Artificial intelligence-based prediction of transfusion in the intensive care unit in patients with gastrointestinal bleeding

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ABSTRACT

Objective Gastrointestinal (GI) bleeding commonly requires intensive care unit (ICU) in cases of potential haemodynamic compromise or likely urgent intervention. However, many patients admitted to the ICU stop bleeding and do not require further intervention, including blood transfusion. The present work proposes an artificial intelligence (AI) solution for the prediction of rebleeding in patients with GI bleeding admitted to ICU.

Methods A machine learning algorithm was trained and tested using two publicly available ICU databases, the Medical Information Mart for Intensive Care V1.4 database and eICU Collaborative Research Database using freedom from transfusion as a proxy for patients who potentially did not require ICU-level care. Multiple initial observation time frames were explored using readily available data including labs, demographics and clinical parameters for a total of 20 covariates.

Results The optimal model used a 5-hour observation period to achieve an area under the curve of the receiving operating curve (ROC-AUC) of greater than 0.80. The model was robust when tested against both ICU databases with a similar ROC-AUC for all.

Conclusions The potential disruptive impact of AI in healthcare innovation is acknowledged, but awareness of AI-related risk on healthcare applications and current limitations should be considered before implementation and deployment. The proposed algorithm is not meant to replace but to inform clinical decision making. Prospective clinical trial validation as a triage tool is warranted.

INTRODUCTION

Gastrointestinal (GI) haemorrhage is a common condition that frequently requires hospitalisation, often in the intensive care unit (ICU) with considerable associated morbidity. In particular, ICU admission is associated with increased costs and a greater rate of complications and poor outcomes compared with ward admission. Some patients are initially admitted to the ICU for haemodynamic instability but stabilise without further intervention and are discharged to the ward the following day.

Previous instruments, such as the Rockall or the Blatchford score have been applied to triage patients based on the likelihood of mortality, recurrent/ongoing bleeding, need for hospitalisation and requirement for endoscopic intervention. However, these models are validated only for upper GI bleeding with a focus on endoscopic intervention and mortality and do not assist in informing level of monitoring for hospitalised patients. Currently, there is no model to assist in triaging patients with GI bleeding including those with an undifferentiated source to an appropriate acuity of care.

We identified the need for blood transfusion as a surrogate for persistent bleeding. Previous prospective studies have shown that up to half of patients with GI bleeding may not require transfusion. We used an ICU database to train a prediction model but

Summary

What is already known?

- Gastrointestinal bleeding is a severe event that requires admission to the ICU.
- Many patients in the ICU for gastrointestinal bleeding undergo only increased monitoring without intervention.
- ICU stay is associated with increased cost and morbidity.

What does this paper add?

- An algorithmic approach using artificial intelligence on readily available electronic data can accurately predict ICU transfusion need.
- Using this approach to identify patients at low risk for ongoing bleeding and transfusion could be validated prospectively to identify patients who may not require ICU-level care.
focused on the first few hours on arrival as a proxy of the patient’s state in the emergency department.

The use of artificial intelligence (AI) represents an opportunity for more effective and efficient care delivery by predicting disease trajectory and complications.7–12 Previous work in GI bleeding has used methods such as artificial neural networks,13 support vector machines13 to predict the need for intervention; and fuzzy models15 to identify which lab test is likely to contribute information gain and influence clinical management of patients with GI bleeding in the ICU. This study focused on using machine learning to predict transfusion to better identify those patients who continue to bleed.

METHODS
This study is reported in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology statement.16

Database description
Data were collected from the Medical Information Mart for Intensive Care-III (MIMIC-III) V.1.417 and in the eICU Collaborative Research Database V.2.0 (eICU-CRD).18 Both databases contain information from patients admitted to the ICU. The MIMIC-III database collects detailed haemodynamic and clinical parameters from all ICU patients admitted to a single major academic medical centre between 2008 and 2014, whereas the eICU-CRD is a multicentre database with high granularity data for over 200 000 admissions to ICUs monitored by an eICU19 across the USA.

Ethical approval
Both databases are previously de-identified and have been reviewed by the institutional review boards (IRB) of their hosting organisations and determined to be exempt from subsequent IRB.

Definition of outcome
The outcome of this study is ongoing GI bleeding after admission to the ICU. Since this outcome variable is not encoded, blood transfusions were used as surrogate marker.

Software
Models were developed in Python V.3.7 using data science packages including pandas V.0.25.3 (data wrangling),20 NumPy V.1.17.5 (computations),21 SciPy V.1.4.1 (hypothesis testing),22 Scikit-learn V.0.22.1 (modelling)23 and Hyperopt V.0.2.3 (hyperparameter optimisation).24

Data preparation
We included non-pregnant adult patients (≥18 years old) admitted to the ICU and diagnosed with GI bleeding based on the International Classification of Diseases (ICD-9) codes (see table A1, online supplemental digital content 1). For patients with multiple ICU admissions within a single hospitalisation event, only the first ICU stay was considered. The inclusion criteria for each database are further detailed in figure 1.

