Driving Towards Safety: Online PPG-based Drowsiness Detection with TCNs

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Contribution

We propose a solution to detect driver’s drowsiness using a Temporal Convolutional Network (TCN)

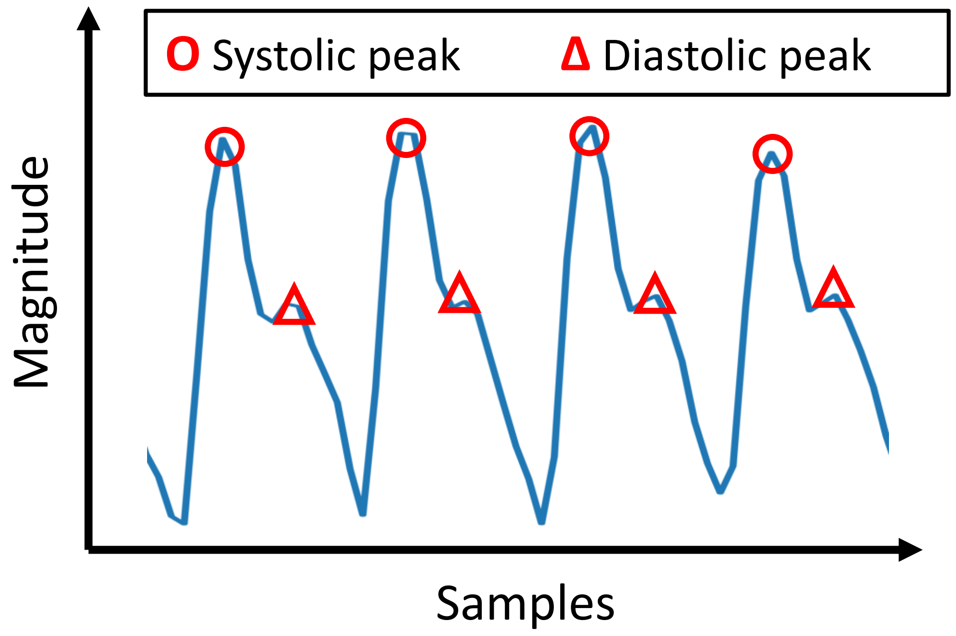
- Based on PPG signal collected in an unobtrusive way
- Validated on 16 subjects in a realistic driving simulator
- Deployed onto a parallel ultra-low-power MCU to ensure embedded real-time operation

Outline

1. Background
   - Motivation
   - PPG signal
   - KSS scale
2. Proposed setup
   - Dataset collection
   - PPG data acquisition
   - A TCN to classify driver’s state deployed on GAP9 ULP SoC
3. Experimental results
   - Classification accuracy
   - Profiling on MCU
4. Conclusions

