 16 and 32 features.

Hypothesis: In this study, we expect that the end-to-end approach using an autoencoder will have a higher accuracy detecting epileptic seizures based on EEG signals than the feature-based approach that relies on handcrafted feature extraction and PCA.

Materials and Methods

Dataset

For this study, the UBonn dataset from the Department of Epileptology, University of Bonn, Germany, was used [1]. The dataset consists of five sets (Z, N, O, F, S), each containing 100 single-channel EEG signals. The data in set Z and O are EEG signals from 5 healthy volunteers. Set N and F are the EEG signals from 5 epileptic patients during seizure-free intervals. Only set S contains signals during seizure activity. Since the purpose of this study is to categorize EEG signals into two categories, a non-seizure group is generated, while set S makes up the seizure group. The available signals are separated into a training, validation and testing set by randomly selecting 70% of each group's recordings for the training, 15% for the testing and 15% for the validation set.

Preprocessing

Autoencoder pipeline: At first, we applied a fifth-order Butterworth bandpass filter [8,11] with a 0.5 Hz and a 40 Hz cutoff frequency to eliminate the extra signal noise and unwanted artifacts. In the next preprocessing step we normalized the data [10] to a range between 0 and 1 using min-max scaling because we use a sigmoid activation function later on, which is sensitive for this range [7]. In order to provide enough training examples for the autoencoder and the classifier, we separated each EEG signal into 16 epochs of 256 samples by utilizing the non-overlapping sliding window technique [7].
Handcrafted feature pipeline: As a first step in the handcrafted feature pipeline, we standardized the data by removing the mean and scaling to unit variance. After that, we windowed the data. Then we applied Daubechies (Db4) wavelet threshold denoising as it has showcased the best performance compared to other methods [5]. In our implementation we used a decomposition level of 5 and the so-called universal threshold $\lambda = \sigma\sqrt{2\log N}$, where λ is the wavelet threshold, σ is the standard deviation of the noise and N is the length of the sample signals. [12]

Feature extraction

Handcrafted feature pipeline: Systems that use wavelet domain feature extraction methods have been widely used and shown to produce superior signal processing results for EEG seizure detection. In this study, we applied a fifth-level discrete wavelet transform (DWT) to break the signal into 6 clinically relevant sub-bands. As the mother wavelet we chose to use Daubechies order four (Db4) due to its orthogonal properties [12]. After decomposing the signal, we calculated 8 statistical features from the wavelet coefficients of each subband. These features can be seen in 1. In total, 48 features were extracted. However, the extracted features may still contain redundant or irrelevant features, that could negatively affect the accuracy of the classification process. Thus, we applied Principal Component Analysis (PCA) to further reduce the dimensionality of the extracted features.