Missing records were imputed with the last observation available carried forward. Patients missing their first value were imputed with the intra-subject median. In order to take into account the dynamics of the observed features within the training window (eg, increasing, decreasing trends), we adopted a feature engineering approach (see text, online supplemental digital content 2). Also, non-normally distributed features (skewness >3) were log-transformed25 in order to obtain a normal distribution for improved model performance.

Figure 1  Inclusion criteria for the cohort extracted from the (A) eICU-CRD and (B) MIMIC-III. eICU-CRD, eICU Collaborative Research Database; ICD-9, International Classification of Diseases-9; ICU, intensive care unit; GI, gastrointestinal; MIMIC-III, Medical Information Mart for Intensive Care-III.
Feature selection has been performed by recursively discarding features that do not reduce accuracy performance when eliminated. This procedure is called recursive feature elimination (RFE), a method used to remove non-predictive covariates with a greedy approach (see text, online supplemental digital content 3). Final input datasets gather 4333 first ICU admissions from the MIMIC-III database and 10520 first ICU admissions from the eICU-CRD along with 20 covariates. Input variables include several laboratory analyses and demographic information that are available in each database. Detailed information of these features is described in table 1.

**Prediction time windows**

Several time windows were assessed for data extraction of the training/testing data and the data for the output variable (blood transfusion) that was predicted. Four different time windows starting from ICU admission (hour 0) were evaluated: training time from 0 to 3 hours/prediction time 4–24 hours, training time 0–4 hours/prediction time 5–24 hours, training time 0–5 hours/prediction time 6–24 hours, training time 0–6 hours/prediction time 7–24 hours. The training timeframe contains the covariates recorded during that time frame for each ICU stay. All training time windows include information recorded prior to the ICU admission (up to −1 hour). The prediction time window is when the surrogate variable (blood transfusion) was recorded (see figure 2).

This analysis helped us to find the optimal training/prediction time windows. The selected time windows were those that achieved the best predictive performance. In addition to that, the best training time window is the one that gathered the highest amount of data before a blood transfusion. Except from that, there is no other contextual detail that was considered during this analysis.

**Table 1** List of covariates, the output variable and demographic information for each cohort. Continuous variables are stated as mean (IQR), otherwise are the number of occurrences. Only a subset of these variables (selected by recursive feature elimination procedure) enters in the final models.

|                  | MIMIC-III (n=4314) | eICU-CRD (n=10 306) |
|------------------|---------------------|----------------------|
| **Demographics** |                     |                      |
| Age at admission (years) | 83.5 (56–81)       | 76.7 (56–79)       |
| Gender (n) |                     |                      |
| Male | 2491                 | 5927                 |
| Female | 1823               | 4379               |
| **Output variable (transfusion)** | | |
| Transfused patients (n, % wrt total number of patients) | 2077 (48.15%) | 2712 (26.31%) |
| **Covariates** |                     |                      |
| Heart rate (bpm) | 92.9 (79.0–105.7) | 94.0 (79.9–106.5) |
| Mean blood pressure (mm Hg) | 78.9 (68.5–87.8) | 78.4 (67.6–87.5) |
| Systolic blood pressure (mm Hg) | 114.5 (99.0–129.0) | 108.1 (93–121) |
| Diastolic blood pressure (mm Hg) | 60.3 (54.7–65.2) | 62.6 (56.0–68.2) |
| Respiratory rate (breaths/min) | 21.2 (18.0–24.0) | 21.9 (17.8–24.4) |
| Haematocrit (%) | 28.4 (23.8–32.6) | 26.5 (20.7–31.6) |
| Haemoglobin (g/L) | 97 (80–112) | 87 (67–104) |
| White blood cell (×10⁹/L) | 11.8 (7.2–14.1) | 11.7 (7.4–14.4) |
| Platelet (×10⁹/L) | 227.5 (137.0–286.0) | 207 (129.0–263.0) |
| Creatinine (mg/dL) | 1.79 (0.85–1.88) | 1.73 (0.80–1.90) |
| Blood urea nitrogen (mg/dL) | 39.5 (19.0–51.0) | 39.2 (19.0–51.0) |
| Potassium (mEq/L) | 4.34 (3.80–4.70) | 4.38 (3.80–4.80) |
| Bicarbonate (mEq/L) | 22.6 (20.0–26.0) | 22.7 (20.0–26.0) |
| Amount blood transfused (mL) | 601.0 (375.0–750.0) | 571.9 (324.0–700.0) |
| Glucose (mg/dL) | 160.2 (106.0–174.0) | 153.2 (105.0–176.0) |
| Albumin (g/dL) | 3.17 (3.2–3.2) | 2.96 (2.8–3.1) |
| Temperature (°C) | 36.3 (36.0–36.7) | 36.4 (36.4–36.5) |
| Partial thromboplastin time (s) | 37.3 (26.1–37.9) | 35.3 (26.0–37.0) |

eICU-CRD, eICU Collaborative Research Database; ICU, intensive care unit; MIMIC-III, Medical Information Mart for Intensive Care-III.
also provides the probability that a patient will bleed the physician could in principle perform standard sensitivity–specificity trade-off decisions.

Given that eICU-CRD exhibits target imbalance (26% transfused patients against 74% non-transfused patients) classifiers trained on this dataset are imbalance-aware in order not to skew predictions towards the majority class (ie, predicting all patients as low risk patients, which is not desirable).

