Classification of Automated Driving System

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Introduction

- Rise of autonomous vehicles introduces variety of automated and self-driving systems.
- SDVs separate hardware from software to support flexible deployment of ADS
- Vehicles may soon run different automated driving software -both OEM and aftermarket solutions using SDVs
- ADS continuously updated with new features and safety improvements through OTA updates
- Customers may choose different systems from different vendors for various driving (e.g. urban vs highway)

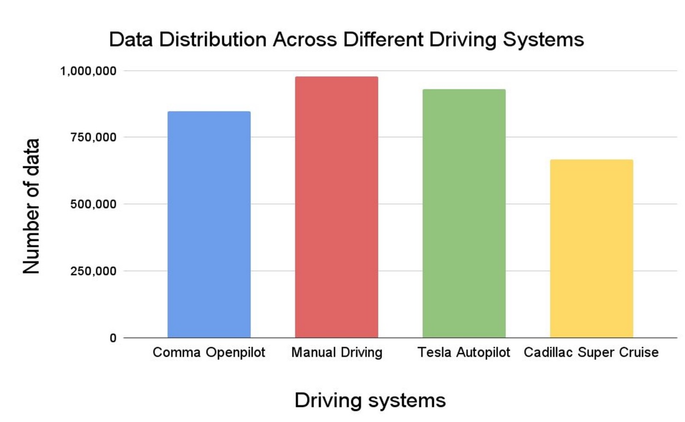
Problem Statement

- Multiple ADS per vehicle requires verifying which ADS is active at any time
- Software can lie
  - Eg: Dieselgate scandal shows valid software can hide real behaviour
- Imagine an accident occurs in such hybrid world. Who's at fault?
- Most research has focused on differentiating human drivers and their behaviours only
- There is a need to classify driving systems (human and automated) for safety and accountability

Method: Data Collection and Preprocessing

Data Sources:

- Used three publicly available telematics datasets:
  - Comma2k19 Dataset (aftermarket solution)
  - Tesla-on-Road Dataset (OEM)
  - Cadillac-on-Road Dataset (OEM)



Feature Selection:

- Used TSFRESH to select 22 relevant features from carstate event of Comma dataset
- Correlation Analysis to remove correlated features resulting 17 features
- Compared 17 selected features with other dataset and found 11 common features in all dataset and 14 features common in Comma and Cadillac dataset

Comma	Cadillac	Tesla
vEgo (m/s)	VehicleSpeed (mph)	Veh_speed (kph)
aEgo	ActVehAccel (m/s^2)	RCM_longitudinalAccel (m/s^2)
Gas	gasPedalandACC	Pedal_accel
yawRate	Inertial1YawRate (deg/s)	RCM_yawRate (rad/s)
standstill (0|1)	VehMovState (1|2 |3 |4)	veh_state_drive (0|1|2|5)
brakePressed (0|1)	BrkPedTrvlAchvd (0 |1)	veh_brake_state (0 |1)
brakeLights (0|1)	BrkLtsAtv (0|1)	ESP_brakeApply (0|1)
steeringAngleDeg (deg)	SteeringWheelAngle (deg)	veh_steering_angle (deg)
steeringRateDeg (deg/s)	SteeringWheelRate (deg/s)	veh_steering_speedps (D/S)
leftBlinker (0|1)	TurnSignals (0|1|2)	VCLEFT_turnSignalStatus (0|1)
rightBlinker (0|1)	TurnSignals (0|1|2)	VCRIGHT_turnSignalStatus (0|1)
steeringPressed (0|1)	LKATorqueDeliveredStatus (0|1)	No similar feature
steeringTorque	LKADriverAppldTrq (Nm)	No similar feature
brake	BrkPdlPos (% full)	No similar feature

Fig: Comparison of common features across datasets

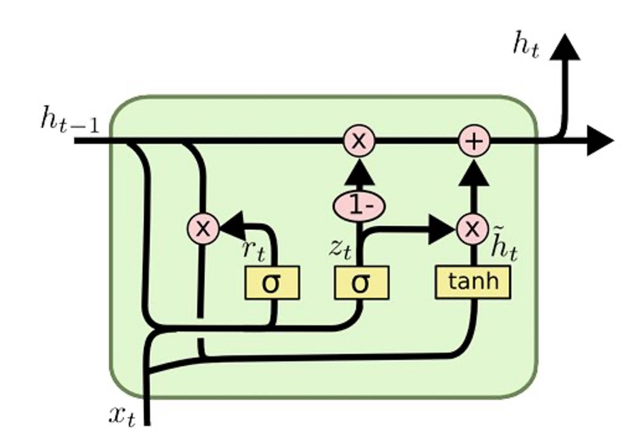
Data Preparation

- Standardize sampling rate to 10Hz in all dataset
- Standardize names of features and units across all dataset
- Merge dataset into unified dataset with 11 features

