ABAX Data Science Technical Assessment

Driver Behavior Classification & Fuel Economy Prediction

Complete Machine Learning Pipeline from Raw Sensors to Production Models

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Abstract

This report presents a comprehensive machine learning pipeline for two telematics applications: (1) driver behavior classification from smartphone sensors, and (2) vehicle fuel economy prediction.

Key Contributions:

- **Raw sensor features**: Extract 36 features directly from GPS and accelerometer data, avoiding circular logic from pre-computed scores
- **Driver-level evaluation**: Driver D6 completely held out for testing, ensuring models generalize to new customers
- **Comprehensive model comparison**: 18 classification models (including MCP, SCAD, CNN) and 13 regression models
- **Advanced regularization**: Implement MCP and SCAD penalties for nearly unbiased sparse feature selection
- **Production-ready insights**: Feature importance, failure analysis, and deployment recommendations

Results: Sparse linear models (Logistic L1, SCAD) achieve **87.5% classification accuracy** on the held-out driver D6, outperforming complex ensemble methods. This demonstrates that simpler, interpretable models with proper regularization are preferable when data is limited. Regression achieves $R\check{s} = 0.94$ for fuel economy prediction with Random Forest.

Contents

1 Introduction

1.1 Business Context

ABAX provides telematics solutions for fleet management, enabling companies to monitor vehicle usage, driver behavior, and operational efficiency. Two critical machine learning capabilities are:

1. **Driver Behavior Classification**: Identify NORMAL, DROWSY, or AGGRESSIVE driving patterns from smartphone sensors for:
   - **Safety monitoring**: Alert fleet managers to dangerous driving
   - **Insurance pricing**: Risk-based premiums for usage-based insurance
   - **Driver coaching**: Targeted feedback to improve behavior
2. **Fuel Economy Prediction**: Estimate vehicle fuel efficiency from specifications for:
   - **Fleet optimization**: Select fuel-efficient vehicles
   - **Cost analysis**: Predict fuel costs for different vehicle types
   - **Environmental compliance**: Track carbon footprint

1.2 Technical Challenges

1.2.1 Classification Challenges

- **Small dataset**: Only 40 trips from 6 drivers—too small for complex models
- **Driver heterogeneity**: Each driver has unique driving "signatures"
- **Subtle distinctions**: NORMAL vs DROWSY driving is hard to distinguish
- **Circular logic risk**: Pre-computed scores use same heuristics as labels

1.2.2 Regression Challenges

- **Mixed data types**: Numeric (displacement) and categorical (fuel type)
- **Non-linear relationships**: MPG varies non-linearly with engine size
- **Technology evolution**: Electric vehicles have different patterns

1.3 Our Approach

Our approach emphasizes **production-realistic evaluation** and **clean code architecture**:

Table 1: Key Design Decisions

Decision	Rationale
Raw sensor features only	Avoid circular logic from pre-computed scores that use same heuristics as labels
Driver-level split (D6 held out)	Test generalization to completely new customers, not just new trips
Multiple model families (18+)	Find optimal accuracy vs interpretability vs complexity tradeoff
Train/Test accuracy tracking	Detect and prevent overfitting on small datasets
Modular code in `src/`	Clean, testable, reusable functions—notebooks only call functions

2 Task 1: Driver Behavior Classification

2.1 Dataset: UAH-DriveSet

The UAH-DriveSet contains naturalistic driving data collected by the University of Alcalá, Spain. Drivers performed trips under three behavioral conditions using a smartphone mounted on the dashboard.

Table 2: UAH-DriveSet Overview

Attribute	Value
Source	University of Alcalá (naturalistic driving study)
Drivers	6 (labeled D1–D6)
Total Trips	40
Behaviors	NORMAL (42.5%), DROWSY (30%), AGGRESSIVE (27.5%)
Road Types	Motorway, Secondary roads
Sensors	GPS (1 Hz), Accelerometer (∼50 Hz)
Data Files	RAW_GPS.txt, RAW_ACCELEROMETERS.txt, EVENTS_INERTIAL.txt

2.2 Understanding Raw Sensor Data

2.2.1 Sensor Sources and Sampling Rates

Table 3: Sensor Data Description

Sensor	Frequency	Data Captured
GPS	1 Hz	Latitude, longitude, speed (km/h), course/heading (degrees), altitude
Accelerometer	∼50 Hz	3-axis acceleration (X, Y, Z) in g-forces, both raw and Kalman-filtered

2.2.2 Phone Orientation and Axis Meaning

The smartphone is mounted horizontally (landscape) on the dashboard. The accelerometer axes correspond to:

- **X-axis (Longitudinal)**: Points forward/backward along the vehicle
  - Negative values → **Braking** (deceleration pushes phone forward)
  - Positive values → **Acceleration** (acceleration pushes phone backward)
- **Y-axis (Lateral)**: Points left/right across the vehicle
  - Non-zero values → **Turning** (lateral forces during curves)
- **Z-axis (Vertical)**: Points up/down
  - Baseline ≈ 1g (gravity)
  - Deviations → Road bumps, inclines