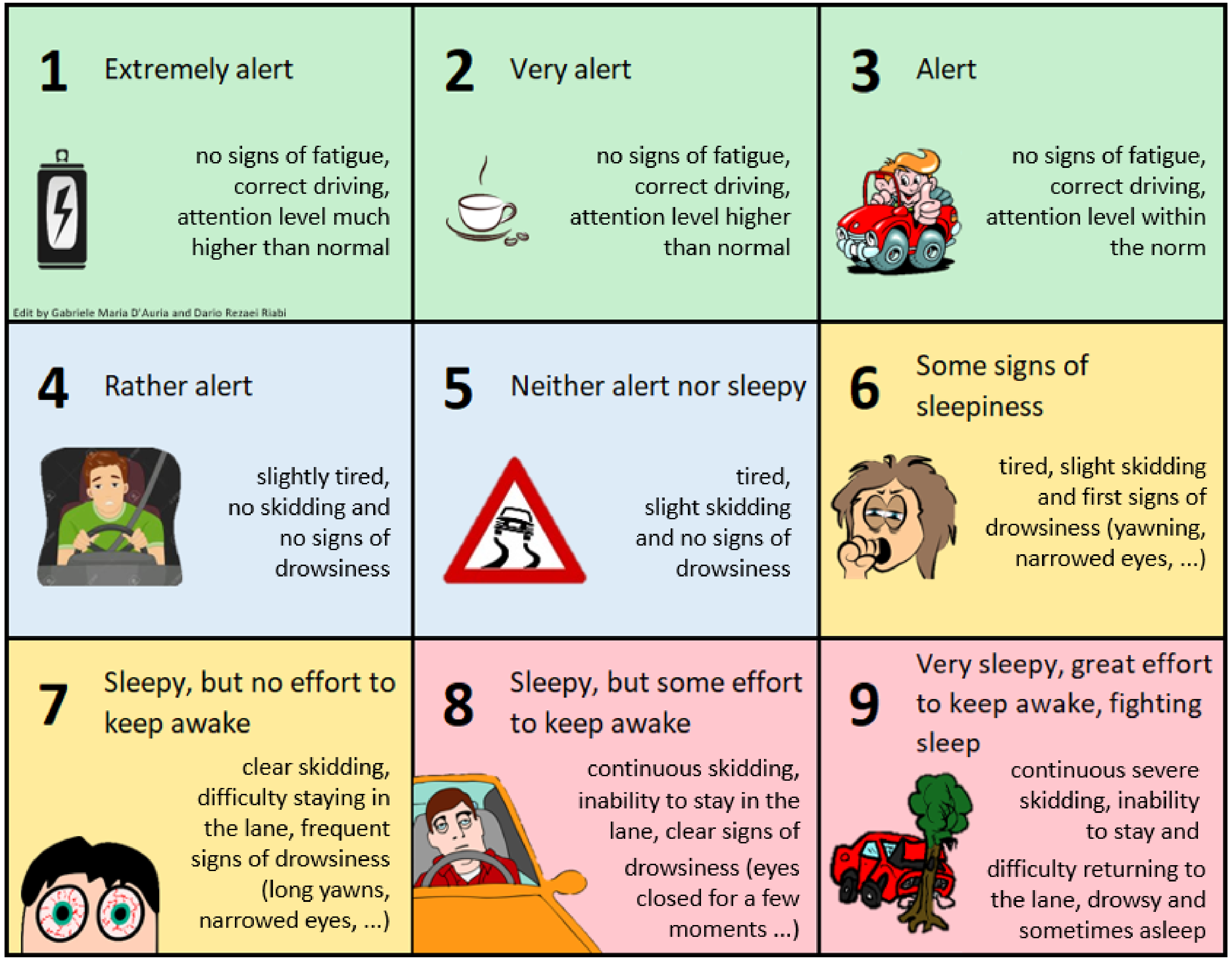
Background

- Drowsiness and fatigue are one the most important cause of car accidents[1]
- Direct measurement of sleep and wake states primarily relies on EEG
- Photoplethysmography (PPG) can be used for non-invasive assessment of the autonomic nervous system and as an unobtrusive indirect method to detect driver's drowsiness
- PPG is an optical-type signal, based on an LED-diode pair, that measures the change in blood volume in the microvascular bed



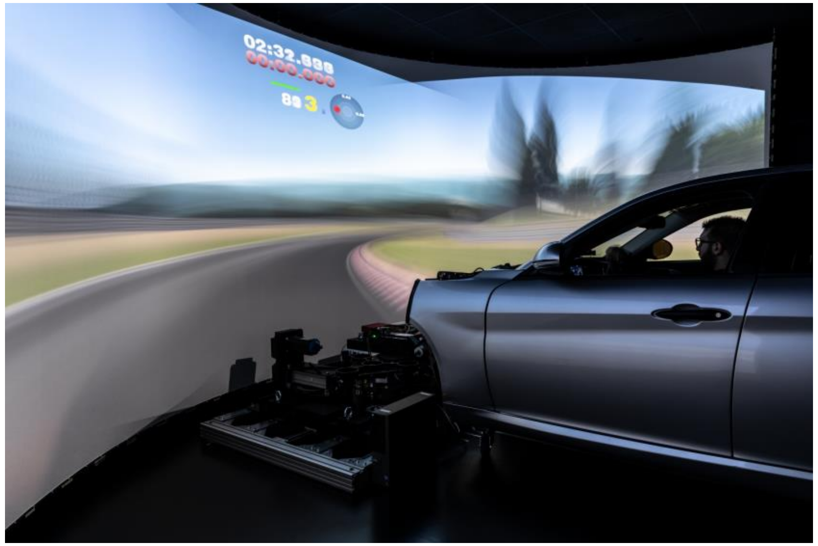
[1]World Health Organization. Global status report on road safety 2018: summary. Technical report, World Health Organization,2018.

