Mind in Motion

Machine Learning for Depression Classification using Motor Actigraphy Data

Final Presentation

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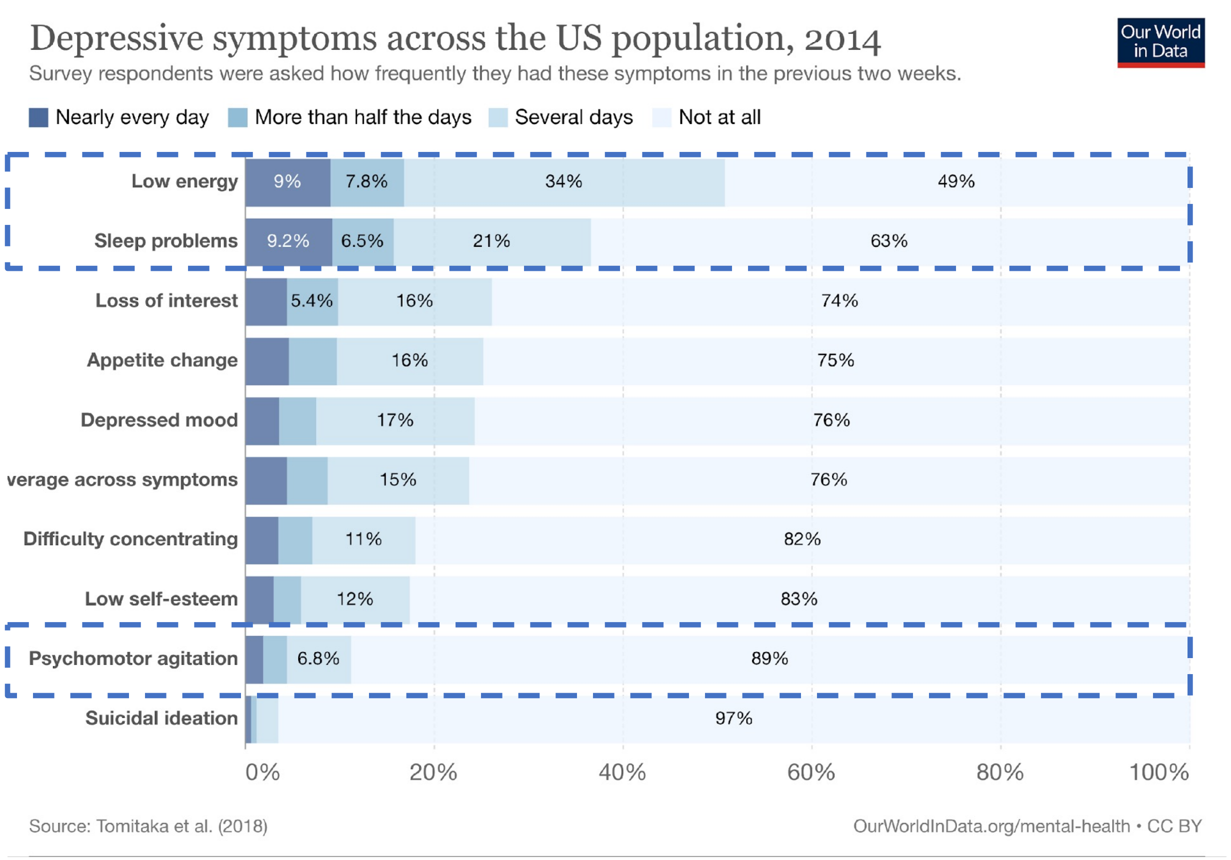
Motivation



RELATED TO MOTOR ACTIVITY

Depression

- World's leading cause of disability
- Associated with disrupted biological rhythms and changes in motor activity
- Subjective diagnosis (DSM-5 criteria)

Motor actigraphy data

- Non-invasive
- Available through wearables (e.g., Fitbit)
- Potentially objective method of diagnosing depression

