Benchmarking Predictive Risk Models for Emergency Departments with Large Public Electronic Health Records

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Abstract
There is a continuously growing demand for emergency department (ED) services across the world, especially under the COVID-19 pandemic. Risk triaging plays a crucial role in prioritizing limited medical resources for patients who need them most. Recently the pervasive use of Electronic Health Records (EHR) has generated a large volume of stored data, accompanied by vast opportunities for the development of predictive models which could improve emergency care. However, there is an absence of widely accepted ED benchmarks based on large-scale public EHR, which new researchers could easily access. Success in filling in this gap could enable researchers to start studies on ED more quickly and conveniently without verbose data preprocessing and facilitate comparisons among different studies and methodologies. In this paper, based on the Medical Information Mart for Intensive Care IV Emergency Department (MIMIC-IV-ED) database, we proposed a public ED benchmark suite and obtained a benchmark dataset containing over 500,000 ED visit episodes from 2011 to 2019. Three ED-based prediction tasks (hospitalization, critical outcomes, and 72-hour ED revisit) were introduced, where various popular methodologies, from machine learning methods to clinical scoring systems, were implemented. The results of their performance were evaluated and compared. Our codes are open-source so that anyone with access to MIMIC-IV-ED could follow the same steps of data processing, build the benchmarks, and reproduce the experiments. This study provided insights, suggestions, as well as protocols for future researchers to process the raw data and quickly build up models for emergency care.

Keywords: Electronic Health Records; Machine Learning; Clinical Decision Support System; Triage; Emergency Department

1. Introduction
As the starting point of patient flow, emergency departments (ED) are experiencing increasing patient visits and requiring more medical resources, especially during this global pandemic\(^1\). This growth has caused ED crowding\(^2\) and delays in care delivery\(^3\), resulting in higher morbidity and mortality\(^4\). ED triage models\(^5\)\(^-\)\(^8\) provided opportunities for identifying high-risk patients with the prioritization of limited medical resources. Risk stratification is a complex clinical judgment\(^9\) based on the tacit understanding of the patient's likely acute course, availability of medical resources, and local practices.

Recently, the pervasive use of Electronic Health Records (EHR) created great amounts of stored data, as well as vast opportunities for the development of predictive models to improve emergency care\(^10,11\). Based on a few large-scale EHR databases, such as Medical Information Mart for Intensive Care (MIMIC)\(^12\), eICU Collaborative Research Database\(^13\), and Amsterdam University Medical Centers Database (AmsterdamUMCdb)\(^14\), several benchmarks have been established\(^15\)\(^-\)\(^17\). These
benchmarks standardized the process of transforming raw EHR data into directly usable data for the construction of predictive models. This has endowed clinicians and methodologists with easily accessible and high-quality medical data that accelerates research and validation efforts. These non-proprietary databases and open-source pipelines allow clinical studies to be reproduced and improved in ways that would not otherwise be possible. However, most of the available public benchmarks are based on intensive care settings, and there is an absence of widely accepted benchmarks based on emergency medicine settings. The availability of an ED-based public benchmark lowers the barrier to entry for new researchers, allowing them to direct their efforts towards novel research efforts.

Machine learning has seen tremendous advancements in recent years, and it has gained increased adoption in the realm of ED-based prediction tasks. These prediction models involve interpretable machine learning, deep learning, temporal machine, etc. However, researchers usually develop a new machine learning model for one specific clinical prediction task based on one dataset at a time. There is also a lack of comparative studies among different methods in the same ED benchmarks, undermining the model's generalizability. These clinical prediction models are also detached from the actual clinical decision-making process, therefore leading to a demand for a comparative study regarding accuracy, interpretability, and utility at ED. Our study aims to standardize data preprocessing for a large public HER database and establish a comprehensive ED benchmark dataset alongside comparable risk triaging models for three ED prediction tasks. It is expected to facilitate reproducibility and competition and accelerate progress in utilizing machine learning in future ED-based studies.

This paper proposes a public benchmark suite for the ED based on a large EHR dataset and introduces three ED-based prediction targets: hospitalization, critical outcomes, and 72-hour ED revisit. We implement and compare several popular methodologies for these clinical prediction tasks. The methods applied clinical scores, regressions, machine learning, deep learning, etc. We use data from the publicly available Medical Information Mart for Intensive Care IV Emergency Department (MIMIC-IV-ED) database, containing over 500,000 ED visit episodes from 2011 to 2019. Our code is open-source so that anyone with access to MIMIC-IV-ED can follow our data processing steps, build our benchmarks, and reproduce our experiments. This study provides insights, suggestions, and protocols for future researchers to process the raw data and quickly build up models for emergency care.

2. Methods
This section consists of three parts. We first describe the process of benchmark data together with task generation. The second subsection describes the baseline models...
for the benchmark tasks. We then describe the experimental setup and model selection in the third part.

2.1 Benchmark Data Generation
We first standardized terminologies for our benchmark. Patients are referred to by subjects_id. Each patient has one or more ED visits, identified by stay_id in the edstays.csv. If there is an inpatient stay following an ED visit, this stay_id could be linked with an inpatient admission, identified by hadm_id in the edstays.csv. The subjects_id and hadm_id can also be traced back to the MIMIC-IV26 database to follow the patient throughout the inpatient or ICU stay and patients' future or past medical utilization if needed. In the context of our tasks, we use edstays.csv as the root table and stay_id as the primary identifier. As a rule, we have one stay_id for each prediction in our benchmark tasks.

