Development and Validation of Machine Learning Algorithms to Predict 1-Year Ischemic Stroke and Bleeding Events in Patients with Atrial Fibrillation and Cancer

MSR45

Bang Truong, PhD[1]; Jingyi Zheng, PhD[2]; Lori Hornsby, PharmD[2], Brent I. Fox, PharmD, PhD[1]; Chiahung Chou, PhD[1]; Jingjing Qian, PhD[1].
[1] Department of Health Outcomes Research and Policy, Auburn University Harrison College of Pharmacy, Auburn, AL, USA
[2] Department of Mathematics and Statistics, Auburn University College of Sciences and Mathematics, Auburn, AL, USA
[3] Department of Pharmacy Practice, Auburn University Harrison College of Pharmacy, Auburn, AL, USA

INTRODUCTION

❑CHA_2DS_2-VASc and HAS-BLED scores have been widely used to assess risks of stroke and bleeding in patients with atrial fibrillation (AFib). However, these tools are not highly predictive in patients with AFib and cancer.

❑We leverage machine learning (ML) to develop and validate new assessment tools to predict risk of stroke and bleeding events among patients with AFib and cancer.

METHODS

❑ ***Design***

- ***Study design***: retrospective cohort study.
- ***Data***: SEER-Medicare database (2011-2019).
- ***Inclusion criteria***: aged ≥66, newly diagnosed non-valvular AFib (NVAF) from 1/1/2012 to 12/31/2018 with a record of breast, lung, or prostate cancer, continuously enroll in Medicare part A, B, D, and without Medicare Advantage or HMO for ≥12 months before and ≥12 months after NVAF diagnosis.
- ***Exclusion criteria***: valvular diseases, repair or replacement, VTE, or joint replacement during baseline or patients who initiated OACs within 12 months before or after NVAF diagnosis.

❑ ***Developing ML models***

- Outcomes: ischemic stroke and major bleeding.
- Features: from literature review and based on availability in SEER-Medicare data, including demographics, socioeconomic factors, comorbidities, cancer characteristics, cancer treatment, and medication history.
- Splitting ratio: 70% training :30% testing.
- ML models: elastic net logistic regression, random forest (RF), support vector machine (SVM), extreme gradient boosting (XGBoost), and neural network (NN) with 10-fold cross-validation (CV).

❑ ***Model performance and comparison***

- Imbalance classification problem (outcomes <10%) → Shift the decision threshold to the true event probability.
- Model discrimination metrics: AUC and DeLong's test to compare AUC across models.
- Compare the performances of ML models with CHA_2DS_2-VASc and HAS-BLED scores.
- Other metrics: sensitivity, specificity, F2 score, and feature importance plots.
- Model calibration: Brier score.

- ***Sensitivity analysis***: Synthetic Minority Oversampling Technique (SMOTE) to account for imbalance distribution of the outcome variables.

REFERENCES AND ADDITIONAL INFO

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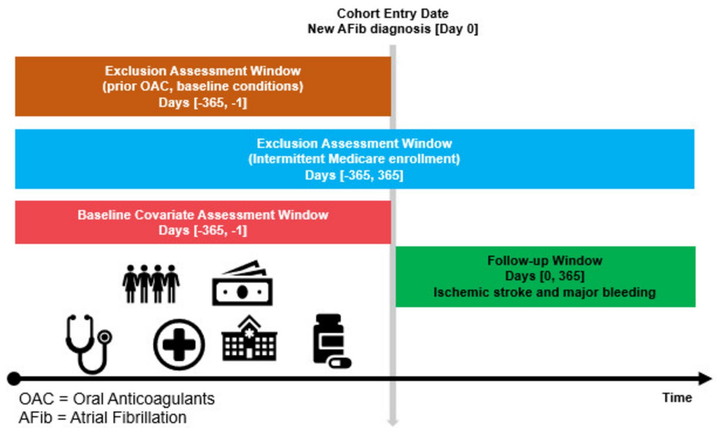