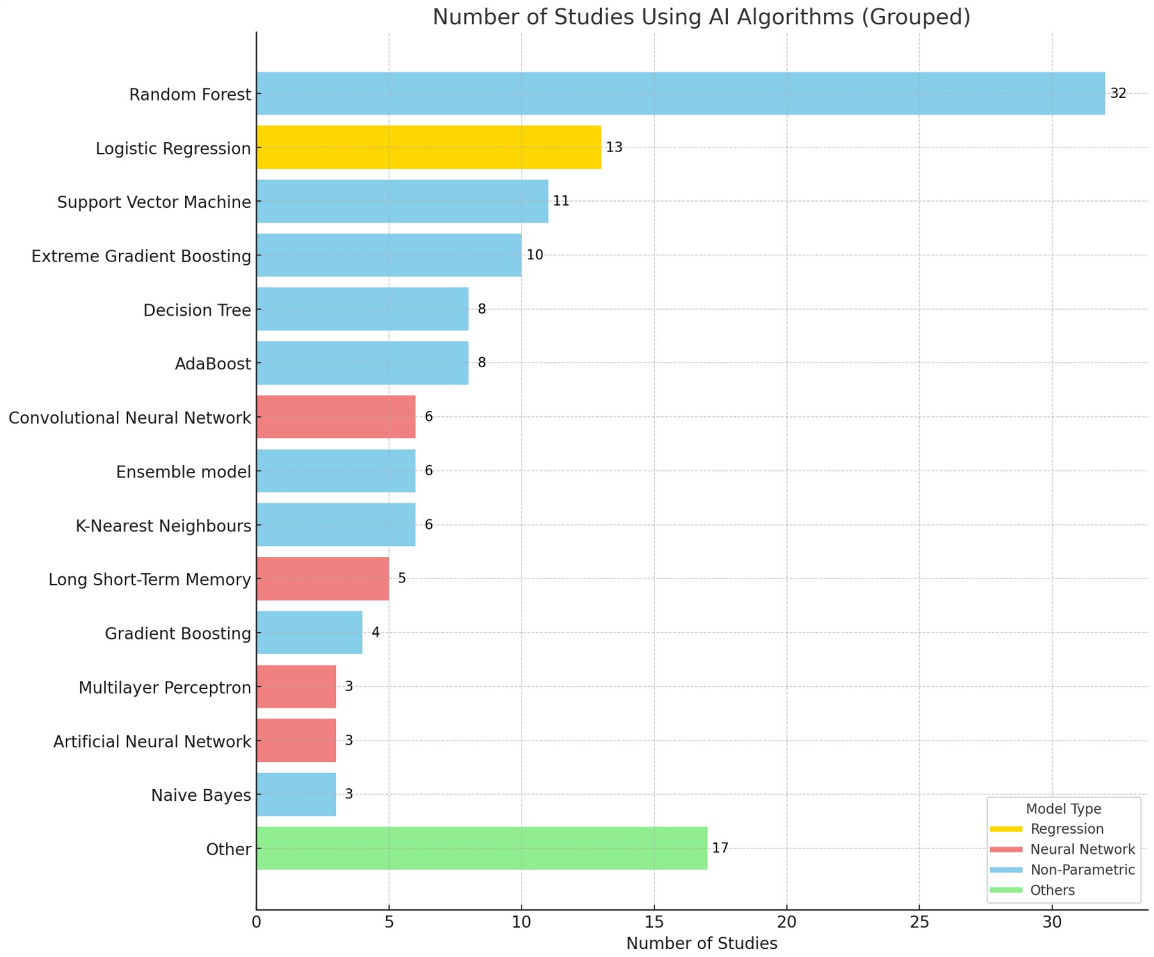
Research question

Can machine learning algorithms be used to accurately classify patients into depression status (normal, mild and moderate) using motor actigraphy data?

•Sources: UpToDate, WHO, Our World in Data

Past Studies

- **54 studies** used AI with wearables for depression
- **Non-parametric methods** were predominant
- **AI accuracy:** 70–89%
- **AdaBoost** excelled in performance, whereas logistic regression and decision trees were less effective



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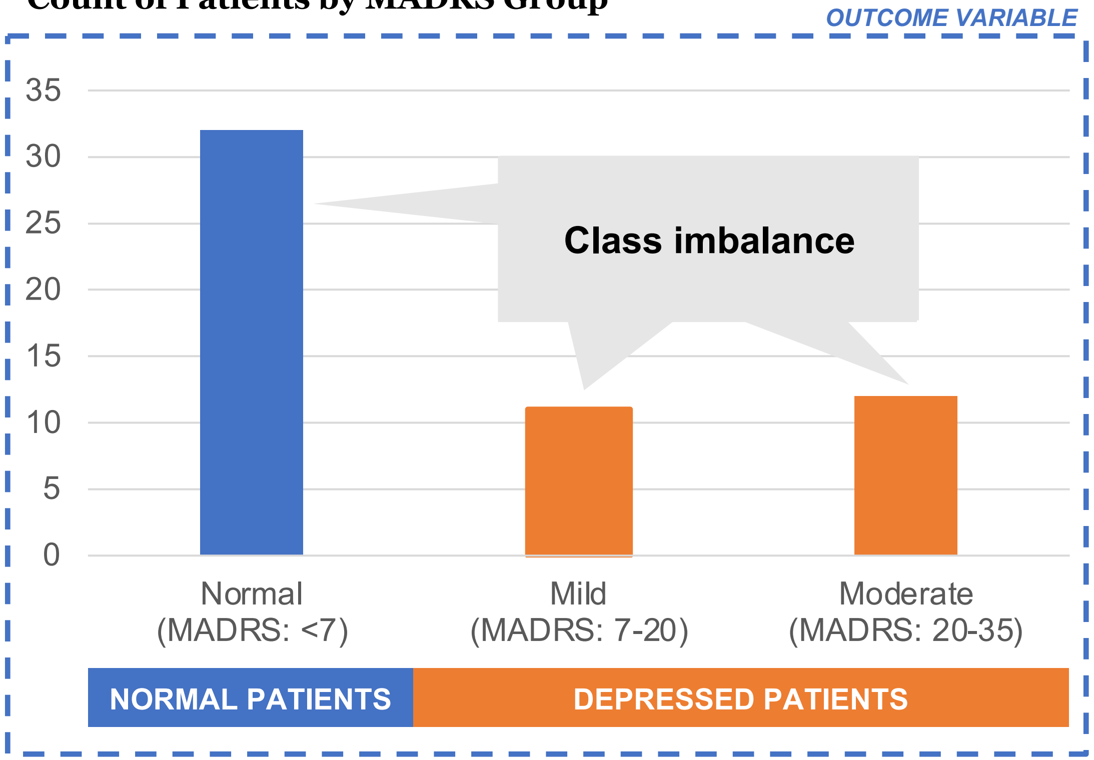
Source: Abd-Alrazaq, A., AlSaad, R., Shuweihdi, F. et al. (2023). Systematic review and meta-analysis of performance of wearable artificial intelligence in detecting and predicting depression. npj Digital Medicine, 6, 84. DOI: 10.1038/s41746-023-00828-5