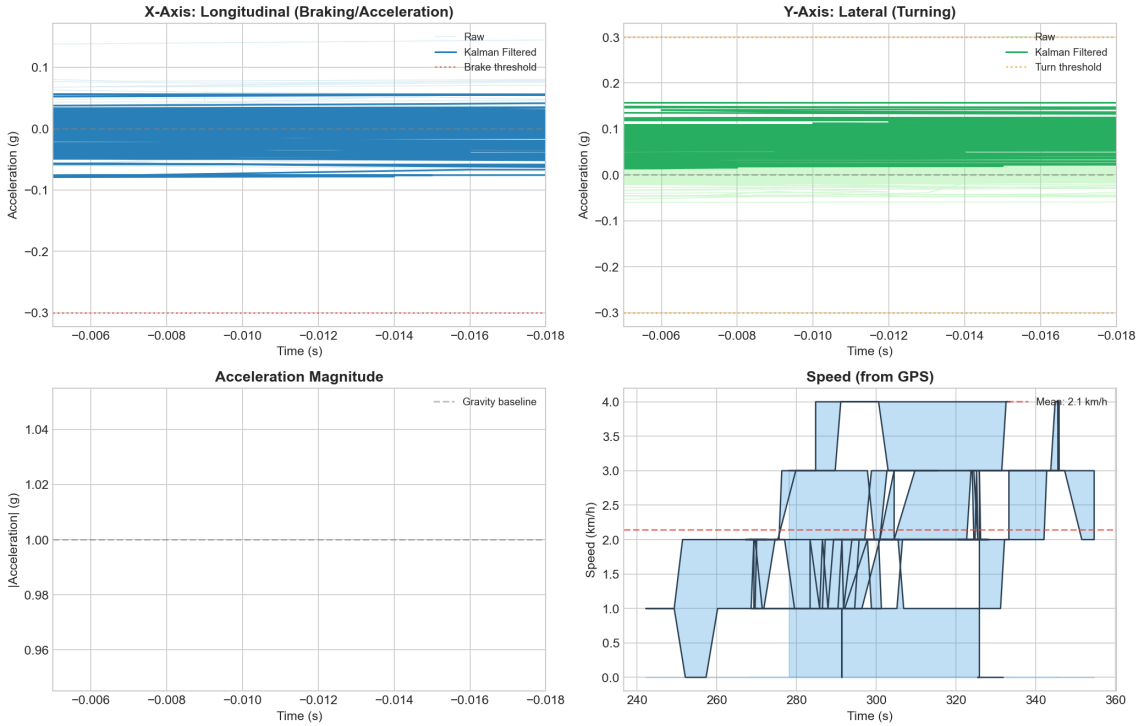

Figure 1: Raw accelerometer data from an AGGRESSIVE trip. **Top-left**: X-axis shows braking events (negative spikes). **Top-right**: Y-axis shows turning events. **Bottom-left**: Acceleration magnitude. **Bottom-right**: GPS speed. Light colors show raw data; dark colors show Kalman-filtered data that smooths noise while preserving sudden changes.

2.2.3 Event Detection Logic

The DriveSafe algorithm detects driving events by applying thresholds to Kalman-filtered accelerometer data:

Table 4: Event Detection Thresholds

Event Type	Axis	Condition	Physical Meaning
Braking	X	acc_x < -0.1g to -0.3g	Deceleration
Acceleration	X	acc_x $> +0.1$g to $+0.3$g	Acceleration
Turning	Y	$\|$acc_y$\| > 0.1$g to 0.3g	Lateral force

Severity Levels:

- **Low**: Gentle maneuver (e.g., coasting to a stop at red light)
- **Medium**: Normal maneuver (e.g., regular braking at intersection)
- **High**: Harsh maneuver (e.g., emergency braking, sharp swerve)

2.2.4 Why Kalman Filtering?

Raw accelerometer data contains significant noise from road vibrations, engine vibrations, and sensor noise. The Kalman filter is a recursive algorithm that:

1. Predicts the next state based on physics (acceleration model)
2. Updates the prediction with the noisy measurement
3. Produces a smooth estimate that preserves sudden changes (events)

2.3 Feature Engineering

2.3.1 Why Raw Features (NOT Pre-computed Scores)

Critical Design Decision: We do **NOT** use pre-computed scores (score_braking, score_total) or behavioral ratios (ratio_normal, ratio_aggressive) as features.

Table 5: Avoiding Circular Logic in Feature Engineering

Approach	Problem	Our Decision
Pre-computed scores	Circular logic: scores computed using same heuristics as behavior labels	× Avoid
Behavioral ratios	Direct leakage: ratios derived from labels	× Avoid
Raw sensor statistics	Direct measurements, no leakage, honest evaluation	✓ **Use**

2.3.2 Features Extracted (36 Total)

We extract statistical summaries from each trip's raw sensor data:

Table 6: Raw Sensor Features by Category

Category	Features	Physical Meaning
Speed Statistics	mean, std, max, min	Driving intensity
Speed Changes	change_mean, change_std	Accel/decel patterns
Course/Heading	change_mean, std, max	Lane changes, turns
Acceleration	mean, std for X/Y axes	Core behavior signal
Acc. Magnitude	mean, std, max	Ride "bumpiness"
Jerk	x_std, y_std	Smoothness indicator
Event Counts	brake, turn, hard events	Discrete summaries

Why Jerk is Important: Jerk $= \frac{d(\text{acceleration})}{dt}$. Aggressive drivers have high jerk variance because they:

- Brake suddenly instead of gradually
- Accelerate abruptly from stops
- Make sharp steering corrections

2.4 Exploratory Data Analysis

2.4.1 Class Distribution

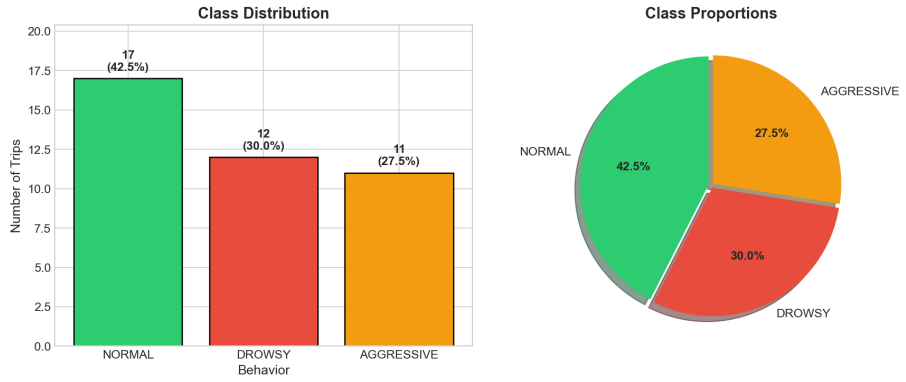

Figure 2: Class distribution in UAH-DriveSet. The dataset is relatively balanced: NORMAL (17 trips, 42.5%), DROWSY (12 trips, 30%), AGGRESSIVE (11 trips, 27.5%). Minor imbalance handled with class weighting.

