A Deep Recurrent Neural Network for ADHD detection using EEG

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Introduction

- The Objective of this project is to detect Attention Deficit / Hyperactivity Disorder (ADHD) by automatically classifying EEG signals into two classes - Healthy or ADHD
- For this project, a public ADHD dataset collected by Nasrabadi (Nasrabadiet al 2021) at the Psychiatrist Clinic of Roozbeh Hospital in Tehran, Iran is used. It comprises EEG signals of 61 children with Attention Deficit Hyperactivity Disorder(ADHD) and 60 healthy children.
- IC-DRNN is a novel deep gated RNN that takes inspiration from 1D convolution layers, Long Short Term Memory units, inception modules, and densely connected networks.

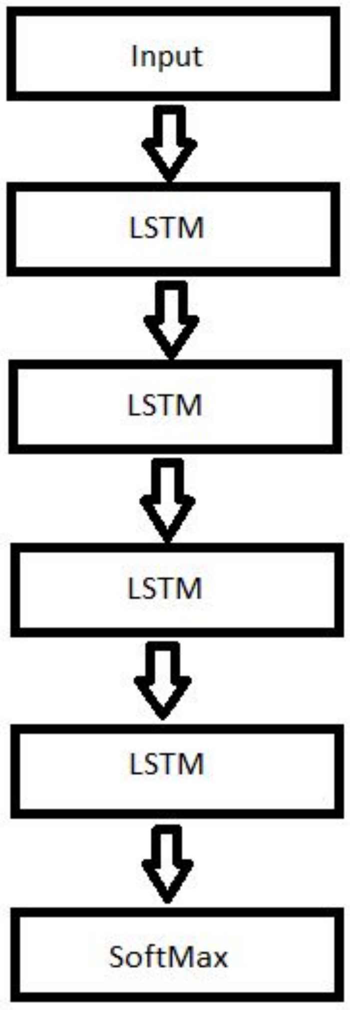
Data Preprocessing

- The data must first be pre-processed to remove the external and biological noises. First the data is re-referenced. Then, the data is filtered between 0 to 50 Hz.
- The pre-processed data is then divided into three-second epochs before being fed into the deep learning model.
- The obtained dataset is then scaled using standard scaler to unit variance and 0 mean.

LSTM Layers

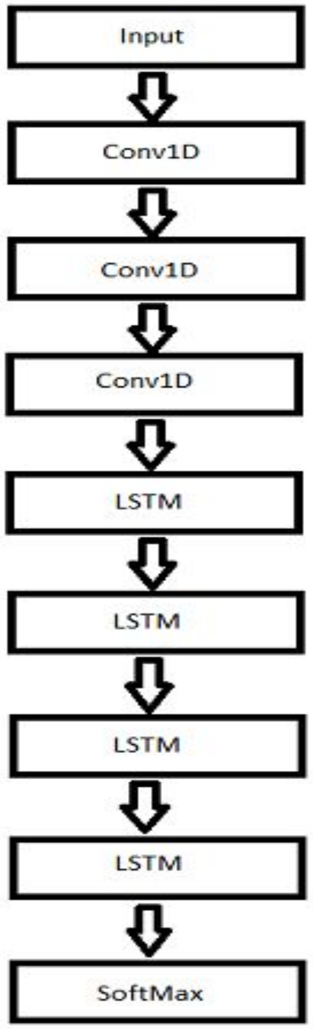
-Considering the input is a time series, an first approach is to stack multiple LSTM layers.

-However, when applied to relatively long input time-series data (as opposed to embedding vectors in the case of natural language processing), this approach turns out to be computationally very intensive and time consuming to train.



