Aggressive Driver Behavior Detection using Parallel Convolutional Neural Networks on Simulated and Real Driving Data

Zehra Camlica*, Jim Quesenberry**, Daniel Carballo**, and **Mark Crowley***

*Dept of Electrical and Computer Engineering
University of Waterloo
Waterloo, Canada

**Corporate Research and Development
Magna Int.
Troy, MI, USA

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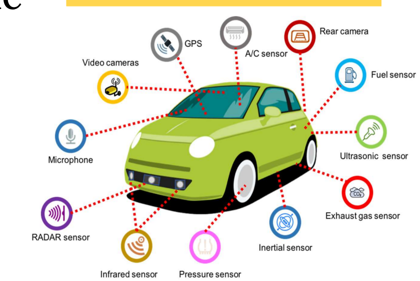
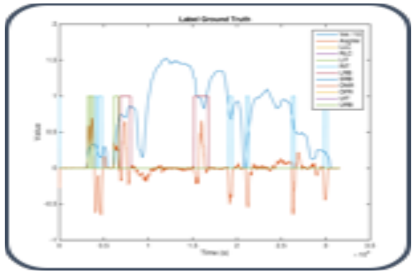
Introduction

- Three main contributing factors to road traffic accidents [1]:
  - human error,
  - vehicle failure and
  - road conditions
- To improve road safety :
  - define driver actions
  - analyze driver characteristics

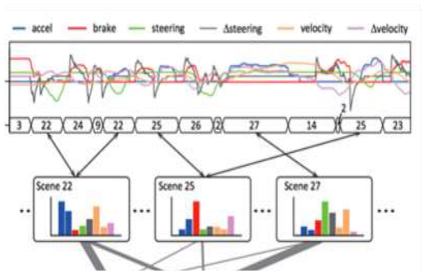
Measurement



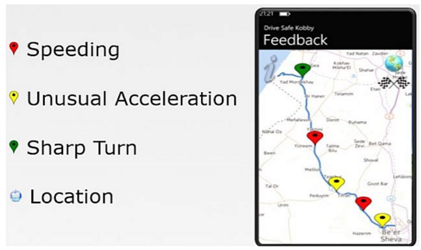
Event Detection



Analysis



Feedback

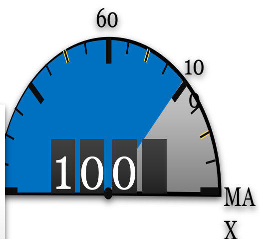


[1] N. A. Stanton, G. H. Walker, and P. M. Salmon, Human factors in automotive engineering and technology. Ashgate Publishing, Ltd.,2015

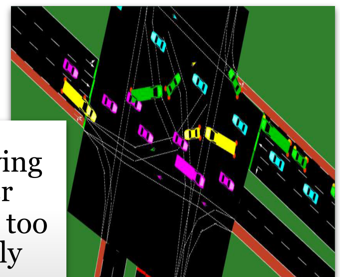
Aggressive driving

“Operates a motor vehicle in a *selfish, impatient, bold or pushy manner, without regard* for the rights or safety that directly affects the other users of the streets and highways.”[2]

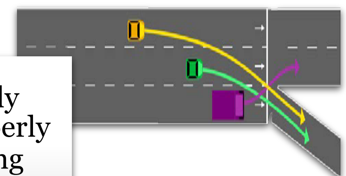
Exceeding speed



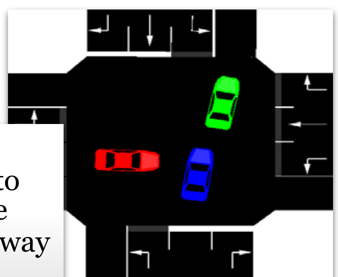
Following other vehicle too closely



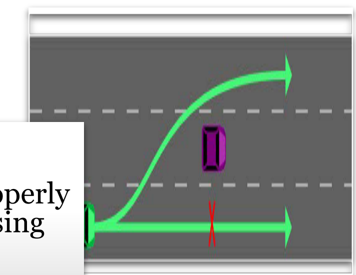
Unsafely improperly changing lanes



Failing to yield the right of way



Improperly passing



Violating traffic control and signal devices

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[2]-The National Cooperative Highway Research Program (NCHRP)

Objective

Develop a **cost efficient aggressive /normal** driver behavior classification method to address **spatio-temporal data problems** with using Convolution Neural Networks

- Indirect data from smartphone (not directly from driver)
- Non-visual data (privacy and cost concerns)
- High dimensional data: Multivariate time series (IMU and GPS)
  - Noisy and missing
  - Complex relations between variables
  - Wide variety with-in the classes

Outline

I. Background
II. Parallel Convolutional Neural Networks
III. Datasets
IV. Results
V. Conclusion and Future work

Background and literature review

- common techniques to analyze driver behaviors using time series

- Dynamic Time Warping + KNN classifier[3]
  - Time complexity is high
  - Preprocessing needed
  - Need prior knowledge the events and characteristics templates
- Arima modelling [4]
  - Statistical perspective, using different type of time series features
  - Linear function
- RNN –LSTM [5]
  - Temporal
  - Time complexity
  - Data requirements
- 1-D CNN [6]
  - Miss relation between variables like spatial information

[3]-Johnson, Derick, and Mohan M. Trivedi. "Driving style recognition using a smartphone as a sensor platform." *Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on*. IEEE, 2011.
[4]-J. Guo, H. He and C. Sun, "ARIMA-Based Road Gradient and Vehicle Velocity Prediction for Hybrid Electric Vehicle Energy Management," in *IEEE Transactions on Vehicular Technology*, 2019
[5]-Saleh, Khaled, Mohammed Hossny, and Saeid Nahavandi. "Driving behavior classification based on sensor data fusion using LSTM recurrent neural networks." *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017.
[6]-Y. Zhang, J. Li, Y. Guo, C. Xu, J. Bao and Y. Song, "Vehicle Driving Behavior Recognition Based on Multi-View Convolutional Neural Network With Joint Data Augmentation," in *IEEE Transactions on Vehicular Technology*, vol. 68, no. 5, pp. 4223-4234, May 2019, doi: 10.1109/TVT.2019.2903110.