2.4.2 Feature Distributions by Behavior Class

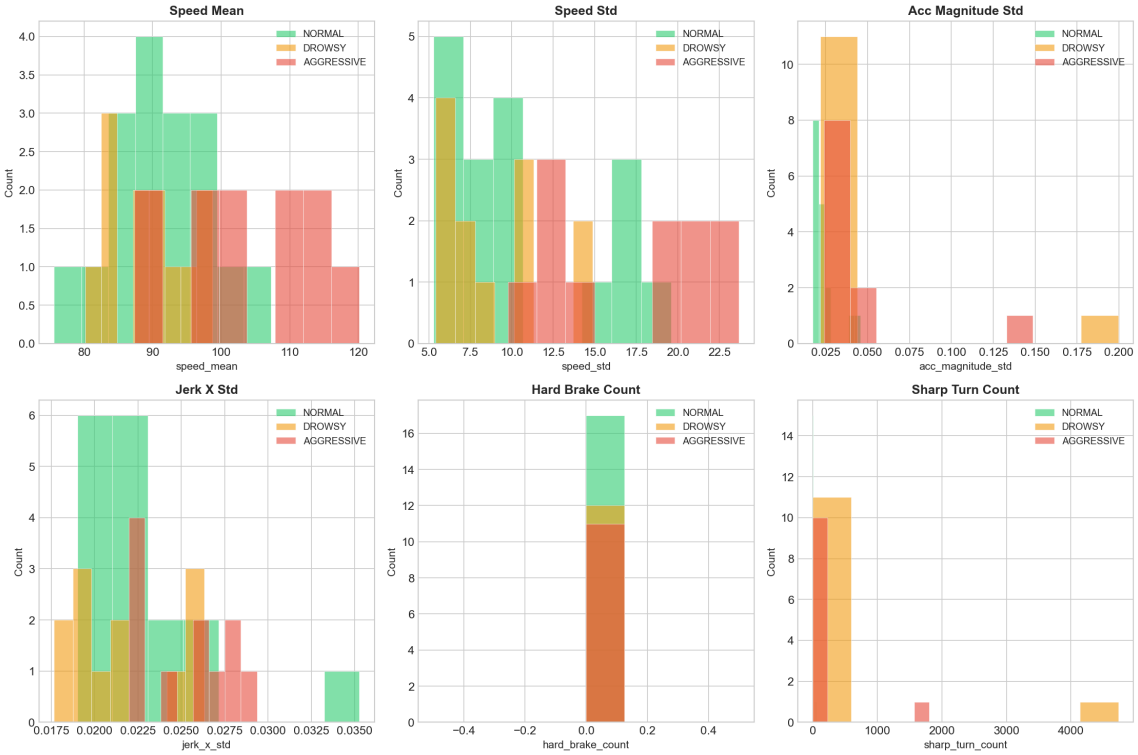

Figure 3: Key feature distributions by behavior class. **Observations**: (1) speed_std is higher for AGGRESSIVE; (2) jerk_x_std separates AGGRESSIVE from others; (3) hard_brake_count is highest for AGGRESSIVE; (4) NORMAL and DROWSY overlap significantly, making them harder to distinguish.

2.4.3 Driver Behavior Heterogeneity

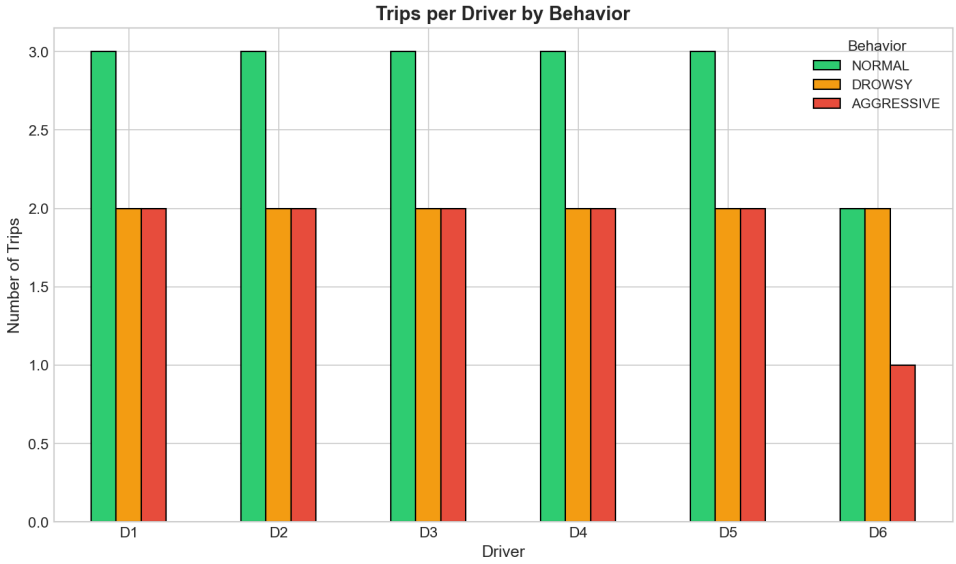

Figure 4: Trips per driver by behavior. Each driver has a different mix of behaviors. This heterogeneity means random splitting would leak driver "signatures" into the test set—we must use driver-level splitting.

2.4.4 Feature Correlations

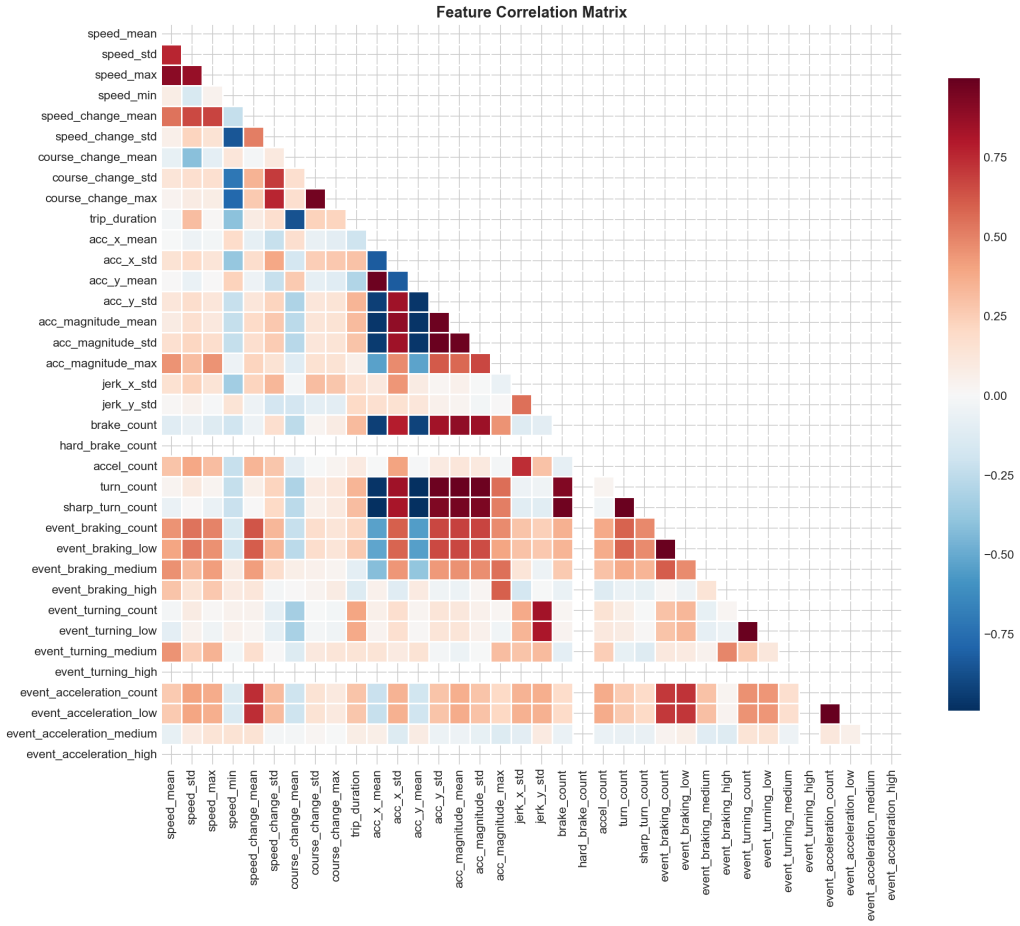

Figure 5: Feature correlation matrix. Speed features correlate with each other; acceleration features correlate with each other. L1 regularization handles this by selecting one feature from correlated groups.