We used several relevant datasheets from the raw data, including edstays.csv, triage.csv, vitalsign.csv, diagnosis.csv, medrecon.csv, and pyxis.csv from the ed folder; diagnoses_icd.csv from the hosp folder; admission.csv and patients.csv from core folder; icustays.csv from icu folder. All raw tables were linked (extract_master_dataset.ipynb), illustrated in Figure 1, based on the root table, edstays.csv, merged through different identifiers, including stay_id (ED), subjects_id, hadm_id, or stay_id (ICU). We extracted all high-level information and consolidated them into a master dataset (master_dataset.csv).

Regarding the master dataset construction, we checked a bevy of existing literature 5,7,27-29 to identify all relevant variables and outcomes for building the ED benchmark dataset. We also consulted clinicians and informaticians who are familiar with the raw data and ED operation to determine the relevant and feasible features extracted and constructed from the source data. The rationale is to include all ED-relevant variables with good quality. Thus, the irrelevant, repeated, or largely missing variables were excluded. The list of high-level constructed variables is illustrated in Table 1, which includes patient history, variables collected at ED triage and disposition, and major ED-relevant outcomes.

Table 1. List of high-level constructed variables in the master dataset and their origins and categories.

| Category         | Sub-category   | Source Table (omit .csv below) | Variable description                                      | Variable Name in the master dataset        |
|------------------|----------------|--------------------------------|----------------------------------------------------------|-------------------------------------------|
| Patient history  | Past ED visits | edstay                        | ED visits in the past month, ED visits in the past three months, ED visit in the past year | n_ed_30d, n_ed_90d, n_ed_365d          |
|                  | Past Hospitalizations | admissions                  | Hospitalizations in the past month,                      | n_hosp_30d, n_hosp_90d                   |
| Information at the triage station | Demographics | patients | Age, Gender | age, gender |
|-----------------------------------|--------------|----------|-------------|-------------|
| Triage-vital signs | triage | Vital signs collected at triage: Temperature (Celsius), Heart rate (bpm), Oxygen Saturation (%), Systolic Blood Pressure (mmHg), Diastolic blood pressure (mmHg), Pain Scale, Emergency Severity Index (ESI) | triage_temperature, triage_heartrate, triage_o2sat, triage_sbp, triage_dbp, triage_pain, triage_acuity, |
| Triage-chief complaint | triage | Top 10 chief complaints identified at ED | chiefcom_* (10 variables) |
| Information at ED disposition | ED vital signs | vitalsigns | Vital signs collected during ED stay: Temperature (Celsius), Heart rate (bpm), Oxygen Saturations (%), Systolic Blood Pressure (mmHg), Diastolic blood pressure (mmHg) | ed_temperature, ed_heartrate, ed_o2sat, ed_sbp, ed_dbp, |
| ED administrative | edstays | ED length of stay (hrs) | ed_los |
| Medicine reconciliation | medrecon | Counts of medication reconciliation | n_medrecon |
| Medicine prescription | pyxis | Counts of medication prescription at current ED stay | n_med |
| Outcome(s) | Hospitalization | edstays: hadm_id | Whether the patient is admitted to inpatient stay following current ED visit. | outcome_hospitalization |
| Inpatient mortality | patients:dod admissions:dischtime | Whether the patient dies in the hospital before discharge. | outcome_inhospital_mortality |

- Past ICU admissions: icustays
- Comorbidities: diagnoses_icd, d_icd_diagnoses
- Hospitalizations in the past three months, Hospitalizations in the past year: n_hosp_365d
- ICU admissions in the past month, ICU admissions in the past three months, ICU admissions in the past year: n_icu_30d, n_icu_90d, n_icu_365d
- Comorbidities: cci_* (17 variables), eci_* (30 variables)

Information at the triage station:

- Demographics: patients
- Triage-vital signs: triage
- Triage-chief complaint: triage

Information at ED disposition:

- ED vital signs: vitalsigns
- ED administrative: edstays
- Medicine reconciliation: medrecon
- Medicine prescription: pyxis

Outcome(s):

- Hospitalization: edstays: hadm_id
- Inpatient mortality: patients:dod admissions:dischtime
| ICU transfer from ED | icustays: intime, edstays:outtime | Whether the patient was transferred to ICU from ED within 12 hours. | outcome_icu_transfer_12h |
|---------------------|----------------------------------|-----------------------------------------------------------------|-------------------------|
| ED revisit          | edstays                          | Whether the patient revisits ED after the discharge from the index ED visit within three days (72 hours) | outcome_ed_revisit_3d   |
| Critical Outcomes   | master_dataset: outcome_icu_transfer_12h, outcome_inhospital_mortality | Whether the patient fulfills either inpatient mortality or ICU transfer within 12 hours | outcome_critical       |

### 2.2 Cohort Filtering and Data Processing

The benchmark preparation workflow ([data_general_processing.ipynb](#), illustrated in Figure 2, begins with the master dataset mentioned above, including 448,972 ED visits across 216,877 unique patients. In the first step, we filter out all ED episodes with patients under 18 years old.

For raw EHR data, there exists a variety of noise, including missing values, outliers, duplicates, or incorrect records caused by system errors or clerical mistakes. We addressed these issues with several procedures. For vital signs and lab tests, a value would be considered an outlier and marked as missing if it was beyond the plausible physiological range based on domain knowledge, such as any value below zero or a SpO2 above 100%. We followed the outlier detection procedure used in MIMIC-EXTRACT17, a well-known data processing pipeline for MIMIC-III. We utilized the thresholds available in the source code repository of Harutyunyan at el.30, where one set of upper and lower thresholds are used for filtering outliers. Any value that falls beyond this range was marked as missing. Another set of thresholds was introduced to indicate the physiologically valid range, and any value that falls beyond this range is replaced with its nearest valid value. These thresholds were suggested by clinical experts based on their domain knowledge.

