## RESEARCH

# Identifying inpatient hospitalizations with continuous electroencephalogram monitoring from administrative data

Marta Fernandes[1,2]*, M. Brandon Westover[3] and Sahar F. Zafar[1,2]

## Abstract

**Background** Continuous electroencephalography (cEEG) is increasingly utilized in hospitalized patients to detect and treat seizures. Epidemiologic and observational studies using administrative datasets can provide insights into the comparative and cost effectiveness of cEEG utilization. Defining patient cohorts that underwent acute inpatient cEEG from administrative datasets is limited by the lack of validated codes differentiating elective epilepsy monitoring unit (EMU) admissions from acute inpatient hospitalization with cEEG utilization. Our aim was to develop hospital administrative data-based models to identify acute inpatient admissions with cEEG monitoring and distinguish them from EMU admissions.

**Methods** This was a single center retrospective cohort study of adult (≥ 18 years old) inpatient admissions with a cEEG procedure (EMU or acute inpatient) between January 2016-April 2022. The gold standard for acute inpatient cEEG vs. EMU was obtained from the local EEG recording platform. An extreme gradient boosting model was trained to classify admissions as acute inpatient cEEG vs. EMU using administrative data including demographics, diagnostic and procedure codes, and medications.

**Results** There were 9,523 patients in our cohort with 10,783 hospital admissions (8.5% EMU, 91.5% acute inpatient cEEG); with average age of 59 (SD 18.2) years; 46.2% were female. The model achieved an area under the receiver operating curve of 0.92 (95% CI [0.91–0.94]) and area under the precision-recall curve of 0.99 [0.98–0.99] for classification of acute inpatient cEEG.

**Conclusions** Our model has the potential to identify cEEG monitoring admissions in larger cohorts and can serve as a tool to enable large-scale, administrative data-based studies of EEG utilization.

**Keywords** Health services research, EMU, EEG, Electronic health records, Machine learning

*Correspondence:
Marta Fernandes
mbentofernandes@mgh.harvard.edu
[1]Department of Neurology, Massachusetts General Hospital (MGH), 55 Fruit Street, Boston, MA 02114, USA
[2]Harvard Medical School, Boston, MA, USA
[3]Department of Neurology, Beth Israel Deaconess Medical Center, Boston, MA, USA

## Background

Continuous electroencephalography (cEEG) is increasingly utilized in hospitalized patients with acute brain injury or altered mental status to detect seizures and other seizure-like patterns that can worsen outcomes [1]. In the United States, there has been a 10-fold increase in the use of cEEG in acute inpatient setting, particularly in critical care [2, 3]. Detection of seizures and other seizure-like patterns on cEEG frequently results in anti-seizure medication (ASM) treatment escalation [4–8]. However, there is limited data on whether cEEG-guided ASM escalation improves outcomes [9]. At the same time, cEEG is resource intensive with limited availability in smaller health care facilities, being utilized more frequently in larger, urban and academic centers [2, 3]. Epidemiologic studies and observational studies using large administrative datasets can provide insights into the comparative effectiveness and cost effectiveness of cEEG utilization in acutely ill patients, and guide policies and protocols that can improve access to cEEG for patients where indicated (e.g., identifying patients that may benefit most from transfer to centers performing cEEG), develop cEEG utilization quality measures, generate evidence for rigorous randomized trials on cEEG guided anti-seizure treatment, and ultimately improve outcomes.

Prior work examining administrative datasets has shown that cEEG monitoring in hospitalized critically ill patients is associated with lower in-hospital mortality [2, 3]. However, a limitation of prior studies that have used administrative datasets is the lack of validated codes differentiating elective epilepsy monitoring unit (EMU) admissions from acute inpatient hospitalization with cEEG utilization. Acute inpatient cEEG and EMU EEG have the same International Classification of Diseases (ICD) and Current Procedural Terminology (CPT) codes. As a result, prior work has excluded all patients that were elective admissions or were not mechanically ventilated to define patient cohorts that underwent acute inpatient continuous EEG monitoring, resulting in potential selection bias. The aim of this study is to develop hospital administrative data-based models to identify acute inpatient admissions with cEEG monitoring.