Parallel CNN Classification for Aggressive Driver Behavior

- Parallel CNNs method uses:
  - multi task analysis
  - to classify aggressive/normal driver behaviors
  - on big SUMO micro-traffic-Webots simulated dataset
  - On DBL real world-driven dataset
  - validated with the UAH real dataset
- Dataset 1 - Recorded more than 500 trips for Simulated data (20 minutes for each):
  - Position, velocity and angle information (100 Hz)
  - Different window sizes for sliding window
  - Labelled according to simulator parameters
  - Label classes based on maneuver types and behaviour types
- Dataset 2 - Collected more than 100 trips from 60 participants (approximately 80 minutes for each)

Behavioral Types	Manoeuvre Types
Normal/Safe	Right Turn
	Left Turn
Aggressive	Right Lane-Change
	Left Lane-Change

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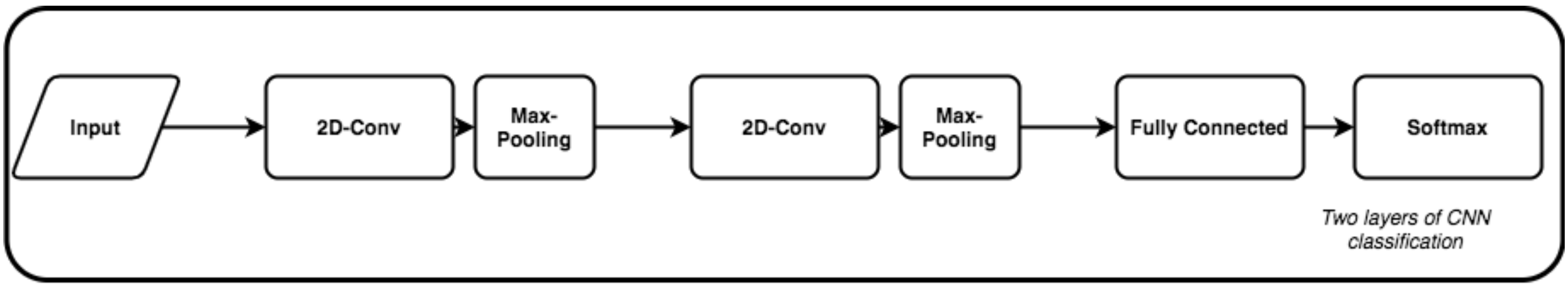
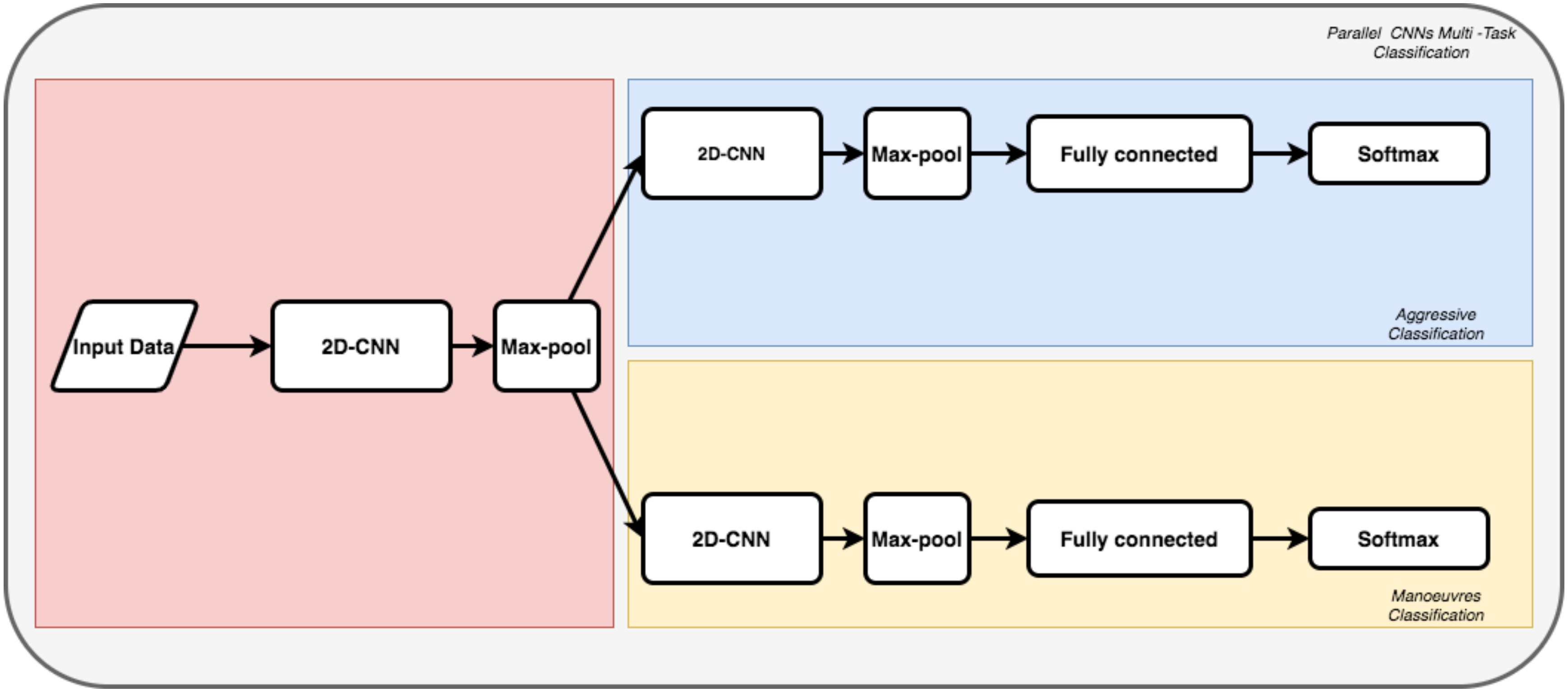
Single-Task CNN classification