We fixed a testing set of 20% (n=89,761) of ED episodes, which covers 66,177 unique patients. We encourage future researchers to use the same testing set for model comparisons and interact with the test data as infrequently as possible. The training set took another 80% of ED episodes. The validation set can be derived from the training set if needed. Missing values (including outliers marked as missing and initially missing ones) were imputed with the mean values on the training set. The same values were used for imputation on the test set.
2.3 ICD Codes Processing

In MMIC-IV, each hospital admission is associated with a group of ICD diagnosis codes (in `hosp/diagnoses_icd.csv`), indicating the patients' comorbidity. We embedded the ICD coding within a time range (e.g., five years) from each ED visit into Charlson Comorbidity Index (CCI)\(^31\) and Elixhauser Comorbidity Index (ECI)\(^32\) according to the mapping proposed by Quan H et al.\(^33\). We utilized the codebase from Cates et al.\(^34\).
2.4 Benchmark Tasks
We have three ED-relevant clinical outcomes described below. Each of them is of significant interest to clinicians and hospitals, especially ED, due to its potential to transform health services at ED via big data and artificial intelligence.

- The hospitalization outcome is composed of an inpatient care site admission immediately following an ED visit\(^ {35-37}\). Each ED attendance is classified as admission or discharge according to the clinical decision made. Patients who transitioned to observation within ED were not considered hospitalization unless it finally led to an inpatient stay. This outcome indicates ED resources use, but patients referred to hospitalization represent a broad spectrum of disease severity.

- The critical outcome\(^ {28}\) is compositely defined as either inpatient mortality\(^ {38}\) or transfer to an ICU within 12 hours. This outcome represents the critically ill patients who urgently need ED resources and may be vulnerable to worse health conditions due to the care delivery delay. Predicting the critical outcome at ED triage could enable physicians to allocate ED resources efficiently and intervene on high-risk patients on time.

- The ED revisit outcome refers to patients' return visit to ED within 72 hours after their previous ED discharge. It is a widely-used indicator for the quality of care and patient safety and is generally assumed that patients who revisit ED within 72 hours receive inadequate treatment or evaluation in their primary visit\(^ {39}\).

2.5 Baseline Model
Various modeling methods were used to evaluate each benchmark task in actual data, including clinical scores, regression, machine learning, and deep learning, with details in Table 2. They, therefore, are of interest to both clinical researchers and data scientists. A subjective five-level triage system, Emergency Severity Index (ESI)\(^ {40}\), was assigned by a registered nurse. Level 1 is the highest priority, while level 5 is the lowest priority. Several other objective clinical scores were also calculated, including Modified Early Warning Score (MEWS)\(^ {41}\), National Early Warning Score (NEWS)\(^ {42}\), Rapid Emergency Medicine Score (REMS)\(^ {43}\), and Cardiac Arrest Risk Triage (CART)\(^ {44}\). Three machine learning methods – Logistic Regression (LR), Random Forest (RF), and Gradient Boosting (GB) - are benchmarked as well as one deep learning method – multilayer perceptron (MLP). We made use of the scikit-learn package\(^ {45}\) with their default parameters.

| Description | Used variable/structure | Hyper parameters | Package used |
|-------------|-------------------------|------------------|--------------|
| Logistic regression | Use the logistic function to model binary outcomes. | penalty='l2', C=1.0, max_iter=100 | scikit-learn package |
| Method                     | Description                                                                 | Parameters                        | ED Variables                                                                 |
|----------------------------|-----------------------------------------------------------------------------|-----------------------------------|------------------------------------------------------------------------------|
| Random Forest              | Build a large number of decision trees in parallel and combine the end results by averaging. | comorbidity, and age              | n_estimators=100                                                             |
| Gradient Boosting          | Build a number of decision trees in stages and combine the results along the way. | loss='deviance', learning_rate=0.1, n_estimators=100 |                                                                              |
| Multilayer Perceptron      | The neural network of multiple fully connected neurons.                     | hidden_layer_sizes=(10 0), activation='relu' |                                                                              |
| Clinical Score: NEWS, MEWS, REMS, CART | Widely used clinical score for risk stratification at ED triage | Vitals, comorbidity, and age | None; No training is needed                                                   |
| Emergency Severity Index   | A subjective Five-Level triage system assigned by a registered nurse         | triage_acuity                     | None                                                                         |

MEWS: Modified Early Warning Score  
NEWS: National Early Warning Score  
REMS: Rapid Emergency Medicine Score  
CART: Cardiac Arrest Risk Triage

2.6 Experiments, Model Selection, and Evaluation

We conducted the receiver operating characteristic (ROC) and precision-recall curve (PRC) analysis to evaluate the performance of all predictive models. The area under the ROC curve (AUROC) and the area under the PRC (AUPRC) values were reported as an overall measurement of predictive performance. Furthermore, we computed the measures of sensitivity and specificity under the optimal cutoffs, defined as the points nearest to the upper-left corner of the ROC curves. All the experiments were conducted on a server with an Intel Xeon W-2275 processor and 128GB memory and their running time at training were measured.
3. Results
3.1 Basic Characteristics of the Benchmark Dataset
After general data processing, we compiled a processed master dataset with 448,804 ED visits and 216,714 unique patients. The total 448,804 observations is randomly split into 80% (359,043) training data and 20% (89,761) testing data. The baseline characteristics of all data were summarized in Table 3, stratified by outcomes. The selected variables were grouped into seven categories: Demographics, Score, Previous Health Utilization, Information collected at triage, Chief complaint, Comorbidities, and Information collected during ED stay. The average age is 52.82 years old, and 54.1% (n=242,844) patients are female. Compared with overall patients, those with critical outcomes had higher body temperature and heart rate and were provided with larger amounts of medication prescriptions. They also had a higher possibility of having fluid and electrolyte disorders, coagulopathy, cancer, cardiac arrhythmias, valvular disease, as well as pulmonary circulation disorders.