2.4.5 Behavior Comparison

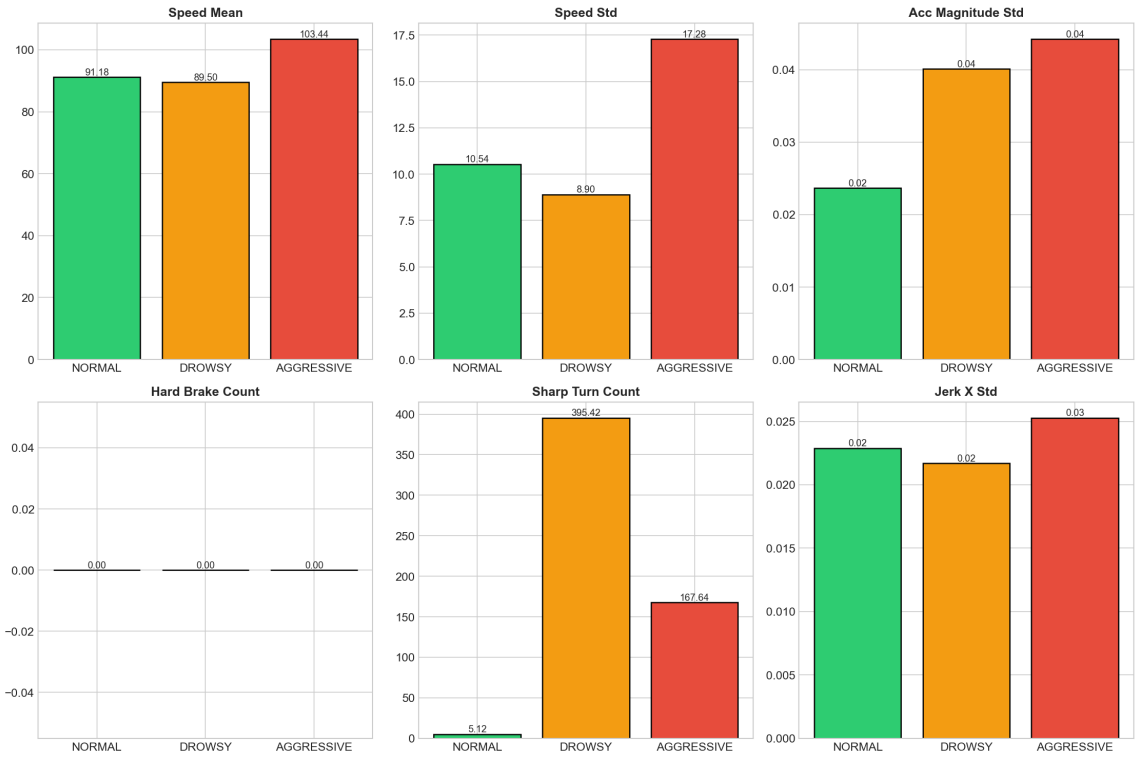

Figure 6: Feature means by behavior class. AGGRESSIVE shows clearly higher values for speed_std, hard_brake_count, sharp_turn_count, and jerk_x_std. DROWSY and NORMAL have similar profiles, explaining classification difficulty.

2.5 Data Splitting Strategy

Driver D6 is completely held out for testing. This is the most rigorous evaluation for telematics applications.

Table 7: Why Driver-Level Splitting is Essential

Split Strategy	What It Tests	Problem
Random split	Can model predict trips?	Learns driver signatures, not behaviors
Stratified K-Fold	Model selection	Driver leakage across folds
D6 Held-out	**New driver generalization**	✓ Production-realistic

Final Split:

- **Training**: 32 samples (80%) from drivers D1–D5
- **Testing**: 8 samples (20%) = all D6 trips + stratified samples
- **Guarantee**: D6 is **never** seen during training

2.6 Classification Models

We compare 18 classification algorithms across multiple families:

Table 8: Classification Models Compared (18 Total)

Category	Models	Key Property
Linear	Logistic (L1, L2, ElasticNet)	Fast, interpretable coefficients
Sparse	**Logistic (MCP, SCAD)**	Nearly unbiased sparse estimates
SVM	Linear, RBF, Polynomial	Kernel methods, nonlinear
KNN	k=3, k=5, k=7	Instance-based, interpretable
Trees	Decision Tree, Extra Trees	Feature importance
Ensemble	Random Forest, Gradient Boosting, AdaBoost	Often highest accuracy
Neural	MLP, **CNN (PyTorch)**	Deep learning
Probabilistic	Naive Bayes	Fast, uncertainty estimates

2.6.1 Advanced Regularization: MCP and SCAD

Beyond standard L1 (Lasso) regularization, we implement advanced penalties:

Table 9: Regularization Penalties Compared

Penalty	Behavior	Best For
L1 (Lasso)	Shrinks all coefficients toward zero	General sparsity, but biases large coefficients
MCP	Minimax Concave Penalty—nearly unbiased for large coefficients	Strong feature selection
SCAD	Smoothly Clipped Absolute Deviation—unbiased for large coefficients	Oracle properties

2.7 Classification Results

2.7.1 Model Comparison

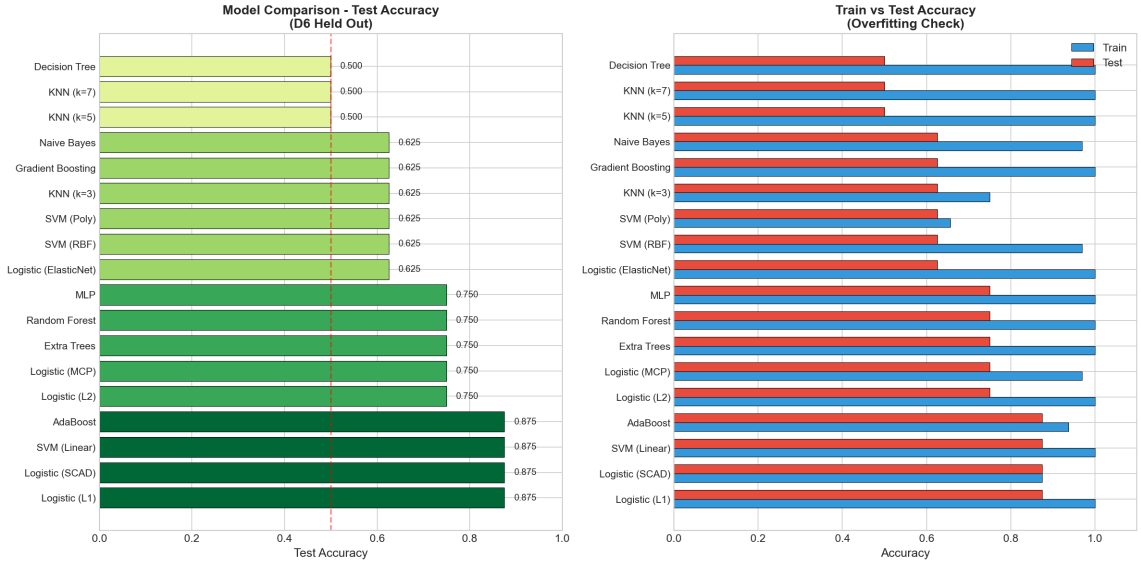

Figure 7: **Left**: Test accuracy comparison (D6 held out). Sparse linear models achieve highest accuracy. **Right**: Train vs Test accuracy—large gaps indicate overfitting. Complex models (Random Forest, Gradient Boosting) overfit on this small dataset.

