End-to-End Deep Learning, Patient-Level Insomnia Classification

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***Abstract*— In this paper we propose a novel deep learning based, end-to-end approach for patient-level insomnia classification with two distinct model architectures based off one-dimensional (1D) and two-dimensional (2D) versions of the computer vision Convolutional Neural Network (CNN), AlexNet. We achieved up to 94.4% and 88.9% patient-level classification accuracy via our 1D and 2D models respectively.**

***Clinical Relevance*— Clinical diagnosis of insomnia is traditionally a time-consuming process. The proposed work could be coupled with existing wearable technology to deliver patients with a quick a pathway to an insomnia diagnosis.**

I. Introduction

In insomnia, an individual experiences difficulty initiating sleep, struggles to maintain sleep, and/or is dissatisfied with their sleep quality [1]. Insomnia diagnosis is time-consuming, done via interviews, questionnaires and electroencephalogram (EEG) analysis from overnight polysomnography. End-to-end machine learning approaches can help automate this process. End-to-end one dimensional (1D) CNN networks [2] and two dimensional (2D) VGGNet CNN models [3] have been used for automated sleep stage scoring, but have found limited application in insomnia diagnosis. Here, we investigate how frame-level classification obtained from 1D and 2D variants of the popular computer vision CNN, AlexNet [4] can be used to produce patient level insomnia classification.

II. Methods

We used the public CAP sleep database [5], specifically the EEG channel with the most patient data, C4-A1, to obtain 9 CL and 9 I patients. Each EEG frame was classed as CL or I based on the patient label and assigned its corresponding sleep stage label, Wake (W), Stage 1 (S1), Stage 2 (S2), Slow Wave Sleep (SWS) and Rapid Eye Movement (REM).

In the 1D frame-level classifier, after pre-processing, the EEG data was augmented, then frame-level classification performed with the 1D version of the AlexNet classifier. In the 2D classifier, after pre-processing, the EEG was converted to a multi-taper spectrogram, the images augmented, and frame-level classification performed with the 2D version of the AlexNet classifier. 9-Fold cross-validation was employed with 7 folds for training and 1-fold each for validation and testing; each fold had frames from one CL and one I patient.

We considered three approaches to obtain patient-level classification from the frame-level results: 1) ALL – patient classified as I, if majority frames across S1, S2, SWS and REM classed as I, 2) OR – patient classified as I if majority frames within one or more of a group of sleep stage subsets classed as I, and 3) AND – patient classified as I if majority frames within all chosen sleep stage subsets classed as I.

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III. Results

On a frame level, the best performing 1D classifier was trained on REM only (accuracy = 74.4%) while the best 2D classifier was trained on S2 only (acc. = 76.0%). Both augmenting the training data and the selection of sleep stages used for training significantly impacted performance; training with S1 performed the worst for both classifiers. As shown in Fig. 1, the patient-level classifier that used the ALL (S1+ S2 + SWS + REM) frame-level results outperformed all other patient-level classifiers, including the OR and AND ensemble classifiers which combined frame-level classifiers trained on individual sleep stages.

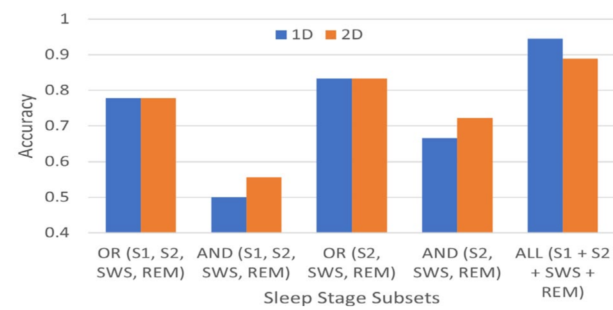

Figure 1. Patient-level Classifier Performance using 1D and 2D results.

IV. Conclusion

Our patient-level classification results show that CL/I frame-level 1D and 2D variants of the AlexNet CNN classifiers can be used to obtain accuracies of up to 94% and 88.9% respectively. However, our results show that to achieve this it is crucial the training data variability and quantity be maximized by using frames from all sleep stages and applying data augmentation.

References

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