Data Overview

Data Source

Depresjon: A Motor Activity Database of Depression Episodes in Unipolar and Bipolar Patients

Count of Patients by MADRS Group



Summary Statistics

Variable	Values	Count	%
Gender	Female	30	55%
	Male	25	45%
Affective Type	Normal	32	58%
	Unipolar	15	27%
	Bipolar	8	15%
Days of Observation	Mean	13 days	
Age	Mean	40 years	
Education	Mean	11 years	

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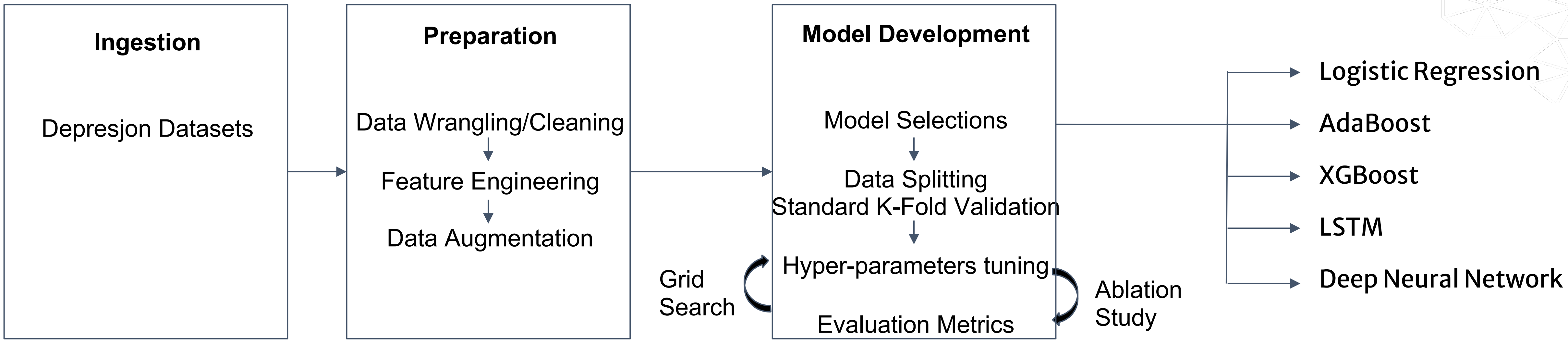
Source: Enrique Garcia-Ceja, Michael Riegler, Petter Jakobsen, Jim Tørresen, Tine Nordgreen, Ketil J. Oedegaard, Ole Bernt Fasmer. "Depresjon: A Motor Activity Database of Depression Episodes in Unipolar and Bipolar Patients." Proceedings of the 9th ACM on Multimedia Systems Conference (MMSys'18), 2018. DOI: 10.1145/3204949.3208125

Approach



Baseline Accuracy : 33.33%

Feature Engineering

Feature Extraction

57 Features

- Activity distribution metrics
- Activity proportions by time of day / week
- Active / inactive bout metrics
- Cosine parameters

