13th Symposium of the European Association for Research in Transportation (hEART2025)
10-12 June 2025, Munich, Germany

Classifying Vehicle Cornering Behavior using Mobile Sensor Data

Aristotelis Tsoutsanis, George Yannis

National Technical University of Athens, Department of Transportation Planning and Engineering, Athens, Greece

Introduction

Cornering behavior plays a critical role in vehicle stability and road safety. Sharp or aggressive turns significantly increase the **risk of rollovers** and **loss of control**. With the growing availability of mobile sensors—like accelerometers, gyroscopes, and GPS—mounted on smartphones, it is now feasible to monitor such behaviors at scale and in real-time. These capabilities are increasingly valuable in contexts such as driver monitoring, usage-based insurance, and the development of intelligent transportation systems.

A full overview of the pipeline is shown in the Figure 1.

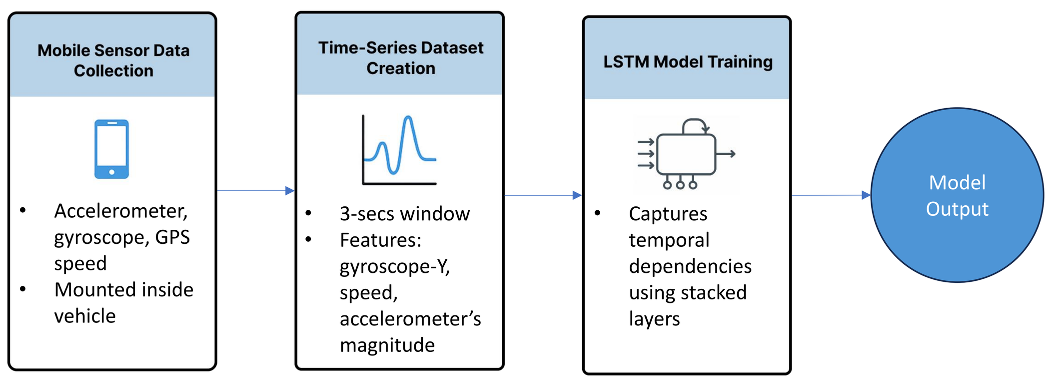

Figure 1: Schematic overview of the data processing and classification pipeline for vehicle cornering behavior.

Objectives

This study leverages smartphone sensor data to **classify vehicle cornering events** as either normal or aggressive, aiming to support safer driving and enable more responsive safety systems.

Data Collection

For the purpose of this analysis, data were collected from over 100 trips and 588,904 mobile readings in two different driving modes: **Normal** and **Aggressive**, from three drivers, each with over 6 years of experience. The driving session took place in Athens, Greece, covering a mix of urban and suburban road conditions.

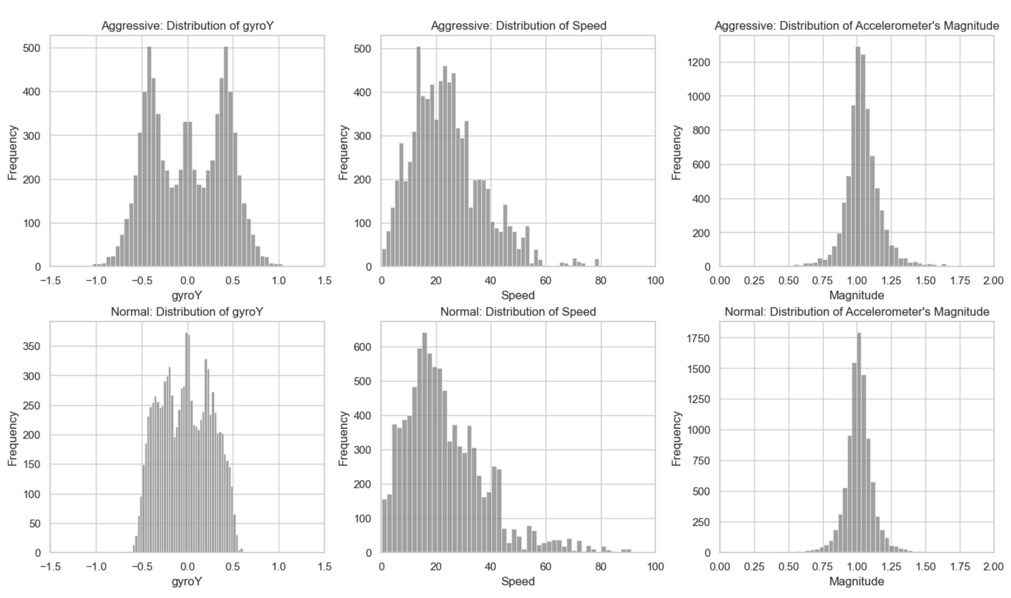

Figure 2: Distribution of normal and aggressive turns

A **custom mobile app** for iOS was created to capture telematics data that consist of accelerometer (3 axes), gyroscope (3 axes), and GPS speed. The sampling rates of accelerometer and gyroscope data were set to 5Hz, while GPS speed was recorded at 1Hz. The smartphone was mounted inside the vehicle as shown in Figure 3.