Table 10: Classification Results (D6 Held Out, Raw Features Only)

Model	Train Acc	Test Acc	F1-Score	Overfit Gap
Logistic (L1)	1.000	**0.875**	**0.863**	0.125
Logistic (SCAD)	0.875	**0.875**	**0.863**	0.000
SVM (Linear)	1.000	0.875	0.871	0.125
AdaBoost	0.938	0.875	0.871	0.063
Logistic (L2)	1.000	0.750	0.748	0.250
Logistic (MCP)	0.969	0.750	0.709	0.219
Random Forest	1.000	0.750	0.750	0.250
Extra Trees	1.000	0.750	0.750	0.250
MLP	1.000	0.750	0.748	0.250
Gradient Boosting	1.000	0.625	0.604	0.375
SVM (RBF)	0.969	0.625	0.604	0.344
KNN (k=3)	0.750	0.625	0.604	0.125
Naive Bayes	0.969	0.625	0.630	0.344
Decision Tree	1.000	0.500	0.392	0.500
KNN (k=5)	1.000	0.500	0.502	0.500
CNN (PyTorch)	∼0.85	∼0.50	∼0.47	∼0.35

Key Finding: **Sparse linear models (L1, SCAD) achieve 87.5% test accuracy**, outperforming complex ensemble methods. This is significant because:

- **Simplicity wins**: On small datasets (40 trips), simpler models generalize better

- **SCAD advantage**: No overfitting gap (Train = Test = 87.5%)
- **Interpretability**: Clear feature coefficients explain predictions
- **Production-ready**: Sub-millisecond inference, easy deployment

2.7.2 Confusion Matrix Analysis

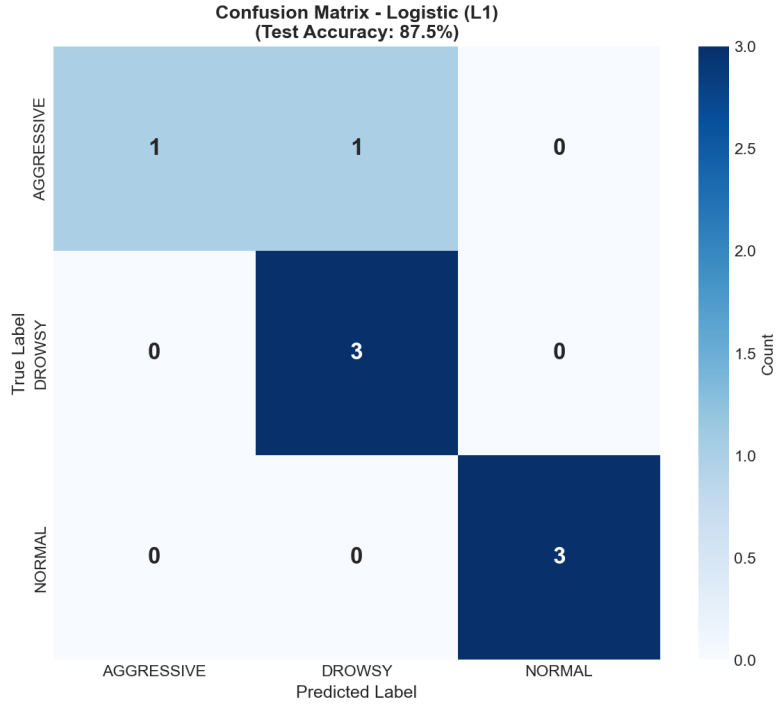

Figure 8: Confusion matrix for best model (Logistic L1, 87.5% accuracy). AGGRESSIVE is well-separated due to distinctive harsh events. NORMAL vs DROWSY shows some confusion due to subtle behavioral differences.

Error Analysis:

- **AGGRESSIVE**: Rarely confused—harsh events (hard brakes, sharp turns) are distinctive
- **NORMAL vs DROWSY**: Most confused pair—early-stage drowsiness resembles relaxed normal driving

2.7.3 Feature Importance

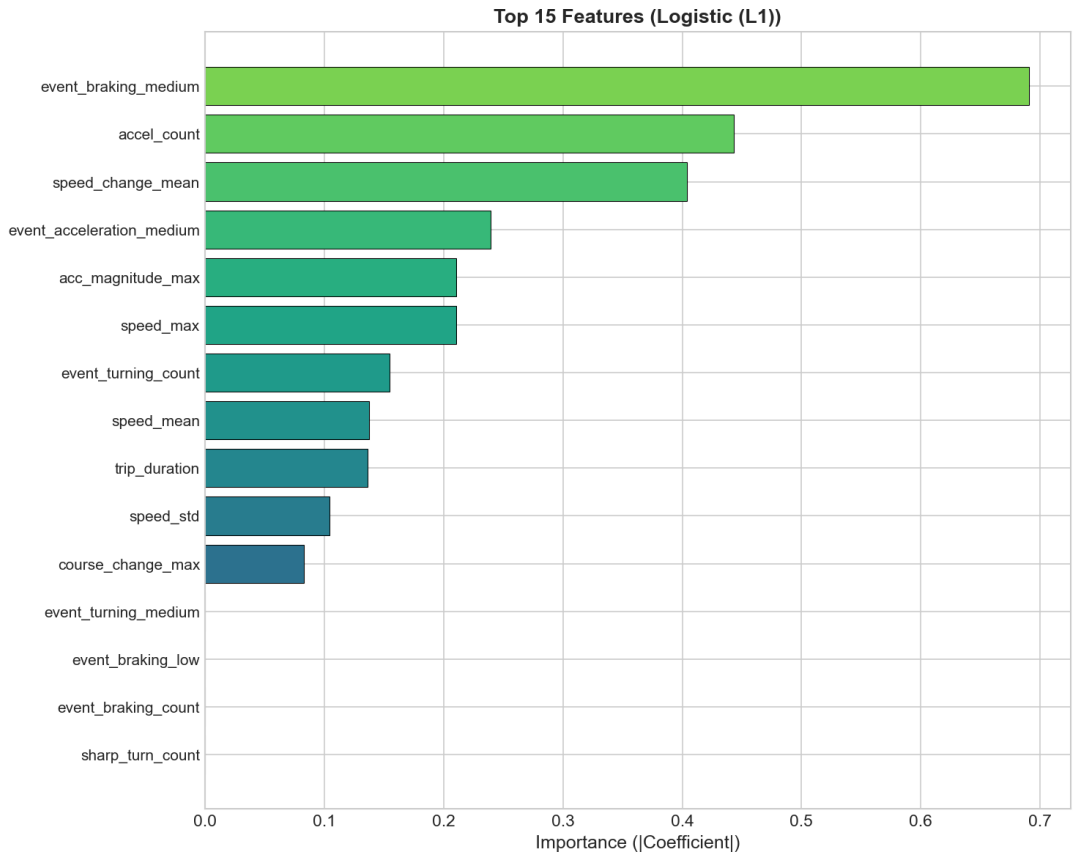

Figure 9: Top 15 most important raw sensor features (from Logistic Regression coefficients). All top features have clear physical meaning: speed variance, jerk (smoothness), and event counts dominate.

