Detection of Cannabis Impaired Driving from Vehicle-based Inputs using Machine Learning Methods

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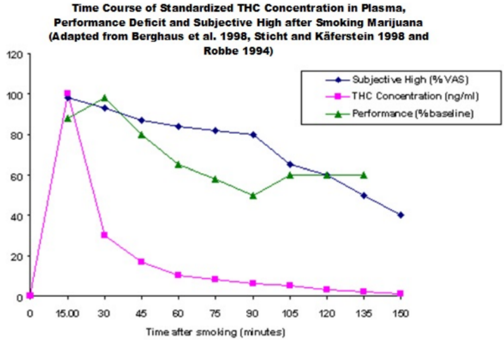
Direct detection of cannabis impairment is complicated by the tenuous relationship between blood THC and degree of impairment



NHTSA Marijuana-Impaired Driving Report to Congress (July 2017)

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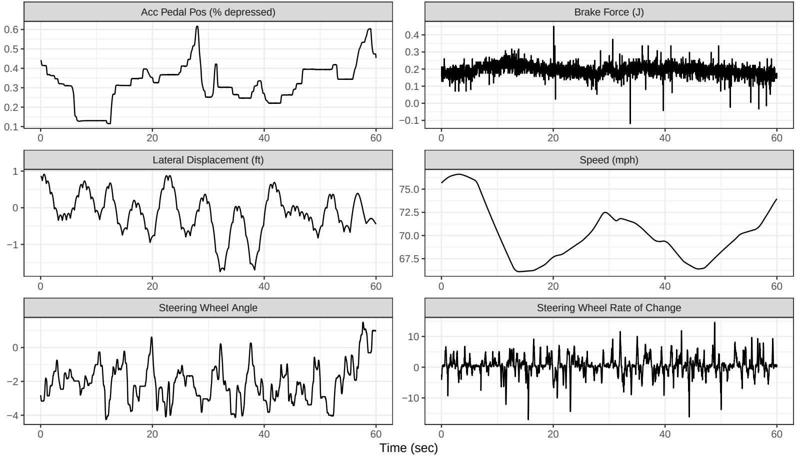
Data collection

- Within-subjects experimental design (n = 18 subjects, 6 conditions)
  - low-THC (~2.9%), high-THC (~6.7%), or placebo (~0%) vaporized cannabis
  - low-dose alcohol, or placebo
  - Various driver inputs and vehicle states were recorded at 60 Hz

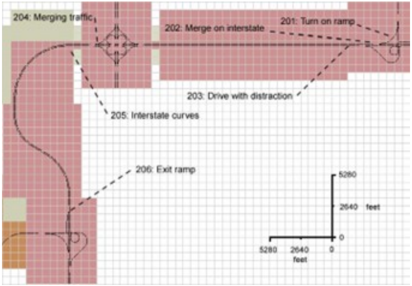
Vehicle-based inputs

We use 6 different vehicle-based inputs:



Drive scenario

We focus on a ∼3-minute straight section of 4-lane divided expressway (speed limit 70 mph) with an embedded distraction task



- We divide this scenario into 60-second samples of vehicle inputs
  - 162 non-overlapping samples, or 270 samples w/ 50% overlap

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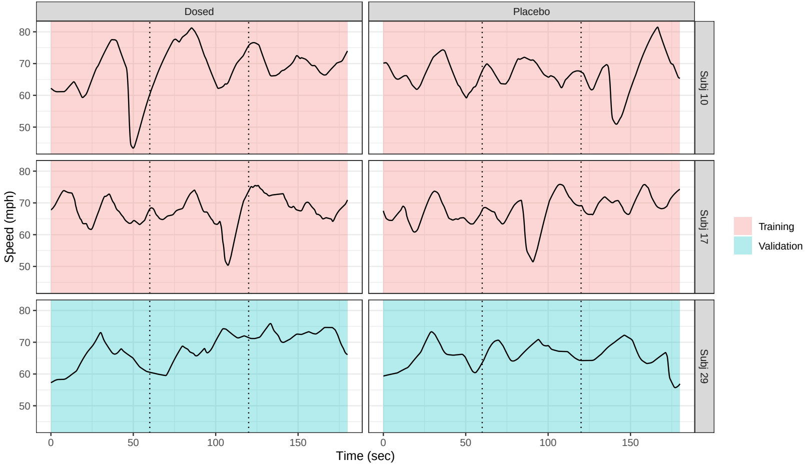
Training and evaluation