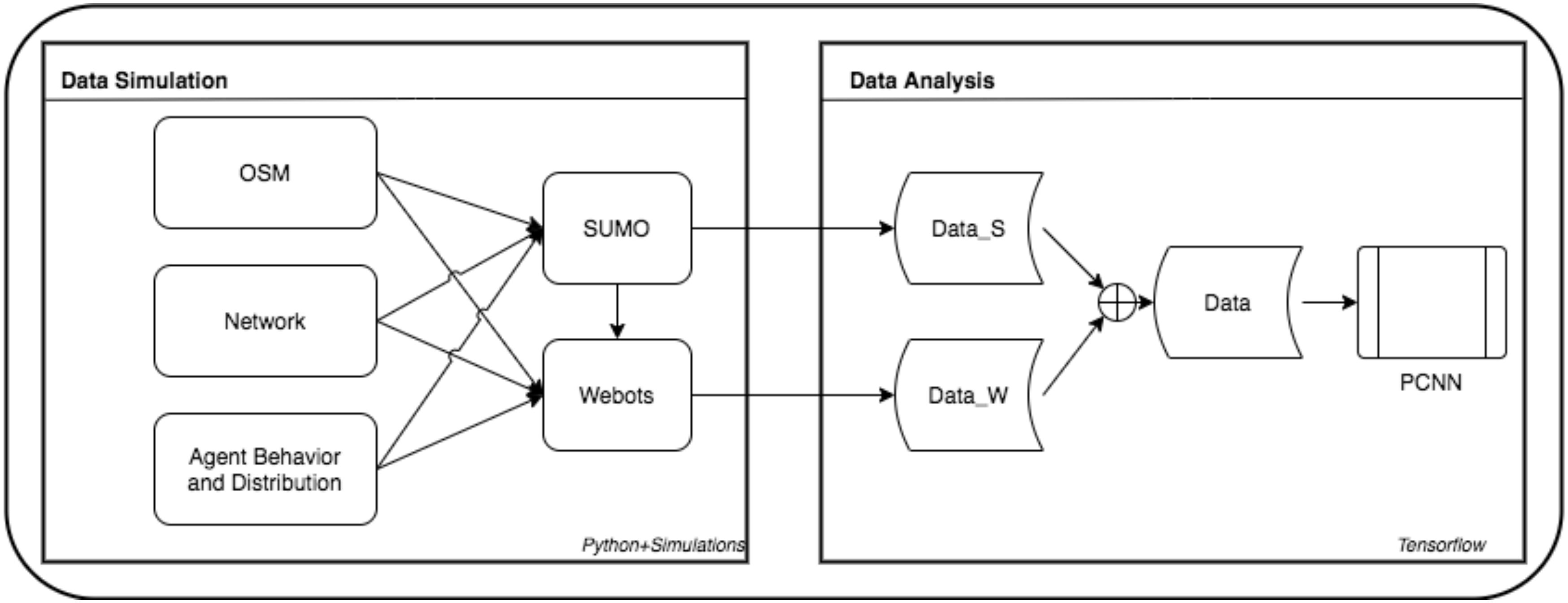
PCNN Model Architecture



Datasets

Dataset	Size	Classes	Labelling	Preprocess	Task	Sensors
SUMO + Webots Simulator	More than 150 hours of driving	2 behavior , 4 maneuvers	Automatically labelling based on simulator parameters	Sliding window, angle rotation, Time2image conv.	Multi task classification	GPS, gyroscope
DBL project	More than 120 hours driving	2 behavior , 9 maneuvers	Automatically labelled based on thresholds, and driving score, Manually labelled	Sliding window	Multi task classification	GPS, IMU

PCNN General Architecture for Simulated Dataset



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Dataset 1 - SUMO Micro Traffic Simulator and Webots

The general simulating phase

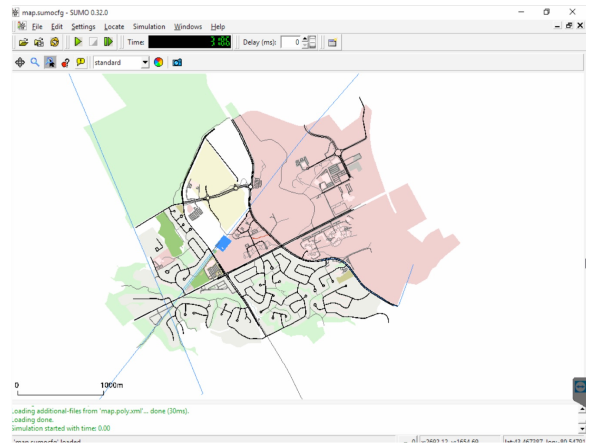
- Open Street Map is downloaded
- Network is created from OSM
- Total number of vehicles randomly selected
- Different vehicle types with different driving behaviours (aggressive and normal) based on parameters from [7],[8],[9]
- Then, the probability of these vehicle types are distributed randomly
- Random trips are created