Permutation feature importance\(^{28}\) of the five most important covariates is estimated for each model. Moreover, the partial dependence function\(^ {29}\) function of the outcome with respect to the most important variable is estimated (see text, online supplemental digital content 5).

In order to assess the goodness of the classifier during testing, we estimated the model’s accuracy, sensitivity (recall or true classification positive rate), specificity (true negative classification rate) and area under the curve of the receiving operating curve (ROC-AUC).

To conclude, models are calibrated through Platt’s scaling\(^ {30,31}\) to obtain reliable probability estimates. The effects of the calibration can be diagnosed visually with the calibration curves (see text, online supplemental digital content 6).

RESULTS

The best results are achieved when the models are trained on the MIMIC-III dataset (see table A2, online supplemental digital content 7), and the lowest values are observed in the models trained on the eICU-CRD data (see table A3, online supplemental digital content 8). When both datasets are merged (see table A4, online supplemental digital content 9), the performance does not improve considerably, but we can observe a significant improvement in terms of sensitivity. Of note, the sensitivity obtained in the models trained with MIMIC-III is the highest among all other models; which indicates that it is better to detect true positive cases or patients that would require transfusion.

It is also interesting to highlight that the models trained on MIMIC-III (see table A2, online supplemental digital content 7) have a greater discriminative power on the eICU-CRD testing set than the models trained only on the eICU-CRD data (see table A3, online supplemental digital content 8) and even if these are tested on the same database. Thus, a model trained on MIMIC-III is capable of generalising better to patients that the model does not train on.

These observations could be explained by the fact the MIMIC-III input dataset is not skewed (48.14% of the entries required transfusion) as the input dataset from the eICU-CRD (26.31% of the entries required transfusion). This imbalance could skew the model predictions towards the majority class (the most frequent label in the population) that are the patients that did not bleed (not required transfusion).
To avoid these misclassifications, the decision threshold was tuned during the optimisation procedure. In case the models were optimised only in terms of accuracy, it could have pushed the model to predict the majority class (non-transfused). By using the customised loss function, it was forced to jointly maximise precision and the recall of the final model notwithstanding the accuracy.

Looking at the results reported in table 2, online supplemental tables A5–A7 (see tables A, online supplemental digital content 10–12) we notice that the performances of all the time windows are satisfying and the overall best ones are obtained when the training phase is performed with data collected in the time window 0–5 hours and the prediction time window is from 6 to 24. Hence, in the following, we will mainly focus on this subdivision.

The models achieve greater ROC-AUC values when they are tested on the MIMIC-III dataset (>0.80) compared with the models tested on the eICU-CRD (0.76–0.79) as shown in table 2. Only accuracy and specificity improve when the models are trained in the eICU-CRD, but no improvement is detected in terms of sensitivity. The highest true classification positive rate is achieved in the models trained on the MIMIC-III, a critical metric being that it indicates how good are the models to predict the need of transfusions (true positives). We remark that this behaviour was expected since the eICU-CRD dataset has a larger variety of patients and hospitals than on the MIMIC-III. Therefore, adding more training data with different characteristics is beneficial for the former but not for the latter.

The highest value of ROC-AUC is achieved when the model is both trained and tested in the MIMIC-III (0.81) as verified in figure 3 as well. When the same model is tested in the eICU-CRD dataset, we observed lower ROC-AUC values. This metric is improved (0.79) when the model is trained with both datasets, but tested in the same dataset. In terms of the ability to predict transfusion, the model trained in MIMIC-III and tested on the eICU-CRD dataset achieves the best sensitivity (0.93).

**Table 2** Results for the time window composed by the pair training time of 0–5 hours/prediction time 6–24 hours

| Training sets | Testing sets | ROC-AUC | Accuracy | Specificity | Sensitivity |
|---------------|--------------|---------|----------|-------------|-------------|
| MIMIC-III     | eICU-CRD     | 0.8141  | 0.7470   | 0.6482      | 0.8536      |
| eICU-CRD      | MIMIC-III    | 0.7634  | 0.5021   | 0.3502      | 0.9277      |
| MIMIC-III     | eICU-CRD     | 0.8017  | 0.7470   | 0.7982      | 0.6917      |
| eICU-CRD      | MIMIC-III    | 0.7858  | 0.7060   | 0.6872      | 0.7581      |
| MIMIC-III+eICU-CRD | MIMIC-III | 0.8035  | 0.7488   | 0.7143      | 0.7861      |
| eICU-CRD      | MIMIC-III+eICU-CRD | 0.7908  | 0.6884   | 0.6535      | 0.7861      |

eICU-CRD, eICU Collaborative Research Database; MIMIC-III, Medical Information Mart for Intensive Care-III; ROC-AUC, area under the curve of the receiving operating curve.