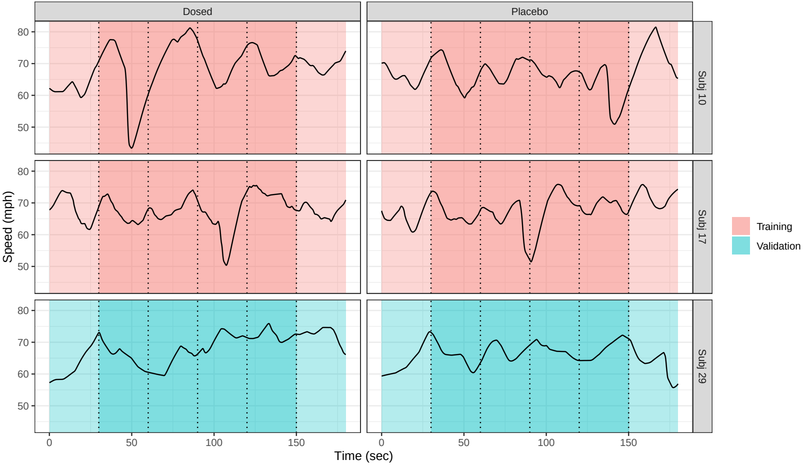
We use 3 different validation schemes (mixed, split, overlapping) repeated 10x with different random splits:

- 60-second samples that do not overlap
  - **Mixed-subject scheme**: 108 of 162 samples used for training, the other 54 for evaluation, without considering the subject they came from
  - **Split-subject scheme**: all samples from 12 subjects used for training, all samples from the other 6 subjects used for validation
- **Overlapping scheme**: 60-second samples with 50% overlap
  - Subjects must be split to prevent data leakage

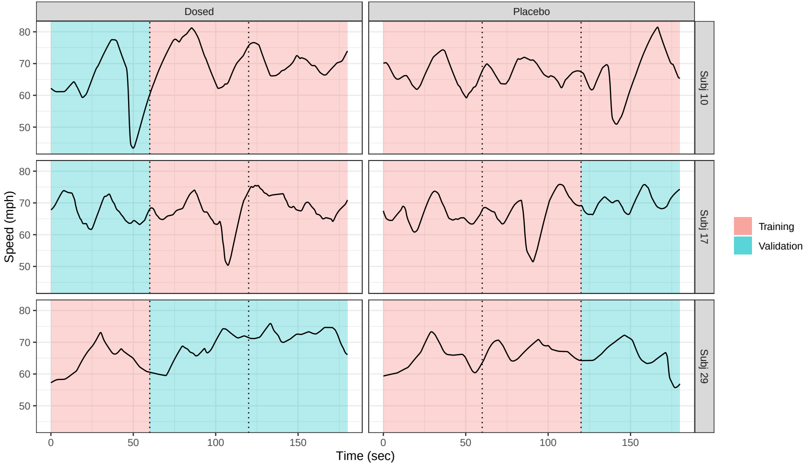
Split-Subjects (non-overlapping)



Split-Subjects (overlapping)



Mixed-Subjects (non-overlapping)