SUMO

- Simulate traffic of multiple vehicles
- Pass this data to Webots in parallel…

Webots

- Adds 'sensors' to virutal vehicles: camera, lidar, radar, imu, gyro, gps…



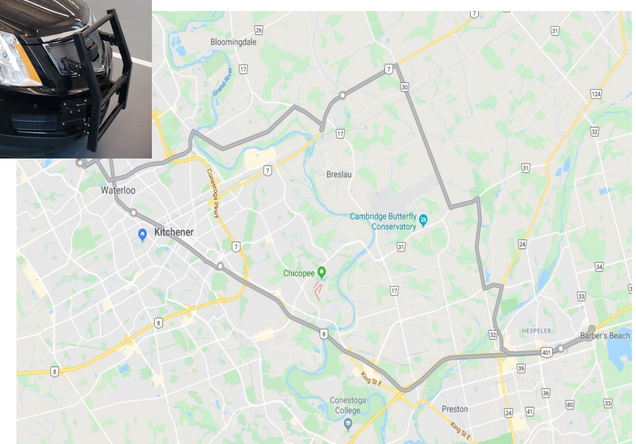
Parameters	Normal Driver Behaviour	Aggressive Driver Behaviour
acc(m/s^2)	2.6	3.2
decel(m/s^2)	4.5	5.5
sigma $(0-1)$	0.5	0.3
maxSpeed(m/s)	23	35
minGap(m)	2.5	0.9
tau (s)	1.5	1
impatience$(0-1)$	0	1
lcAssertive$(0-1)$	0	0.9

TABLE III: SUMO Parameters for aggressive and normal driver bahaviors

Dataset II- Magna Driver Behavior Learning (DBL)

- 50 participants driving around Waterloo region
- 2010 Cadillac SRX
  - with a top mounted Lidar,
  - a front and two rear facing radar,
  - camera sensors and

  on board computers and displays
- The planned route(2 times),
  - 57.6 km(1 hour 10 min)
  - 12 Right turns,
  - 11 Left Turns,
  - one forced left lane change,
  - three forced right lane changes and
  - two straight roundabouts
- Exit survey



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Extracted and Transformed Features

The goal in this part of the project was:

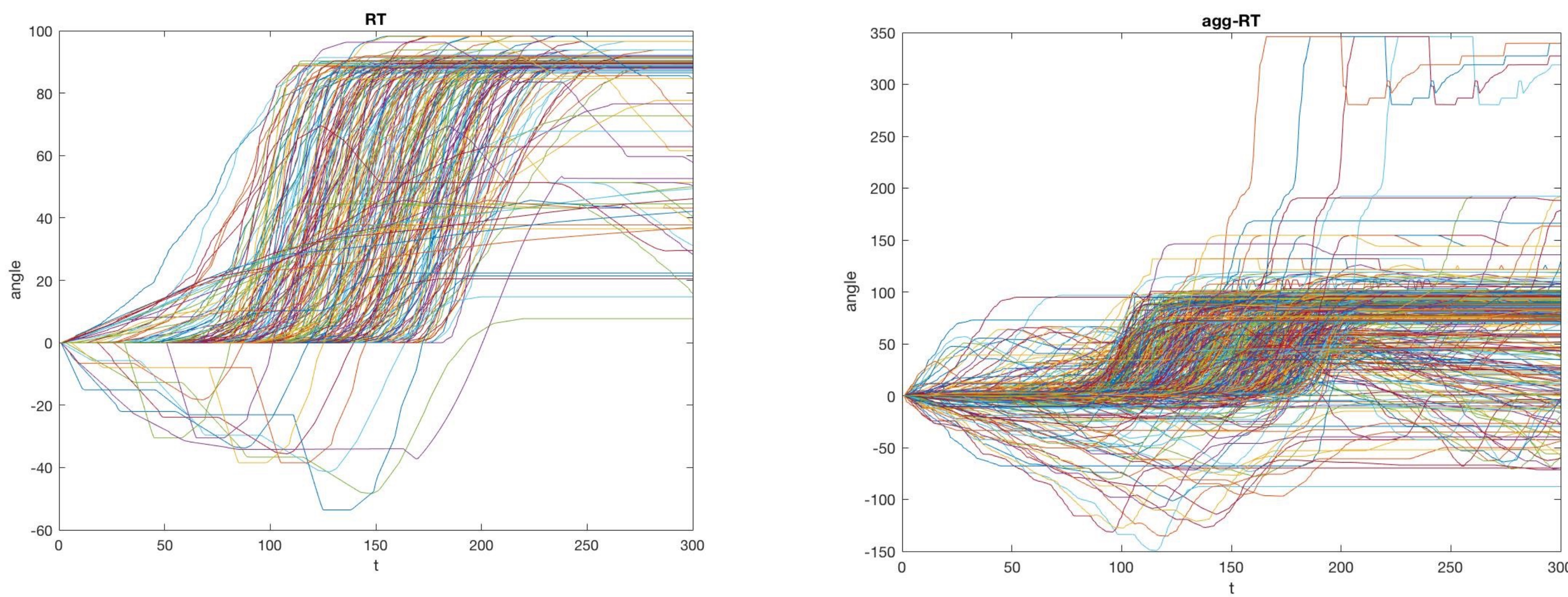
- to use minimal features from the data
- and maximize the contextual power of CNNs for this problem

