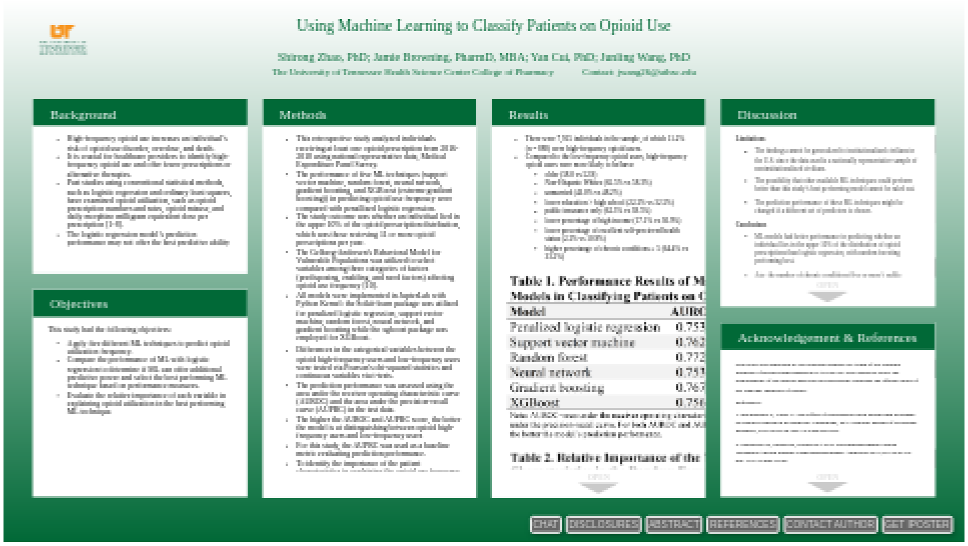
Using Machine Learning to Classify Patients on Opioid Use



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PRESENTED AT:

BACKGROUND

- High-frequency opioid use increases an individual's risk of opioid use disorder, overdose, and death.
- It is crucial for healthcare providers to identify high-frequency opioid use and offer fewer prescriptions or alternative therapies.
- Past studies using conventional statistical methods, such as logistic regression and ordinary least squares, have examined opioid utilization, such as opioid prescription numbers and rates, opioid misuse, and daily morphine milligram equivalent dose per prescription [1-8].
- The logistic regression model's prediction performance may not offer the best predictive ability and quality compared to alternative methods such as machine learning (ML) [9].

OBJECTIVES

This study had the following objectives:

- Apply five different ML techniques to predict opioid utilization frequency.
- Compare the performance of ML with logistic regression to determine if ML can offer additional predictive power and select the best performing ML technique based on performance measures.
- Evaluate the relative importance of each variable in explaining opioid utilization in the best performing ML technique.

METHODS

- This retrospective study analyzed individuals receiving at least one opioid prescription from 2016-2018 using national representative data, Medical Expenditure Panel Survey.
- The performance of five ML techniques (support vector machine, random forest, neural network, gradient boosting, and XGBoost (extreme gradient boosting)) in predicting opioid use freqneucy were compared with penallized logistic regression.
- The study outcome was whether an individual lied in the upper 10% of the opioid prescription distribution, which was those recieving 11 or more opioid prescriptions per year.
- The Gelberg-Andersen's Behavioral Model for Vulnerable Populations was utilized to select variables among three categories of factors (predisposing, enabling, and need factors) affecting opioid use frequency [10].
- All models were implemented in JupterLab with Python Kernel: the Scikit-learn package was utilized for penalized logistic regression, support vector machine, random forest, neural network, and gradient boosting while the xgboost package was employed for XGBoost.

- Differences in the categorical variables between the opioid high-frequency users and low-frequency users were tested via Pearson's chi-squared statistics and continuous variables via t-tests.
- The prediction performance was assessed using the area under the receiver operating characteristic curve (AUROC) and the area under the precision-recall curve (AUPRC) in the test data.
- The higher the AUROC and AUPRC score, the better the model is at distinguishing between opioid high-frequency users and low-frequency users
- For this study, the AUPRC was used as a baseline metric evaluating prediction performance.
- To identify the importance of the patient characteristics in explaining the opioid use frequency, the relative importance of each characteristic in the best performing model was computed.