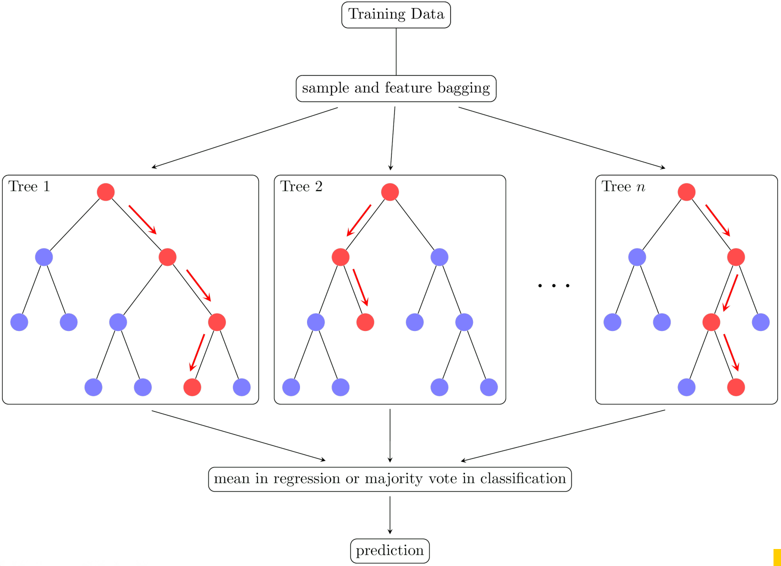
Machine learning methods

1. **Feature engineering**
   - Process each sample's multivariate time series into a collection of derived features (ie: max Δ-speed over 2-seconds)
   - Model input is a "standard" data matrix (# samples, # derived features)
   - *Random forest*, *gradient boosted trees* (`xgboost`), and *logistic regression* algorithms
2. **Deep learning**
   - The entire multivariate time series of each sample is used
   - Model input is a 3-d array (# samples, # channels, # time steps)
   - *Inception time* neural network and *MINIROCKET* convolutional kernel classifier

Feature engineering

- For rolling windows of 0.1-sec, 0.2-sec, 0.5-sec, and 1-sec:
  - Extract the average range, maximum range, and standard deviation of ranges as predictive features for each of the following inputs:
    - Brake pedal force
    - Accelerator pedal position
    - Steering wheel angle
    - Vehicle speed
    - Vehicle lateral position
    - Vehicle heading
- For the entire 60-sec sample:
  - Extract the average value, maximum value, and standard deviation of each input listed above

Random forest



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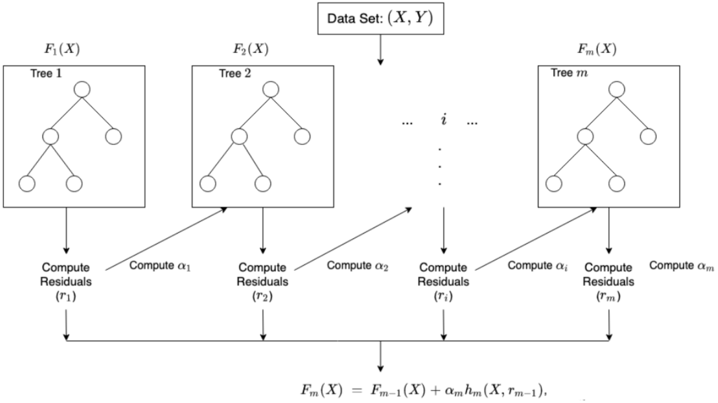
Gradient boosted trees (xgboost)



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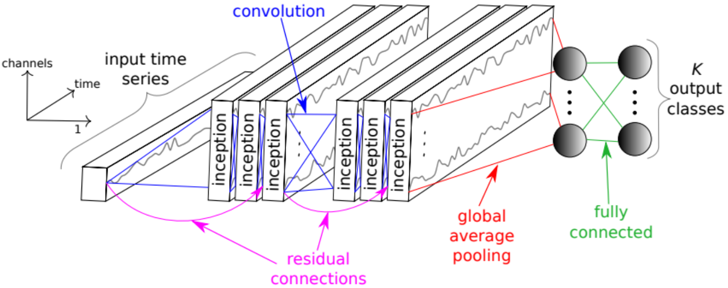
Inception time (architecture overview)



Inception time is an ensemble of neural networks, each contains 6 sequential inception modules with residual connections followed by pooling and one or more fully connected layers.

