

# Using Machine Learning on Naturalistic Driving Data to Predict Mild Cognitive Impairment

Mentor: Dr. Teresa Wu, Ph.D

Anushka Limaye, Biomedical Engineering



## Objective

To implement machine learning models in Python using extracted turning data to seek the answer to this question: does naturalistic driving signature data aid cognitive diagnosis and Alzheimer Disease risk

## Background

Due to the lack of FDA-approved medications for controlling Alzheimer's Disease, it would be optimal to treat Mild Cognitive Impairment (MCI) [1]. One promising approach is to collect continuous data from individuals in what is known as "free-living conditions", such as driving [2].



An ASU team in collaborating with TF Health Corp. is developing biosensor array technology to pull biometric data with driving sensors, GPS data to identify markers for Alzheimer's Disease early detection

## Feature Engineering- Identifying Turns

- Calculation of peaks in latitude and longitude data
- Smoothing accelerometer and gyroscope data during turns:
- Final data frame for modeling:



- Isolated gradients that met a 30° angle threshold
- Used Numpy and Pandas

- Both sensors ran at 24 Hz, so readings were averaged per sec
- Calculated radial acceleration:  $\frac{\Delta gyro_z}{\Delta t}$

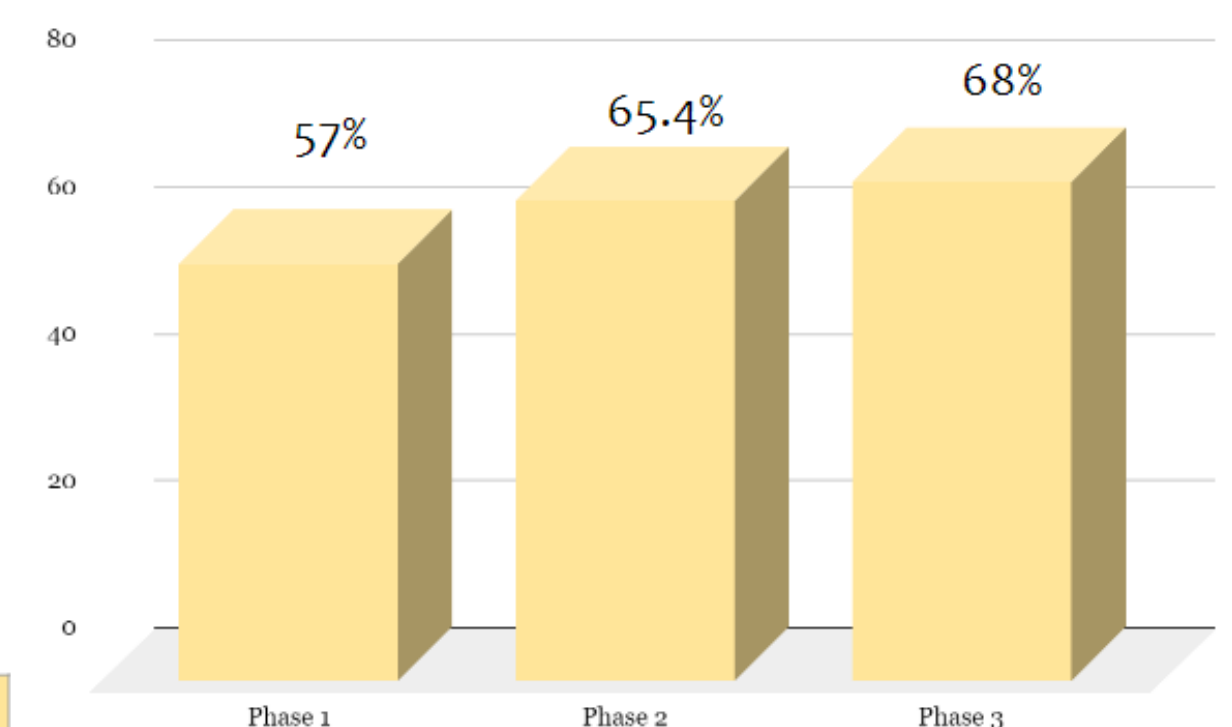
- Means of each parameter during all turns (Phase II)
- Max, min, median of each parameter to represent each turn (Phase III)