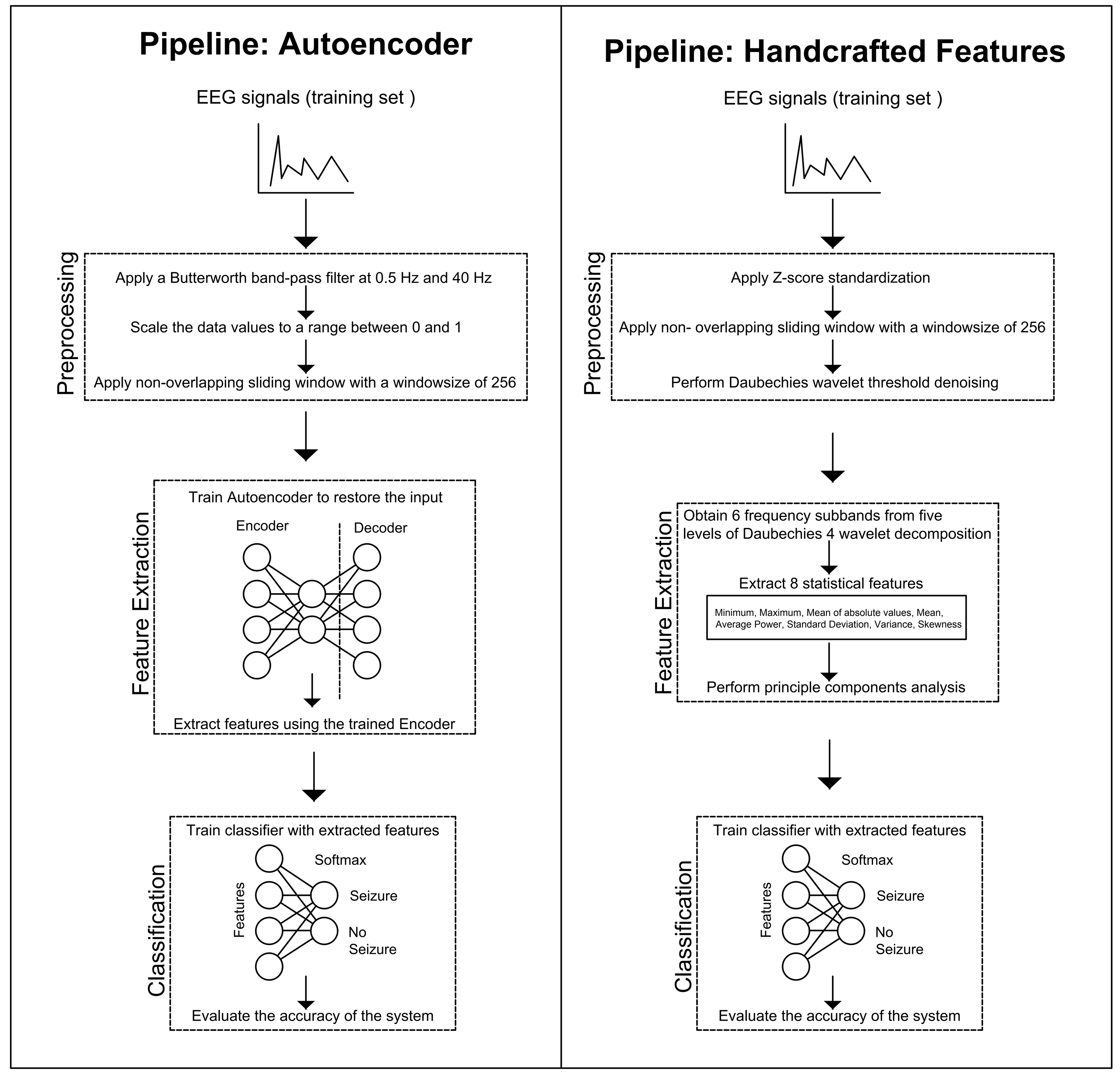

Fig. 1: Feature-based vs. end-to-end approach

Autoencoder pipeline: We used a stacked sparse autoencoder (SSAE) to learn the high level representations from the preprocessed data. The model consists of 6 fully-connected layers with 128, 64, 32, 64, 128 and 256 nodes. The first 3 layers make up the encoder, with the third layer being the bottleneck layer representing the extracted features. Apart from the last layer, the exponential linear unit (ELU) is used as the activation function. ELUs can alleviate the vanishing gradient problem while increasing learning speed by pushing mean unit activations closer to zero [2]. The use of ELU seems to achieve a lower reconstruction error and is shown to perform better than alternatives in tasks of dimension reduction using stacked autoencoders [6]. Sigmoid is used as the activation for the last layer to reconstruct the input in the range of 0 to 1. The weights are initialized according to [4].
The model is trained using the Adam optimizer with a learning rate of 0.001. Mean squared error is used as the loss and evaluation metric. To achieve sparse representations, an L1 penalty is added to the cost function for the activations of the bottleneck layer with a coefficient of 0.001.

Classification

The classifier model consists of 3 fully connected layers with 32, 16 and 2 nodes. The rectified linear unit (ReLU) is used as the activation function for the first two layers. A probability vector for the two classes is obtained by a softmax activation in the last layer.
The Adam optimizer is used to train the model with a learning rate of 0.0001 and the sparse categorical crossentropy as loss. Accuracy of the model is computed by selecting the class with an output value greater than 0.5 and taking the percentage of correct predictions. Additionally, the balanced accuracy is calculated by weighting using the ratio of class labels in the dataset.

