From Prediction To Interpretation: Machine Learning-based Insights Into Suicidal Ideation Among ADHD Patients

Samuel Ayemere, MSc[1]; Maryam Pathan, BPharm[1]; Mohammad A. Al-Mamun, PhD[2]*

1. Department of Pharmaceutical Systems and Policy, School of Pharmacy, West Virginia University, Morgantown, WV, USA
2. School of Systems Science and Industrial Engineering, Binghamton University, Binghamton, NY, USA
*Corresponding author

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BACKGROUND

- Although suicidal ideation(SI) is a major health concern, little is known about the risk factors that contribute to its onset and progression.[1]
- Attention-Deficit/Hyperactivity Disorder (ADHD) is linked to increased SI through its core symptoms of inattention, hyperactivity, and impulsivity, as well as frequent comorbidities such as depression, anxiety, and substance use disorders.[2]
- Few studies have been carried out to determine the risk factors, but none have implemented machine learning methods.[3]

OBJECTIVE

- To investigate key contributing factors that lead to SI among individuals with (ADHD) using machine learning methods in West Virginia, United States.

METHODS

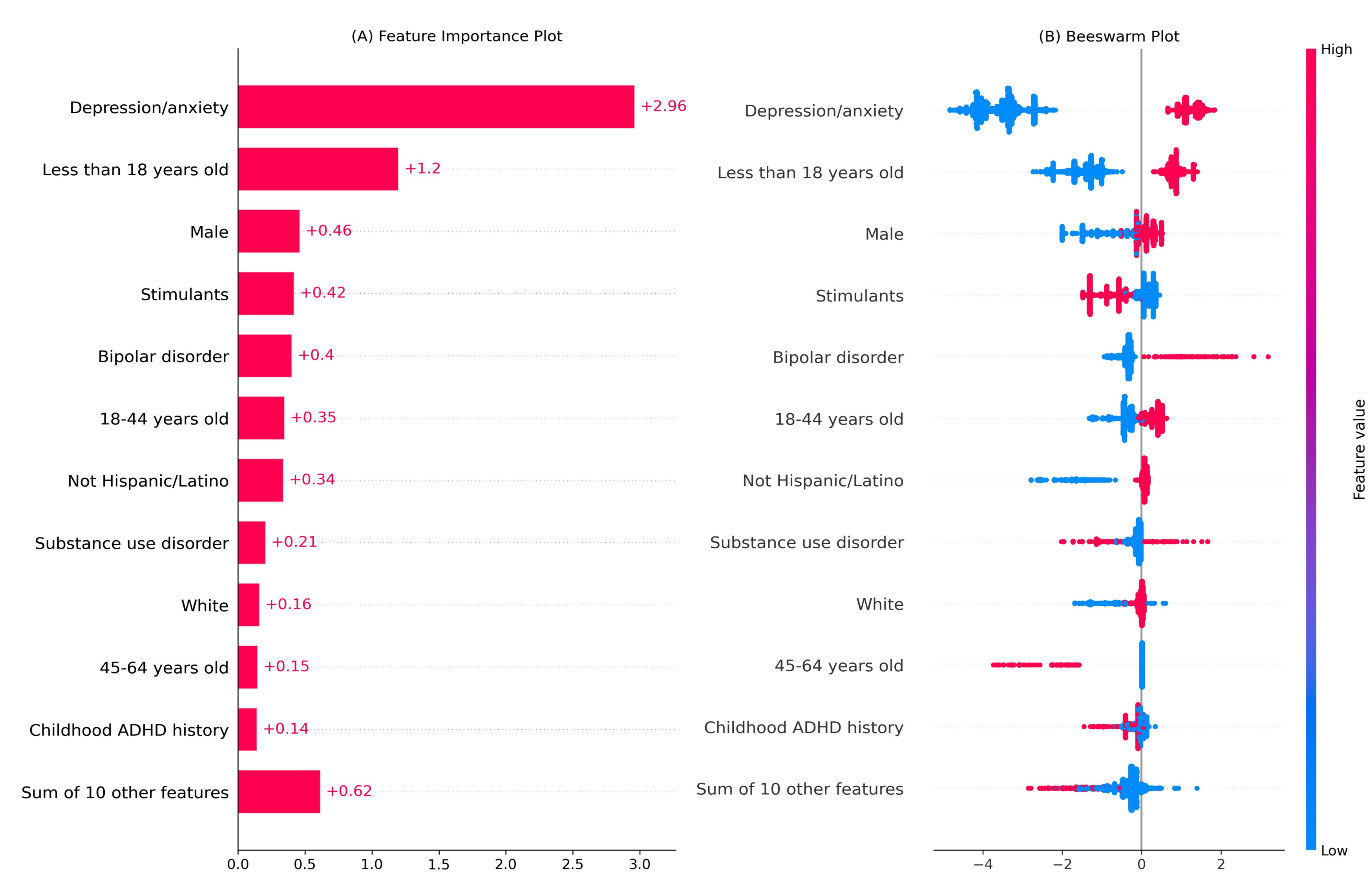
- **Study design**: Retrospective longitudinal study.
- **Data source**: TriNetX Research Network containing de-identified Electronic Health Records (2007 to 2023).
- **Inclusion criteria**: ADHD patients with medication data.
- **Exclusion criteria:** Prior SI, history of self-harm/suicide attempts, or the same first medication date for stimulants and non-stimulants initiation.
- **Study timeline and follow-up:** Baseline covariates assessed during the 12-month baseline period. Follow-up continued until first occurrence of SI, medication discontinuation /switching, death, or end of the study period.
- **Target variable:** Suicidal ideation.
- **Analysis:** Logistic regression(LR), Random Forest(RF), Extreme gradient boost(XGBoost), SMOTE.
- **Model evaluation:** The primary performance metric was the area under the precision-recall curve (AUPRC). AUPRC is often used in situations where classes are heavily imbalanced. The secondary metrics assessed include: the area under the receiver operating characteristic curve (AUROC), recall, precision, and F1-score. The final model was selected based on the highest mean AUPRC and a good balance of sensitivity and specificity.
- **Model interpretation:** SHapley Additive exPlanations (SHAP) provided global explanations by ranking the overall importance of each feature and how each feature influenced predictions using beeswarm plots.

