

## **Title: Driver Behavior Classification using Traditional ML and Deep Learning Models**

This repository contains the source code for the study titled:

**"Temporal and modal contributions to smartphone-based multimodal driving behavior classification: A comparative study of classical, deep learning, and patch-based time series transformer models"**

The goal of this research is to classify driver behavior into three categories (AGGRESSIVE, NORMAL, and CALM) based on OBD-II, motion sensor, and audio signal data. The experiments explore the effects of different feature subsets and time window lengths using both classical machine learning algorithms and deep learning architectures.

---

### **Repository Structure:**

- 1-run\_standard\_ml.py: Runs ML models: Logistic Regression, SVM, Naive Bayes, ANN
  - 3-run\_all\_patchtst.py: Runs PatchTST transformer-based model
  - 4-statistics.py: Performs statistical testing (ANOVA, Mann-Whitney U)
  - 5-statistics.py: Post-hoc tests (Tukey HSD, visualization)
  - DL codes/
    - main.py: Main script for training deep learning models
    - models.py: Model definitions: CNN, LSTM, GRU, InceptionTime, TCN, RCNN, TabNet
    - trainer.py: Training loop with early stopping and fold-wise metric saving
    - utils.py: Data loading, metric plotting, saving results
- 

### **Dataset Description:**

This study utilizes a curated dataset compiled from OBD-II signals, smartphone sensor readings (accelerometer, gyroscope, magnetometer, GPS), Overpass road metadata, and ambient audio recordings.

- The dataset is organized into 3 classes: AGGRESSIVE, NORMAL, and CALM.
- Each data file is a CSV of size 150x37, corresponding to a 3-second time window at 50Hz.
- The 37 features include:
  - Motion features (gravity, acceleration, rotation)
  - Engine data (RPM, load, speed, MAF, MAP)
  - Road metadata (surface, oneway, highway type, max speed)

- Audio features (RMS, ZCR, Spectral Centroid, Bandwidth, Rolloff, Entropy, etc.)

Note: Some columns are categorical and are handled via encoding in the preprocessing pipeline.

---

### **Preprocessing & Setup:**

- Categorical columns are label-encoded (e.g., road type, surface).
  - All features are normalized using StandardScaler.
  - Sliding windows with overlap are used to generate more training data.
  - Cross-validation is stratified 10-fold.
  - Experiments are deterministic via fixed seed settings.
- 

### **Models and Training:**

*Classical ML:*

- Logistic Regression
- Support Vector Machine
- Naive Bayes
- Artificial Neural Network (MLP)

*Deep Learning (DL):*

- CNN
- LSTM
- GRU
- CNN + LSTM
- LSTM + GRU
- InceptionTime
- TCN
- RCNN
- TabNet
- PatchTST (Transformer-based)

DL models are trained using PyTorch, with early stopping and performance logging.

---

### Evaluation:

- Accuracy, Precision, Recall, and F1-score metrics are computed.
  - Additional visualizations include confusion matrices, ROC curves, and training-validation plots.
  - Results are averaged across folds with standard deviations.
- 

### Statistical Analysis:

- ANOVA
- Mann-Whitney U
- Tukey HSD

Analysis covers:

- Model comparisons
  - Feature set impacts
  - Effect of time window length
- 

### Reproducibility:

- All experiments run with:
    - Python 3.10
    - PyTorch 2.1
    - scikit-learn, NumPy, Pandas, Matplotlib
  - Random seed = 42 ensures consistent results.
- 

### Citation:

If you use this codebase or replicate this study, please cite:

Sağbaşı, E. A., et al. (2025). *Temporal and modal contributions to smartphone-based multimodal driving behavior classification: A comparative study of classical, deep learning, and patch-based time series transformer models*. PeerJ Computer Science, Under Review.

---

### Contact:

Ensar Arif Sağbaşı

Muğla Sıtkı Koçman University – Information Systems Engineering Department

Email: arifsagbas[at]mu.edu.tr