## Methods

### Study cohort

In this study, we conducted a retrospective analysis of adult patients (≥18 years old) admitted to a single center between January 1st 2016 and April 30th 2022. The research protocol was approved by the Mass General Brigham (MGB) Institutional Review Board and a waiver of informed consent was obtained. The selection of patients for our cohort was performed considering the aim of the study in identifying acute inpatient admissions with cEEG monitoring. Figure 1 shows the patient selection flow chart. Patients were included if they underwent cEEG monitoring (either in the EMU or as part of an acute inpatient hospitalization). Our institution is a Level 4 Epilepsy Center approved by the National Association of Epilepsy Centers. Our EMU is also accredited by the American Board of Registration of Electroencephalographic and Evoked Potential Technologists. The EMU has 11 acquisition units (5 adult beds, 4 pediatric and 2 portable units). The average EMU volume is 174/year with approximately 16% diagnostic, 68% Phase 1 and 14% Phase 2. The average volume of acute inpatient cEEG at our center is approximately 1600/year.

### Study outcome variables

Our study outcome consisted of a binary variable indicating whether an inpatient admission with a cEEG procedure was performed in the acute inpatient hospital setting (cEEG) or in the EMU setting (EMU). From here on "cEEG" will refer to acute inpatient admissions with continuous EEG monitoring, and "EMU" will refer to epilepsy monitoring unit admissions. Reference standard for cEEG vs. EMU was determined using the local hospital Natus EEG database that contains all the hospital EEG data.

### Study covariates

The study covariates for the hospital admissions in our study cohort are presented in Table A2 from the Additional File. Diagnoses and procedures were defined using ICD and CPT codes and are presented in Table A1 from the Additional File. The binary covariates considered were indication ('1' for presence and '0' for absence) of daily laboratory values acquired, inpatient medications ordered, procedures performed, type of admission – elective, emergency and urgent, primary and secondary diagnoses of traumatic brain injury (TBI), stroke and epilepsy, seizures or convulsions, death at discharge, discharged to home or self-care and female sex. The numerical covariates consisted of the number of distinct procedures, number of distinct medications, days of hospital length of stay (LOS) and age at admission. For modeling covariates, we used procedures and medications that are more likely to be used in inpatient and high illness acuity settings to distinguish from the epilepsy monitoring unit setting [10–14]. Numerical covariates were normalized using the min-max normalization [15] where the minimum and maximum reference values for each covariate were calculated from a training set. The data splitting into training and testing sets is detailed in the following section. Regarding outliers preprocessing, we identified one outlier for hospital LOS, which we imputed with the median LOS.

The procedures (Table A1 from the Additional File) considered were the following: abdomen/pelvis computerized tomography (CT) scan, arterial line, chest X-ray, head CT scan, lumbar puncture, magnetic resonance imaging (MRI), mechanical ventilation, transthoracic echocardiogram, and tube feed orders. The number of procedures consisted of the sum of the distinct procedures performed during the hospital stay, varying in the range between zero and nine.

The set of inpatient medications considered were the following: cefepime, ceftriaxone, dexmedetomidine, dobutamine, dopamine, enoxaparin, epinephrine, heparin, midazolam, nicardipine, norepinephrine, phenylephrine, piperacillin, piperacillin/tazobactam, propofol, vancomycin and vasopressin. The number of medications consisted of the sum of the distinct inpatient medications ordered during the hospital stay, varying in the range between zero and seventeen.