Karolinska Sleepiness Scale - KSS



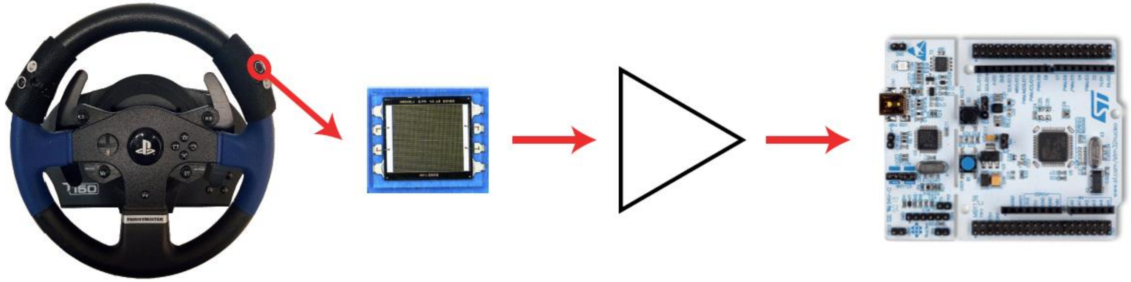
- KSS is a 9-point scale to measure the level of drowsiness using a self-report questionnaire
- KSS scores as the ground truth labels for our classification model, binarized into two classes, Alert and Drowsy
- 1-6 score -> Alert ; 7-9 score -> Drowsy

Data Collection



Maserati Driver-In-the-Loop Driving Simulator:

- Real vehicle cockpit
- Immersive experience
- Realistic simulator environment



ANGELS[1] acquisition system:

- Two PPG probes integrated into the steering wheel
- 1Ksps dual PPG channels
- IR and RED LED and a SiPM to acquire PPG data

[1]Amidei, Andrea, et al. "ANGELS-Smart Steering Wheel for Driver Safety." 2023 9th International Workshop on Advances in Sensors and Interfaces (IWASI). IEEE, 2023

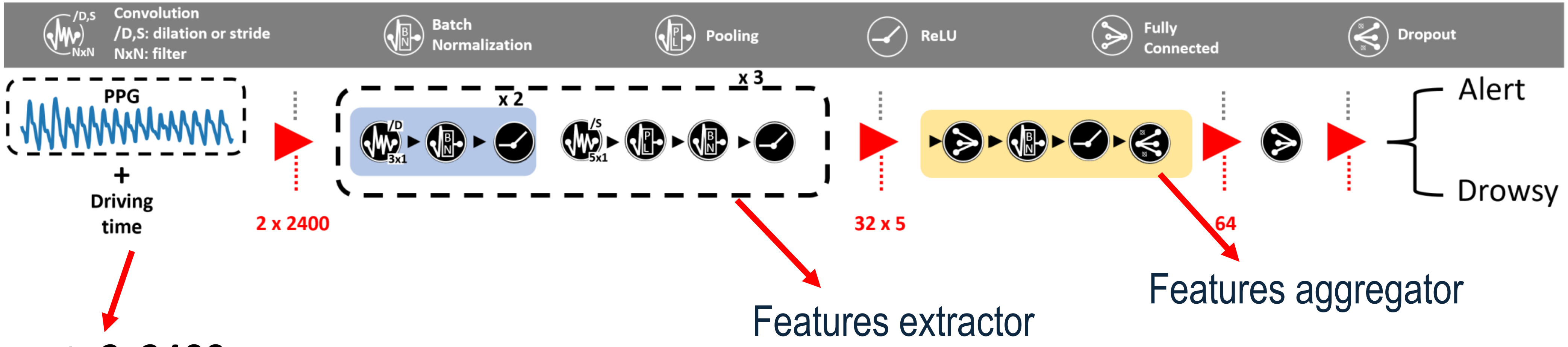
Data Collection

Experimental protocol:
- Night-time recording sessions with the simulation room maintained completely dark and sound-isolated
- Highway driving scenario with light traffic
- Tablet inside the cockpit to report the KSS score every 5 minutes
- The recording time was not fixed, but the driving sessions ended when the driver fell asleep, or the driving style became very dangerous

Final dataset:
- 21 subjects (7 of them as a direct contribution of this work)
- A total of 22h of recordings
- 5 subjects excluded (no sign of drowsiness)

TCN Architecture

TEMPONet[1] architecture adapted for drowsiness detection.



