



ELTE

FACULTY OF
INFORMATICS

ELTE – Chung-Ang AI Conference

AI in the Vehicle

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Supervisor: János Botzheim, PhD

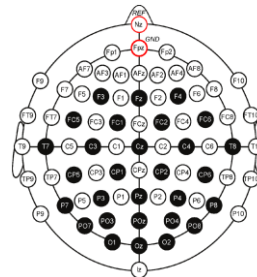
Corporate Advisor: Zoltán Kárász, PhD

Agenda

- Multi-Scale Object Detection with Temporal Stabilization

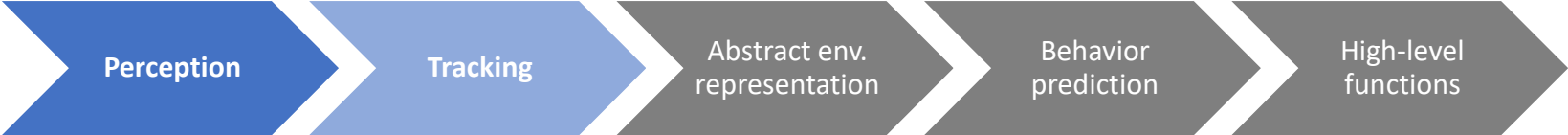


- Embedded Feature Selection for Highly Redundant Use-cases

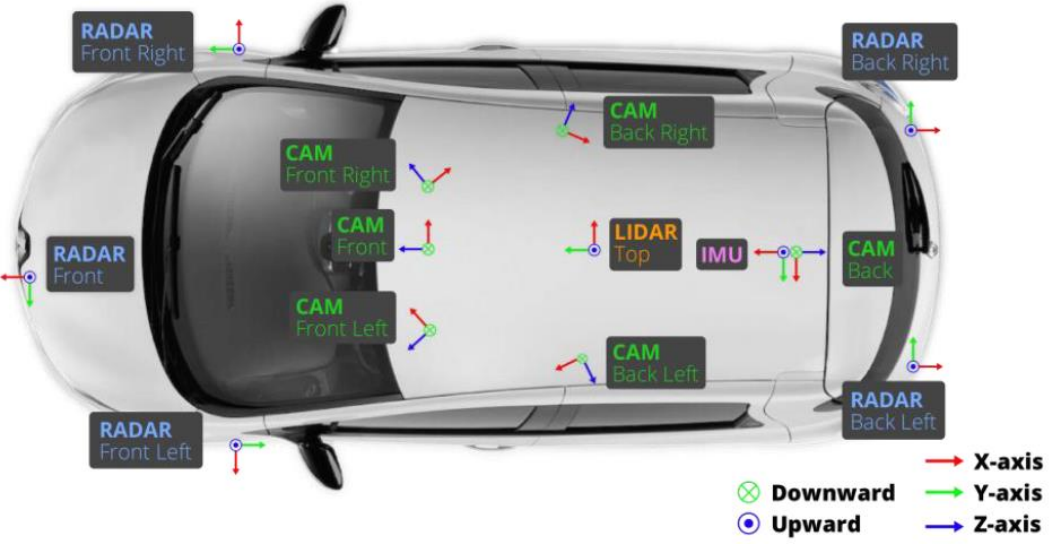


Driving Assist Systems

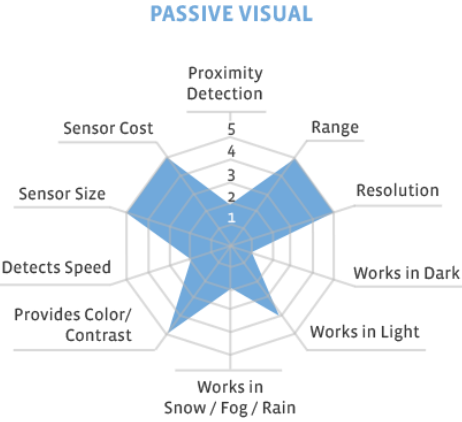
Abstract system-pipeline:



A possible sensorical setup:



Our selected sensor:



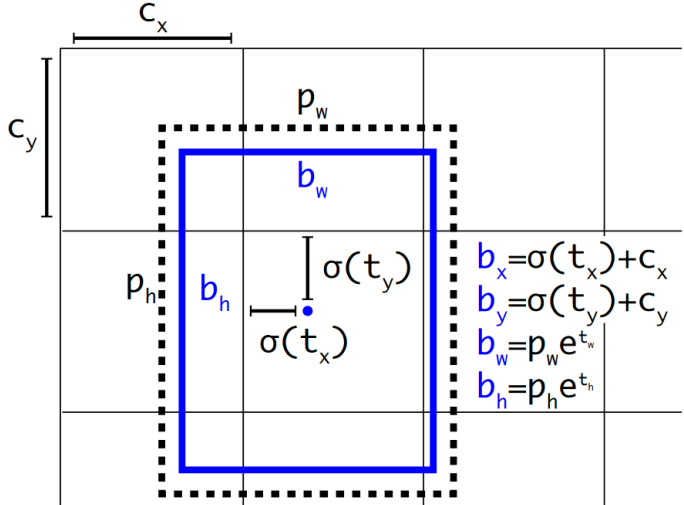
Holger Caesar, Varun Bankiti, Alex H. Lang, Sourabh Vora, Venice Erin Liong, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, & Oscar Beijbom. (2020). nuScenes: A multimodal dataset for autonomous driving.

Temporal Stabilization

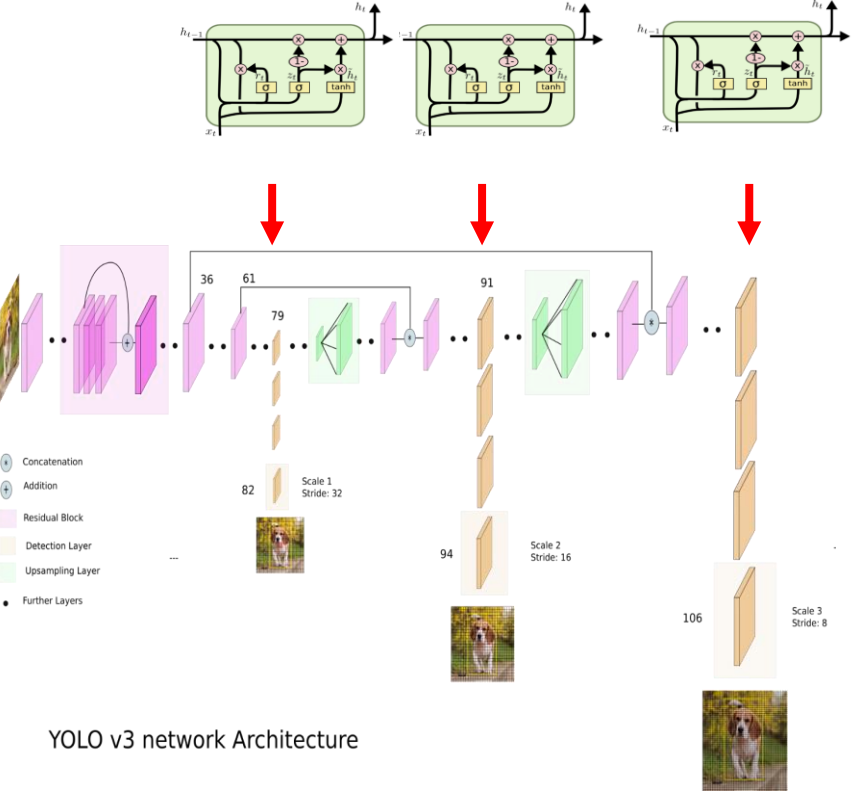
Challenges:



Anchor-based object representation:



YOLOv3 and its GRU extension:



Andreas Geiger, Philip Lenz, & Raquel Urtasun (2012). Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite. In Conference on Computer Vision and Pattern Recognition (CVPR).

Joseph Redmon, & Ali Farhadi. (2018). YOLOv3: An Incremental Improvement.
 Juan Terven, & Diana Cordova-Esparza. (2023). A Comprehensive Review of YOLO: From YOLOv1 and Beyond.

YOLO v3 network Architecture

Temporal Stabilization Results

YOLOv3 with pretrained encoder:

Class	Original YOLOv3			1 GRU ext.			3 GRU ext.		
	TP	FP	mAP	TP	FP	mAP	TP	FP	mAP
Car	2529	238	86.2%	2595	171	91.8%	2616	171	92.1%
Truck	246	19	90.1%	258	49	95.6%	259	145	94.6%
Pedestr.	396	52	76.4%	394	139	78.7%	404	412	82.2%
Cyclist	166	109	80.0%	171	86	85.6%	172	163	86.9%
	mAP=80.94%			mAP=87.45%			mAP=88.11%		

YOLOv3 without pretrained encoder:

Class	Original YOLOv3			3 GRU ext.		
	TP	FP	mAP	TP	FP	mAP
Car	2452	251	85.9%	2518	488	86.9%
Truck	235	42	84.2%	241	73	87.0%
Pedestr.	328	156	59.3%	343	323	59.9%
Cyclist	144	60	71.0%	149	131	69.7%
	mAP=75.95%			mAP=77.95%		

Prev. sample:



Curr. sample + YOLO:

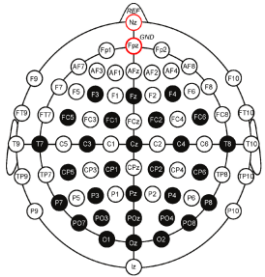


Curr. Sample + YOLO + GRU

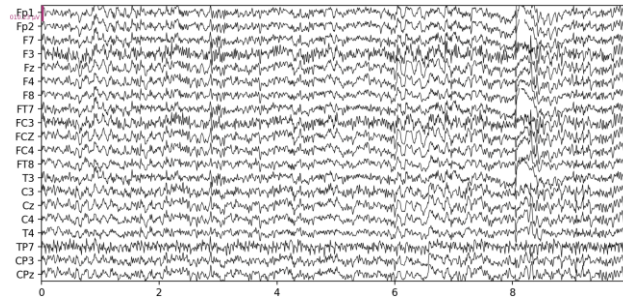


Drowsiness Detection

EEG electrode setup



EEG signals



Handcrafted feature extraction

α -PSD, β -PSD, θ -PSD,

*PSD:power spectral density

$$\frac{\theta + \alpha}{\beta}, \frac{\alpha}{\beta'}, \frac{\theta + \alpha}{\alpha + \beta'}, \frac{\theta}{\beta'}, \frac{\theta}{\theta + \alpha'}, \frac{\alpha}{\theta + \alpha'}, \frac{\theta + \alpha}{\theta + \beta}$$

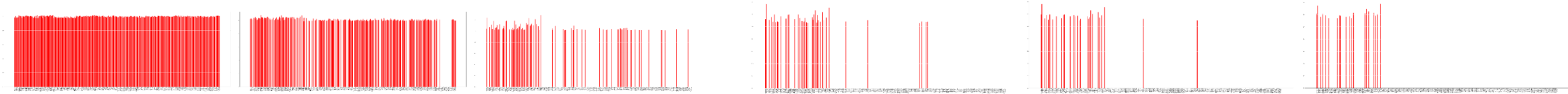
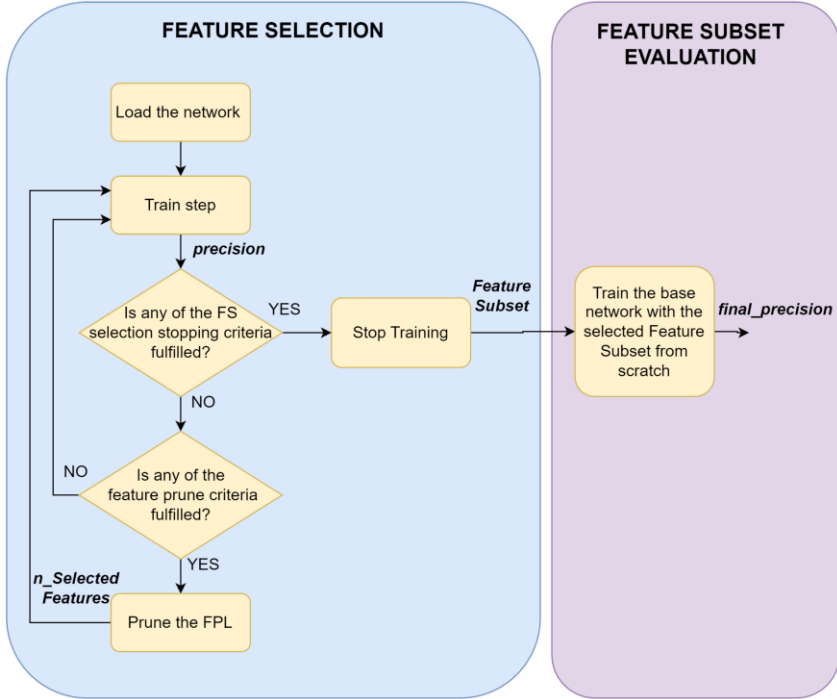
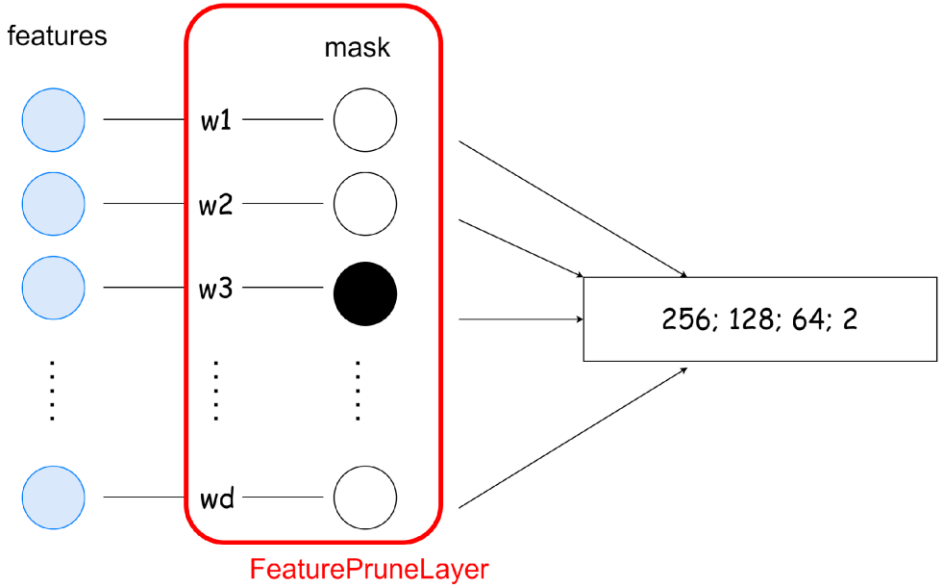