### Modeling design and evaluation

We performed a random sampling of hospital admissions in our cohort to create training (70%) and hold-out testing (30%) sets with distinct patients. With the training set we developed an extreme gradient boosting model (XGBoost) [16] and performed hyperparameter tuning in 100 iterations of 10-fold cross validation. The hyperparameter tunning methodology is described in Additional File section A.2. We selected a threshold for binary classification on the training data that achieved a positive predictive value (PPV) yielding a balance between false positives and false negative predictions. We assessed both the positive and negative predictive values (PPV and NPV, respectively). We evaluated model performance using the area under the precision recall-curve (AUPRC) [17], showing the trade-off between PPV and sensitivity, also called true positive rate or recall, for different thresholds. We also evaluated the area under the receiver operating characteristic (AUROC), which quantifies the tradeoff between sensitivity and false positive rate (also known as 1- specificity), across different decision thresholds [18]. Given the imbalance in our dataset, we present the macro average [19] performance for the classification, and the performance for each class (EMU vs. cEEG). A macro-average calculates performance metrics independently for both classes and then takes the average, giving both classes equal weight [19]. We performed 1000 bootstrapping iterations to calculate 95% confidence intervals (CI) in the hold-out test set, an external and independent test set not used for model training or validation. We assessed covariate importance using SHapley Additive exPlanations (SHAP) [20], which estimates the contribution of each feature to the model's predictions.

## Results

### Cohort characteristics

Our cohort comprised 9,523 patients and a total of 10,783 hospital admissions, after applying inclusion and exclusion criteria (Fig. 1). The average age of the cohort was 59 years (standard deviation (SD) 18.2), with the majority being males (53.8%), White (75.5%) and non-Hispanic (82.7%) (Table 1). The majority of admissions (91.5%) were acute inpatient hospitalizations (i.e., cEEG rather than EMU). Demographic characteristics were approximately the same at the hospital admission level (Table A2 from the Additional File; counting all admissions separately) as those at the patient level (Table 1; counting each patient only once).

### Modeling results

The XGboost model was trained with all study covariates described in the Methods section (Table A2 from the Additional File). Model performance evaluated on the testing set is presented in Table 2. The hyperparameters selected during training in 10-fold cross validation are presented in Table A3 from the Additional File. We experimented different thresholds for fixed values of PPV between 95% and 98% (Table A4 from the Additional File). When setting PPV to 98%, the binary threshold was 0.80 and yielded a balanced sensitivity and specificity. The model achieved a macro AUROC of 0.92 (95% CI [0.91–0.94]) and AUPRC of 0.99 [0.98–0.99]. The AUROC and AUPRC curves are presented in Figure A1 from the Additional File. There were 130 (4%) misclassifications of acute inpatient cEEG incorrectly classified as EMU admissions, and 73 (26.6%) misclassifications of EMU admissions incorrectly classified as acute inpatient cEEG, as presented in Fig. 2. When analyzing misclassifications, 130 cEEG admissions incorrectly classified as EMU, we observed that 79% (N=102) of admissions were elective and 90% (N=117) discharged to home or self-care. For the EMU admissions incorrectly classified as acute inpatient cEEG we observed that 71% (N=52) were emergency and 93% of the admissions (N=68) had daily laboratory values acquired, a higher proportion when compared with that of the EMU class (59%, Table A2 from the Additional File).