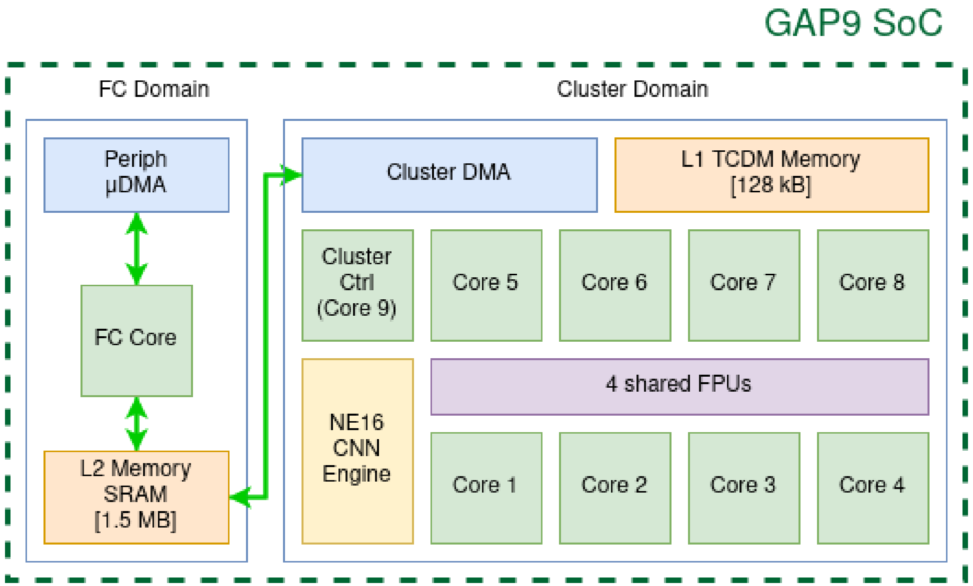
Input: 2x2400

- One PPG channel (left hand) downsampled at 20sps
- Window of 2 minutes with a step size of 30s
- Driving time DT(t) = 1 − e−t/τ where the time constant τ is heuristically set to 2 h.

DT saturates at ∼ 9 h, which is the driving limit recommended by EU regulations[2]

[1]M. Zanghieri et al., "Robust real-time embedded EMG recognition frame-work using temporal convolutional networks on a multicore IoT processor," IEEE Transactions on Biomedical Circuits and Systems, vol. 14, no. 2, pp.244–256, 2020.
[2]https://transport.ec.europa.eu/transport-modes/road/social-provisions/driving-time-and-rest-periods_en

GAP9[1] SoC



To test the feasibility of our model in a real driving application, we deployed our model on GAP9[3]

- 9-core RISC-V compute cluster
- an AI accelerator
- single-core RISC-V controller

Deployment steps

ONNX

Trained model → Post training 8-bit quantization $\xrightarrow{\text{NNTool + Autotiler}}$ C code of the network

[1]https://greenwaves-technologies.com/gap9 processor/

Experimental Results

All the experiments were conducted on 16 subjects
(5 subjects excluded because of class unbalance)

		Avg ± Std
F1 Score	FP32	77.30% ± 15.26%
	INT8	**77.80% ± 14.83%**
Accuracy	FP32	77.03% ± 14.75%
	INT8	**76.93% ± 14.40%**

We evaluate our model using a LOSO cross-validation scheme with 16 folds. Each fold contains 13 subjects for training, 2 subjects for validation, and 1 subject for the test.

