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Can Your Phone Detect a Dangerous Corner?

**Self-Supervised Harsh Cornering
Detection at Scale via Smartphone
Telematics**

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OSEven Telematics

Transport Research Arena 2026 ·
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What We'll Cover

From the problem to the pipeline — and the numbers that matter

- 01 Why Cornering? — Motivation & Background
- 02 Data in the Wild — Collection & Preprocessing
- 03 Self-Supervised Pipeline
- 04 How Well Does It Work? — Results & Discussion
- 05 What's Next — Conclusions & Future Work



Motivation & Background

- Harsh cornering is linked to vehicle instability and elevated rollover risk
- Rollovers = ~3% of crashes but ~1/3 of passenger fatalities (Padmanaban & Husher, 2005)
- Smartphones with accelerometers, gyroscopes & GPS enable large-scale driving behaviour monitoring
- Prior work has focused on longitudinal events (hard braking/acceleration); cornering remains under-explored
- Key challenges: arbitrary phone orientation, no ground-truth labels, sensor noise
- **Goal:** self-supervised, scalable detection of harsh cornering without manual annotation

Data Collection & Preprocessing

4,017

trips

1.76M

data points

1,900

validated turns

1 Hz

sampling rate



Source & Sensors

- › OSeven Telematics — anonymised naturalistic driving data
- › GPS: lat/lon, speed, heading
- › Accelerometer: 3-axis
- › Gyroscope: 3-axis
- › Diverse road environments



Yaw Rate Estimation

- › GPS heading changes normalised over 1–4 second horizons
- › Sensor-fusion-free proxy for cornering behaviour
- › Robust across vehicle types and sensor placements