**Figure 3** ROC plot for all the test sets. Model is trained on (A) the MIMIC-III training set, (B) the eICU-CRD and (C) on the training set that contains both the MIMIC-III and the eICU-CRD. AUC, area under the curve; eICU-CRD, eICU Collaborative Research Database; ICU, intensive care unit; MIMIC-III, Medical Information Mart for Intensive Care-III; ROC, receiving operating curve.
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Figure 4 Feature importance plots for all the training sets. Model is trained on (A) the MIMIC-III training set, (B) the eICU-CRD and (C) on the training set that contains both the MIMIC-III and the eICU-CRD. eICU-CRD, eICU Collaborative Research Database; ICU, intensive care unit; MIMIC-III, Medical Information Mart for Intensive Care-III.

The most important features (see figure 4) to predict the need of transfusion are the haematocrit and the amount of blood already transfused during the training time window (0–5 hours) with the corresponding time pattern features (slope and intercept of haematocrit). Because of the importance of haematocrit, the interaction between this feature and the output variable was assessed visually in the partial dependence plots shown in figure 5.

Figure 5 Partial dependence plot of the need of transfusion on haematocrit for all the training sets. Model is trained on (A) the MIMIC-III training set, (B) the eICU-CRD and (C) on the training set that contains both the MIMIC-III and the eICU-CRD. eICU-CRD, eICU Collaborative Research Database; ICU, intensive care unit; MIMIC-III, Medical Information Mart for Intensive Care.

Despite the three plots do not have identical shapes, the same trend is verified in the three plots: haematocrit is inversely proportional to the output variable. That implies that if values of haematocrit decreases, the probability of needing blood transfusion increases. Moreover, the partial dependence function shown in figure 5 highlights the presence of a discriminative threshold in the model with respect to haematocrit. It indicates that if the value of haematocrit is greater than this threshold, the probability of bleeding increases substantially. We remark that the value for this threshold seems to be dependent on the dataset that is used for training, where this shift is more noticeable (figure 5A).

DISCUSSION

GI bleeding remains a common reason for ICU admission. In a dataset consisting of over 10 000 patients admitted to the ICU with GI haemorrhage (both upper and lower), under half require transfusion during their ICU admission.32 We present a model based on observations from the first 5 hours of ICU admission to predict the need for transfusion in the next 24 hours of admission with a high level of accuracy (overall AUC of 0.80). The patient’s vital signs and laboratory test findings during the first few hours in the ICU are a good proxy of the measurements in the emergency department.

In the clinical setting, the need for transfusion has been an outcome of interest for GI haemorrhage. Prior work from Villanueva et al6 found that even in active upper GI bleeding, up to half of patients do not require transfusion. Furthermore, it has been established that while the minority of patients with upper GI bleeding require hospitalisation, this can be a significant driver of costs. By identifying patients who will no longer require transfusion, it is possible to safely triage these patients to a regular ward, or even discharged to home if ambulatory monitoring can be provided.

Previous work in this area has focused either on upper or lower GI bleeding separately. In a 2016 analysis by Robertson et al,32 the Rockall, AIMS65 and Glasgow-Blatchford Score (GBS) were all used to predict outcomes for upper GI bleeding. In their population, a total of 62% of the patients required a blood transfusion. They found the GBS to be the best predictor with an ROC-AUC of 0.90. Both the AIMS65 (ROC-AUC 0.72) and full (ROC-AUC 0.68)/pre-endoscopy (ROC-AUC 0.66) Rockall scores were considerably less accurate. However, the use of these scores to predict the need for transfusion has limitations. First, the only score with an ROC-AUC over 0.8, the GBS was validated only on upper GI bleeding (primarily ulcer-related in the initial validation). Furthermore, relying on clinical data input from the healthcare providers, for example, presence of melena, presentation with syncope, presence of heart failure, introduces opportunities for error and bias. Attempts to generalise the use of GBS to lower GI bleeding have found some success but focuses primarily on the prediction of mortality and
need for an intervention instead of transfusion, and with suboptimal accuracy.

The sensitivity, or recall, of the models trained on MIMIC-III is the highest among all other models. A high recall means the algorithm identifies the majority of patients who require transfusion. For the use case presented, sensitivity is more important than precision, or the true positive rate. When several models have similar ROC-AUC, sensitivity should be prioritised over precision. The consequence of missing patients who eventually bleed and sending them to the regular floor or even discharging them home is worse than over-calling persistent bleeders and getting them admitted to the ICU. The context in which the algorithm will be used and for what purpose are crucial to the model building.

Even when models are externally validated in another dataset, there is no guarantee that it will perform well in another patient population. External validation does not circumvent the need to evaluate algorithms trained elsewhere using local data prior to deployment. The performance of any predictive model is dependent on the database used to train the algorithm, and thus, the features available as candidate variables. The relationship between the features and the output of an algorithm is influenced by local practice patterns. In addition, model performance should be continuously monitored after deployment as accuracy almost always wanes over time, requiring model re-calibration.

We submit the potential disruptive impact of AI-based technologies in precision medicine and in clinical decision-support systems. Nonetheless, we are aware of AI-related risks on healthcare applications and the pitfalls that have occurred in the past. Although we reduced the risk of misclassification in the design of our models, we propose a human in the loop system for decision support. A final decision still rests on the healthcare provider after a careful clinical assessment which now includes input from the algorithm. Moreover, before implementation to a real clinical setting, the algorithm requires regulatory approval, human factors engineering to incorporate it into the workflow and prospective evaluation of its impact on hard clinical endpoints including patient harm from false negative predictions.