Higher accuracy wrt other SoA PPG-based approach

No significant drop using int8 quantization

Experimental Results

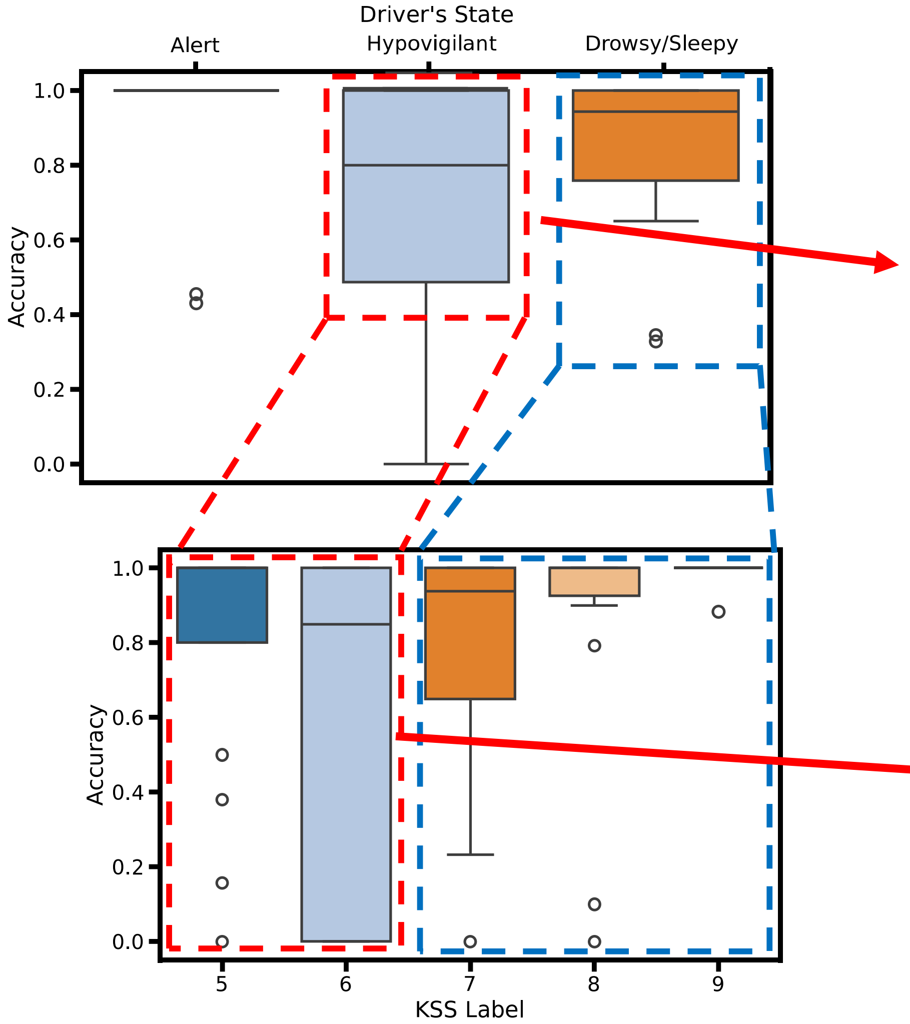
We extend our analysis by arranging the original reported KSS scores into three groups—alert (1–4), hypovigilant (5–6) and drowsy (7–9)—and evaluating the binary predictions for each of them.

- We compute the accuracy of the model's predictions against the three groups, and we obtain a **91.42%** of accuracy for **alert**, a **68.63%** of accuracy for **hypovigilant** and a **83.48%** of accuracy for **drowsy**.

- We obtain a false positive ratio (**FPR**) of **8.21%** for **alert**, a **FPR** of **32.43%** for hypolvigilant and a false negative ratio (**FNR**) of **13.92%** for drowsy.

Experimental Results

We further divide the hypovigilant and drowsy groups into their original KSS scores (i.e., 5–9), and we evaluate the model's predictions



Heightened variability and lower median accuracy in the hypovigilant state

Significant variability in the accuracy on score 6

Deployment on GAP9

Frequency [Mhz]	240.00
Voltage [v]	0.65
L1 [kB]	63.16
L2 [kB]	29.51
Flash[kB]	24.71
Parameters [#]	24.07k
OPs	1.51M
Inference Time [ms]	4.83
Energy/Inference [μJ]	117.40
Accuracy	76.93 %

The network requires 1.51 MOPs to be executed, resulting in a time per inference of 4.83 ms, totally compatible with the online constraint of a new prediction every 30 s, and an energy consumption of only ~ 117 μJ[1].

[1]The energy consumption is referred only to the processing part, not considering the acquisition

Conclusions

- The proposed model achieves a SoA average cross-validated accuracy of 77.60% across 16 subjects
- Our model is able to effectively reduce the number of false alarms when the driver is clearly awake, as evidenced by our low FPR of 8.21% in the alert group
- The proposed approach can be integrated with others, e.g., based on driving events, to further reduce the FNR
- Leveraging the computational capabilities of the GAP9 processor opens avenues for system scalability, potentially exploring the integration of other types of sensors

Thanks for your attention

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