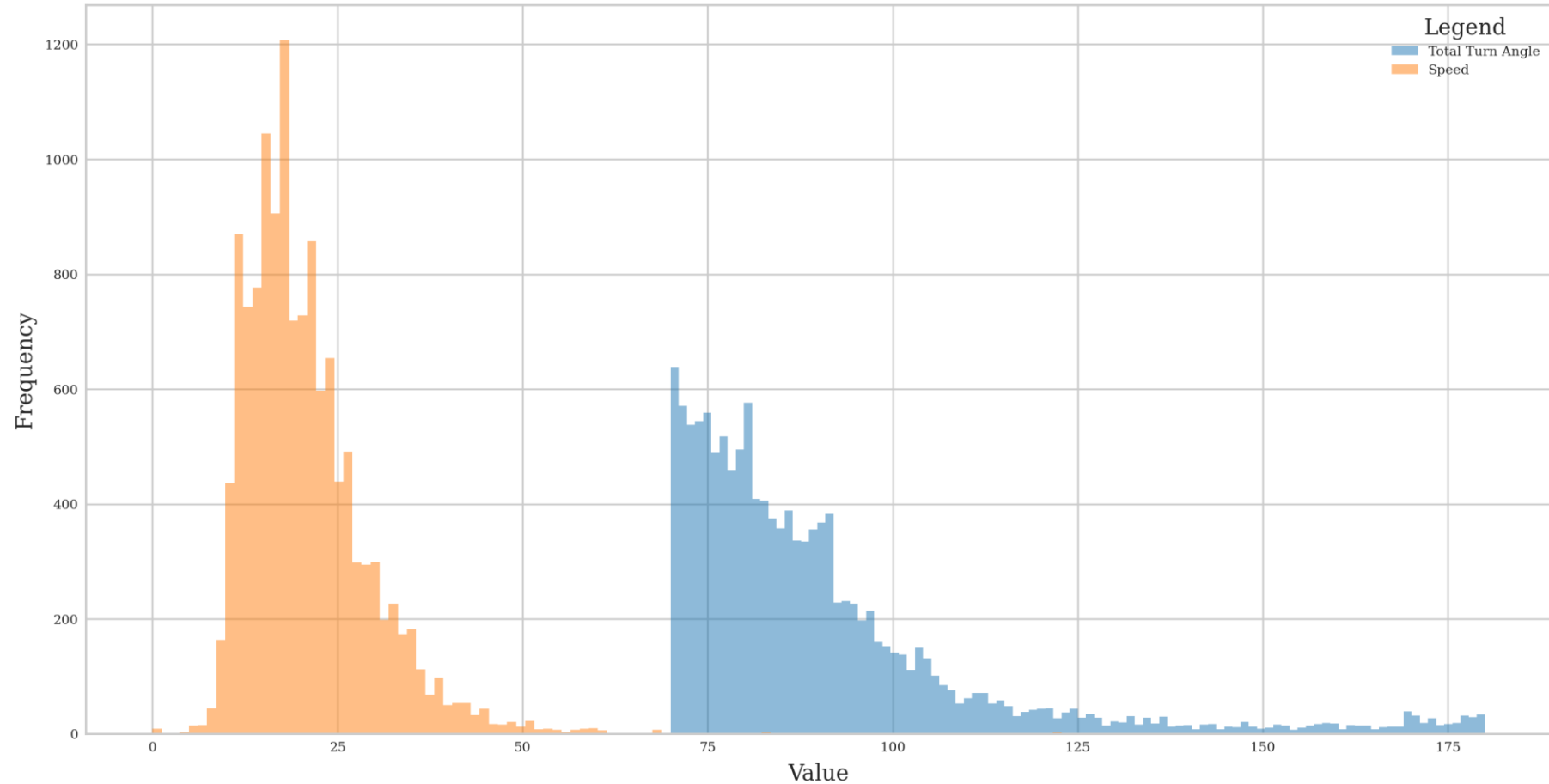
Validation & Invariance

- › OpenStreetMap intersection check within 15 m
- › 1,900 turn events validated against map data
- › 3-axis Euclidean magnitudes for orientation invariance

Distribution of Turn Events

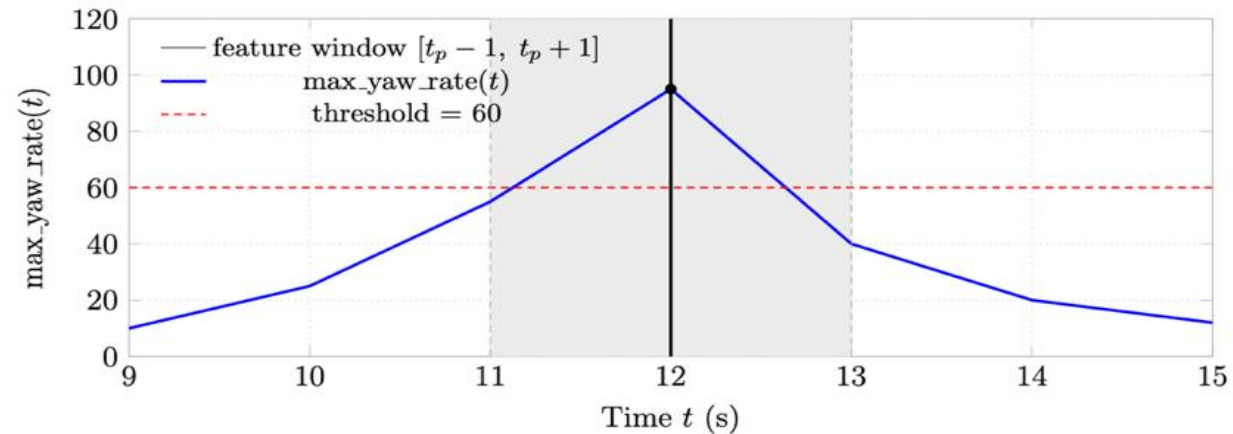