RESULTS

Table 1: Comparison of machine learning model performance metrics across SMOTE sampling ratios for predicting suicidal ideation.

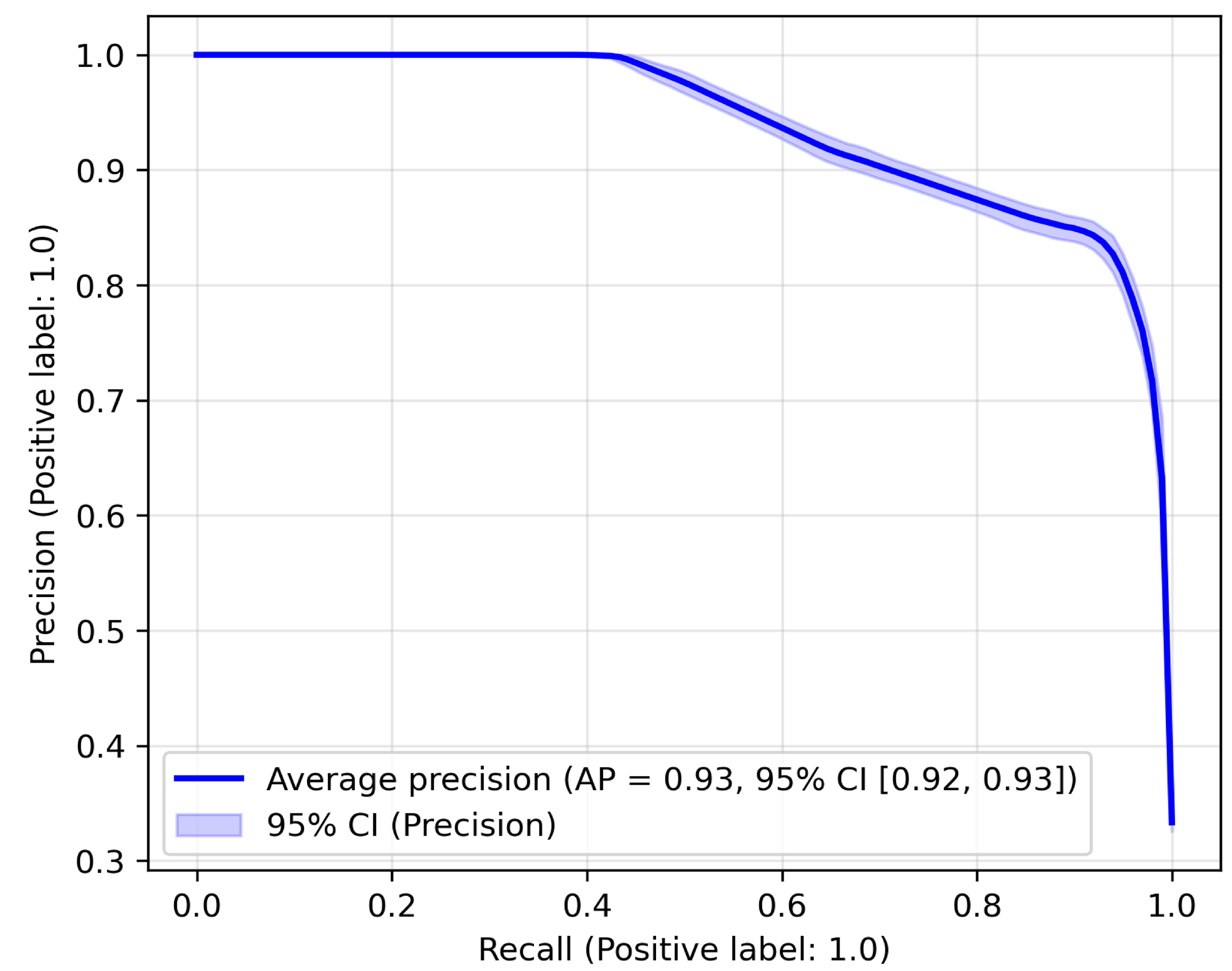
Model	SMOTE ratio	AUPRC	Accuracy	F1 score	Recall	Precision	AUC
LR	0.2	0.62± 0.02	0.88 ± 0.02	0.64 ± 0.03	0.67 ± 0.05	0.62 ± 0.05	0.92 ± 0.02
	0.3	0.71± 0.01	0.87 ± 0.02	0.73 ± 0.03	0.78 ± 0.04	0.69 ± 0.04	0.92 ± 0.02
	0.5	0.80± 0.02	0.86 ± 0.01	0.80 ± 0.03	0.82 ± 0.04	0.78 ± 0.03	0.92 ± 0.02
RF	0.2	0.73± 0.01	0.89 ± 0.03	0.70 ± 0.07	0.79 ± 0.05	0.63 ± 0.07	0.94 ± 0.03
	0.3	0.83± 0.01	0.89 ± 0.03	0.79 ± 0.05	0.86 ± 0.06	0.72 ± 0.05	0.95 ± 0.02
	0.5	0.86± 0.01	0.88 ± 0.03	0.83 ± 0.03	0.87 ± 0.05	0.80 ± 0.04	0.94 ± 0.02
XGBoost	0.2	0.84± 0.01	0.85 ± 0.03	0.69 ± 0.05	0.95 ± 0.07	0.54 ± 0.05	0.95 ± 0.04
	0.3	0.89± 0.01	0.84 ± 0.03	0.74 ± 0.04	0.97 ± 0.05	0.60 ± 0.04	0.96 ± 0.03
	0.5	**0.93± 0.01**	**0.85 ± 0.03**	**0.93± 0.01**	**0.98 ± 0.03**	**0.70 ± 0.03**	**0.96 ± 0.03**

Figure 1: SHAP summary plots showing the top-ranked features and the directional effects of these predictors on suicidal ideation risk in the XGBoost model with a SMOTE sampling ratio of 0.5.



RESULTS

Figure 2: Precision-Recall curve demonstrating predictive performance of the XGBoost model.



LIMITATIONS

- The findings may have limited generalizability because the study population was predominantly White and non-Hispanic from West Virginia, highlighting the need for a national-level study with a more diverse population. In addition, SMOTE generates synthetic data derived from existing minority samples, models may learn overly specific patterns from the augmented data.

CONCLUSIONS

- Age <18 years, male gender, stimulant use, and psychiatric comorbidities like depression or anxiety, and bipolar disorders were identified as key factors associated with SI in ADHD. Integrating ML-based SI risk prediction in clinical decision-making among individuals with ADHD may support earlier risk stratification, targeted monitoring, and timely intervention.

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Author Contact: Mohammad A. Al-Mamun (malmamun1@binghamton.edu) ; Samuel Ayemere (sa00215@mix.wvu.edu)