Figure 1. Study design and timeline

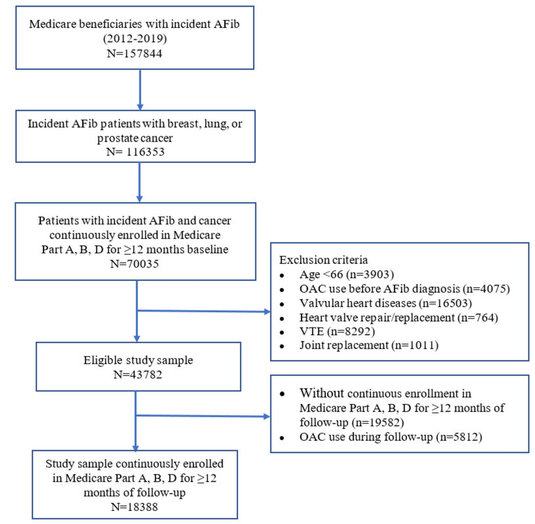

Figure 2. Study sample flowchart

RESULTS

❑ The final cohort consisted of 18388 patients, of whom 523 (2.84%) had ischemic stroke and 221 (1.20%) had major bleeding within one year after AFib diagnosis

❑ Mean age was 76.59±7.13, 8483 (46.13%) were female, and the majority were White (85.11%), residing in the Northeast (39.13%), or West (34.40%) region. The median duration from cancer diagnosis to AFib onset was 17 (IQR 2-40) months.

Table 1. Performance of machine learning models in prediction of stroke and major bleeding (using original data)

	Sensitivity	Specificity	AUROC	p-value	F2 score	Brier score
Ischemic stroke prediction						
Elastic net	0.698	0.574	0.684 (0.641-0.727)	Reference	0.183	0.055
RF	0.868	0.801	0.916 (0.887-0.945)	<0.001	0.375	0.035
XGBoost	0.723	0.608	0.737 (0.698-0.777)	0.005	0.202	0.054
SVM	0.434	0.589	0.545 (0.502-0.588)	<0.001	0.121	0.055
NN	0.692	0.511	0.625 (0.579-0.672)	0.023	0.161	0.056
CHA_2DS_2-VASc	0.829	0.268	0.580 (0.534-0.623)	-	-	-
Major bleeding prediction						
Elastic net	0.424	0.689	0.575 (0.503-0.649)	Reference	0.070	0.023
RF	0.515	0.671	0.623 (0.554-0.692)	0.0003	0.081	0.024
XGBoost	0.439	0.641	0.578 (0.510-0.646)	0.7210	0.064	0.024
SVM	0.652	0.357	0.546 (0.472-0.619)	0.0726	0.056	0.024
NN	0.470	0.497	0.504 (0.432-0.575)	0.0122	0.051	0.024
HAS-BLED	0.052	0.960	0.574 (0.506-0.637)	-	-	-

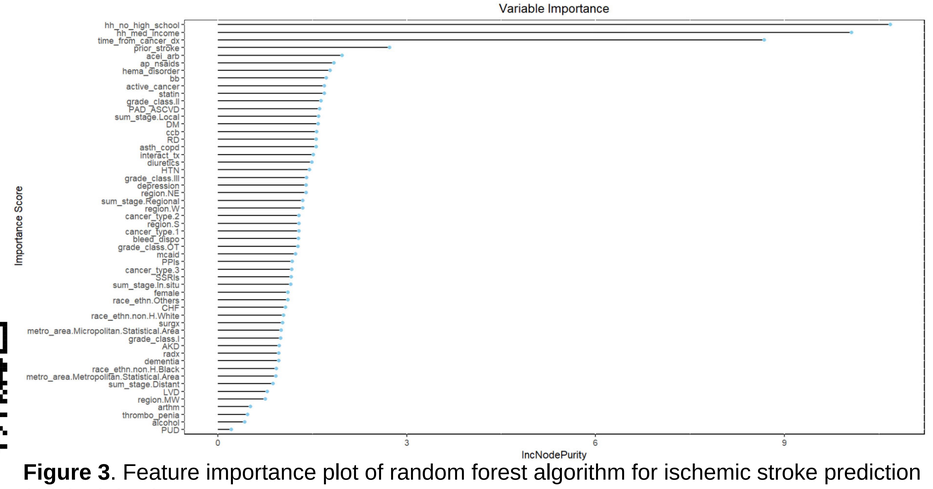

Figure 3. Feature importance plot of random forest algorithm for ischemic stroke prediction (original data)

❑ In prediction of ischemic stroke, RF significantly outperformed other ML models. However, the performance of ML algorithms in prediction of major bleeding was poor with highest AUC achieved by RF

❑ RF models performed better than CHA_2DS_2-VASc and HAS-BLED scores.

❑ SMOTE did not improve the performance of the ML algorithms.

CONCLUSION

Our study demonstrated a promising application of ML in stroke prediction among patients with AFib and cancer. This tool may be leveraged in assisting clinicians to identify patients at high risk of stroke and optimize treatment decisions.