A Deep Learning Approach to the Classification of EEG Normality

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Background

The relatively low cost and noninvasive nature of EEGs have made them a popular tool in the identification of disease over the past few decades [1]. Traditional interpretation of EEG signals for clinical purposes have been largely dependent on the input of trained professionals, which often results in extensive lag time between the duration in which an EEG is taken and the production of an EEG report [2]. Additionally, said interpretation can be highly subjective, increasing the possibility of a misdiagnosis that could potentially be life-threatening in some scenarios.

In the past decade, complex machine learning algorithms have had numerous impacts on the field of medicine, as models with capabilities to diagnose and provide prognosis with incredible accuracy have emerged [1]. The recent creation of large clinical databases with patient readings and information offers extensive data which could be utilized for the development of deep learning models.

Methodology

Data Selection:
The data utilized was from the TUH Abnormal EEG Corpus [2]. The dataset consists of approximately 2,993 patient EEG recordings labeled as either clinically abnormal and normal. The Dataset contains 1,499 abnormal and 1,528 normal EEG sessions respectively. Each recording utilizes a standard 1020 montage (Fig. 2), but for the purpose of our study, not all of the data was utilized due to variations in channel numbers. The dataset was roughly balanced among gender, age, and other demographic factors (Fig. 3) [4].

Data Preparation:
Previous studies have noted the ability of trained clinicians to determine EEG normality using only the first few minutes of an EEG recording [2, 4]. For the purpose of consistency, our model was also trained on the first three minutes of each EEG recording, to allow our results to be compared to the performance of trained clinicians.

All samples were preprocessed using high-pass filtering (0.1 Hz bound) and resampling (250 Hz). High-pass filtering was performed on EEG raw signals in other studies utilizing deep-learning models for the purpose of reducing bandwidth of the data and reducing noise [1, 4]. Resampling was performed to ensure that the sample frequency among each recording was consistent. Lastly, some channels and recordings were dropped due to the fact that channel number and positions were not consistent among all recordings.

The kNN, RF, and Logistic Regression were trained and tested on a total of 1,639 values taken as an average of each channel from each recording. This averaging was done to convert time-series data into plausible inputs for the non-time-series models.

The LSTM was trained on a subset of preprocessed EEG recordings, at 130 samples total, due to time constraints on training the model on all of the 1,639 preprocessed recordings.

Model Development:
The stacked LSTM model utilizes one LSTM layer followed by a dropout (0.2), another LSTM layer, and a Dense layer (Fig. 4). This architecture was adapted from similar models developed for Emotion Recognition tasks [1, 5].

The kNN was cycled through various values for k to produce the value resulting in the most optimal performance of the model. The RF was also cycled through various values for estimators.

Model Comparisons:
Out of the four models evaluated, the LSTM performed with the highest AUC (0.80). Of the non-deep learning classifiers, the kNN with k = 20 had the highest AUC of 0.68.

Model:

Table 1: Comparison of AUC for Models

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM-RNN</td>
<td>0.80</td>
</tr>
<tr>
<td>kNN (k = 20)</td>
<td>0.68</td>
</tr>
<tr>
<td>RF (estimators = 200)</td>
<td>0.66</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.53</td>
</tr>
</tbody>
</table>

Results

The use of deep learning for EEG abnormality classification presents an important step forward in the overall automation of EEG report production. In this work, we present a novel LSTM RNN for EEG abnormality classification with an AUC of 0.80, which is comparable to other state-of-the-art models (AUC ~0.82). We see that the LSTM performs significantly greater than that of non-deep classifiers tested (AUCs 0.68, 0.66, 0.53).

To our knowledge, LSTMs have not been implemented in the context of EEG abnormality classification. Despite only training and testing on a shortened dataset (130 samples), a relatively high AUC was achieved. Further training and optimization presents promise for surpassing the current state-of-the-art model.

We demonstrate that a time-series deep-learning approach can be utilized to accurately classify abnormality, allowing for objective assistance to trained professionals in a clinical setting and reduction in the time necessary to produce EEG reports.

Future Steps

The main goal moving forward for our model is to train and evaluate the model on the full dataset of ~2,993 patient recordings. As of now, we were only able to train on a shortened dataset due to time constraints. Utilizing more data is typically shown to increase accuracy when dealing with neural networks [1]. So training on the full TUH Abnormal EEG corpus will be a key step in reducing overfitting.

Another avenue for increasing data amount would be to utilize a longer portion of the EEG recording. As of now, only the first three minutes of each recording was used for the sake of comparison against the performance of trained professionals. However, the use of the full recording would lead to a 6 fold increase in the training data.

We would also like to explore the avenues of artifact removal in the preprocessing of our data. The presence of artifacts in EEG data can introduce unwanted noise and variation in the data that could potentially be harmful to the model’s ability to detect patterns. Previous studies have noted the importance of artifact removal or repair prior to training on raw EEG signals [1, 2].

Conclusion

Acknowledgements

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References