Feature Selection

Greedy feature selection (correlation-based) score

+

Decision-tree feature importance score

=

Composite feature importance score

↓

Rank of feature importance

Top 30 Features

Feature Correlation

	Normal	Mild	Moderate
Activity Entropy (by Hour)	0.42	-0.25	-0.26
Activity Entropy (by Minute)	0.54	-0.33	-0.33
Activity Intraday Variability	0.28	-0.26	-0.09
Activity Kurtosis (by Day)	-0.31	0.12	0.26
Activity Kurtosis (by Hour)	-0.48	0.33	0.26
Activity Kurtosis (by Minute)	-0.24	0.05	0.23
Activity Mean (Overall)	0.46	-0.32	-0.25
Activity Mean (Weekdays, 00:00 - 06:00)	0.33	-0.07	-0.32
Activity Mean (Weekdays, 06:00 - 12:00)	0.44	-0.16	-0.36
Activity Mean (Weekends, 12:00 – 18:00)	0.18	-0.12	-0.10
Activity Mean (Weekends, 12:00 – 18:00)	0.38	-0.39	-0.09
Activity Mean (Weekends, 06:00 – 12:00)	0.45	-0.20	-0.34
% Activity (00:00 – 06:00)	-0.07	0.30	-0.20
% Activity (12:00 – 18:00)	-0.14	-0.18	0.34
% Activity (18:00 – 00:00)	0.03	-0.39	0.33
% Activity (06:00 – 12:00)	0.15	0.17	-0.33
% Activity (Weekdays)	0.17	0.00	-0.21
Activity Skewness (by Day)	-0.45	0.28	0.26
Activity Skewness (by Hour)	-0.48	0.33	0.27
Activity Skewness (by Minute)	-0.33	0.21	0.19
Activity Standard Deviation (by Hour)	0.28	-0.17	-0.18
Active Bout Duration Standard Kurtosis	0.30	-0.14	-0.22
Active Bout Duration Standard Deviation	0.32	-0.20	-0.19
Number of Active Bouts	0.45	-0.34	-0.22
Inactive Bout Duration Coef. of Variation	0.33	-0.14	-0.26
Inactive Bout Duration Entropy	-0.21	0.10	0.16
Inactive Bout Duration Mean	-0.41	0.30	0.21
Inactive Bout Duration Standard Deviation	-0.05	0.09	-0.03
Cosine Amplitude (by Day of Week)	-0.19	0.25	-0.02
Cosine Phase (by Minute of Day)	-0.14	0.23	-0.05

Color scale: 0.4, 0.2, 0.0, −0.2, −0.4

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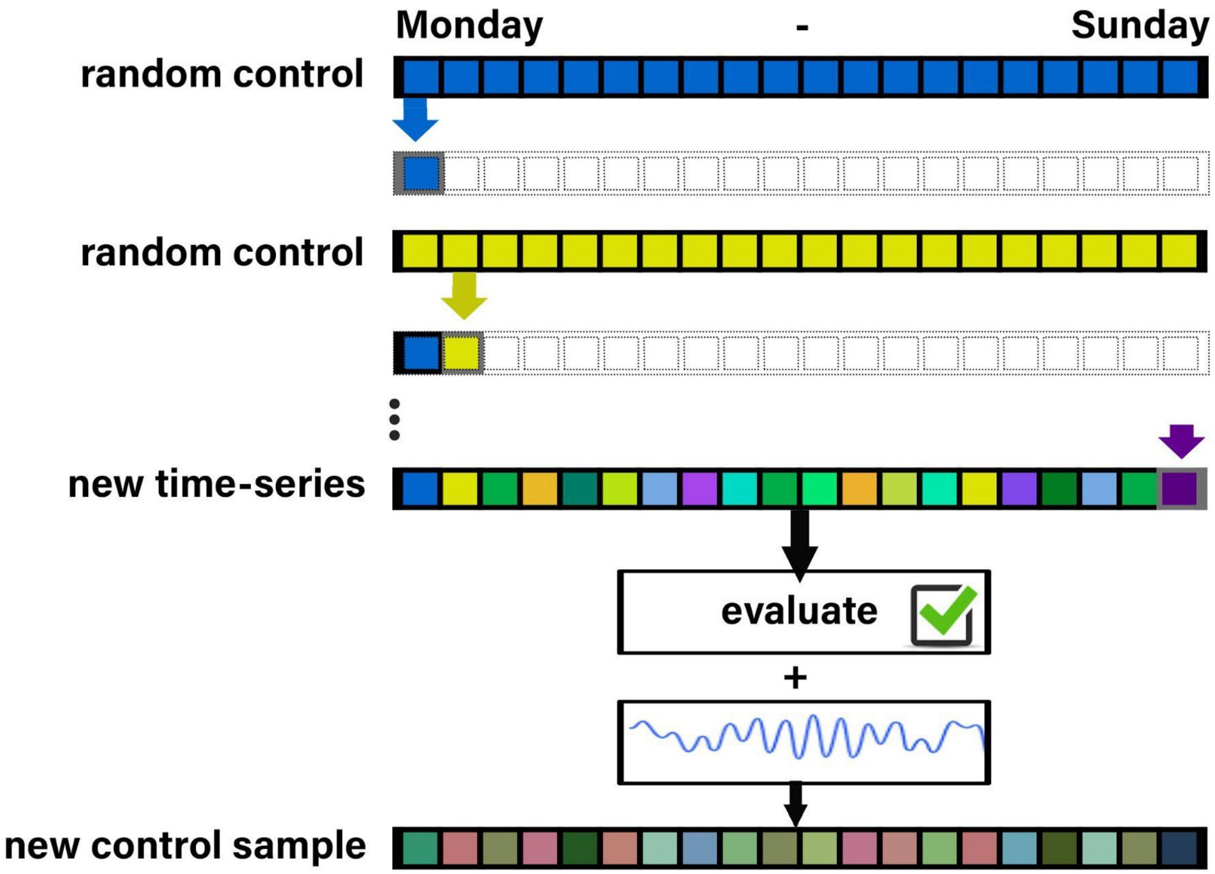
Data Augmentation via Cross-Subject Data Fusion