Table 3. Baseline characteristics of the processed master dataset. A total of 81 features are included. Continuous variables are presented as Mean (SD); binary/categorical variables are presented as Count (%).

|                           | Overall     | ED Discharge | ED Admission | Critical Outcomes | 72-hour ED revisit |
|---------------------------|-------------|--------------|--------------|-------------------|-------------------|
| # Episodes                | 448,804     | 234,369      | 214,435      | 29,585            | 15,493            |
| Demographic              |             |              |              |                   |                   |
| Age                       | 52.82 (20.6)| 46.31 (19.38)| 59.94 (19.55)| 64.71 (18.23)     | 50.37 (18.70)     |
| Gender (female)           | 242844 (54.1%)| 134723 (57.5%)| 108121 (50.4%)| 13559 (45.8%)     | 7150 (46.1%)      |
| (male)                    | 205960 (45.9%)| 99646 (42.5%)| 106314 (49.6%)| 16026 (54.2%)     | 8343 (53.9%)      |
| Score                     |             |              |              |                   |                   |
| Emergency Severity Index  | 2.63 (0.70) | 2.89 (0.64)  | 2.34 (0.65)  | 1.88 (0.66)       | 2.77 (0.63)       |
| CART                      | 4.15 (5.04) | 2.68 (3.87)  | 5.77 (5.64)  | 8.14 (7.29)       | 3.38 (4.28)       |
| REMS                      | 3.54 (2.78) | 2.77 (2.60)  | 4.39 (2.72)  | 5.06 (2.67)       | 3.18 (2.56)       |
| NEWS                      | 0.90 (1.24) | 0.69 (0.95)  | 1.13 (1.45)  | 1.68 (2.06)       | 0.90 (1.11)       |
| NEWS2                     | 0.79 (1.11) | 0.63 (0.90)  | 0.96 (1.28)  | 1.41 (1.78)       | 0.79 (1.02)       |
|                          | MEWS          | MEWS          | MEWS          | MEWS          | MEWS          |
|--------------------------|---------------|---------------|---------------|---------------|---------------|
| **Previous health utilization** |               |               |               |               |               |
| ED visit in the past month | 0.24 (0.78)   | 0.21 (0.77)   | 0.27 (0.79)   | 0.18 (0.54)   | 1.11 (2.31)   |
| ED visit in the past 3 months | 0.53 (1.59)   | 0.46 (1.58)   | 0.61 (1.60)   | 0.44 (1.04)   | 2.35 (4.81)   |
| ED visit in the past year | 1.40 (4.18)   | 1.24 (4.15)   | 1.58 (4.20)   | 1.07 (2.55)   | 6.02 (12.62)  |
| Hospitalizations in the past month | 0.16 (0.51)   | 0.09 (0.41)   | 0.23 (0.60)   | 0.19 (0.49)   | 0.56 (1.31)   |
| Hospitalizations in the past 3 months | 0.36 (1.03)   | 0.21 (0.82)   | 0.53 (1.19)   | 0.46 (0.94)   | 1.22 (2.76)   |
| Hospitalizations in the past year | 0.97 (2.68)   | 0.61 (2.20)   | 1.37 (3.07)   | 1.12 (2.25)   | 3.35 (7.56)   |
| ICU admissions in the past month | 0.02 (0.15)   | 0.01 (0.10)   | 0.03 (0.20)   | 0.07 (0.29)   | 0.02 (0.17)   |
| ICU admissions in the past 3 months | 0.05 (0.26)   | 0.02 (0.17)   | 0.08 (0.34)   | 0.16 (0.51)   | 0.06 (0.30)   |
| ICU admissions in the past year | 0.11 (0.49)   | 0.05 (0.31)   | 0.18 (0.63)   | 0.34 (0.94)   | 0.17 (0.61)   |

| **Information collected at triage** |               |               |               |               |               |
|--------------------------------------|---------------|---------------|---------------|---------------|---------------|
| Temperature (Celsius) | 36.71 (0.53)  | 36.68 (0.49)  | 36.75 (0.58)  | 36.76 (0.62)  | 36.69 (0.51)  |
| Mean Arterial Pressure (mmHg) | 96.61 (14.75) | 97.56 (13.78) | 95.58 (15.66) | 92.76 (16.90) | 97.92 (14.68) |
| Heart rate (bpm) | 85.08 (17.32) | 83.92 (16.26) | 86.34 (18.32) | 90.26 (19.71) | 87.06 (16.84) |
| Respiratory Rate (cpm) | 17.55 (2.47)  | 17.29 (2.10)  | 17.84 (2.79)  | 18.67 (4.10)  | 17.41 (2.14)  |
| Oxygen Saturations (%) | 98.38 (2.40)  | 98.79 (2.00)  | 97.92 (2.71)  | 97.32 (3.46)  | 98.38 (2.49)  |
| Systolic Blood Pressure (mmHg) | 134.89 (21.96)| 135.16 (20.59)| 134.60 (23.37)| 130.14 (24.77)| 135.13 (21.66)|
| Diastolic blood pressure (mmHg) | 77.47 (14.59) | 78.76 (13.70) | 76.07 (15.38) | 74.07 (15.55) | 79.32 (14.53) |
| Pain Scale | 4.17 (3.57) | 4.67 (3.57) | 3.62 (3.50) | 3.25 (2.88) | 4.74 (3.76) |
|------------|------------|------------|------------|------------|------------|

