DeepIoT—Embedded Deep Learning Algorithms for eHealth IoT

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CSEM is bringing the rapidly-advancing technology of deep learning to the world of the Internet of Things (IoT). Building on its experience in the fields of healthcare, IoT, and artificial intelligence (AI), CSEM is developing deep learning algorithms to diagnose and analyze sleep patterns. The algorithms are designed to be reliable for consumer healthcare applications and to be integrated into low-power wearables with limited computational resources.

Deep learning is a branch of machine learning based on artificial neural networks that hierarchically model high-level abstractions in data. Thanks to the recent availability of large-scale labeled datasets and powerful hardware to process them, the field has enjoyed great success in many fields including computer vision, natural language processing and speech analysis. The technology is likely to be disruptive in many application domains and expected to render conventional machine learning techniques obsolete. Consequently, the technology is increasingly being adopted in the rapidly-growing wearables and IoT markets within the framework of wellness and healthcare Industry 4.0.

The estimated amount of health and fitness trackers worldwide in 2015 was around 25 million units [1], and the number of manufacturers in the wearables market is growing fast. According to CCS Insight, the wearable market (e.g., smart watches, fitness bands, etc.) is expected to grow in value from just over $10 billion in 2017 to almost $17 billion by 2021.

In this race of building AI-powered wearables, the know-how of CSEM represents a competitive advantage with respect to other industrial players thanks to its long-term experience on low-power embedded systems and healthcare-related data analytics applications. CSEM is actively involved in several industrial projects regarding health tracking that would benefit from the deep learning technology. Examples of current customers comprise manufacturers of wrist devices, armpods, connected running shoes, and smart textiles, with whom data-driven health tracker systems have been developed.

As a proof of concept (PoC), CSEM developed several deep learning architectures for sleep staging and evaluated two embedded implementations with different levels of spatiotemporal abstraction:

- Multi-Layer Recurrent Neural Networks (ML-RNNs): RNNs are powerful architectures designed to model long-term temporal relations in the data. They have been shown to work very well in natural language processing applications.
- Convolutional Neural Networks (CNNs): CNNs are neural networks that can hierarchically capture local patterns with increasing semantic complexity in spatiotemporal data.

The data for the PoC is taken from the PhysioNet/Computing in Cardiology Challenge 2018 [2]. The dataset is contributed by the Massachusetts General Hospital and includes 1985 subjects which were monitored at a sleep laboratory for the diagnosis of sleep disorders. However, ground truth sleep stage annotations are publicly released only for 994 subjects, which is what we used for the PoC.

The dataset is split into training and test subsets with 90% of subjects used for training and the rest for testing. The input to the algorithms is a short temporal sequence (5 minutes) of heart-rate variability (HRV) values and a binary value that denotes whether the subject moved. Both inputs are derived using efficient algorithms from raw sensor readings. The output is a three-class vector that signify the likelihood of a subject's sleep stage: WAKE, REM and NREM.

The deep learning algorithms are compared against a hand-designed baseline algorithm, which is based on the analysis of the HRV spectrogram and motion sequences (Table 1). Both, the CNN and ML-RNN architectures employ fully connected and normalization layers, and the latter is based on an efficient version of LSTM networks with forget gates.

Table 1: Performance comparison of the developed algorithms.

	Mean Classification Accuracy	No of Parameters
Baseline	47%	N/A
ML-RNN	68%	1.2 M
CNN	76%	107 K

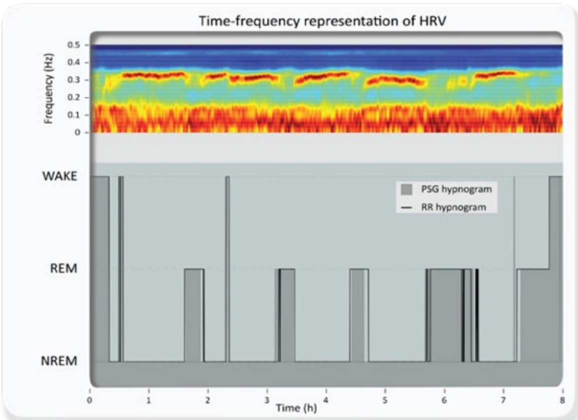

Figure 1: Sleep staging result for a healthy patient. The dark gray bands are hand-labeled by physicians and the solid black line is automatically computed by the analysis of HRV.

The RNN-based network brings about 20% improvement in mean accuracy over the baseline method and the CNN about 30%. Higher accuracy obtained by the CNN network suggests that high frequency patterns in the data, which RNNs are ineffective at modeling, is informative for the sleep staging task.

Both architectures are small in size and require limited computational resources to run. Future work includes optimizing them and embedding them on a resource-limited processor such as nRF52 SoC from Nordic Semiconductors in one of our low-power wearable systems.

[1] http://www.statista.com/statistics/413265/health-and-fitness-tracker-worldwide-unit-sales-region/

[2] https://www.physionet.org/challenge/2018/