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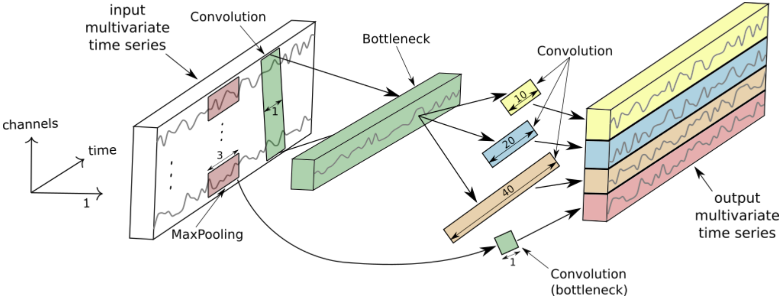
Inception time (inception modules)



- Each inception module begins with a "bottleneck" layer that reduces the dimension of the input multivariate time series (to $m = 1$ in this diagram).
- Different convolutional kernels are slid along the bottleneck output to produce a multivariate time series that is passed forward.

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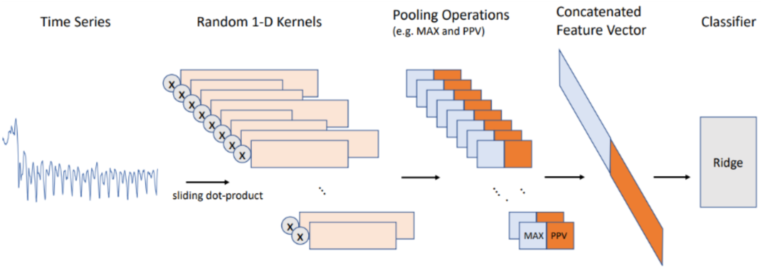
MINIROCKET



Time Series
Random 1-D Kernels
Pooling Operations
(e.g. MAX and PPV)
Concatenated
Feature Vector
Classifier
sliding dot-product
MAX
PPV
Ridge

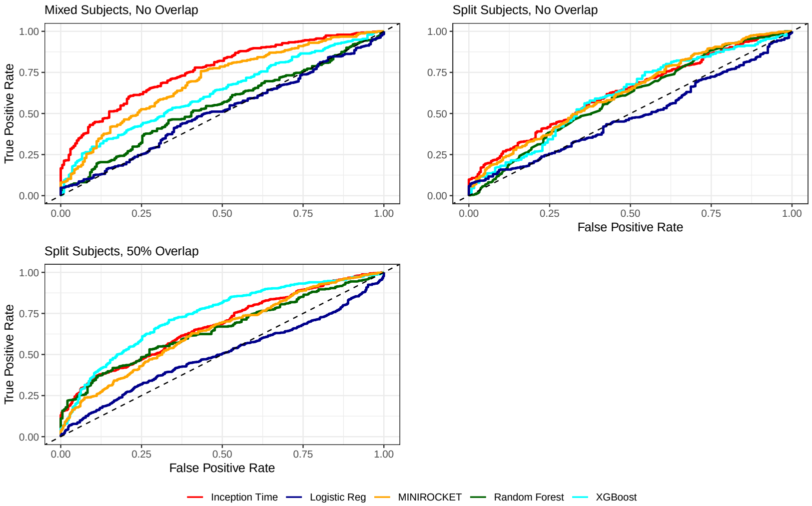
Results (top performers)

Scheme	Top Model	Bal Acc	AUC	TPR (w/ 0 FP)
Mixed (No-over)	Inception Time	0.63	0.76	0.167
Split (No-over)	Inception Time	0.55	0.63	0.098
Split (50% overlap)	XGBoost	0.66	0.74	0.049

Results (full table)

Model	Validation Scheme	Accuracy	Balanced Accuracy	AUC	TPR (w/ 0 FP)
Inception Time	Mixed (No-over)	.72	0.625	.76	0.167
	Split (No-over)	.64	0.55	.63	0.098
	Split (50% overlap)	.67	0.595	.68	0.132
MINIROCKET	Mixed (No-over)	.63	0.64	.70	0.080
	Split (No-over)	.59	0.575	.61	0.056
	Split (50% overlap)	.59	0.595	.62	0.035
XGBoost	Mixed (No-over)	.66	0.585	.62	0.005
	Split (No-over)	.66	0.565	.64	0.012
	Split (50% overlap)	.71	0.66	.74	0.049
Random Forest	Mixed (No-over)	.62	0.515	.59	0.005
	Split (No-over)	.67	0.565	.61	0.002
	Split (50% overlap)	.65	0.6	.67	0.111
Logistic Reg	Mixed (No-over)	.59	0.475	.51	0.048
	Split (No-over)	.61	0.49	.52	0.009
	Split (50% overlap)	.65	0.545	.61	0.009