There are key strengths to the model we presented. First, the calculation can be completely automated without clinician input of symptoms and past medical history. Furthermore, it does not require identification of the source of bleeding—upper versus lower. The model performed well on held out test sets from two different databases, one of them collected from more than 200 hospitals across the USA.

Despite model validation on two databases, the algorithm is not guaranteed to perform accurately in a different institution. We present a reproducible methodology that other hospitals can employ to develop their own algorithm, as different patient demographics and practice patterns would undoubtedly modify the relationship of the features with the outcome being predicted, that is, the need for blood transfusion. At the very least, medical AI algorithms require evaluation on data from the local population prior to prospective evaluation using hard clinical endpoints.

Going forward, this work presents a methodology to build a clinical AI-based model that potentially can be implemented for prediction of the need for transfusion. The algorithm is not meant to replace but to inform decision making, specifically around identification of patients who may not benefit from an ICU-level of care. A prospective trial is warranted to assess the utility of this model in clinical usage.

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 Contributors All authors contributed to writing the manuscript. FC, RL, ARA, collaborated on the data extraction, modeling, visualisation and analysis. YA, AZ, MMN, FG guided data extraction. DJS and LAC interpreted, validated results, design of the work and supervised data extraction. SMV, JS, RB and SF reviewed the paper and supervised the work.

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Competing interests None declared.

Patient consent for publication Not required.

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Data availability statement The data that support the findings of this paper employ data from MIMIC-III and eICU-CRD databases. The access to these datasets is controlled and researchers should request access on the PhysioNet
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Table A 1 – ICD-9 codes included for this study.

| ICD-9 code | Description                                                      |
|------------|------------------------------------------------------------------|
| 530.7      | GASTROESOPHAGEAL LACERATION-HEMORRHAGE SYNDROME                  |
| 569.3      | HEMORRHAGE OF RECTUM AND ANUS                                     |
| 578.0      | HEMATEMESIS                                                      |
| 578.1      | BLOOD IN STOOL                                                  |
| 578.9      | HEMORRHAGE OF GASTROINTESTINAL TRACT, UNSPECIFIED                |
| 530.21     | ULCER OF ESOPHAGUS WITH BLEEDING                                 |
| 530.82     | ESOPHAGEAL HEMORRHAGE                                           |
| 531.00     | ACUTE GASTRIC ULCER WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 531.01     | ACUTE GASTRIC ULCER WITH HEMORRHAGE, WITH OBSTRUCTION            |
| 531.20     | ACUTE GASTRIC ULCER WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 531.21     | ACUTE GASTRIC ULCER WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 531.40     | CHRONIC OR UNSPECIFIED GASTRIC ULCER WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 531.41     | CHRONIC OR UNSPECIFIED GASTRIC ULCER WITH HEMORRHAGE, WITH OBSTRUCTION |
| 531.60     | CHRONIC OR UNSPECIFIED GASTRIC ULCER WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 531.61     | CHRONIC OR UNSPECIFIED GASTRIC ULCER WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 532.00     | ACUTE DUODENAL ULCER WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 532.01     | ACUTE DUODENAL ULCER WITH HEMORRHAGE, WITH OBSTRUCTION            |
| 532.20     | ACUTE DUODENAL ULCER WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 532.21     | ACUTE DUODENAL ULCER WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 532.40     | CHRONIC OR UNSPECIFIED DUODENAL ULCER WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 532.41     | CHRONIC OR UNSPECIFIED DUODENAL ULCER WITH HEMORRHAGE, WITH OBSTRUCTION |
| 532.60     | CHRONIC OR UNSPECIFIED DUODENAL ULCER WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 532.61     | CHRONIC OR UNSPECIFIED DUODENAL ULCER WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 533.00     | ACUTE PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 533.01     | ACUTE PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE, WITH OBSTRUCTION |
| 533.20     | ACUTE PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| ICD Code | Description |
|----------|-------------|
| 533.21   | ACUTE PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 533.40   | CHRONIC OR UNSPECIFIED PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 533.41   | CHRONIC OR UNSPECIFIED PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE, WITH OBSTRUCTION |
| 533.60   | CHRONIC OR UNSPECIFIED PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 533.61   | CHRONIC OR UNSPECIFIED PEPTIC ULCER OF UNSPECIFIED SITE WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 534.00   | ACUTE GASTROJEJUNAL ULCER WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 534.01   | ACUTE GASTROJEJUNAL ULCER, WITH HEMORRHAGE, WITH OBSTRUCTION |
| 534.20   | ACUTE GASTROJEJUNAL ULCER WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 534.21   | ACUTE GASTROJEJUNAL ULCER WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 534.40   | CHRONIC OR UNSPECIFIED GASTROJEJUNAL ULCER WITH HEMORRHAGE, WITHOUT MENTION OF OBSTRUCTION |
| 534.41   | CHRONIC OR UNSPECIFIED GASTROJEJUNAL ULCER, WITH HEMORRHAGE, WITH OBSTRUCTION |
| 534.60   | CHRONIC OR UNSPECIFIED GASTROJEJUNAL ULCER WITH HEMORRHAGE AND PERFORATION, WITHOUT MENTION OF OBSTRUCTION |
| 534.61   | CHRONIC OR UNSPECIFIED GASTROJEJUNAL ULCER WITH HEMORRHAGE AND PERFORATION, WITH OBSTRUCTION |
| 535.01   | ACUTE GASTRITIS, WITH HEMORRHAGE |
| 535.11   | ATROPHIC GASTRITIS, WITH HEMORRHAGE |
| 535.21   | GASTRIC MUCOSAL HYPERTROPHY, WITH HEMORRHAGE |
| 535.31   | ALCOHOLIC GASTRITIS, WITH HEMORRHAGE |
| 535.41   | OTHER SPECIFIED GASTRITIS, WITH HEMORRHAGE |
| 535.51   | UNSPECIFIED GASTRITIS AND GASTRODUODENITIS, WITH HEMORRHAGE |
| 535.61   | DUODENITIS, WITH HEMORRHAGE |
| 535.71   | EOSINOPHILIC GASTRITIS, WITH HEMORRHAGE |
| 537.84   | DIEULAFY LESION (HEMORRHAGIC) OF STOMACH AND DUODENUM |
| 562.02   | DIVERTICULOSIS OF SMALL INTESTINE WITH HEMORRHAGE |
| 562.03   | DIVERTICULITIS OF SMALL INTESTINE WITH HEMORRHAGE |
| 562.12   | DIVERTICULOSIS OF COLON WITH HEMORRHAGE |
| 562.13   | DIVERTICULITIS OF COLON WITH HEMORRHAGE |
| 569.85   | ANGIODYSPLASIA OF INTESTINE WITH HEMORRHAGE |