## Ablation Study Results

28 total experiments	Category 1		Category 2	
	<ul style="list-style-type: none"> <li>I = base: speed, radial acc, gyro: z</li> <li>II: base + acc: x</li> <li>III: base + acc: y</li> </ul>	<ul style="list-style-type: none"> <li>IV: base + acc: x, y</li> <li>V: base + acc: x, y, z</li> <li>VII: base + acc: z</li> <li>VI: base + acc: x, y, z + gyro: x,y,z</li> </ul>	<ul style="list-style-type: none"> <li>I_turn, no medians</li> <li>II_turn, no medians</li> <li>III_turn, no medians</li> <li>IV_turn, no medians</li> <li>V_turn, no medians</li> <li>VI_turn, no medians</li> <li>VII_turn, no medians</li> </ul>	<ul style="list-style-type: none"> <li>I_no turn, no medians</li> <li>II_no turn, no medians</li> <li>III_no turn, no medians</li> <li>IV_no turn, no medians</li> <li>V_no turn, no medians</li> <li>VI_no turn, no medians</li> <li>VII_no turn, no medians</li> </ul>
<b>Best</b>	VII: 62%		II, III, IV, V, VII: 62%	
Category 3		Category 4		
<ul style="list-style-type: none"> <li>I_turn, medians</li> <li>II_turn, medians</li> <li>III_turn, medians</li> <li>IV_turn, medians</li> <li>V_turn, medians</li> <li>VI_turn, medians</li> <li>VII_turn, medians</li> </ul>	<ul style="list-style-type: none"> <li>I_no turn, medians</li> <li>II_no turn, medians</li> <li>III_no turn, medians</li> <li>IV_no turn, medians</li> <li>V_no turn, medians</li> <li>VI_no turn, medians</li> <li>VII_no turn, medians</li> </ul>			
<b>Best</b>	V: 67%		V, VII: 68%	

**Top Performing Experiment: V, Cat 4**  
Increased accuracy by a min of -0.3% to a max of 4.2% with a mean of 0.61% and std of 1.495%

Classifier	Accuracy	Balanced_Accuracy	AUC	Precision	Recall
GaussianNB	62%	55%	56%	45%	27%
GradientBoostingClassifier	43%	44%	50%	31%	38%
LogisticRegression	65%	58%	59%	44%	30%
RandomForestClassifier	56%	54%	45%	33%	45%
SVC	68%	59%	64%	53%	35%



**Phase 1:** used summarized statistics of all data

**Phase 2:** used means of turn data

**Phase 3:** used summarized statistics of turn data

## Conclusion

- Experiment V is the best performing, which includes the accelerometer sensor in the x, y, z direction along with the radial acceleration, speed, and gyroscope in the z direction.
- Utilizing the medians in testing groups positively impacts the prediction, implying that more descriptive statistics help
- Excluding the turn number improved accuracy, showing that driving patterns for prediction are independent of trip progression.

## Acknowledgements

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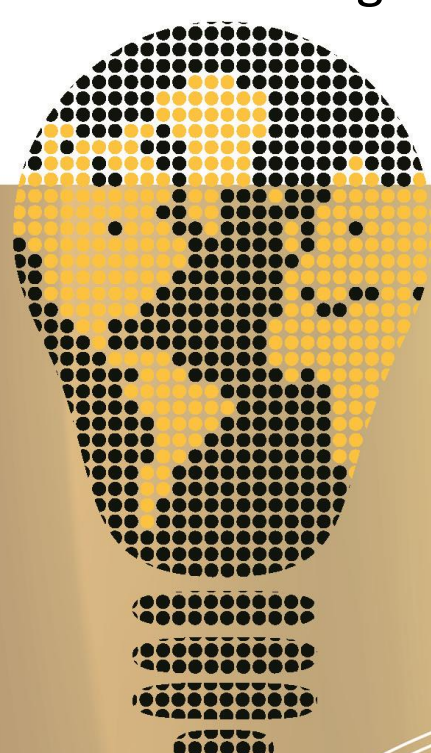
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## Future Work

- Add descriptive statistics to each parameter: avg, std dev, range, coefficient of variation
  - Test one by one into the models of the best experiments
  - Find combinations that lead to significant results
- Make new conclusions to perform additional experiments
- Honors Thesis: develop my own models using these findings in hopes to attain better results that can help accurate prediction of MCI

## References

- [1]Alzheimer's Association: Earlier Diagnosis. [https://www.alz.org/alzheimers-dementia/research\\_progress/earlier-diagnosis](https://www.alz.org/alzheimers-dementia/research_progress/earlier-diagnosis)
- [2]Gauthier, S.; Reisberg, B.; Zaudig, M.; Petersen, R. C.; Ritchie, K.; Broich, K.; Belleville, S.; Brodaty, H.; Bennett, D.; Chertkow, H.; Cummings, J. L.; de Leon, M.; Feldman, H.; Ganguli, M.; Hampel, H.; Scheltens, P.; Tierney, M. C.; Whitehouse, P.; Winblad, B., Mild cognitive impairment (International Psychogeriatric Association Expert Conference on mild cognitive impairment). Lancet 2006, 367 (9518), 1262-1270..



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