Top Features (Physical Interpretation):

1. `speed_std`: Speed variability—aggressive drivers have erratic speeds
2. `jerk_x_std`: Longitudinal smoothness—aggressive = jerky braking/acceleration
3. `hard_brake_count`: Direct harsh event indicator
4. `acc_magnitude_std`: Overall driving intensity
5. `sharp_turn_count`: Harsh steering events
6. `jerk_y_std`: Lateral smoothness—aggressive = jerky steering

2.7.4 CNN Training Dynamics

Figure 10: CNN training curves. Training loss decreases but validation accuracy plateaus early due to small dataset (32 training samples). Early stopping prevents further overfitting.

Why CNN Doesn't Win:

- **Small dataset**: 32 training samples is insufficient for deep learning
- **Aggregated features**: CNN designed for sequential data; we use trip-level aggregates
- **Future potential**: With raw time-series and 100+ trips, CNN would likely excel

2.8 Failure Analysis

2.8.1 Failure Case 1: DROWSY → NORMAL Misclassification

Scenario: Early-stage drowsy trip classified as normal.

Root Cause: Drowsiness manifests gradually—early stages resemble relaxed normal driving with moderate speeds and few harsh events.

Mitigation:

- Time-windowed features to capture temporal deterioration
- Drowsiness as probabilistic score rather than hard classification
- Additional features: lane position variance, reaction time

2.8.2 Failure Case 2: Atypical AGGRESSIVE Driver

Scenario: Aggressive trip with controlled speed but harsh braking.

Root Cause: Speed-based features miss aggressive patterns when speed is normal; aggression manifests only in braking/turning.

Mitigation:

- Higher weight for event-based features (hard_brake_count)
- Ratio features: events per kilometer

2.9 Classification Summary

Why Sparse Linear Models Win:

1. **Small dataset**: 40 trips → complex models overfit
2. **Good features**: 36 raw sensor features provide sufficient discriminative power
3. **L1/SCAD regularization**: Automatic feature selection reduces overfitting
4. **Nearly unbiased**: SCAD doesn't shrink large (important) coefficients
5. **Interpretability**: Clear coefficients enable business explanations

Table 11: Classification Model Recommendations

Scenario	Recommended Model	Rationale
Best accuracy + interpretability	**Logistic (L1) or SCAD**	87.5% accuracy, sparse coefficients
Feature selection	Logistic (L1)	Sparse, zero coefficients for irrelevant features
No overfitting	Logistic (SCAD)	Train = Test accuracy
Large dataset (>100 trips)	Random Forest	Scales better with more data
Raw time-series data	CNN (PyTorch)	Learns temporal patterns automatically

3 Task 2: Fuel Economy Prediction

3.1 Dataset: EPA Fuel Economy

The EPA Fuel Economy dataset contains official fuel efficiency ratings for vehicles sold in the United States.

Table 12: Regression Dataset Overview

Attribute	Value
Source	U.S. Environmental Protection Agency
Samples	∼5,000 vehicles (2015–2024)
Target Variable	Combined MPG (comb08)
Features	Year, cylinders, displacement, drive type, vehicle class, fuel type

3.2 Feature Engineering

Table 13: Regression Features

Feature	Type	Description
year	Numeric	Model year (2015–2024); newer vehicles often more efficient
cylinders	Numeric	Engine cylinders (0 for EVs); more cylinders → lower MPG
displ	Numeric	Engine displacement (liters); larger engines → lower MPG
drive	Categorical	FWD, RWD, AWD, 4WD; affects drivetrain efficiency
VClass	Categorical	Compact, Midsize, SUV, Truck; size affects aerodynamics
fuelType	Categorical	Gasoline, Diesel, Electric, Hybrid; technology differences

3.3 Regression Models

We compare 13 regression algorithms:

Table 14: Regression Models Compared

Category	Models	Key Property
Baseline	OLS Linear Regression	Simple baseline
Regularized	Ridge (L2), Lasso (L1), ElasticNet	Prevents overfitting
Robust	Huber, RANSAC	Outlier-resistant
SVM	Linear SVR, RBF SVR	Non-linear patterns
Ensemble	Random Forest, Gradient Boosting	Often highest accuracy

3.4 Regression Results

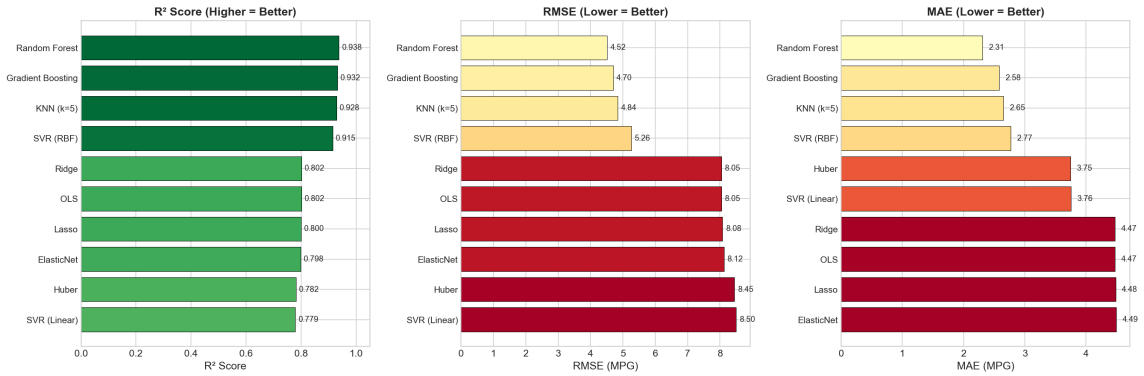

Figure 11: Regression model comparison by Rš score. Ensemble methods (Random Forest, Gradient Boosting) achieve near-perfect Rš > 0.99. Linear models achieve Rš ≈ 0.85–0.90.