Process Overview

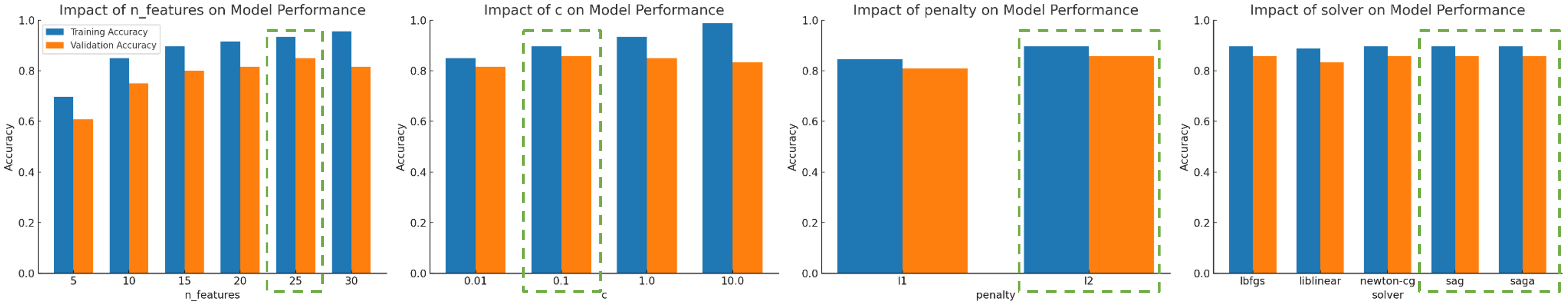
- Randomly select sample
- Time-segment slicing
- Repeat – incorporating slices from different random subjects
- Assess the quality
- Add noise

	Control	Mild	Moderate
Before	23	11	12
After	40	40	40

Logistic Regression

Best hyperparameter(s)

Ablation analysis suggests optimal hyperparameters are: n_features=25, c=0.1, penalty=L2, solver=sag/saga