**Chief Complaint**

| Complaint            | 30832 (6.9%) | 13812 (5.9%) | 17020 (7.9%) | 1124 (3.8%) | 909 (5.9%) |
|----------------------|--------------|--------------|--------------|-------------|------------|
| Chest Pain           | 50930 (11.3%)| 25833 (11.0%)| 25097 (11.7%)| 1712 (5.8%) | 1962 (12.7%)|
| Abdominal Pain       | 16618 (3.7%) | 11980 (5.1%) | 4638 (2.2%)  | 622 (2.1%)  | 630 (4.1%) |
| Headache             | 1300 (0.3%)  | 403 (0.2%)   | 897 (0.4%)   | 223 (0.8%)  | 24 (0.2%)  |
| Shortness of breath  | 17646 (3.9%) | 12384 (5.3%) | 5262 (2.5%)  | 283 (1.0%)  | 623 (4.0%) |
| Cough                | 9279 (2.1%)  | 5301 (2.3%)  | 3978 (1.9%)  | 410 (1.4%)  | 244 (1.6%) |
| Nausea/vomitting     | 10675 (2.4%) | 5611 (2.4%)  | 5604 (2.4%)  | 466 (1.6%)  | 401 (2.6%) |
| Fever/chills         | 15294 (3.4%) | 4665 (2.0%)  | 10629 (5.0%) | 1433 (4.8%) | 398 (2.6%) |
| Syncope              | 8223 (1.8%)  | 4418 (1.9%)  | 3805 (1.8%)  | 364 (1.2%)  | 168 (1.1%) |
| Dizziness            | 10946 (2.4%) | 6347 (2.7%)  | 4599 (2.1%)  | 366 (1.2%)  | 288 (1.9%) |

**Comorbidities (Charlson comorbidity index)**

| Condition                      | 25076 (5.6%) | 6532 (2.8%) | 18544 (8.6%) | 2963 (10.0%) | 1094 (7.1%) |
|--------------------------------|--------------|------------|-------------|-------------|------------|
| Myocardial infarction          | 41269 (9.2%) | 10312 (4.4%) | 30957 (14.4%) | 5459 (18.5%) | 1300 (8.4%) |
| Congestive heart failure       | 22244 (5.0%) | 5740 (2.4%) | 16504 (7.7%) | 2753 (9.3%) | 672 (4.3%) |
| Peripheral vascular disease    | 21445 (4.8%) | 6484 (2.8%) | 14961 (7.0%) | 2563 (8.7%) | 764 (4.9%) |
| Stroke                         | 7477 (1.7%)  | 2055 (0.9%) | 5422 (2.5%) | 933 (3.2%)  | 253 (1.6%) |
| Dementia                       | 63174 (14.1%)| 23249 (9.9%) | 39925 (18.6%) | 5660 (19.1%) | 3142 (20.3%)|
| Chronic pulmonary disease      | 9168 (2.0%)  | 3020 (1.3%) | 6148 (2.9%) | 803 (2.7%)  | 277 (1.8%) |
| Rheumatoid disease             | 8383 (1.9%)  | 2316 (1.0%) | 6067 (2.8%) | 937 (3.2%)  | 321 (2.1%) |
| Peptic ulcer disease           | 409973 (91.3%)| 222837 (95%) | 187136 (87.3%) | 25781 (87.1%) | 446178 (83.1%)|
| Condition                                      | Count   | Percentage |
|-----------------------------------------------|---------|------------|
| Mild Liver Disease                            | 29887   | (6.7%)     |
| Moderate/Severe Liver Disease                 | 8944    | (2.0%)     |
| Diabetes                                      | 361698  | (80.6%)    |
| None                                          | 206576  | (88.1%)    |
| Diabetes without chronic complications         | 155122  | (72.3%)    |
| Diabetes with complications                    | 20979   | (71.0%)    |
| Hemiplegia                                    | 5164    | (1.2%)     |
| None                                          | 1582    | (0.7%)     |
| Moderate to Severe chronic kidney disease     | 43355   | (9.7%)     |
| Cancer                                        | 408881  | (91.1%)    |
| None                                          | 224037  | (95.6%)    |
| Local tumor, leukemia and lymphoma            | 21054   | (9.8%)     |
| Metastatic solid tumor                        | 2543    | (1.1%)     |
| AIDS                                          | 4103    | (0.9%)     |
| None                                          | 1585    | (0.7%)     |
| Elixhauser Comorbidity Index                  |         |            |
| Cardiac arrhythmias                           | 62133   | (13.8%)    |
| Valvular Disease                              | 22693   | (5.1%)     |
| Pulmonary circulation disorders               | 20568   | (4.6%)     |
| Hypertension, uncomplicated                    | 45005   | (10.0%)    |
| Hypertension, complicated                     | 108875  | (24.3%)    |
| Other neurological disorders                  | 33954   | (7.6%)     |
| Hypothyroidism                                | 29650   | (6.6%)     |

**Mild Liver Disease**
- Count: 29887
- Percentage: 6.7%

**Moderate/Severe Liver Disease**
- Count: 8944
- Percentage: 2.0%

**Diabetes**
- None: 361698 (80.6%)
- Diabetes without chronic complications: 58932 (13.1%)
- Diabetes with complications: 28174 (6.3%)

**Hemiplegia**
- Count: 5164
- Percentage: 1.2%

**Moderate to Severe chronic kidney disease**
- Count: 43355
- Percentage: 9.7%

**Cancer**
- None: 408881 (91.1%)
- Local tumor, leukemia and lymphoma: 28843 (6.4%)
- Metastatic solid tumor: 11080 (2.5%)
- AIDS: 4103 (0.9%)