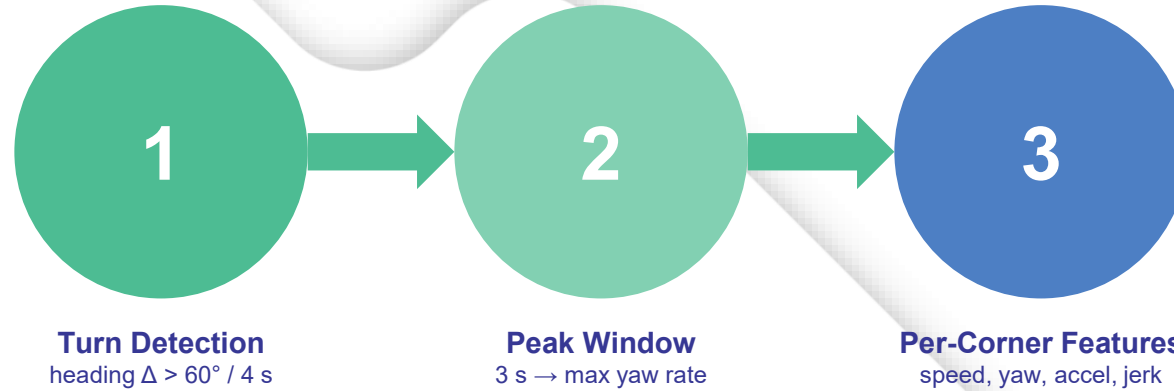
- 1,900 validated turn events
- The histogram shows the distribution of total turn angles and vehicle speeds across all turning events in the dataset
- Predominantly involving 70°–180° turns at speeds below 30 km/h