ML Methodology

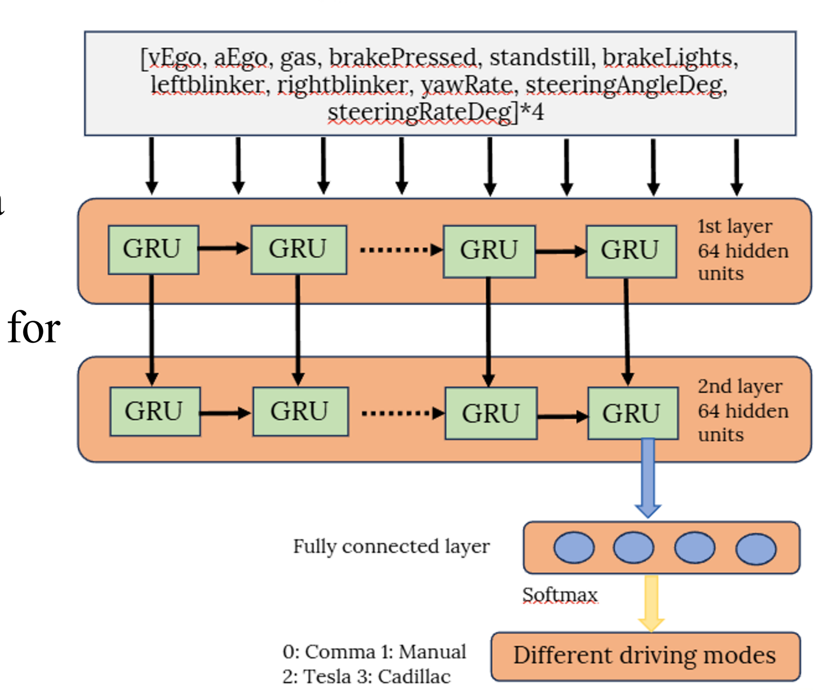
GRU: Gated Recurrent Unit:

- Simpler and faster RNN designed for handling sequential data and capturing long-term dependencies



Model Architecture

- Two-layer GRU-based classifier designed for sequential telematics data
- Trained on sequences of 4 timesteps
- Fully Connected layer at the final step for classification
- Batch size: 64, Epochs 100 with early stopping
- Optimizer: Adam
- Loss Function: CrossEntropyLoss



Model Training and Result

Trained model with 70% data and rest 30% were used for validation and testing

Experiment with 11 features

- Cadillac Super Cruise is detected almost perfectly
- Comma Openpilot rarely misses true cases but has some false positives
- Model "struggles" to classify manual driving

Type of Driving	Precision	Recall	F1-score
Comma Openpilot	0.88	0.96	0.92
Manual Driving	0.92	0.79	0.85
Tesla Autopilot	0.91	0.97	0.93
Cadillac Super Cruise	0.97	0.98	0.97

Fig: Performance Metric of Experiment with 11 features

Experiment with 14 features

- Enhanced detection for all driving types, especially manual driving recognition
- Additional three features: steering torque, steering pressed and brake created clearer boundaries between automated driving and manual driving

Type of Driving	Precision	Recall	F1-score
Comma Openpilot	0.97	0.96	0.97
Manual Driving	0.94	0.95	0.94
Cadillac Super Cruise	0.99	0.99	0.99

Fig: Performance Metric of Experiment with 14 features

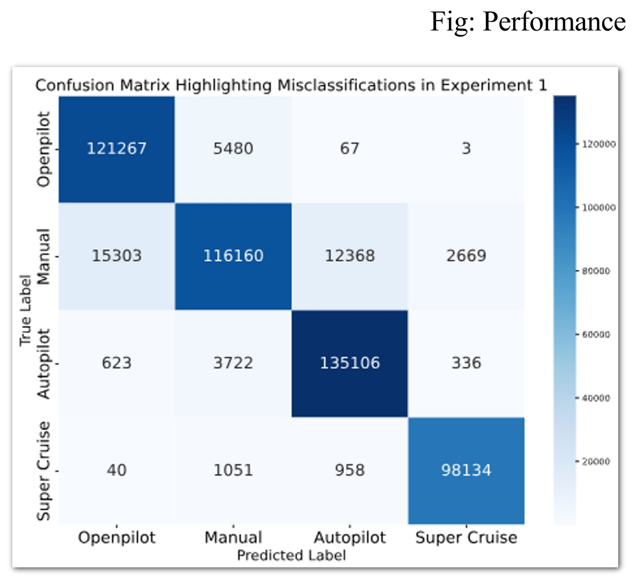


Fig: Confusion matrix with 11 features

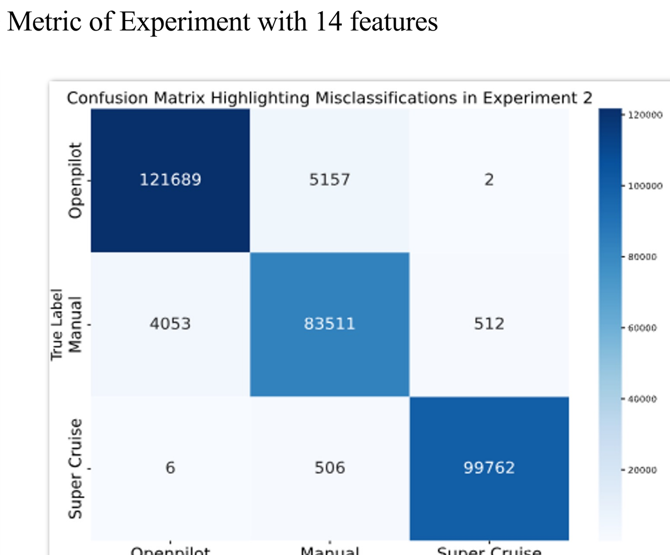


Fig: Confusion matrix with 14 features

Conclusions and Future Work

- Developed automated driving system classification model verifies the active automated system with over F1-score 90%
- Identified key features affecting classification (speed, acceleration, brake and steering angle)
- Our research is applicable to accident forensics, cybersecurity and regulatory compliance
- Significant challenges in handling heterogenous telematics datasets:
  - Difference in sampling rates, feature availability, units and naming conventions
  - Extensive normalization and preprocessing required for cross-dataset compatibility
- Future work includes:
  - Extending to additional automated driving systems
  - Exploring advanced sequence models like Transformers, xLSTM
  - Testing robustness under noise and adversial conditions
  - Moving toward external verification of ADS behaviour
- Standardization of telematics like VSS would greatly reduce preprocessing effort, improving interoperability and accelerate ADS safety research.

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