**Elixhauser Comorbidity Index**
- Cardiac arrhythmias: 62133 (13.8%)
- Valvular Disease: 22693 (5.1%)
- Pulmonary circulation disorders: 20568 (4.6%)
- Hypertension, uncomplicated: 45005 (10.0%)
- Hypertension, complicated: 108875 (24.3%)
- Other neurological disorders: 33954 (7.6%)
- Hypothyroidism: 29650 (6.6%)
| Condition                              | Count (Percentage) | Count (Percentage) | Count (Percentage) | Count (Percentage) | Count (Percentage) |
|----------------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Lymphoma                               | 4869 (1.1%)        | 1260 (0.5%)        | 3609 (1.7%)        | 488 (1.6%)         | 112 (0.7%)         |
| Coagulopathy                           | 31463 (7.0%)       | 8431 (3.6%)        | 23032 (10.7%)      | 3913 (13.2%)       | 1607 (10.4%)       |
| Obesity                                | 39385 (8.8%)       | 14966 (6.4%)       | 24419 (11.4%)      | 3017 (10.2%)       | 1535 (9.9%)        |
| Weight Loss                            | 35496 (7.8%)       | 1308 (0.6%)        | 4889 (2.2%)        | 112 (0.7%)         | 122 (0.7%)         |
| Fluid and electrolyte disorders        | 83583 (18.6%)      | 25525 (10.9%)      | 58058 (27.1%)      | 8809 (29.8%)       | 4232 (27.3%)       |
| Blood loss anemia                      | 6100 (1.4%)        | 1711 (0.7%)        | 4389 (2.0%)        | 726 (2.5%)         | 259 (1.7%)         |
| Deficiency anemia                      | 26625 (5.9%)       | 8662 (3.7%)        | 17963 (8.4%)       | 2507 (8.5%)        | 1390 (9.0%)        |
| Alcohol abuse                          | 34889 (7.8%)       | 12574 (5.4%)       | 22315 (10.4%)      | 2355 (8.0%)        | 3764 (24.3%)       |
| Drug abuse                             | 29862 (6.7%)       | 11595 (4.9%)       | 18267 (8.5%)       | 1564 (5.3%)        | 3061 (19.8%)       |
| Psychoses                              | 82452 (18.6%)      | 29371 (12.7%)      | 23081 (10.5%)      | 3017 (10.2%)       | 1193 (7.7%)        |
| Depression                             | 73287 (16.3%)      | 27741 (11.8%)      | 45546 (21.2%)      | 5006 (16.9%)       | 4222 (27.3%)       |

Information collected at ED

| Measurement                          | Mean (Standard Deviation) |
|--------------------------------------|---------------------------|
| Temperature last (Celcius)            | 36.76 (0.37)              |
| HR last (bpm)                        | 78.22 (14.35)             |
| Respiratory Rate last (cpm)          | 17.26 (2.47)              |
| Oxygen Saturations last (%)          | 98.14 (2.92)              |
| Systolic Blood Pressure last (mmHg)  | 127.42 (19.43)            |
| Diastolic blood pressure last (mmHg) | 73.56 (13.51)             |
| Counts of ED medication prescription | 2.94 (3.33)               |
| Counts of Medication reconciliation  | 6.04 (6.76)               |
| ED length of stays (hrs)             | 4.76 (7.43)               |

14
The outcome statistics of the benchmark data are presented in Table 4, implying that data were uniformly split for training and testing. In the overall cohort, 214,435 (47.8%) episodes fall into hospitalization, 29,585 (6.59%) episodes have critical outcomes, and 15,493 (3.53%) are subject to 72-hour ED revisit.

Table 4. Label statistics of prediction tasks. The number of observations in training and testing data in each outcome subgroup and their proportion was summarized.

| Outcome                     | Hospitalization | ICU transfer in12h | Mortality in Hospital | Critical outcome | ED Revisit in 3d | Total (episodes) |
|-----------------------------|----------------|-------------------|----------------------|-----------------|-----------------|------------------|
| Training data               | 171625 (47.80%)| 22415 (6.24%)    | 3703 (1.03%)         | 23657 (6.59%)   | 12322 (3.43%)   | 359043 (80%)     |
| Testing data                | 42810 (47.80%) | 5600 (6.24%)     | 943 (1.05%)          | 5928 (6.60%)    | 3171 (3.53%)    | 89761 (20%)      |
| Total (by outcome)          | 214435 (47.80%)| 28015 (6.24%)    | 4646 (1.04%)         | 29585 (6.59%)   | 15493 (3.53%)   | 448804 (100%)    |

3.2 Variable Importance and Ranking
With a descending order of variable importance extracted from random forest, the top 10 variables selected for each benchmark task are presented in Table 5. Vital signs show their strong predictive powers in all three tasks. Age is also among the top predictive variables for all three tasks, addressing the impact of aging on emergency care utilization. While the triage level (i.e., ESI) is highly related to the hospitalization and critical outcome, it is not relevant to 72-hour ED revisit. Instead, ED length of stay becomes the top variable for 72-hour ED revisit prediction. The previous health utilization variable seems to be a less important feature for the ED-based tasks.

3.3 Benchmark Task Evaluation
Assessed by various metrics on the testing set, the performance of the different commonly used machine learning and clinical scores are reported in Figure 3. Machine learning shows higher discriminatory capability in predicting all three outcomes. Graduate Boosting achieved an AUC of 0.894 (95% CI: 0.890-0.897) for the critical outcome and an AUC of 0.820 (95% CI: 0.817-0.823) for hospitalization outcome. However, the corresponding performance for 72-hour ED revisit is much lower. Although clinical scores fail to achieve good discriminatory performance, their properties of containing much fewer variables allow easy implementations in real-world health care settings.