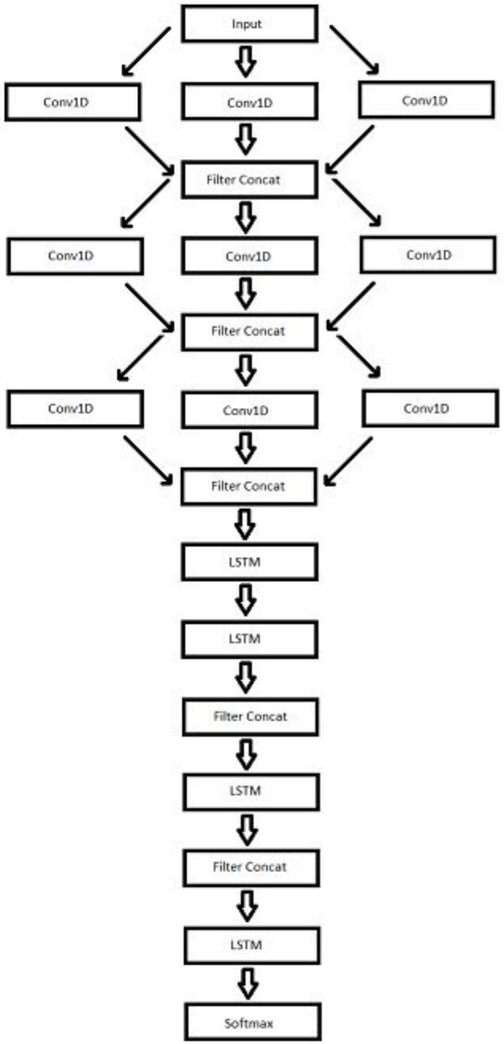
Convolutional Gated Recurrent Neural Network

- Conv1D layers First, learn to sub-sample the signal and, thus, reduce the input vector's length as we move towards higher layers.
- Conv1D layers extract local information from neighbouring time points, a first step towards learning temporal dependencies. Following Conv1D layers, the LSTM layers are responsible for capturing both short- and long-term dependencies.



Inception Modules

- In the previous C-RNN architecture, each Conv1D layer had the capability to extract local information at only one time scale determined by a single fixed filter size, limiting the flexibility of the model.
- To address this problem, multiple filters of varying sizes in each Conv1D layer were used. This allows for the network to extract information over multiple time-scales.

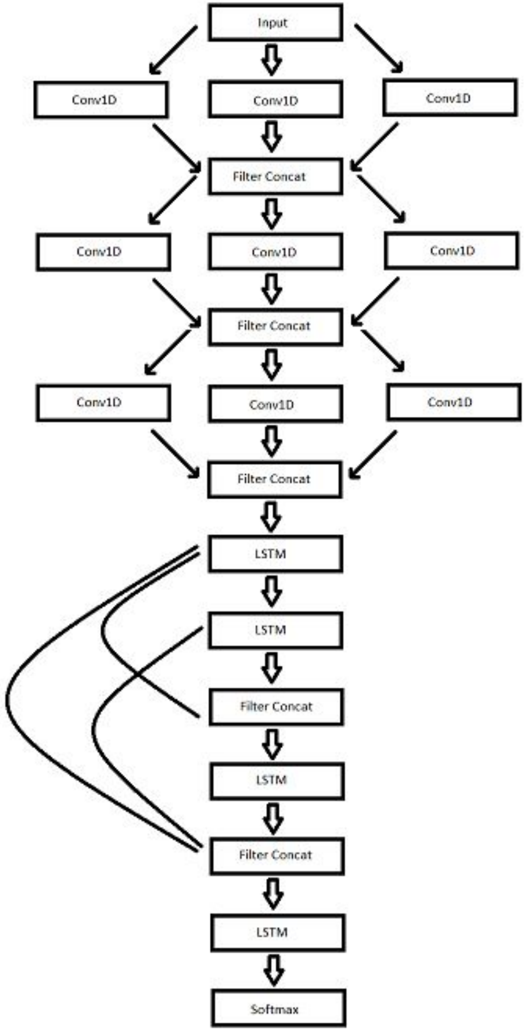


DenseNet Architecture

- The C-RNN architecture is not immune to the problem of degradation which sometimes impedes the training of very deep neural networks.
- For simpler problems that do not need the full potential of the model complexity offered by a C-RNN, the optimization procedure may lead to higher training errors.
- To tackle this issue, skip connections are introduced in the stacked LSTM layers of C-RNN to form the C-DRNN architecture.