Two input images per training window:

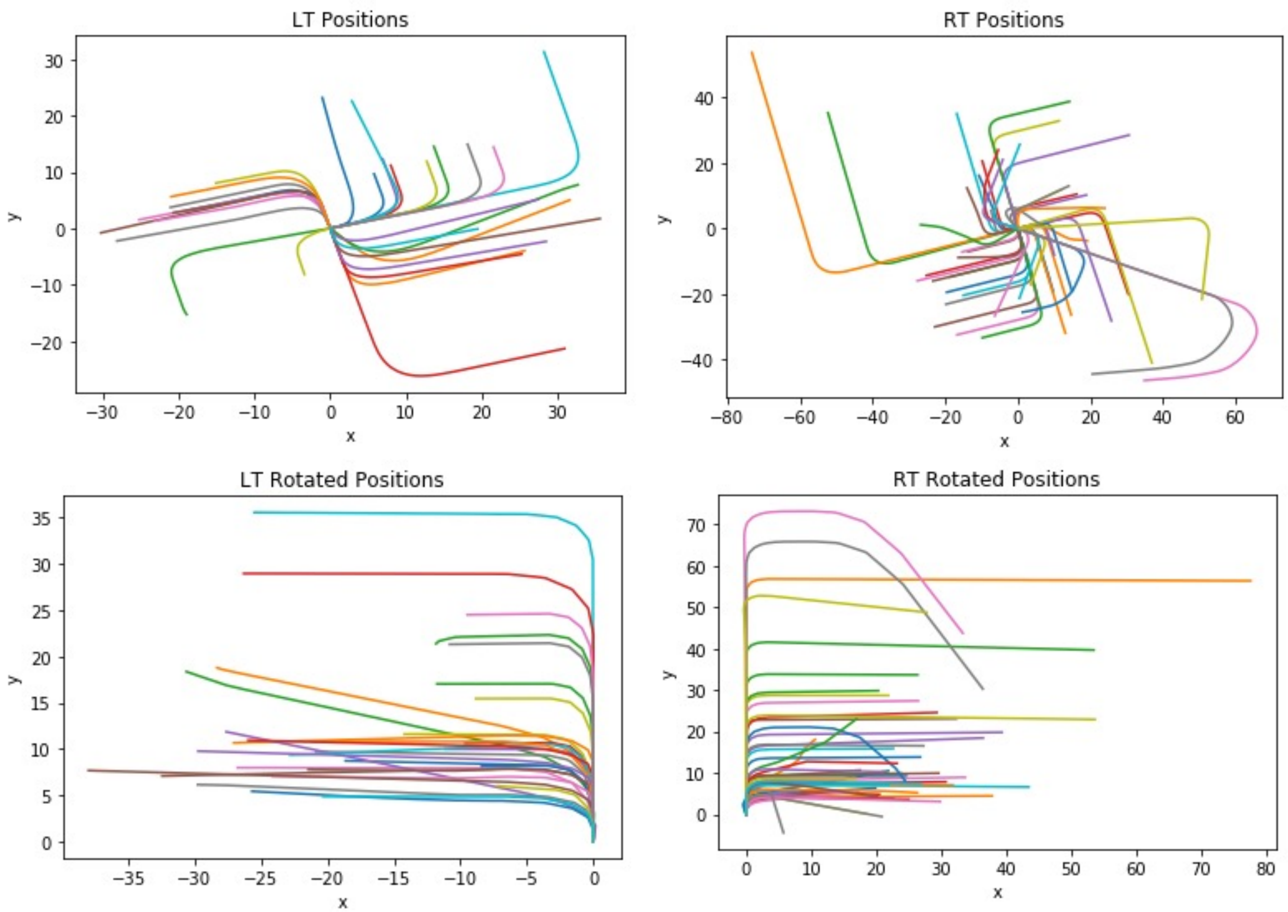
- Plain Time Series for the minimal features
- Time Series with Rotated Location x and y

Plain Time Series for the minimal features

- 2D Data out- put taken from directly simulators. Dimensions are time in time window (300ms) and vehicle features (speed, x, y, angle) from simulations



Time Series with Rotated Location x and y



Cyclic Symmetry [10]

- we translate this into more informative format
- by rotating each (x,y) datapoint so that they are all in the first and second quadrants of the x and y coordinate plane.
- Essentially we **normalize** direction with respect to North