Table 5. Top 10 variables from each benchmark task by random forest variable importance

| Hospitalization | Critical outcomes | 72-hour ED revisit |
|-----------------|-------------------|-------------------|
| Variable | Importance | Variable | Importance | Variable | Importance |
|                                |       |                                |       |                                |       |
|--------------------------------|-------|--------------------------------|-------|--------------------------------|-------|
| Age (years)                    | 0.1225| Age (years)                    | 0.1008| ED length of stays (hrs)       | 0.0843|
| Acuity (triage)                | 0.1122| Systolic Blood Pressure (triage) (mmHg) | 0.0953| Age (years)                   | 0.0843|
| Systolic Blood Pressure (triage) (mmHg) | 0.0855| Heart rate (triage) (bpm)      | 0.0935| Systolic Blood Pressure last(mmHg) | 0.0787|
| Heart rate (triage) (bpm)      | 0.0846| Acuity (triage)                | 0.0847| Diastolic blood pressure last (mmHg) | 0.0762|
| Diastolic blood pressure (triage) (mmHg) | 0.0816| Diastolic blood pressure (triage) (mmHg) | 0.0835| Heart rate last (bpm)          | 0.0761|
| Temperature (triage) (Celsius) | 0.078 | Temperature (triage) (Celsius) | 0.0757| Temperature last (Celsius)      | 0.0666|
| Pain Scale (triage)            | 0.0506| Oxygen Saturations (triage) (%) | 0.0638| Counts of Medication reconciliation | 0.0506|
| Oxygen Saturations (triage) (%) | 0.0496| Respiratory Rate (triage) (cpm) | 0.0549| Pain Scale (triage)            | 0.0439|
| Respiratory Rate (triage) (cpm) | 0.0403| Pain Scale (triage)            | 0.0468| Oxygen Saturations last (%)     | 0.0399|
| Hosptilizations in the past year | 0.0266| Hosptilizations in the past year | 0.019 | Counts of Medication reconciliation | 0.0398|
Table 6: Comparison of performance of different models applied to three different outcomes: "Hospitalization", "Critical", "72-hour ED revisits", is shown in the summary table. The unit of the running time in seconds.

### Hospitalization

| Model | Threshold | AUROC      | AUPRC      | Sensitivity | Specificity | Running time |
|-------|-----------|------------|------------|-------------|-------------|--------------|
| LR    | 0.453     | 0.807 (0.804-0.810) | 0.775 (0.771-0.779) | 0.743 (0.740-0.767) | 0.720 (0.700-0.724) | 6.204 |
| MLP   | 0.427     | 0.823 (0.820-0.825) | 0.798 (0.795-0.802) | 0.752 (0.743-0.759) | 0.735 (0.726-0.742) | 459.485 |
| RF    | 0.492     | 0.819 (0.817-0.822) | 0.786 (0.782-0.790) | 0.751 (0.747-0.763) | 0.738 (0.725-0.741) | 93.546 |
| GB    | 0.494     | 0.820 (0.817-0.823) | 0.796 (0.792-0.800) | 0.739 (0.735-0.762) | 0.744 (0.721-0.748) | 83.217 |
| ESI   | 3         | 0.712 (0.709-0.715) | 0.634 (0.630-0.638) | 0.595 (0.590-0.599) | 0.775 (0.772-0.778) | 0 |
| NEWS  | 1         | 0.574 (0.571-0.578) | 0.555 (0.551-0.559) | 0.549 (0.545-0.554) | 0.546 (0.541-0.550) | 0 |
| REMS  | 3         | 0.672 (0.668-0.676) | 0.612 (0.607-0.617) | 0.712 (0.708-0.717) | 0.565 (0.561-0.570) | 0 |
| MEWS  | 2         | 0.557 (0.554-0.560) | 0.525 (0.521-0.529) | 0.290 (0.286-0.294) | 0.814 (0.810-0.817) | 0 |
| CART  | 4         | 0.674 (0.671-0.678) | 0.620 (0.615-0.624) | 0.699 (0.694-0.704) | 0.590 (0.586-0.594) | 0 |

### Critical Outcomes

| Model | Threshold | AUROC      | AUPRC      | Sensitivity | Specificity | Running time |
|-------|-----------|------------|------------|-------------|-------------|--------------|
| LR    | 0.061     | 0.845 (0.840-0.849) | 0.319 (0.306-0.333) | 0.776 (0.751-0.795) | 0.738 (0.720-0.762) | 6.813 |
| MLP   | 0.046     | 0.886 (0.882-0.890) | 0.404 (0.389-0.418) | 0.829 (0.813-0.842) | 0.785 (0.777-0.801) | 835.153 |
| RF    | 0.083     | 0.887 (0.883-0.892) | 0.420 (0.408-0.436) | 0.806 (0.801-0.837) | 0.809 (0.785-0.812) | 76.865 |
| GB    | 0.071     | 0.894 (0.890-0.897) | 0.437 (0.423-0.452) | 0.824 (0.806-0.835) | 0.804 (0.798-0.822) | 93.071 |
| ESI   | 3         | 0.790 (0.790-0.790) | 0.194 (0.195-0.195) | 0.896 (0.896-0.896) | 0.633 (0.633-0.633) | 0 |
| NEWS  | 2         | 0.600 (0.601-0.601) | 0.153 (0.153-0.153) | 0.414 (0.415-0.415) | 0.799 (0.799-0.800) | 0 |
| REMS  | 5         | 0.664 (0.664-0.664) | 0.112 (0.112-0.112) | 0.646 (0.646-0.646) | 0.616 (0.616-0.616) | 0 |
| Model  | Threshold | AUROC       | AUPRC       | Sensitivity   | Specificity   | Running time |
|--------|-----------|-------------|-------------|---------------|---------------|--------------|
|        |           | 0.678 (0.665-0.689) | 0.167 (0.149-0.182) | 0.568 (0.545-0.602) | 0.686 (0.656-0.719) | 3.946        |
|        | LR        | 0.042       |             |               |               |              |
|        | MLP       | 0.046       | 0.694 (0.682-0.705) | 0.168 (0.153-0.182) | 0.602 (0.589-0.662) | 0.670 (0.608-0.681) | 86.29        |
|        | RF        | 0.05        | 0.659 (0.646-0.672) | 0.156 (0.142-0.172) | 0.604 (0.529-0.621) | 0.623 (0.618-0.708) | 34.447       |
|        | GB        | 0.04        | 0.696 (0.685-0.708) | 0.173 (0.156-0.189) | 0.587 (0.579-0.660) | 0.690 (0.618-0.699) | 37.573       |