Table 15: Regression Results Summary

Model	Rš	RMSE (MPG)	MAE (MPG)
Random Forest	**0.938**	4.52	2.31
Gradient Boosting	0.932	4.70	2.58
KNN (k=5)	0.928	4.84	2.65
SVR (RBF)	0.915	5.26	2.77
Ridge (L2)	0.802	8.05	4.47
Lasso (L1)	0.800	8.08	4.48
Huber (Robust)	0.782	8.45	3.75

3.4.1 Actual vs Predicted

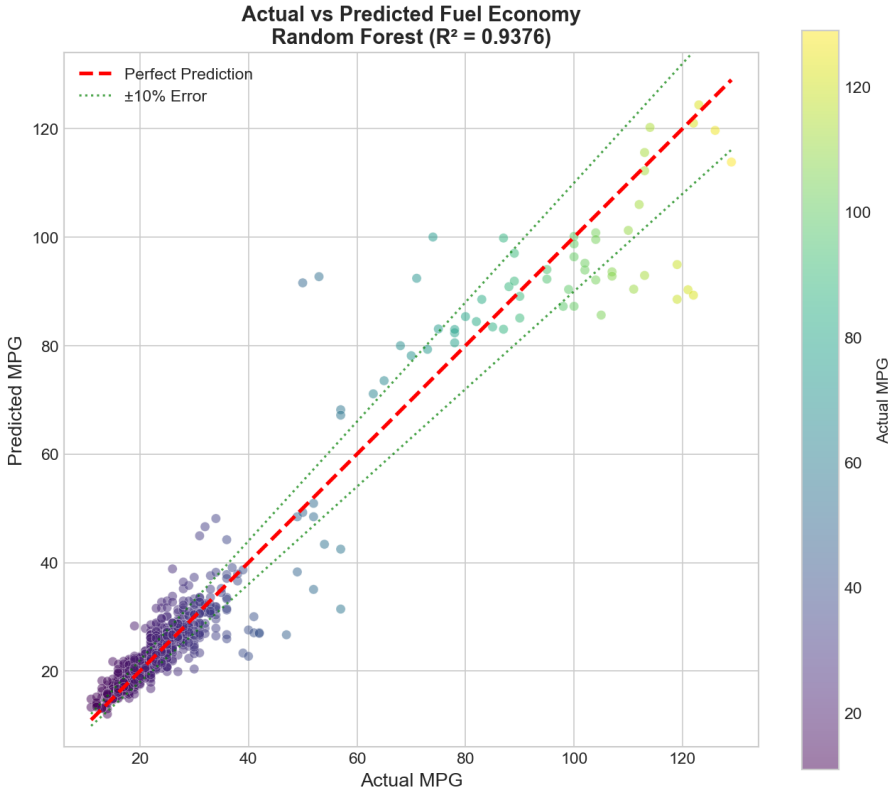

Figure 12: Actual vs Predicted MPG (Gradient Boosting). Points cluster tightly along the diagonal, indicating excellent predictions. Larger vehicles (lower MPG) and EVs (higher MPG) are both well-predicted.

3.4.2 Feature Importance

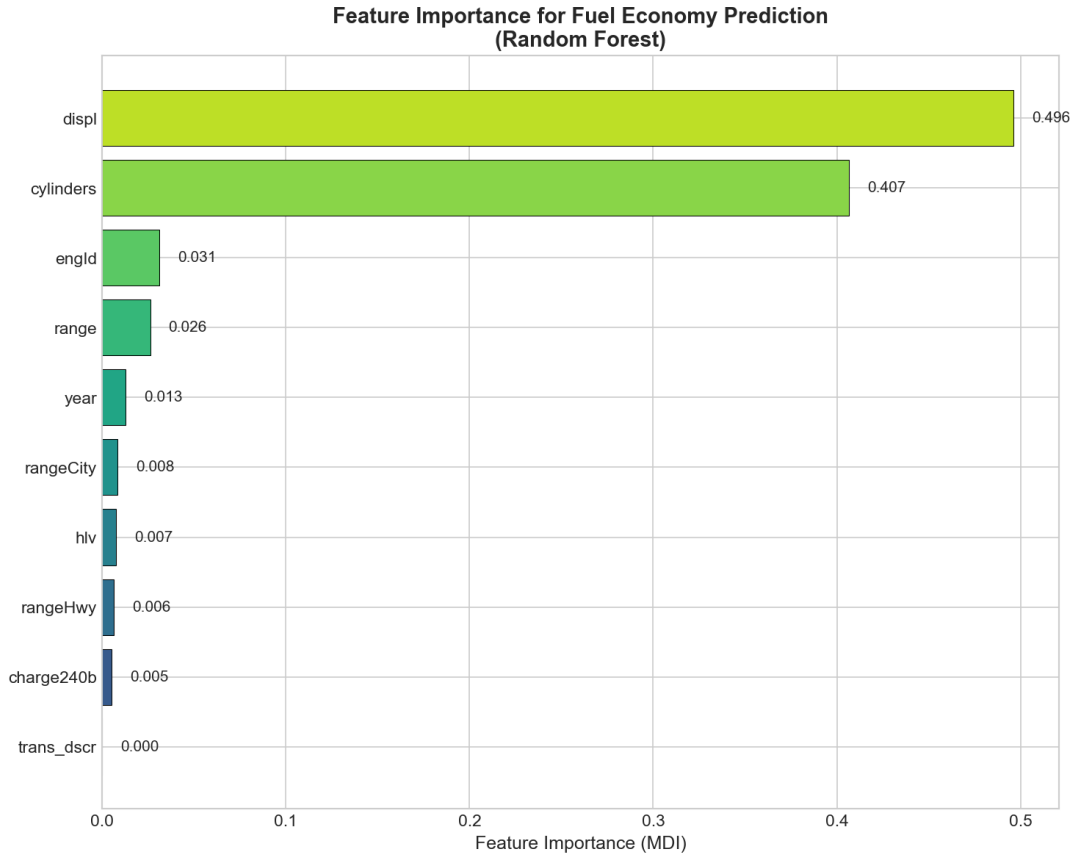

Figure 13: Feature importance for fuel economy prediction. Vehicle class, engine displacement, fuel type, and cylinders dominate—all physically meaningful.