Note: All ICD codes for diagnoses are based on the ICD-9-CM both in MIMIC-III and in the eICU-CRD. The ICD-10 equivalent code can only be queried in the eICU-CRD (not included in Table A1). Nevertheless, it is important to mention that the code field in MIMIC-III is up to six characters long and without decimal point(17). In case the reader wants to query them on
MIMIC-III, just remove the decimal point that is referred to in Table A1 in the respective query code.
Feature construction: time-series

The extraction of time patterns is achieved by fitting a linear regression on the data recorded for a feature $x_t$ during the selected training window for each patient. It results in two values per each entry (patient) from the time-series values of a certain feature $x_t$: the slope ($\beta$) and the intercept ($\alpha$) of a linear regression. The slope contains information about increasing and decreasing trends, whereas the intercept provides insight about the baseline value for that specific patient or how far it is from the origin. For instance, if there is a decreasing trend of feature $x$ over time, it will result in a negative value for $\beta$ (see Figure 6, which contains a graphical example of a negative trend of feature $x$ over time).

![Graphical representation of the extraction of time patterns from time-series values.](image)
Feature engineering: recursive feature elimination

Recursive feature elimination (RFE) works by discarding the covariate with lowest importance from the initial feature set. The model is then re-trained with the resulting feature subset and this process is repeated until a specified number of minimum features to retain is reached. For each iteration of the algorithm the accuracy of the obtained classifier is recorded in order to identify which subset of features delivers maximum performance. This procedure is performed separately on the three training set considered in the analysis framework (See Prediction time windows in the Methodology section), therefore, a different set of feature is considered in each of the validation procedures.
Predictive model structure

The trained classifiers are an ensemble of two different models: a logistic regression (LR) and a random forest (RF) (28) model. The decision of building a model combining these two classification methodologies arises by comparing the most popular classification algorithms in biological sciences (Support Vector Machines (SVM), LR, RF, and Multi-Layer Perceptron (MLP)) on 4 different metrics: accuracy, ROC-AUC, sensitivity and specificity.

This analysis allowed us to verify that LR and RF seem to achieve better performance, compared to SVM models in all training sets [(see Table A2, Supplemental Digital Content 7, which contains the performance metrics when model are trained on MIMIC-III training set); (see Table A3, Supplemental Digital Content 8, which contains the performance metrics when models are trained on the eICU-CRD training set); & (see Table A4, Supplemental Digital Content 9, which contains the performance metrics when models are trained on both databases)]. As expected, the ensemble of these two approaches achieves a better performance in almost all the estimated metrics. Most likely, it allows to account for possible non-linear patterns in the decision boundary of the final classifier that LR may not detect. The two components are trained in a joint optimization procedure that fixes the hyperparameters of both algorithms through a Bayesian modeling. (27)

Bayesian optimization is a heuristic method that is capable of achieving results comparable to a grid search in fewer iterations and without the need to explore a massive hyperparameter space. Bayesian statistics help to focus the search routine in each iteration on areas of the hyperparameters space that seems to be more promising with respect to the specified loss function.
The designed algorithm predicts the probability that a certain patient will bleed (or need a transfusion as surrogate marker) in the predefined forecasting window. Usually, the predicted probabilities $\hat{y}$ in binary classification are mapped into deterministic labels by selecting the output label, or class, with higher probability. This step is essential to estimate specificity, sensitivity, accuracy and the confusion matrix (see Figure 7, which contains the confusion matrices for all the classifiers). However, in classification problems with class imbalance the dataset is biased to the dominant or majority class (the most frequent class). This imbalance can affect the learning of any machine learning algorithm and skew the model predictions towards the majority class.