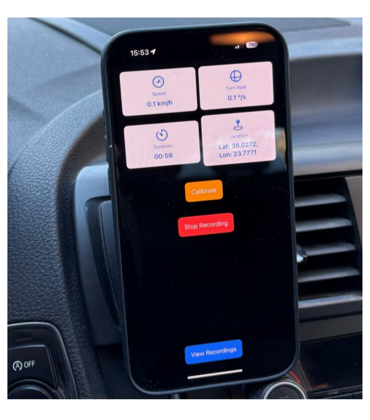

Figure 3: Example of the mounted device during recording

Methodology

- **Coordinate System Alignment**: The device's axes were realigned to the vehicle's frame using a rotation matrix based on a stationary calibration method that can be estimated through an optimization scheme as shown in Algorithm 1.

Algorithm 1 Optimization Algorithm for computing rotation matrix

1: **Compute Rotation Matrix to Align Gravity:**
Require: Captured vector $\mathbf{g} = [g_x, g_y, g_z]^T$ ▷ Coordinate system 2
2: initial_guess $\leftarrow [0, 0, 0]$ ▷ Initial rotational angles
3: target vector $\mathbf{t} \leftarrow [0, -1, 0]^T$ ▷ Coordinate system 1
4: $\mathrm{R} \leftarrow \min(||\mathbf{t} - R_{21} \cdot \mathbf{g}||^2, \text{initial\_guess})$
5: **return** R

- Significant **peaks** on the gyroscope ($\geq 0.2\, rad/s$) were used to identify turning events as shown in Figure 4.
- Model Training: A **stacked 4-layer LSTM** neural network was used to classify turns, trained on balanced time-series windows.

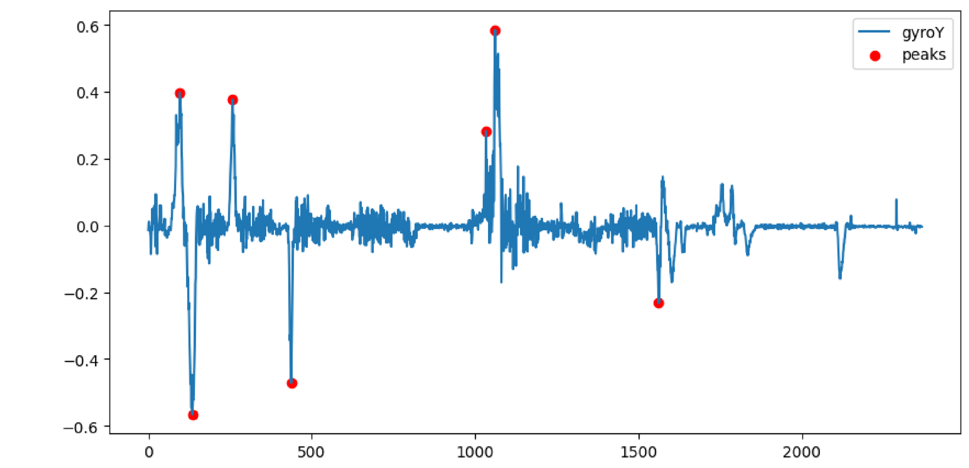

Figure 4: Gyroscope Y-axis with peak detection after data smoothing step

Results

For each peak, a multi-variate time-series window of **3 seconds** was extracted, which corresponds to a complete cornering event. This window was labeled as either normal or aggressive based on the driving mode. A subset of the dataset is shown in the Figure 6.