Results (ROC)



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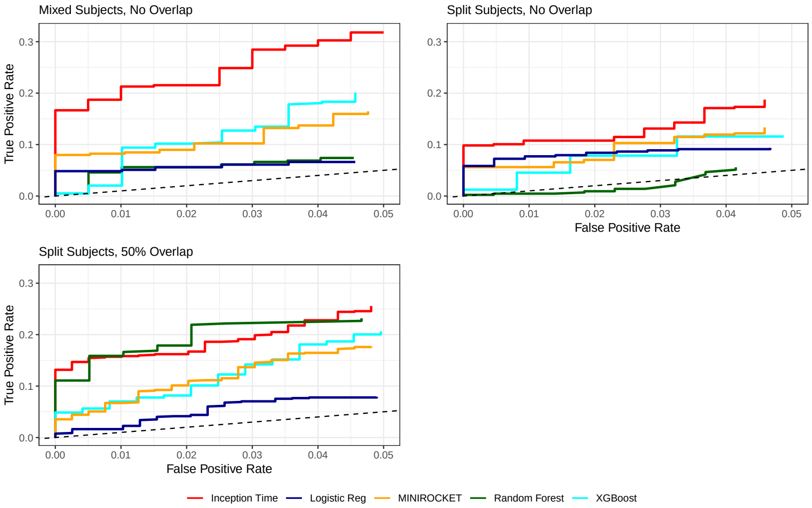
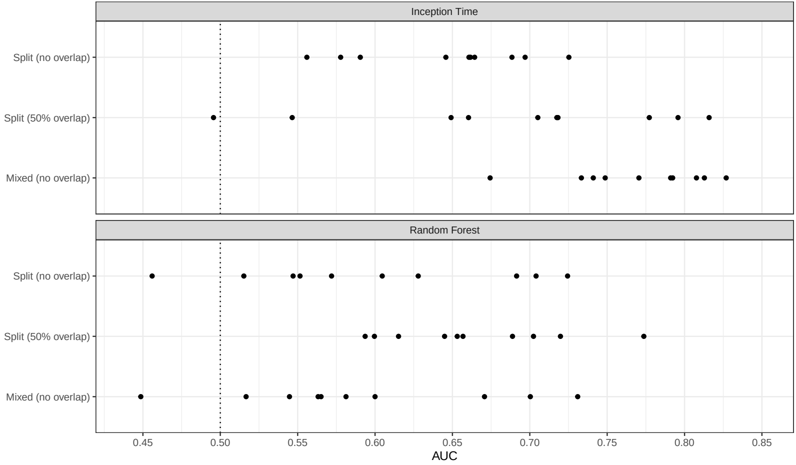
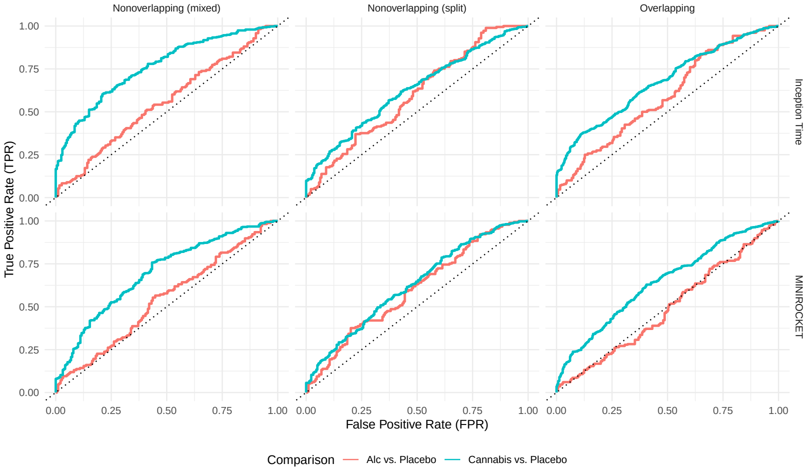
Results (low false positive rate)