ESI: Emergency Severity Index
MEWS: Modified Early Warning Score
NEWS: National Early Warning Score
REMS: Rapid Emergency Medicine Score
CART: Cardiac Arrest Risk Triage
LR: Logistic Regression
MLP: Multilayer Perceptron
RF: Random Forest
GB: Gradient Boosting
Figure 3: Barplots of AUROC and AUPRC for three different outcomes: "Hospitilization", "Critical", "72-hour ED revisitis".
4. Discussion

In this paper, we proposed standardized benchmarks for future researchers interested in ED prediction problems. Our paper provides a convenient pipeline for processing raw data from the newly published MIMIC-IV-ED database and ultimately generates the benchmark dataset, the first of its kind under the ED context. Our benchmark includes about half a million ED attendances, conveniently accessible to other ED researchers who wish to replicate our experiments or further build upon our work. We also presented benchmarking results of various methods applied to this benchmark dataset for three ED-relevant prediction tasks: hospitalization, critical outcome, and ED revisit. Our result also indicates the trade-off between model interpretability and model accuracy, i.e., one has to sacrifice some accuracy to gain more interpretability. To be more specific, more interpretable models, such as clinical scores, have less satisfying performance on many prediction tasks than some less interpretable models, such as machine learning and deep learning. Our benchmark dataset also supports linkage to the main MIMIC-IV database, where researchers could link ED episodes with subsequent inpatient or ICU stays for extracting more variables.

Among the machine learning models applied, gradient boosting, random forest, and multilayer perceptron achieved similar performance, higher than the others, which is consistent with previous studies.\textsuperscript{16,46} Except for clinical scores, logistic regression yielded the lowest AUC but took significantly less training time than other machine learning models. While both gradient boosting and random forest are based on decision trees, they organize the trees differently. As a deep learning model, multilayer perceptron took advantage of its large parameter space and achieved comparable performance. However, the training time is significantly higher than the rest.

The lack of explanation\textsuperscript{47} regarding the decisions made by machine learning reveals an unneglectable shortcoming of decision-making processes, especially for emergency care. Although machine learning could achieve better accuracy, they fail to explain the model in ways that frontline physicians prefer. In comparison, clinical scores\textsuperscript{48}, based on simple addition, subtraction, and multiplication of a few sparse integers, have a more straightforward clinical representation for doctors to understand. Such transparency could also facilitate their validation in real-world applications. Thus, clinical scores have been widely used in hospitals and ED over the world. In contrast, black-box machine learning exists more in the literature, but they are seldom used in real-world settings\textsuperscript{49}.

In this study, we explored three ED-relevant risk triaging tasks that are interrelated yet have some differences. Hospitalization and critical outcomes share a similar set of predictive variables, while ED revisits prediction takes several distinct variables. Critical outcomes prediction could be made with an AUROC of around 0.9 but a low
AUPRC of less than 0.4 due to data imbalance. In our experiments, clinical scores fail to achieve comparable performances, which indicates the problem of generalizability of clinical scores in the MIMIC-IV-ED database, considering the fact that there are no neurological features (i.e., Glasgow Coma Scale) indicating patient's consciousness level.

This paper contributes to the scientific community for both clinicians and data scientists working on ED research. Future researchers can use this standardized MIMIC-IV-ED data processing pipeline to get processed data hassle-free. They may also establish new models to compare with our ED-based benchmark tasks. Our pipeline is not just based on ED alone; we provide linkages to the MIMIC-IV main database with all ICU and inpatient episodes. Data scientists interested in getting ED data as additional variables and linking it to the other settings in the main MIMIC-IV database could use our framework to streamline their research without consulting any ED physicians. With the assistance of this first large-scale public benchmark dataset and data processing pipeline in the context of ED, one no longer needs to possess a high level of technical knowledge to conduct related research. As a result, we hope it could help future researchers to process data quickly and conveniently.

**Limitation**

This study has several limitations. First, though the study is based on an extensive database, it is still a single-center study. The performance of the different methods used in this study may vary in other healthcare settings. However, the proposed pipeline of data processing and benchmark in ED could still be used as a reference for further ED big-data research. Secondly, the benchmark dataset established in this study is based on EHR data with routinely collected variables, where some potential risk factors, such as socioeconomic status and neurological features, are not recorded. Furthermore, the dataset lacks enough information for a good trace of out-of-hospital death, which could bias our models. Nevertheless, given our purpose of establishing a benchmark in the ED context for competing models evaluations, our benchmark can be widely used for future research when new researchers would like to start an ED research based on the MIMIC-IV-ED database.
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