It is verified that this imbalance is more significant in the eICU-CRD, where there are more entries for the “non-bleeding” label (23.31%) and pushing the predictions in favor to this label. In a medical context, this could be undesirable since missing a bleed-event is more costly than missing a non-bleeding one. We addressed this problem by searching during the optimization for a decision threshold $\gamma$ that determines, for example, if a patient with a probability of needing transfusion of 0.31 should be labeled as “bleeding” or “non-bleeding”. This allows to boost the model recall and in exchange for some false positives.

The customized loss function estimated during model optimization takes into consideration the F1-score and accuracy as shown in the following equation:

$$loss = 1 - (0.8 \times F1\_score + 0.2 \times accuracy)$$

By using the above combination of F1-score and accuracy, it is forced the classifiers to jointly maximize precision and the recall of the final model notwithstanding accuracy.
The base ensemble model is a voting classifier (hard voting) composed of one LR model and one RF model. A label (class 1 or 0) is assigned to the most frequent predicted label (i.e. the one which is predicted by at least two classifiers). During the Bayesian optimization, we evaluate 100 voting classifiers on a training set. After this procedure, we kept the best three models and we averaged the predicted probabilities of these three models (soft voting). In addition to that, the threshold $\gamma$ for defining the outcome is chosen during hyperparameter optimization in order to obtain a calibrated model with the best performance.

Figure 7 - Confusion matrices obtained when models are trained on a) the MIMIC-III training set, b) the eICU-CRD, and c) on the training set that contains both the MIMIC-III and the eICU-CRD.
Partial dependence functions

Partial dependence plots are a graphical way to analyze and quantify the marginal effect of one feature on the target response (output variable). The partial dependence functions are obtained by considering the interaction between the target and a feature while marginalizing out the other features in the input dataset. In other words, we can interpret partial dependence plots as the expected target response (in our case the predicted probability function) as a function of the considered feature.

More formally, calling $X_i$ the feature with respect to which we want to compute dependence and $X_{-i}$ the set of complementary features we define the partial dependence of the response $f$ as:

$$pd_{X_i}(x_i) = E_{X_{-i}}[f(x_i, X_i)] = \int f(x_i, x_{-i}) p(x_{-i}) dx_{-i}$$

The integral above cannot be computed analytically and it is therefore approximated as:

$$pd_{X_i}(x_i) \approx \frac{1}{n_{samples}} \sum_{j=1}^{n} f(x_i, x_{-i}^{(j)})$$

where $x_{-i}^{(j)}$ is the value of the $j^{th}$ sample for features $X_{-i}$. The plot is produced when this integral is computed over several values of $x_i$. 
Classifier calibration

The proposed classifier has been calibrated in order to provide a reliable estimation of the probability of bleeding in the considered prediction window. During calibration is fitted a regressor, or calibrator, that maps the output of a classifier to a calibrated probability in a range [0,1]. The calibrator tries to predict the conditional probability where is the output probability of the trained classifier.

Calibration is performed through Platt’s scaling (31), where the regressor depends on a logistic function:

\[ S(x) = \frac{1}{1 + e^{Ax+B}} \]

where A and B are the parameters that are estimated using maximum likelihood estimation.

A well calibrated model should be the one that given a set of patients with predicted bleeding probability close to 0.6, approximately 60% should actually belong to the positive class. This can be verified graphically through calibration or reliability curves. On the horizontal axis is mapped the predicted probability of bleeding, whereas on the vertical axis we see the fraction of those patients who actually bleed. A perfectly calibrated model should therefore fit the diagonal line of the graph.

It was plotted these curves for the developed models and the histograms that show the counts of records that have the same probability outcome (see Figures 8, which contains the calibration curves and histograms for all classifiers). The continuous lines compare the
classifiers when the trained model is tested either in MIMIC-III or eICU-CRD testing subset. It also is verified that the model is better calibrated when the testing set comes from the same database of the training subset. However, reliability increases when the model is trained on the training set that contains information of both datasets (see Figure 8, which shows the calibration curves).

Figure 8 - Calibration curves for the models trained on a) the MIMIC-III training set, b) the eICU-CRD, and c) on the training set that contains both the MIMIC-III and the eICU-CRD and the relative histograms.
Table A2 – Comparison table of several classifiers trained on the MIMIC-III training set.

| Models     | Accuracy   | ROC AUC  | Sensitivity | Specificity |
|------------|------------|----------|-------------|-------------|
|            | MIMIC  | eICU-CRD | MIMIC  | eICU-CRD | MIMIC  | eICU-CRD | MIMIC  | eICU-CRD | MIMIC  | eICU-CRD |
| SVM        | 68.67   | 64.34    | 68.47  | 68.60    | 63.01  | 77.58    | 69.13  | 40.68    |
| LR         | 73.96   | 66.63    | 73.80  | 71.24    | 69.75  | 80.97    | 74.49  | 42.89    |
| RF         | 74.33   | 61.20    | 74.44  | 69.88    | 77.46  | 88.20    | 71.53  | 39.39    |
| MLP        | 64.04   | 62.75    | 63.94  | 63.15    | 61.27  | 64.01    | 62.97  | 37.74    |
| Ensemble model | 74.7 | 50.21    | **81.41** | **76.34** | **85.36** | **92.77** | 64.82 | 35.02 |