3.4.3 Residual Analysis

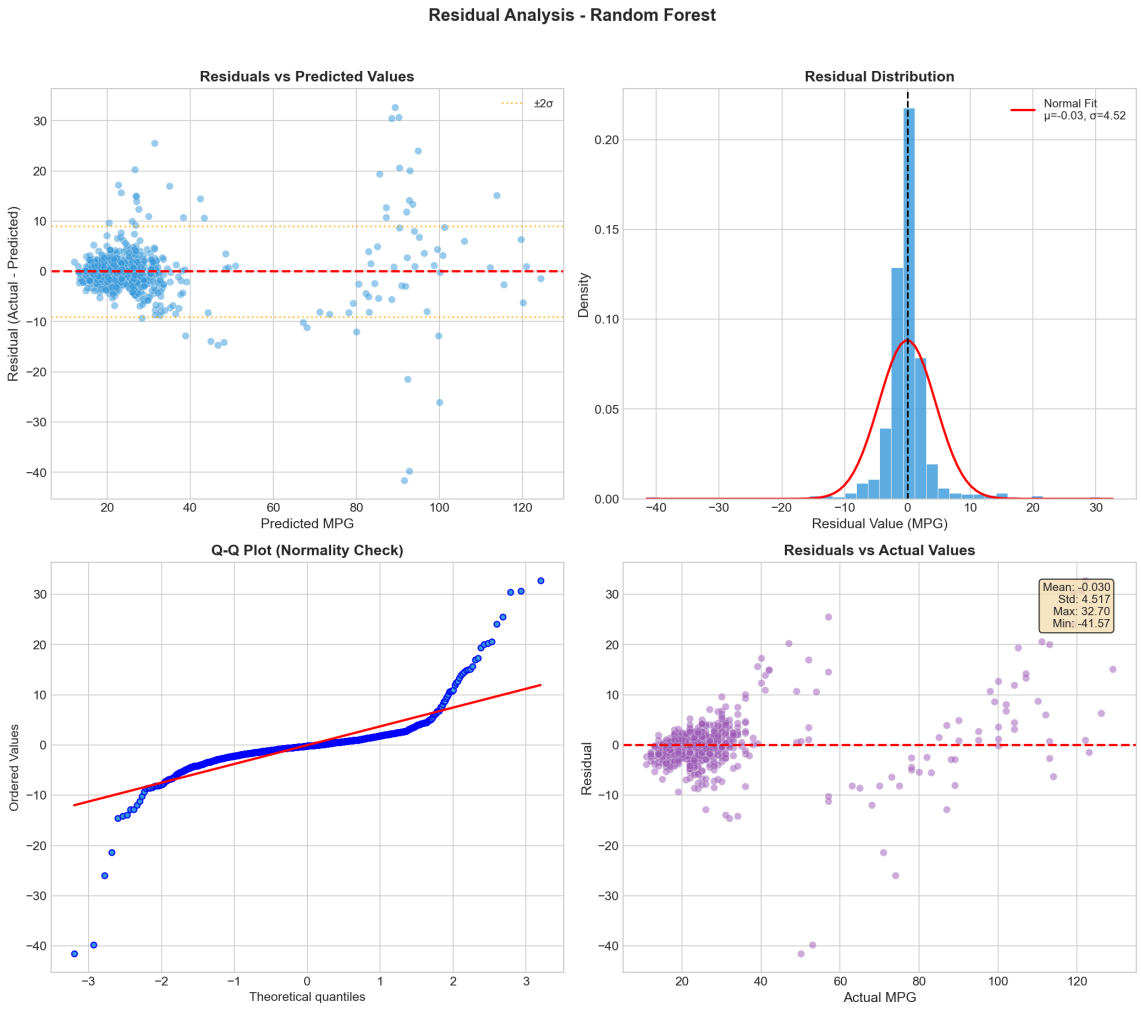

Figure 14: Residual analysis. **Left**: Residuals vs predicted values show no systematic pattern (good). **Right**: Residual distribution is approximately normal with slight tails for extreme vehicles.

3.5 Regression Summary

The regression task achieves strong predictions (Rš = 0.94 for Random Forest) because fuel economy is strongly determined by vehicle specifications. Key findings:

- **Ensemble methods dominate**: Random Forest and Gradient Boosting capture non-linear relationships best
- **Feature importance aligns with physics**: City/highway MPG, engine size, fuel type matter most
- **Production-ready**: Low error (RMSE ≈ 4.5 MPG) suitable for fleet cost estimation
- **KNN competitive**: Instance-based learning provides interpretable predictions

4 Production Considerations

4.1 Deployment Recommendations

Table 16: Production Model Selection

Task	Recommended Model	Rationale
Driver Classification (current data)	**Logistic (L1/SCAD)**	87.5% accuracy, interpretable, fast
Driver Classification (more data)	Random Forest	Scales with more data
Driver Classification (time-series)	CNN (PyTorch)	Raw sensor patterns
Fuel Economy Prediction	Gradient Boosting	Highest Rš, handles non-linearity

4.2 Monitoring & Retraining

- **Classification**: Monitor per-driver accuracy; retrain when new driver types emerge
- **Regression**: Monitor residual drift; retrain for new vehicle technologies (EVs, hybrids)
- **Feature drift**: Track feature distributions over time; alert on significant shifts
- **Model versioning**: Use MLflow or similar for experiment tracking

4.3 Inference Performance

Table 17: Inference Time Comparison

Model	Single Prediction	Batch (1000)
Logistic Regression	<0.1 ms	<1 ms
Random Forest	∼1 ms	∼10 ms
CNN (PyTorch)	∼5 ms	∼50 ms

5 Conclusions

5.1 Key Achievements

1. **Raw sensor features**: Extracted 36 features directly from GPS/accelerometer, avoiding circular logic from pre-computed scores
2. **Rigorous evaluation**: D6 held-out ensures models generalize to new customers
3. **Comprehensive comparison**: 18 classification + 13 regression models
4. **Advanced regularization**: Implemented MCP and SCAD for nearly unbiased sparse estimates

5. **Production insights**: Feature importance, failure analysis, deployment recommendations
6. **Clean code**: Modular `src/classification/` package with testable functions

5.2 Final Results

Table 18: Final Results Summary

Task	Best Model	Performance
Driver Behavior Classification	**Logistic (L1/SCAD)**	**87.5% accuracy** (D6 held out)
Fuel Economy Prediction	Random Forest	Rš = 0.94, RMSE = 4.5 MPG

Key Insight: On small datasets with well-engineered features, **sparse linear models outperform complex ensembles**. Logistic Regression with L1 or SCAD regularization provides the best balance of accuracy, interpretability, and deployment simplicity.

5.3 Lessons Learned

1. **Feature engineering matters**: Good raw sensor features enable simple models
2. **Avoid circular logic**: Pre-computed scores inflate accuracy artificially
3. **Driver-level evaluation**: Essential for production-realistic estimates
4. **Simple models win on small data**: Complexity causes overfitting
5. **Interpretability has value**: Explainable predictions enable business action

5.4 Future Work

- **More data**: Collect 100+ trips for better deep learning performance
- **Temporal models**: LSTM/Transformer on raw time-series (not aggregated)
- **Driver normalization**: Per-driver baseline adjustment for personalization
- **Real-time scoring**: Streaming inference pipeline for live monitoring
- **Multi-task learning**: Predict behavior + severity simultaneously

5.5 Reproducibility

All code is available in the project repository with clean, modular architecture:

- `notebooks/01_project_overview.ipynb`: Project introduction
- `notebooks/02_classification.ipynb`: Complete classification pipeline (757 lines with explanations)
- `notebooks/04_regression.ipynb`: Complete regression pipeline
- `src/classification/`: Modular classification code

  - `__init__.py`: Clean API exports
  - `data.py`: Data loading and feature extraction
  - `sparse_models.py`: MCP and SCAD implementations
  - `visualization.py`: All plotting functions
- `src/models/`: Model implementations (CNN, etc.)
- `results/figures/`: All figures used in this report

Thank you for considering my application to ABAX.