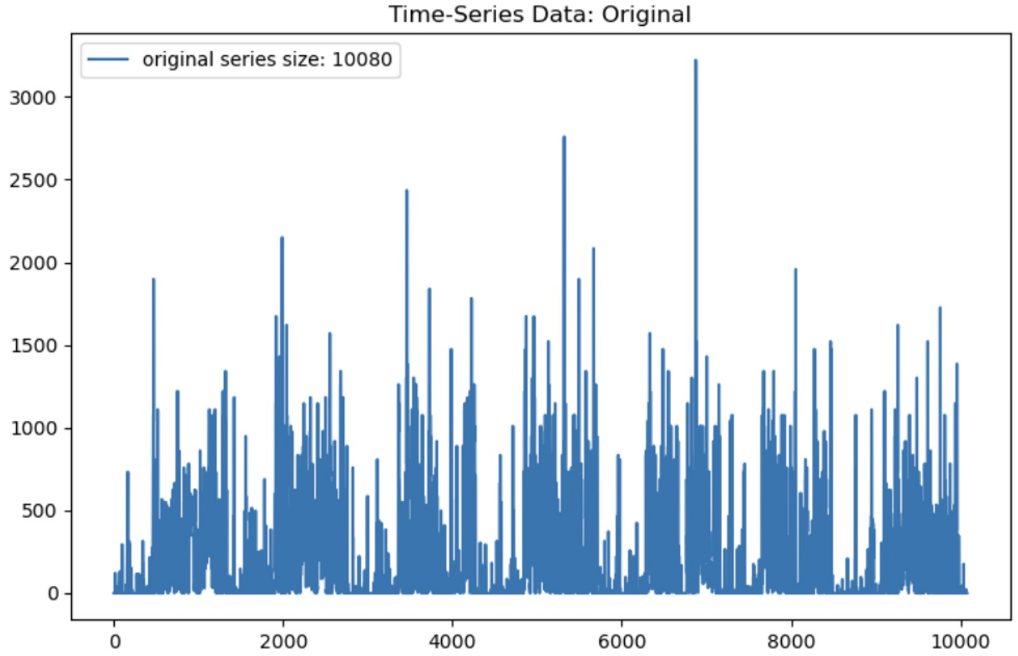
Grid search confirms this

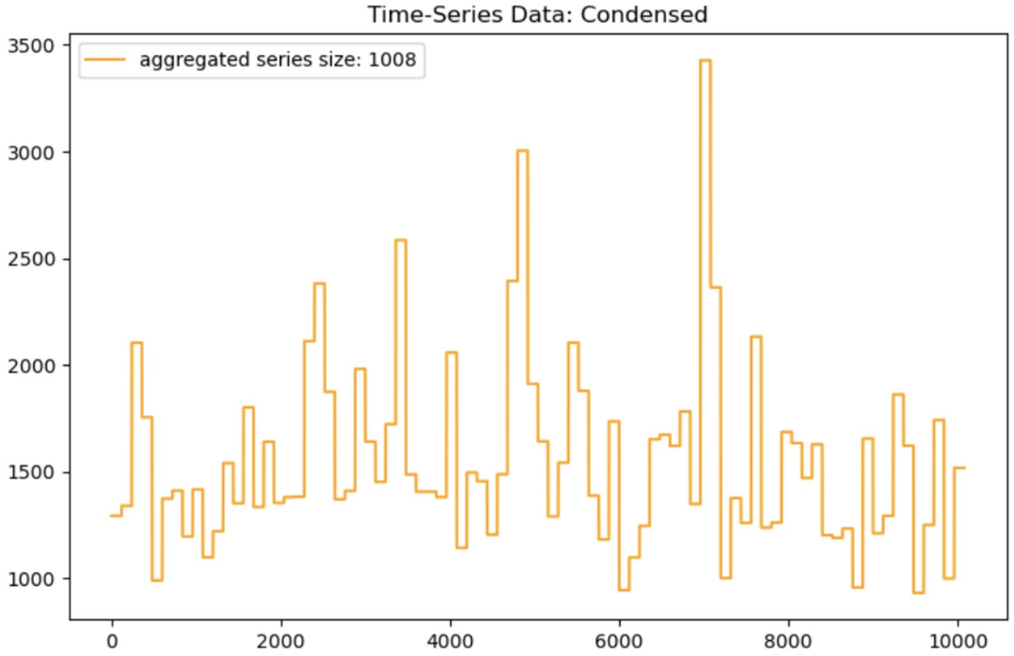
Grid Search Results (Sorted / Ranked by Mean Test Score)

rank	n_features	param_C	param_penalty	param_solver	mean_train_score	mean_test_score	mean_variance
1	25	0.1	l2	sag	0.893750	0.858333	0.035417
2	25	0.1	l2	saga	0.893750	0.858333	0.035417
3	25	0.1	l2	newton-cg	0.895833	0.858333	0.037500
4	25	0.1	l2	lbfgs	0.895833	0.858333	0.037500
5	25	1	l2	newton-cg	0.933333	0.850000	0.083333

LSTM Recurrent Neural Network

Using only time-series readings





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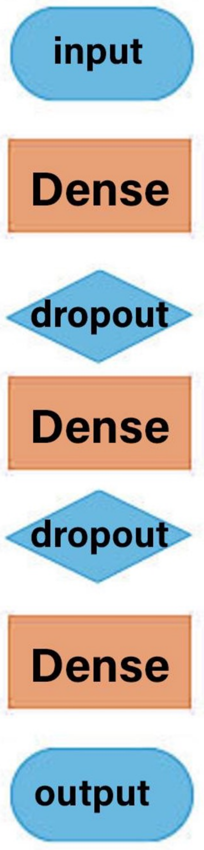
Note: Refer to the notebook at https://github.com/UC-Berkeley-I-School/mids-207-final-project-summer23-Kong-Kauffmann-Soque-Le-Paty/blob/main/notebooks/w207_2_models_and_evaluation.ipynb for hyperparameter tuning and model results

Dense Neural Network

Using selected extracted features

Model performs on par with our best models:

- Accuracy 82.5%
- Precision 85.1%
- Recall 80.0%
- F1-Score 82.4%



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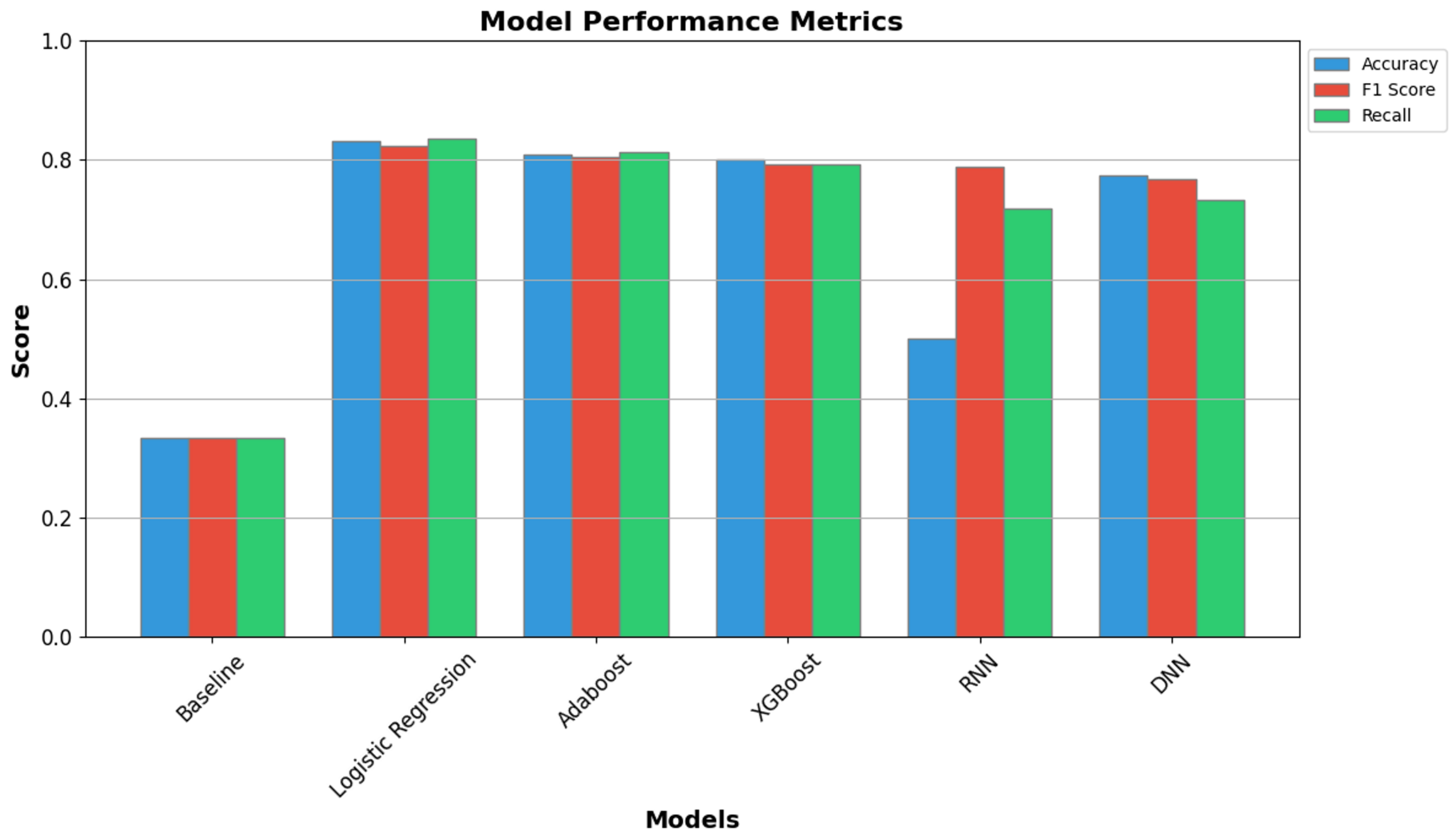
Evaluation



- Statistical tests:
  - ANOVA
  - Post-hoc pairwise comparisons with Bonferroni correction
- Logistic regression significantly outperforms other models
  - 85.83% accuracy
  - 85.74% F1 score
  - 87.8% recall
  - Lowest variance
- Sometimes the simplest model is best!

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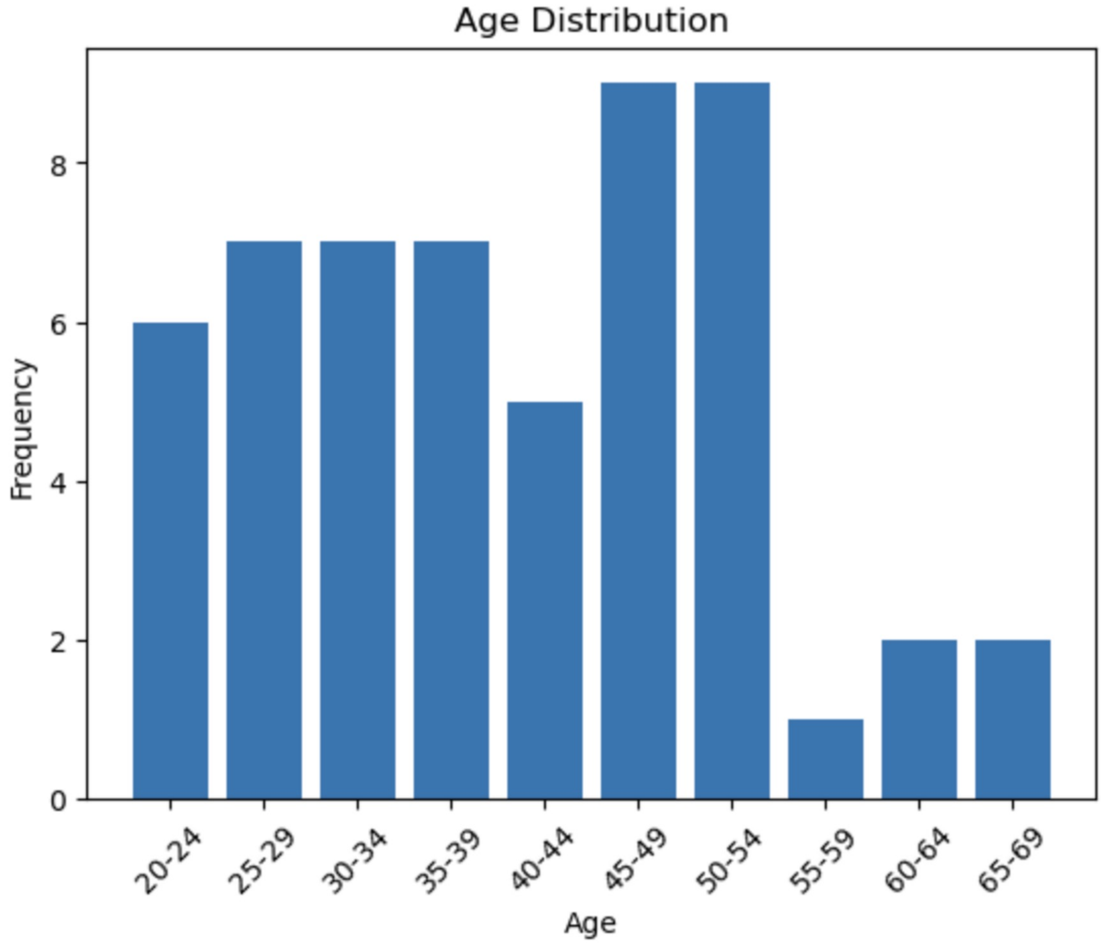
Limitations