Drowsiness
Detection
Function

Challenge: Redundancy

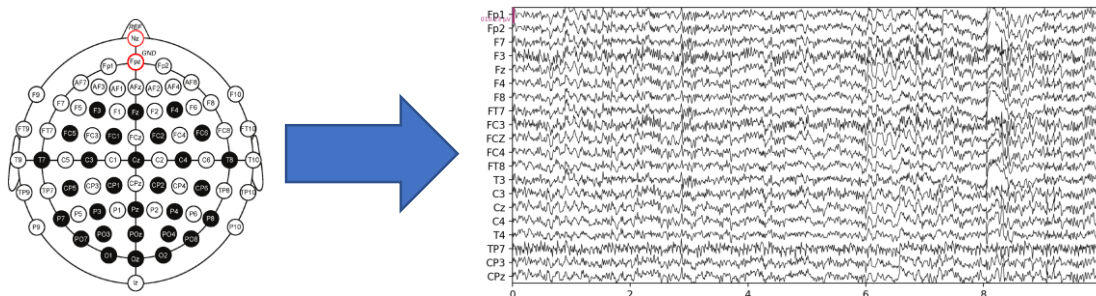
Cui, J. EEG Driver Drowsiness Dataset. 2021. Available online:
https://figshare.com/articles/dataset/EEG_driver_drowsiness_dataset/14273687/3

Embedded Feature Selection



Drowsiness Detection Results

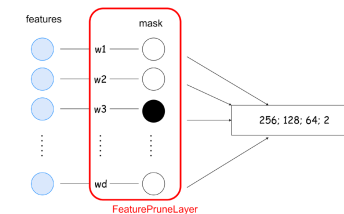
Drowsiness pipeline:



α -PSD, β -PSD, θ -PSD,

*PSD: power spectral density

$$\frac{\theta + \alpha}{\beta}, \frac{\alpha}{\beta'}, \frac{\theta + \alpha}{\alpha + \beta'}, \frac{\theta}{\beta'}, \frac{\theta}{\theta + \alpha'}, \frac{\alpha}{\theta + \alpha'}, \frac{\theta + \alpha}{\theta + \beta}$$



Drowsiness Detection

Results:

All features (#330)	
Precision	Pseudo overfit
0.926	0.037

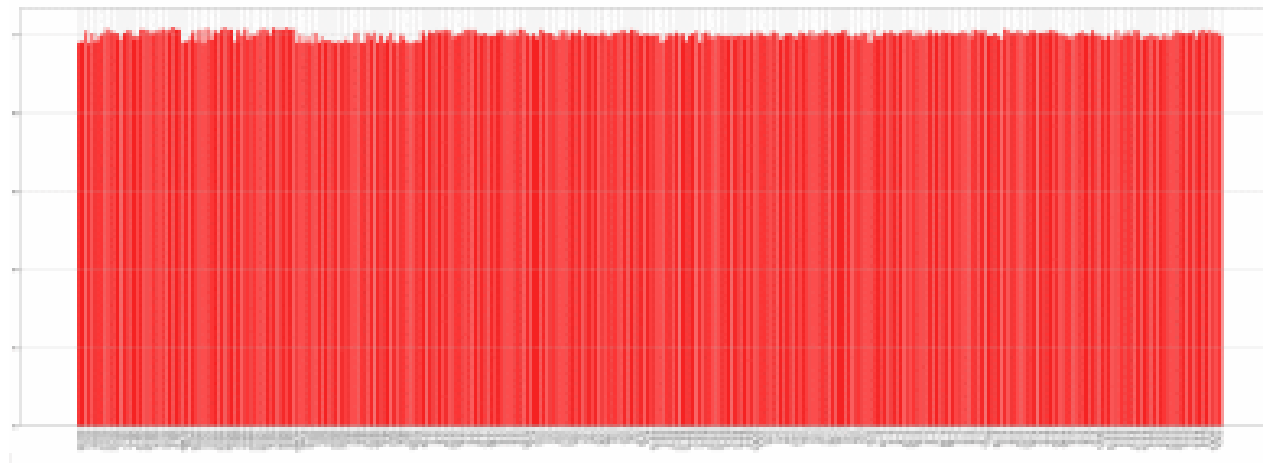
*Precision: on test set

*Pseudo overfit: precision difference between measured on train and test set

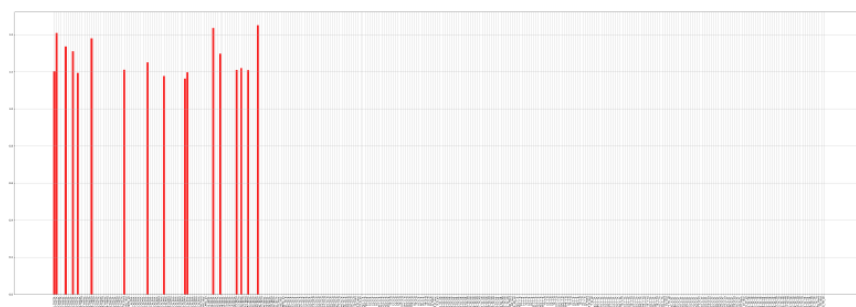
TOP 20% (#66)		TOP 10% (#33)		TOP 5% (#17)	
Precision	Pseudo overfit	Precision	Pseudo overfit	Precision	Pseudo overfit
0.953	0.033	0.941	0.028	0.916	0.01

Bencsik, B., Reményi, J., Szemenyei, M., & Botzheim, J. (2023). Designing an Embedded Feature Selection Algorithm for a Drowsiness Detector Model Based on Electroencephalogram Data. In Sensors (Vol. 23, Issue 4, p. 1874). MDPI AG. <https://doi.org/10.3390/s23041874>

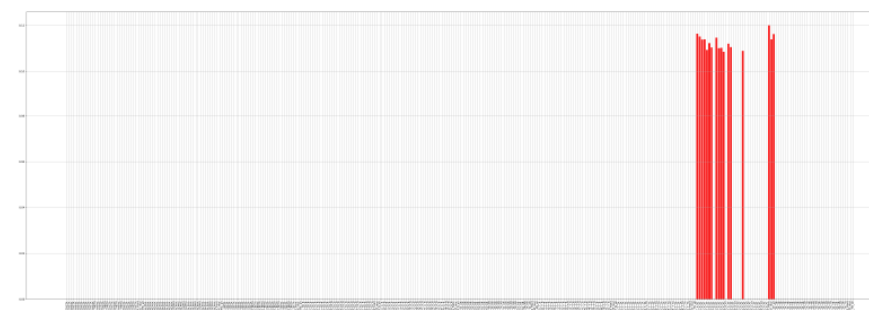
Feature Selection Results



Embedded method



Principal Component Analysis



Vs.

Thank You for Your Attention!



NEMZETI KUTATÁSI, FEJLESZTÉSI
ÉS INNOVÁCIÓS HIVATAL

SUPPORTED BY THE KDP-2021 PROGRAM OF THE MINISTRY OF INNOVATION AND TECHNOLOGY FROM THE SOURCE OF THE NATIONAL RESEARCH, DEVELOPMENT AND INNOVATION FUND.