Since most EMU admissions in our cohort are elective (72.4%) and discharged to home or self-care (82.7%), (Table A2 from the Additional File), we trained a model excluding both the admission type covariates (emergency, urgent and elective) and discharge disposition to home or self-care and evaluated the performance in test (AUROC and AUPRC presented in Figure A2 from the Additional File). The overall macro average model performance (Table A5 from the Additional File) was similar to that of the model using all covariates (Table 2) with an AUROC of 0.90 (95% CI [0.88–0.92]) and AUPRC of 0.99
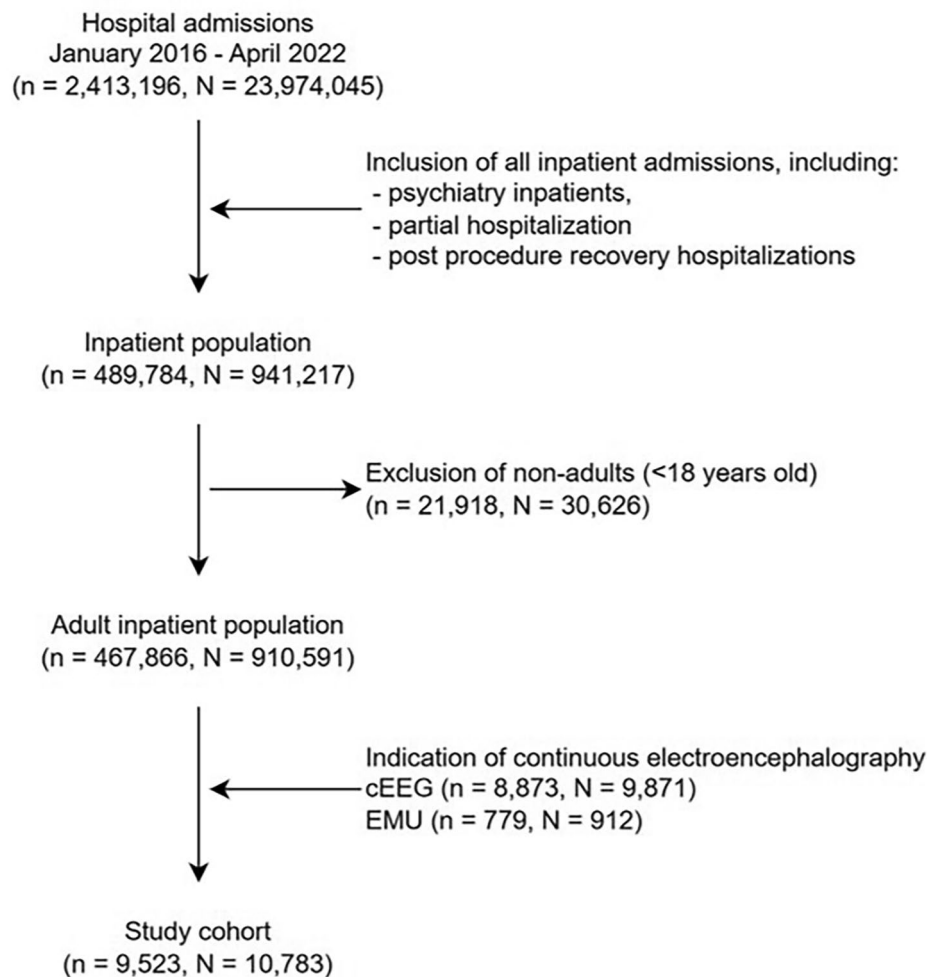
Hospital admissions
January 2016 - April 2022
(n = 2,413,196, N = 23,974,045)

Inclusion of all inpatient admissions, including:
- psychiatry inpatients,
- partial hospitalization
- post procedure recovery hospitalizations

Inpatient population
(n = 489,784, N = 941,217)

Exclusion of non-adults (<18 years old)
(n = 21,918, N = 30,626)

Adult inpatient population
(n = 467,866, N = 910,591)

Indication of continuous electroencephalography
cEEG (n = 8,873, N = 9,871)
EMU (n = 779, N = 912)

Study cohort
(n = 9,523, N = 10,783)

**Fig. 1** Study cohort inclusion and exclusion criteria. **Legend**: N – number of visits; n – number of patients; cEEG – acute inpatient hospitalizations admissions class; EMU – epilepsy monitoring unit admissions class

[0.98–0.99]. However, this model showed a higher number of misclassifications, especially false positives, mainly due to errors in classifying the EMU class.

**Covariates importance**

We analyzed the importance of the covariates in the design of the XGBoost model. The average magnitude of the SHAP values for the 20 top features is presented in Fig. 3, and the SHAP raw values are presented in Figure A3 from the Additional File.