- Small Sample Size
- Unrepresentative Control Group
- Unbalanced Age Group
- Time Period Sampling
- MADRS Score Variability



Biases

- Demographic Balance
- Urban vs. Rural Disparity
- Accessibility Generalization
- Time Period Sampling
- Observer Effect and Compliance

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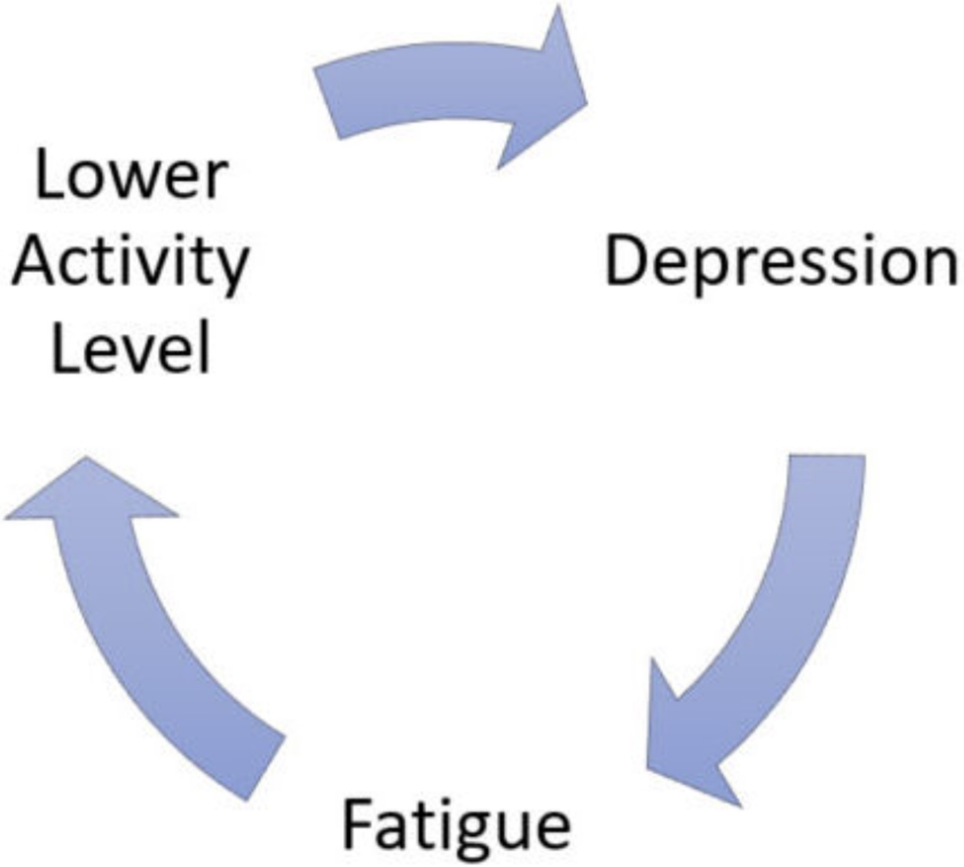
Conclusions



Next Steps:

- Expand the Dataset
- Decide on model: DNN?
- Further fine-tune parameters
- Collaborate with mental health professionals
- Address ethical considerations
- Develop user-friendly tools

Contributions

	Gary Kong	Julia Kauffman	Leo Le	Vishnu Paty	Melia Soque
Literature Search	X	X	X	X	X
Data Wrangling and Cleaning	X				
Feature Extraction and Feature Selection	X				
Data Augmentation		X			
Data Splitting and Cross-validation		X	X	X	X
Model Development and Hyperparameter Tuning	Logistic regression	LTSM Deep neural network	AdaBoost (Lead) XGBoost (Lead)	AdaBoost (Support) XGBoost (Support)	Logistic regression
Model Evaluation				X	

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