* The ensemble model is the final voting classifier that combines LR and RF.
Table A3 – Comparison table of several classifiers trained on the eICU-CRD training set.

| Models       | Accuracy  | ROC AUC  | Sensitivity | Specificity |
|--------------|-----------|----------|-------------|-------------|
|              | MIMIC     | eICU-CRD | MIMIC       | eICU-CRD    | MIMIC       | eICU-CRD    |
| SVM          | 52.36     | 73.96    | 50.81       | 53.5        | 10.02       | 10.32       | 52.53       | 52.63       |
| LR           | 63.21     | 76.79    | 62.06       | 63.06       | 31.98       | 34.07       | 79.05       | 60.47       |
| RF           | 64.50     | 77.84    | 63.37       | 64.43       | 33.53       | 36.14       | 82.08       | 63.97       |
| MLP          | 65.52     | 75.05    | 64.95       | 66.24       | 49.90       | 47.64       | 69.81       | 52.86       |
| Ensemble model | 74.88     | 68.84    | 80.17       | 79.08       | 69.17       | 75.81       | 79.82       | 68.72       |

* The ensemble model is the final voting classifier that combines LR and RF.
Table A4 – Comparison table for several classifiers trained on both MIMIC-III and the eICU-CRD training set.

| Models  | Accuracy | ROC AUC | Sensitivity | Specificity |
|---------|----------|---------|-------------|-------------|
|         | MIMIC    | eICU-CRD | MIMIC    | eICU-CRD | MIMIC    | eICU-CRD | MIMIC    | eICU-CRD | MIMIC    | eICU-CRD |
| SVM     | 66.36    | 74.27   | 66.03     | 64.86 | 57.42 | 44.99 | 67.73     | 51.26 |           |
| LR      | 68.86    | 76.41   | 68.22     | 64.88 | 51.45 | 40.56 | 76.07     | 57.29 |           |
| RF      | 74.79    | 77.76   | 74.73     | 66.09 | 73.22 | 41.45 | 74.07     | 61.49 |           |
| MLP     | 72.10    | 75.05   | 72.01     | 65.38 | 69.56 | 44.99 | 71.63     | 53.04 |           |
| Ensemble model* | 74.88 | 68.84 | 80.35 | 79.08 | 78.61 | 78.61 | 71.43 | 65.35 |

* The ensemble model is the final voting classifier that combines LR and RF.
Table A5 - Training time 0-3 hours/ Prediction time 4-24 hours

| Training sets       | ROC-AUC | Accuracy | Specificity | Sensitivity |
|---------------------|---------|----------|-------------|-------------|
|                     | MIMIC-III | eICU-CRD | MIMIC-III | eICU-CRD | MIMIC-III | eICU-CRD | MIMIC-III | eICU-CRD |
| MIMIC-III           | 81.36    | 76.07    | 73.54      | 62.05      | 77.96     | 51.51     | 79.76     | 86.74     |
| eICU-CRD            | 78.60    | 78.36    | 70.68      | 70.63      | 89.38     | 70.02     | 56.64     | 72.07     |
| MIMIC-III + eICU-CRD| 79.26    | 77.89    | 72.62      | 70.40      | 81.76     | 69.69     | 64.78     | 72.07     |
### Table A6 - Training time 0-4 hours / Prediction time 5-24 hours

| Training sets | ROC-AUC    | Accuracy | Specificity | Sensitivity |
|---------------|------------|----------|-------------|-------------|
|               | MIMIC-III  | eICU-CRD | MIMIC-III   | eICU-CRD    | MIMIC-III  | eICU-CRD    |
| MIMIC-III     | 80.77      | 77.19    | 74.19       | 65.06       | 75.76      | 57.36       | 72.69       | 84.56       |
| eICU-CRD      | 77.76      | 78.49    | 72.06       | 68.73       | 78.22      | 65.01       | 66.18       | 78.14       |
| MIMIC-III +   | 77.26      | 74.69    | 69.20       | 66.64       | 71.21      | 63.99       | 67.27       | 66.36       | eICU-CRD   |
### Table A7 - Training time 0-6 hours/Prediction time 7-24 hours

| Training sets | Testing sets | ROC-AUC | Accuracy | Specificity | Sensitivity |
|---------------|--------------|---------|----------|-------------|-------------|
|               | MIMIC-III    | eICU-CRD | MIMIC-III| eICU-CRD    | MIMIC-III   | eICU-CRD    |
| MIMIC-III     | 81.93        | 78.36    | 74.68    | 65.17       | 72.93       | 58.60       |
| eICU-CRD      | 80.99        | 79.76    | 74.68    | 68.10       | 80.71       | 63.65       |
| MIMIC-III     | 81.18        | 80.08    | 73.47    | 72.85       | 75.47       | 72.76       |
| eICU-CRD      | 71.05        | 73.12    |          |             |             |             |