Convolutional Densely Connected RNNs

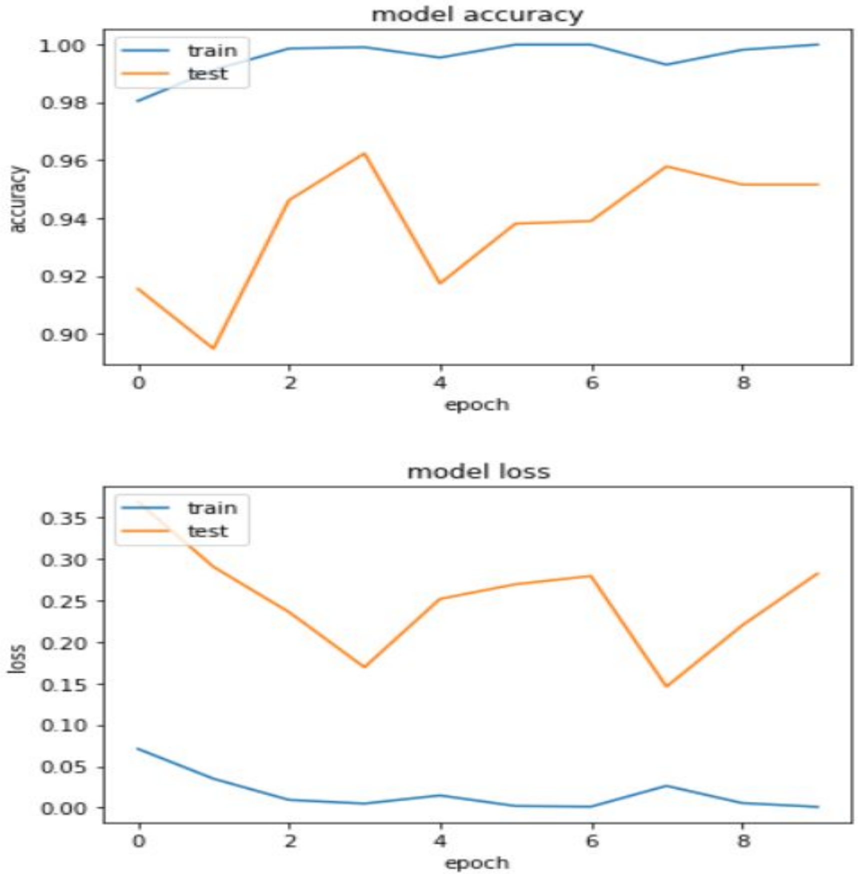
- Each LSTM layer is connected to every other LSTM layer in a feed-forward fashion.
- Intuitively, skip connections will lead to LSTM layers being ignored when the data demands a lower model complexity than offered by the entire network.



Results

- In order to obtain the best performing model, a series of experiments were performed with different batch sizes, different filters, different number of layers and different activation functions.
- The training and validation set are split in such a way that all the EEG segments of a subject lie completely either in the training set or in the validation set. The classification accuracy is maximum for batch size of 32 which is 95.14%.

Accuracy and Loss



Comparison of accuracies

Comparison of accuracies(%) obtained with state-of-the-art methods for automated ADHD detection using EEG signals

Study	Method	Number of subjects	Number of Channels	Split Ratio	Accuracy (%)
Ekhlasi et al(Ekhlasi et al 2021)	Genetic Algorithm, Artificial Neural Network	61 ADHD children 60 Control children	19	70:15:15	89.1
Dahiru Tanko (2022)	EPSPatNet86	61 ADHD children 60 Control children	19	Subject-wise	87.16
Our method	Chrononet	61 ADHD children 60 Control children	19	Subject-wise	95.14

References

1- Roy S., Kiral-Kornek I., Harrer S. (2019) ChronoNet: A Deep Recurrent Neural Network for Abnormal EEG Identification. In: Riaño D., Wilk S., ten Teije A. (eds) Artificial Intelligence in Medicine. AIME 2019. Lecture Notes in Computer Science, vol 11526. Springer, Cham. https://doi.org/10.1007/978-3-030-21642-9_8

2- Tanko D, Barua PD, Dogan S, Tuncer T, Palmer E, Ciaccio EJ, Acharya UR. EPSPatNet86: eight-pointed star pattern learning network for detection ADHD disorder using EEG signals. Physiol Meas. 2022 Apr 4;43(3). doi: 10.1088/1361-6579/ac59dc. PMID: 35377344.

Thank you