Results

We trained the autoencoder using different numbers of features for 40 epochs in order to avoid overfitting. The classifier was trained for 400 epochs in the autoencoder pipeline and for 150 epochs in the handcrafted pipeline. It shows that the classifier trained with handcrafted features achieves over 98% balanced accuracy with only 2 features while the autoencoder pipeline only reaches above 90% with 8 or more features. The best balanced accuracy for the autoencoder was for 32 features with an accuracy of 95.05% while for the handcrafted PCA model it was for 8 features with an accuracy of 99.27%.

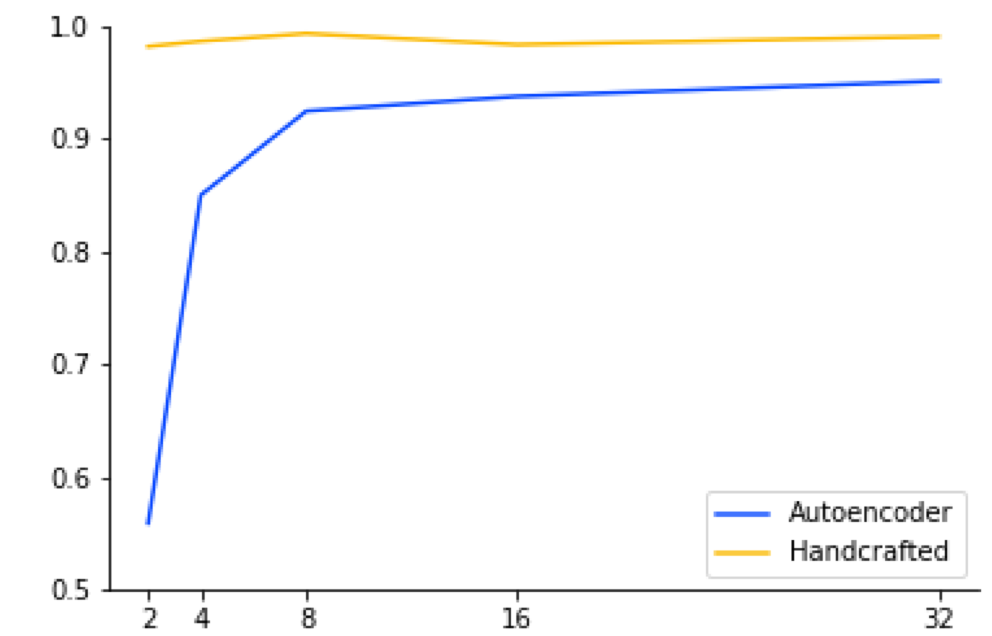

Fig. 2: Accuracy of Autoencoder and Handcrafted Features

In fig. 2 one can see the balanced accuracy of the models depending on the number of features. While the autoencoder performs poorly with less than four features, the PCA already starts with a balanced accuracy of 98.13% and is overall performing better than the autoencoder.

Discussion

The obtained results do not match our hypothesis that a classifier trained using features extracted using an autoencoder has overall a higher accuracy than using handcrafted features with PCA. As other studies show, autoencoder based feature extraction for EEG data can perform worse than statistical methods, especially for a low number of extracted features [13]. The achieved accuracies are obtained using the same number of epochs for each different number of features. This number is optimized for 16 features to avoid overfitting. Instead of manually setting the number of epochs, early stopping could improve training for different numbers of features.
In addition to comparing the resulting accuracy of the two pipelines, the time and effort has to be considered. Using handcrafted features requires extensive expert knowledge on the research topic. Autoencoder on the other hand can extract features without research area specific knowledge and therefore allow a more general usage. But optimizing the hyperparameters of such a system can be challenging.

Conclusion

Our obtained results show that handcrafted feature extraction with PCA performs good on classifying epileptic seizures using EEG data with an accuracy of greater than 99%. The autoencoder model we used is only able to achieve above 95% accuracy. Autoencoder can extract features without requiring expert knowledge but our results indicate that handcrafted features perform better even when considering the needed time and effort.

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