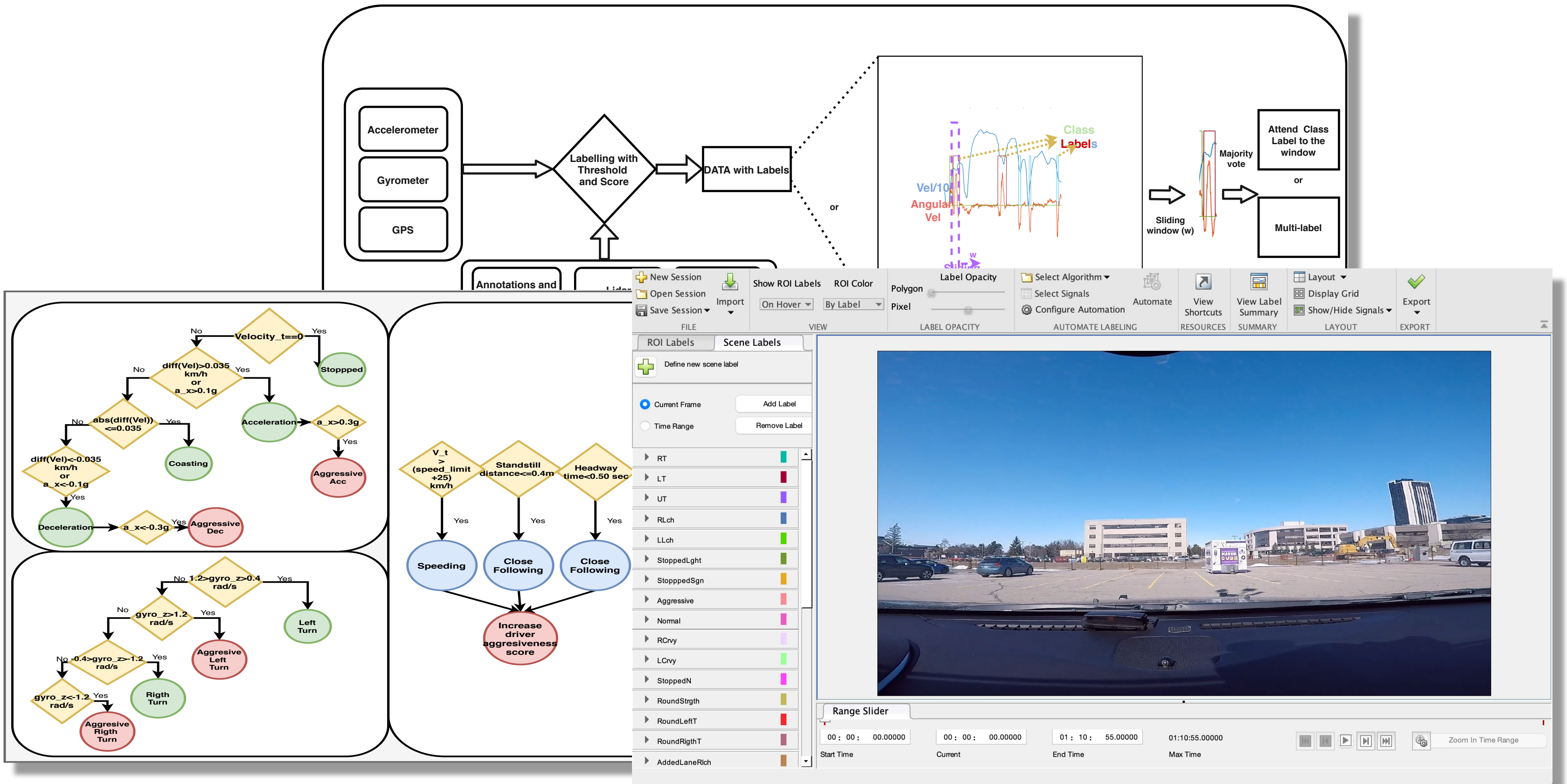
[10]-Dieleman, S., De Fauw, J., & Kavukcuoglu, K. (2016). Exploiting cyclic symmetry in convolutional neural networks. *arXiv preprint arXiv:1602.02660*.

Class Labels

Table 5.1: Labels

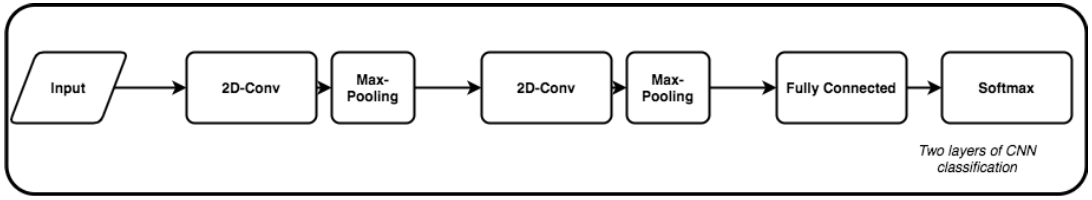
Classes Label	Aggressive or Normal Labels	New Labels
1-Stop	✗	✓
2-Acceleration	✓	✓
3-Coasting	✗	✓
4-Deceleration	✓	✓
5-Left Lane Change	✓	✗
6-Right Lane Change	✓	✗
7-Left Intersection Turn	✓	✗
8-Right Intersection Turn	✓	✗
9-Straight Roundabout	✓	✓

Thresholding and Labelling



Results-Accuracies for different tasks using single task CNN

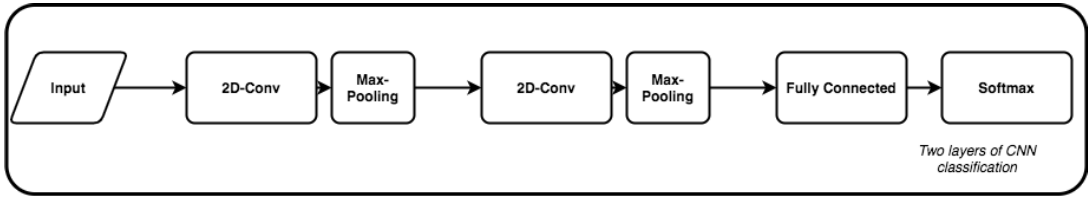
Performance of single-task models trained on individual action labels is high – as expected



Classification Task	Train accuracy (%) on Simulated Dataset	Test accuracy(%) on Simulated Dataset	Train accuracy(%) on Real Driven Dataset	Test accuracy(%) on Real Driven Dataset
Turns Classification	90.2	80.3	92.1	90.5
Lane-changes Classification	88.2	75.6	80.6	72.7
Behavior Classification	65.6	60.8	80.5	78.4
Manoeuvre Classification	82.9	65.0	75.3	71.1
Behavior Classification with Manoeuvres label added to input features	73.1	65.0	88.2	82.7
Manoeuvre Classification with Behavior label added to input features	89.2	70.3	78.2	75