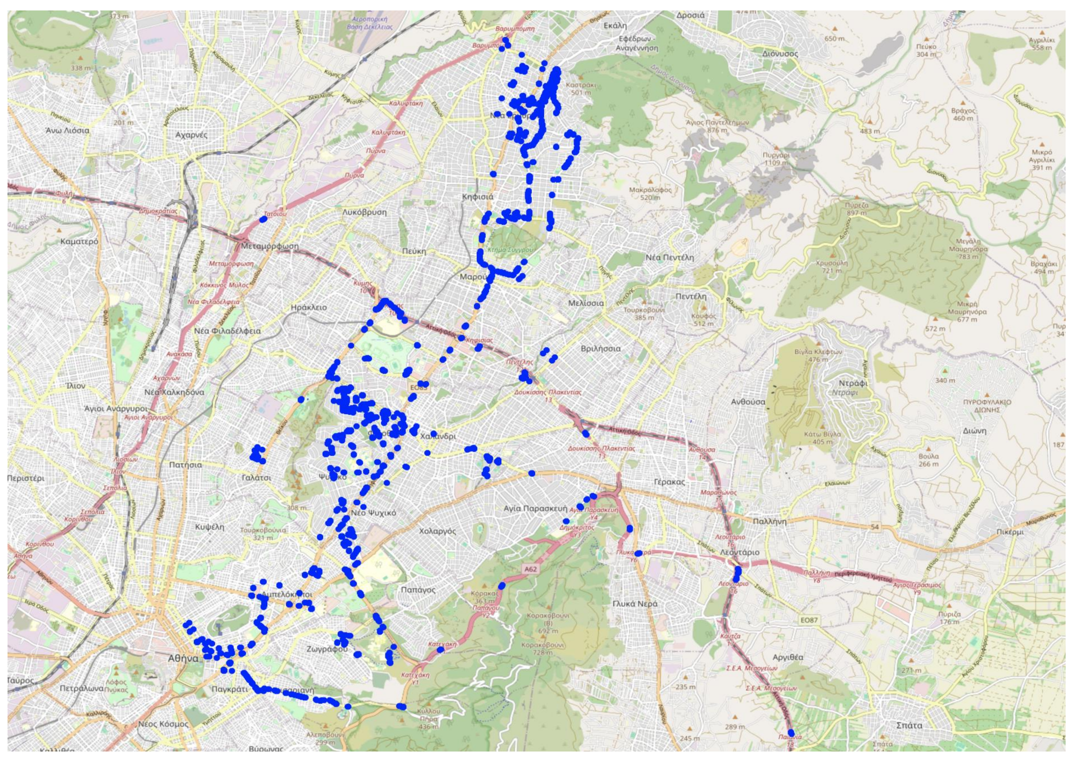

Figure 6: Map displaying detected cornering events

To ensure a balanced dataset suitable for supervised learning, we applied a data augmentation technique to address class imbalance by flipping gyroscope-Y readings in aggressive events and subsequently downsampled the dominant class. The final dataset comprised on a balanced set of 2,424 labeled cornering events (1,212 normal, 1212 aggressive). A **4-layer Long Short-Term Memory** (LSTM) Neural Network was trained on time-series segments capturing gyroscope Y-axis, GPS speed, and accelerometer magnitude. These features were chosen for their ability to jointly capture rotational motion, vehicle dynamics, and overall acceleration forces during cornering maneuvers.

Classification Results

Table 1 provides a summary of the model's classification performance, including accuracy, precision, recall, and F1 score. The model achieved an **accuracy of 84.01%** on the test set. With a precision of 84.61% and recall of 85.27%, the model demonstrates effective detection of both normal and aggressive cornering events. The F1 score of 84.94% reflects a strong balance between precision and recall, making it a more informative metric than accuracy alone in evaluating overall performance.

Table 2 provides an overview of the **key hyperparameters** used during training. These include a learning rate of 0.004, a batch size of 32, and 200 training epochs, optimized using the Adam optimizer. A dropout rate of 0.5 was applied to reduce overfitting. These hyperparameters were selected based on iterative trial-and-error experiments to optimize model performance.

Table 1: Evaluation metrics for our classification model

Metrics	Score
Accuracy	84.01%
Precision	84.61%
Recall	85.27%
F1 Score	84.94%

Table 2: Key hyperparameters used during model training.

Metrics	Score
Learning Rate	0.004
Batch Size	32
Dropout	0.5
Optimizer	Adam
Epochs	200

Conclusions

- A **full pipeline** was implemented, including coordinate alignment, event detection, data augmentation, and deep learning classification.
- The LSTM model demonstrated **strong performance** in identifying risky cornering events using only onboard smartphone sensors.
- This approach has potential applications in **driver behavior monitoring**, **insurance telematics**, and **fleet safety management**.
- The use of only smartphone-based sensors further underscores the practicality of the system, allowing for **scalable deployment** in diverse real-world driving environments
- Future work will include **enriching input features** (e.g. road curvature, traffic signs) and validating the model across **diverse geographical regions**, **road infrastructures**, and **driver demographics** to assess its robustness and generalizability.

Acknowledgments

This research has been conducted within the IVORY project. The project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101119590.

IVORY

Contact Information:
Aristotelis Tsoutsanis, MSCA Researcher
Department of Transportation Planning and Engineering, NTUA
OSeven Telematics
Email: a_tsoutsanis@mail.ntua.gr
Website: https://www.nrso.ntua.gr/p/atsoutsanis/