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POSTER ABSTRACTS

332.THROMBOSIS AND ANTICOAGULATION: CLINICAL AND EPIDEMIOLOGICAL

Machine Learning to Detect Disparities in ICU Mortality Among Patients Receiving Direct Oral Anticoagulants

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INTRODUCTION
The current prescribing practices of direct oral anticoagulants (DOACs) in intensive care unit (ICU) patients and the associated clinical outcomes, including the incidence of major bleeding episodes and mortality, are significant clinical challenges. There is a need for early detection and intervention among patients taking DOACs to prevent adverse clinical outcomes. We hypothesized that machine-learning algorithms could be used to create a more precise and user-friendly diagnostic tool that incorporates a variety of clinical and laboratory data and takes complex interactions into account.
METHODS
This was an observational, retrospective study using routine clinical practice data from MIMIC-IV, a freely accessible electronic health record database. The study included patients who were admitted to the ICU with a DOAC (apixaban, rivaroxaban, dabigatran, or edoxaban) listed as one of the active medications at the time of hospital admission. ICD-9 and ICD-10 codes were utilized to identify cases (Z7901, V5861). Descriptive statistics were reported for all variables of interest. Various machine-learning models were utilized to predict the outcome variable of ICU mortality after accounting for variables from the demographic, laboratory, comorbidity, etc. domains. Model performance was evaluated by comparing the accuracy and Area Under the Receiver Operating Characteristic Curve (AUROC) values.
RESULTS
Overall, there were 3597 cases that met the inclusion criteria. Among these, 1517 (42.2%) were female. The majority of the sample was White (70.5%), and 2093 (58.2%) cases had Medicare insurance. The median [Q1, Q3] age of the sample was 74 [65, 83] years. ICU mortality was reported in 297 cases (8.2%). The mean (*SD*) ICU length of stay was 3.5 (4.6) days among those cases who were discharged alive and 4.2 (4.7) days among those who expired ($p < 0.012$). The median blood urea nitrogen among those discharged alive and expired was 20.0 and 29.5 ($p<0.001$), respectively. Intracranial hemorrhage was reported in 186 (5.6%) and 59 (19.9%) of those discharged alive and expired, respectively ($p<0.001$). The machine learning model results showed that the Random forest classifier performed best in predicting mortality in the ICU, with an AUROC value of 85.3%. The top ten variables associated with ICU mortality by feature importance were pH, WBC count, platelet count, blood urea nitrogen, heart rate, anion gap, partial pressure of carbon dioxide, oxygen saturation, age, and respiratory rate.
CONCLUSION
The Random forest classifier algorithm improved discrimination and calibration compared to other ML models for predicting mortality in the ICU among patients taking DOACs. It has the potential to reduce delayed diagnosis and overtreatment in clinical practice. Future studies will validate this model in broader clinical settings.

Disclosures No relevant conflicts of interest to declare.

Figure 1. Feature importance from Random forest classifier model predicting ICU mortality

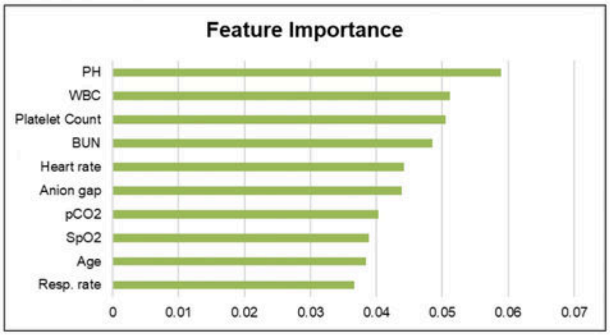

Figure 2. AUROC values comparing the performance of various machine learning models predicting ICU mortality

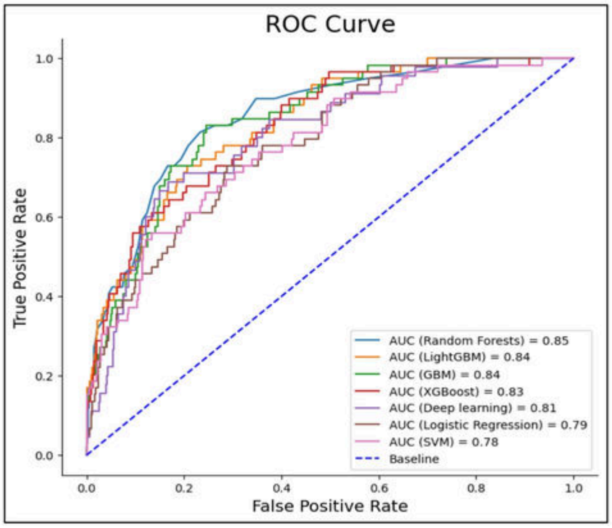

Figure 1

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