Results-Accuracies for different tasks using single task CNN

But performance on combined manoevre's of the two different actions is worse, since it's more complex – as expected



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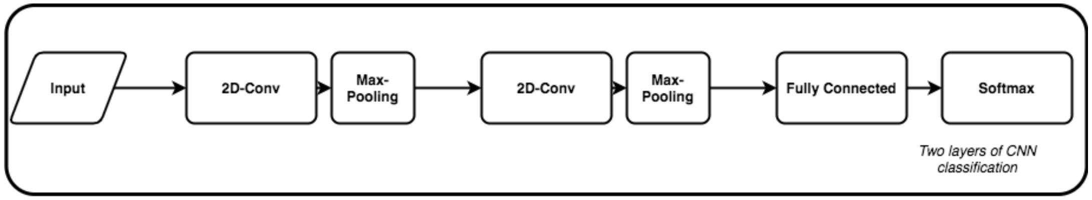
Results-Accuracies for different tasks using single task CNN

The classification of *driving behaviors* such as **aggressiveness** seems to be much harder to learn from this data alone



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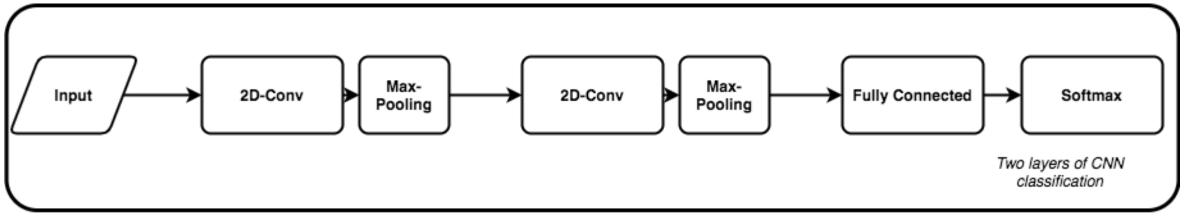
Results-Accuracies for different tasks using single task CNN

Big Questions:

1. Do **behavioral** labels help with **action** classification? **YES!**
2. Do **action** labels help with **behavioral** classification? **YES!**