Challenges (variability)



Cannabis vs. low-dose alcohol? (preliminary results)



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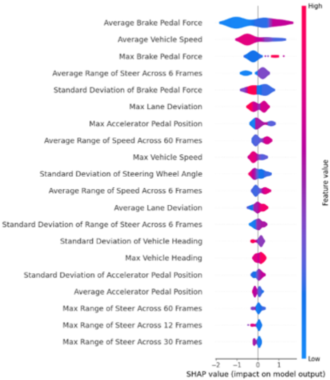
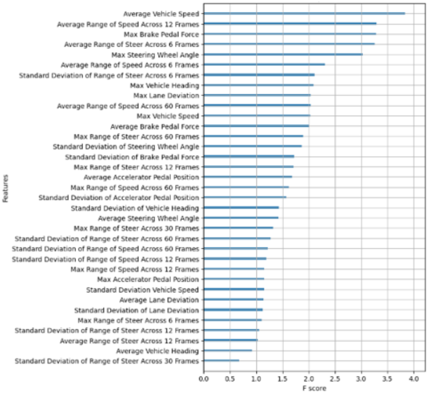
Results (feature importance)

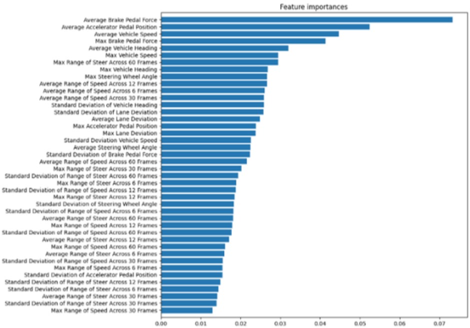
SHAP and gain-based importance for `xgboost`:





Results (feature importance)

SHAP and gain-based importance for Random Forest:



Discussion

- Reliable vehicle-based impairment detection is challenging
  - Modern machine learning methods show some potential, but predictions contain substantial uncertainty
  - Nevertheless, prediction scores may be able to provide complimentary information that can be used in conjunction with other data in law enforcement or other settings

Discussion (cont.)

- Patterns in speed, brake force, and acceleration appear to be the most impactful predictors of impairment
  - This is consistent with the literature showing decreased speed and degraded longitudinal control[4]
  - It is important to acknowledge that this work used data from a 4-lane interstate (75 mph speed limit)

Limitations, future work, and additional considerations

- Small data set, only $n = 18$ subjects
  - Would like to incorporate data from other impaired driving studies, and potentially "control" data from on-road studies
- Single, consistent driving scenario
  - Exploring models across other driving environments/scenarios
  - Two-step approaches to prediction that first match the scenario then utilize the model trained for that scenario
- Difficult to identify the most impactful predictors in Inception Time model
- Unclear privacy concerns in collecting vehicle-based inputs
  - Most influential predictors may also be most difficult to collect

References

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3. Ismail Fawaz, H., Lucas, B., Forestier, G. et al. “InceptionTime: Finding AlexNet for time series classification”. *Data Min Knowl Disc*. (2020) 34, 1936–1962. https://doi.org/10.1007/s10618-020-00710-y
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6. Middlehurst, M., Schäfer, P., Bagnall, A., Bake off redux: a review and experimental evaluation of recent time series classification algorithms. arXiv pre-print, 2023. https://doi.org/10.48550/arXiv.2304.13029

Image Credits

- Random Forest: https://tikz.net/random-forest/
- XGBoost: https://docs.aws.amazon.com/sagemaker/latest/dg/xgboost-HowItWorks.html
- Inception Time: Ismail Fawaz, H., Lucas, B., Forestier, G. et al. "InceptionTime: Finding AlexNet for time series classification". *Data Min Knowl Disc*. (2020) 34, 1936–1962. https://doi.org/10.1007/s10618-020-00710-y
- ROCKET: https://www.aeon-toolkit.org/en/latest/examples/classification/convolution_based.html