Distribution of Total Turn Angle and Speed



Feature Engineering

- Each turn event is isolated by a heading change threshold ($\Delta > 60^\circ$ over 4 s)
- A 3-second peak window captures the most dynamic phase of the manoeuvre
- Per-corner statistics are compiled into a fixed-length vector ready for model input



Features

- Mean & peak speed
- Max yaw rate & angle
- Accel & gyro magnitude
- Jerk & corner duration

\rightarrow fixed-length vector



Self-Supervised Detection Pipeline

① Seed the Labels

Ensemble anomaly detectors find the outliers

② Train the Classifiers

Supervised models learn from pseudo-labels



Step 1: Pseudo-Label Generation

No ground-truth labels → ensemble anomaly detection as seeding strategy

- **Isolation Forest** — ease of isolation via random partitioning
- **Local Outlier Factor (LOF)** — density-based local comparison
- **One-Class SVM** — boundary of the majority class

→ Scores rank-normalised $[0,1]$ and averaged across all three detectors

→ **Top 5% = positive seeds (harsh)**; equal random sample = normal seeds

Step 2: Supervised Classification

Four classifiers trained on pseudo-labelled data (80/20 stratified split):

- **Logistic Regression**

- **linear baseline**

- **SVM**

- **non-linear kernel, highest PR-AUC**

- **Random Forest**

- **balanced ensemble of decision trees**

- **MLP**

- **2-layer (64 units → 16-dim latent), AdamW + early stopping**

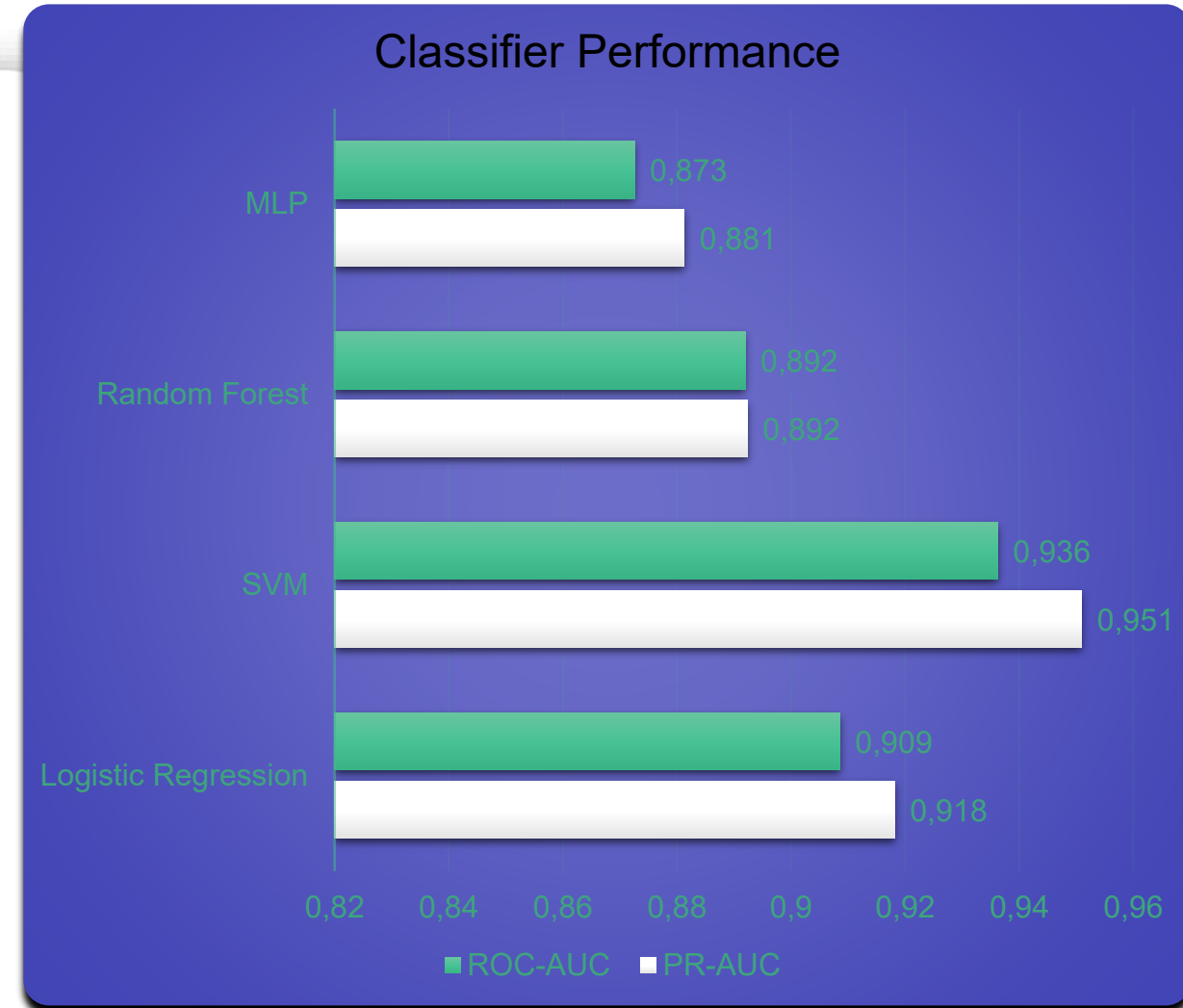
→ **MLP latent embeddings** used for k-means clustering (k=2) and interpretability

→ **latent space silhouette = 0.759**

Results & Discussion

- Logistic Regression: 0.918 / 0.909
- **SVM: 0.951 / 0.936**
- Random Forest: 0.892 / 0.892
- MLP: 0.881 / 0.873

→Key features: yaw rate, accel jerk, gyro magnitude



Conclusions & Future Work

- Self-supervised framework detects harsh cornering without manual annotation
- Orientation-invariant features and OSM validation
- All classifiers AUC >0.87
- MLP latent space silhouette = 0.759 (clear separation)
- Applications: insurance telematics, fleet management, urban safety planning

Future work:

- Validate across diverse regions and OBD data as validator
- Temporal patterns of risky driving; integrate video / CAN-bus data



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