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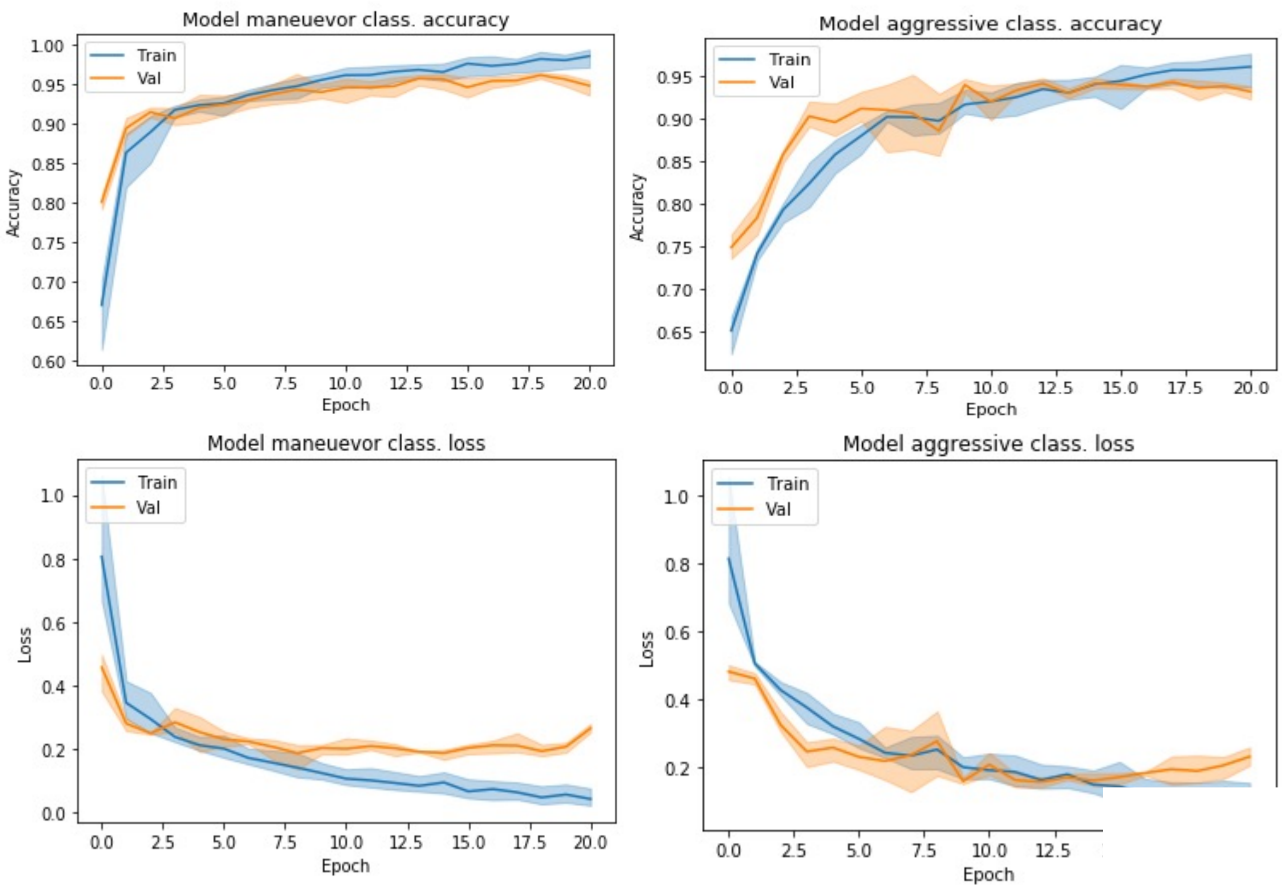
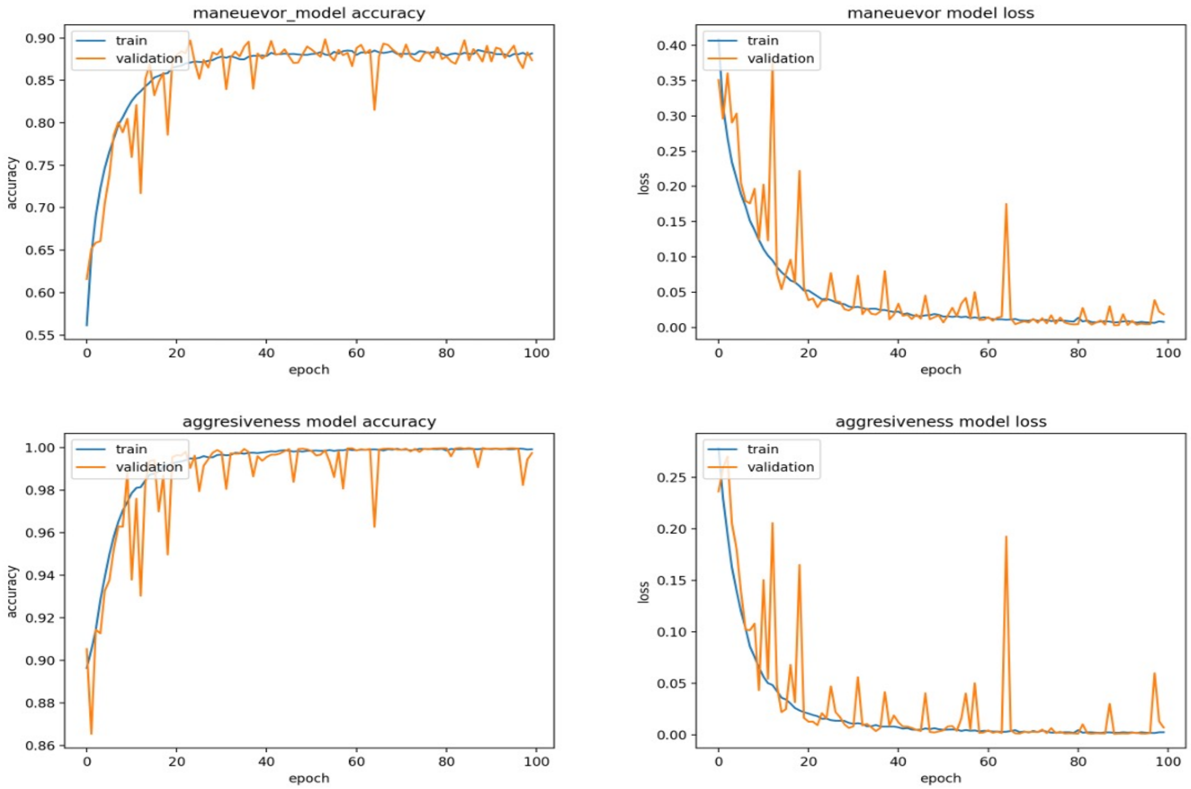
Results-comparison of PCNN results on different datasets and different methods on the simulated dataset

Method	**Manoeuvre Classification** F1 score	**Behavior Classification** F1 score	**Manoeuvre Classification** F1 score	**Behavior Classification** F1 score
Time window size	3sec	3sec	2sec	2sec
PCNN Simulated Time Series Data	0.75	0.65	0.72	0.51
PCNN on Simulated Time Series Data with Rotated x and y	**0.97**	0.94	**0.96**	0.90
PCNN on DBL Time Series Data	0.87	**0.98**	0.85	**0.95**

Results- PCNN model tasks analysis on simulated time series with rotated x and y



Results- PCNN model tasks analysis on real word-driven dataset



Contributions

- The presented work provides a comprehensive analysis of aggressive driver behaviours investigating manoeuvres, aggressive and normal driver behaviours
- A combined simulation procedure (SUMO + Webots) is automated and randomized. Therefore, the simulated dataset is unique and large-scale.
- DBL dataset is large real world driven dataset.
- Parallel-CNN is the first attempt to figure out aggressive driver behaviour by using shared layers of CNNs using time series for multiple tasks .
- The proposed PCNN method works efficiently for driver behavior classification task using simulated dataset.
- PCNN method also is validated by using a small real driving dataset (UAH) collected via smart-phone.
- This study aims to utilize data which can be collected cost-efficiently. Although we will be using in-vehicle sensors to validate method, the method can be applicable to the data that is collected by using basic smartphone sensors.
- The possible application of this study can be an ADAS or driver assessment system for determining insurance.

References

- [1] N. A. Stanton, G. H. Walker, and P. M. Salmon, Human factors in automotive engineering and technology. Ashgate Publishing, Ltd.,2015
- [2]-The National Cooperative Highway Research Program (NCHRP)
- [3]-Johnson, Derick, and Mohan M. Trivedi. "Driving style recognition using a smartphone as a sensor platform." *Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on*. IEEE, 2011.
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(Some of) The Team

Thank you!

THANK YOU!