FACULTY OF APPLIED SCIENCES
UNIVERSITY
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STUDENT
SCIENTIFIC CONFERENCE 2024

Autoencoder-based Hybrid Neural Compression of a Multichannel EEG Dataset: Current Stage of Development

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1 Introduction

The large size of modern multichannel electroencephalography (EEG) signals together with high sampling rate create difficulties in their storage and transmission, which motivates the development of efficient compression algorithms (Das and Kyal, 2021). One of the possible approaches utilizes artificial neural networks (ANNs) to achieve learning-based compression, which can be particularly useful for domain-specific data types (Yang et al., 2023).

This work proposes an ANN model coupled with a compression mechanism combining lossy and lossless compression with user-definable amount of lost information. The presented approach was tested on the National Institute of Mental Health's (NIMH) 256-channel EEG dataset.

2 Outline of the Method

The proposed method is comprised of multiple stages and can be visualised as follows:

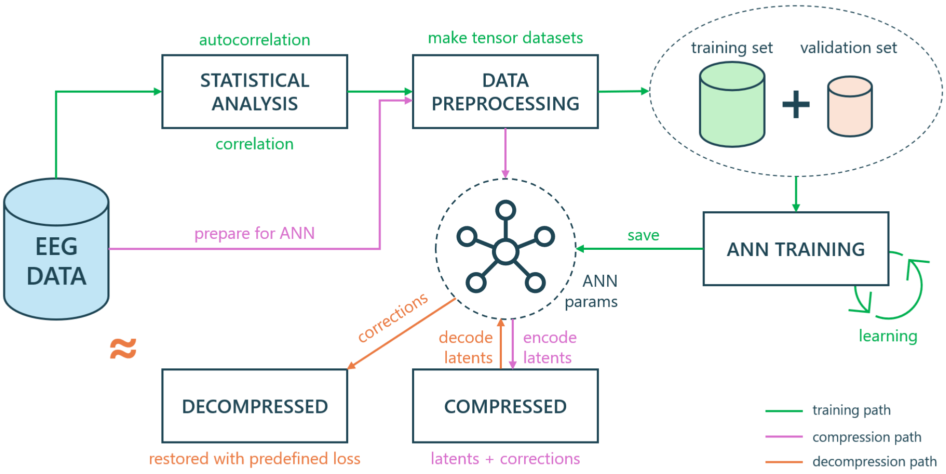

Figure 1: Schema of the proposed method

3 Neural Network Architecture and the Compression Mechanism

The proposed ANN has the form of a convolutional autoencoder with trained mapping of the EEG signal onto itself through the so-called latent space, corresponding to a low dimensional representation of the original data. It can be visualized as follows:

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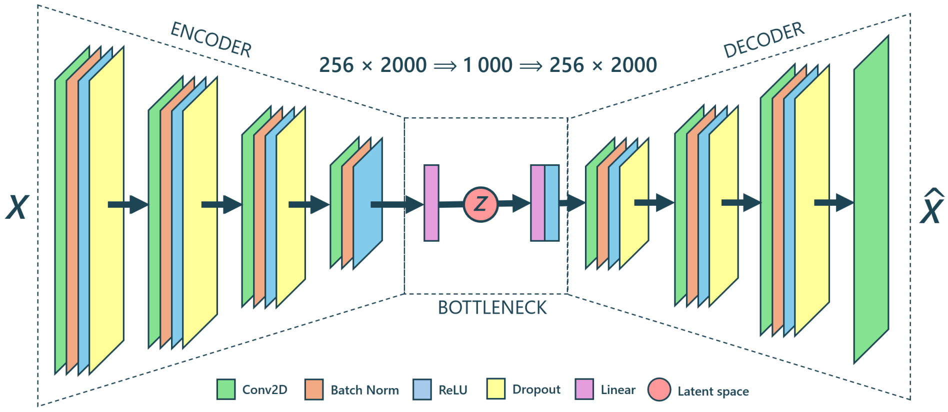

Figure 2: Neural network architecture

The compressed state corresponds to the latent representation Z of the input. The sender knows precisely how the data will be reconstructed by the receiver, allowing it to attach corrections (i.e. original values) to the data points with error higher than the chosen threshold. This results in a hybrid compression in which the lossy part is kept under the threshold and the rest is transferred losslessly. In addition to that, Run-Length Encoding (RLE) is used when encoding the corrections, and the Lempel–Ziv–Markov chain algorithm (LZMA) as the finishing step.

4 Current Results

The compression efficiency was tested on one of the testing datasets (from which the ANN did not learn) with the size of 1.9 GB of float64 values. However, given that the model accepts only float32 values, effectively halving the data size to 950 MB, comparisons to both data types are listed for two selected thresholds:

THRESHOLD	COMPRESSED	WITH LZMA	% of float64	% of float32
5 μV	115 MB	87.4 MB	4.6 %	9.2 %
2 μV	423 MB	318 MB	16.7 %	33.5 %

Table 1: Currently achieved compression

Acknowledgement

I would like to thank doc. Ing. Josef Kohout, Ph.D. and Duc Thien Pham for their ideas and suggestions, which helped to navigate me forward in this work.

References

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