RESULTS

- There were 7,915 individuals in the sample, of which 11.2% (n = 888) were high-frequency opioid users.
- Compared to the low-frequency opioid users, high-frequency opioid users were more likely to be/have:
  - older (58.0 vs 52.9)
  - Non-Hispanic Whites (65.5% vs 58.3%)
  - unmarried (43.0% vs 48.2%)
  - lower education > high school (22.2% vs 32.5%)
  - public insurance only (62.3% vs 38.5%)
  - lower percentage of high income (17.1% vs 30.9%)
  - lower precentage of excellent self-percieved health status (2.2% vs 10.9%)
  - higher percetange of chronic conditions ≥ 5 (64.4% vs 33.2%)

Table 1. Performance Results of Machine Learning Models in Classifying Patients on Opioid Use

Model	AUROC	AUPRC
Penalized logistic regression	0.7537	0.2665
Support vector machine	0.7628	0.2659
Random forest	0.7726	0.2871
Neural network	0.7530	0.2842
Gradient boosting	0.7679	0.2846
XGBoost	0.7563	0.2740

Note: AUROC=area under the receiver operating characteristic curve; AUPRC=area under the precision-recall curve; For both AUROC and AUPRC, the larger the score, the better the model's prediction performance.

Table 2. Relative Importance of the Top 10 Patient Characteristics in the Random Forest

Variables	Relative Importance
Age	0.2273
Number of chronic conditions (≥ 5)	0.2102
Insurance type (public insurance only)	0.1007
Self-perceived health status (fair)	0.0704
Self-perceived health status (poor)	0.0538
Number of chronic conditions (2–4)	0.0473
Self-perceived health status (very good)	0.0458
Poverty category (high income)	0.0350
Race/Ethnicity (Hispanics)	0.0307
Education > high school	0.0226

Note: Random forest was found to be the best performing model. Relative importance of each variable was computed based on the reduction in the Gini criterion used to select split points.

DISCUSSION

Limitations

- The findings cannot be generalized to institutionalized civilians in the U.S. since the data used is a nationally representative sample of noninstitutionalized civilians.

- The possibility that other available ML techniques could perform better than this study's best performing model cannot be ruled out.

- The prediction performance of these ML techniques might be changed if a different set of predictors is chosen.

Conclusions

- ML models had better performance in predicting whether an individual lies in the upper 10% of the distribution of opioid prescriptions than logistic regression, with random foresting performing best.

- Age, the number of chronic conditions (five or more), public insurance only, and self-perceived health status were found to have notable predicting power in the random forest.

- ML models could be a promising and powerful tool in predicting the frequency of opioid use and associated variables.

ACKNOWLEDGEMENT & REFERENCES

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DISCLOSURES

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ABSTRACT

OBJECTIVES : High-frequent opioid use tends to increase an individual's risk of opioid use disorder, overdose, and death. Thus, it is important to predict an individuals' opioid use frequency to improve opioid prescription utilization patterns. This study applied five machine learning techniques to predict opioid use frequency, including support vector machine, random forest, neural network, gradient boosting, and XGBoost (extreme gradient boosting). Additionally, this study compared the performance of these machine learning models with penalized logistic regression.

METHODS : This retrospective study included individuals receiving at least one opioid prescription from 2016-2018 in the national representative data, Medical Expenditure Panel Survey. The study outcome measured whether an individual lied in the upper 10 percent of the opioid prescription distribution. The predictors were selected based on Gelberg-Andersen's Behavioral Model of Health Services Utilization. The prediction performance was assessed using the area under the receiver operating characteristic curve (AUROC) and the area under the precision-recall curve (AUPRC) in the test data. Patient characteristics as predictors for high-frequency use of opioids were ranked by the relative importance in prediction in the test data.

RESULTS : Random forest achieved the highest value of both AUROC (0.7726) and AUPRC (0.2871), outperforming logistic regression. In the best performing model, age, the number of chronic conditions, public insurance, and self-perceived health status had enormous predicting power in opioid use frequency.

CONCLUSIONS : This study demonstrates that machine learning techniques can be a promising and powerful technique in predicting health outcomes.

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