Elective admission was the most important covariate for the model to classify an admission as EMU (left side in Figure A3 from the Additional File). We sought to understand the type of admissions distribution for each class, since EMU admissions are frequently elective. For both train and test sets, 72% of EMU and 11% of acute inpatients (cEEG class) admissions were elective, respectively. Furthermore, we assessed if the EMU non-elective admissions were correlated with the COVID-19 pandemic. According to a study [21], in the setting of the

COVID-19 pandemic, urgent and emergent EMU admissions were required due to increased seizure or event frequency. We confirmed that the non-elective EMU admissions spanned all years of our study period with the following number of admissions per year: 39, 46, 48, 41, 31, 38, 9, from 2016 to 2022, respectively. Since not all EMU admissions were elective, it was important to combine this covariate with others to develop the classification model.

Emergency admissions, orders of medications such as heparin, vasopressin, cefepime or epinephrine, daily laboratory values acquired, mechanical ventilation, transthoracic echocardiogram and chest X-ray and also diagnosis of stroke were important predictors of acute inpatients hospitalizations (cEEG).

The EMU class was associated with younger age at admission (blue color in Figure A3 from the Additional File) when compared to the cEEG class (mostly pink in Figure A3 from the Additional File). The average age (SD) for EMU admissions was 42 (18) while for the

**Table 1** Main characteristics of the study cohort

| Characteristic | Study cohort (n = 9523, N = 10,783) |
|---|---|
| **Age[a], (years, mean (SD))** | 59 (18.2) |
| **Female sex, n (%)** | 4402 (46.2) |
| **Race, n (%)** | |
| White | 7182 (75.5) |
| Black or African American | 818 (8.6) |
| Asian | 329 (3.6) |
| Other [b] | 1173 (12.3) |
| **Ethnicity, n (%)** | |
| Non-Hispanic | 7879 (82.7) |
| Hispanic | 701 (7.4) |
| Unknown | 943 (9.9) |
| **Hospital admissions, N (%)** | |
| EMU | 912 (8.5) |
| cEEG | 9871 (91.5) |
| **Type of admission, N (%)** | |
| Emergency | 6902 (64.0) |
| Urgent | 2146 (20.0) |
| Elective | 1729 (16.0) |
| **Discharge disposition, N (%)** | |
| Deceased | 1897 (17.6) |
| Home or Self Care | 2812 (26.1) |
| **Diagnosis, N (%)** | |
| TBI | 698 (6.5) |
| Stroke | 1507 (14.0) |
| Epilepsy, seizures or convulsions | 6876 (63.8) |
| **Daily laboratory values acquired, N (%)** | 10,127 (93.9) |
| **Top procedures, N (%)** | |
| Chest X-ray | 7052 (65.4) |
| Head CT scan | 6546 (60.7) |
| MRI | 5869 (54.4) |
| **Top medications, N (%)** | |
| Enoxaparin | 7137 (66.2) |
| Propofol | 6067 (56.3) |
| Vancomycin | 5777 (53.6) |
| **Medications[b], (number, median [IQR])** | 5 [1, 8] |
| **Procedures[b], (number, median [IQR])** | 3 [1, 5] |
| **LOS (days, median [IQR])** | 9 [5, 19] |

Legend: cEEG – acute inpatient hospitalizations admissions class; EMU – epilepsy monitoring unit admissions class; IQR – interquartile range; LOS – hospital length of stay; N – number of hospital admissions; n – number of patients; SD – standard deviation

[a] Age at baseline for the first hospital admission in the study period. [b] 'Other' includes 'unknown', 'declined', 'American Indian or Alaska Native' and 'Native Hawaiian or other Pacific Islander'

cEEG class it was 60 (18), a difference of approximately 20 years (Table A2 from the Additional File). The EMU admissions class was also associated with lower number of procedures and medications, when compared to the cEEG class. EMU admissions were also associated with being discharged home, having a diagnosis of epilepsy or seizures, orders of enoxaparin and ceftriaxone. Patients receiving ceftriaxone alone were likely intracranial monitoring admissions.

## Discussion

Our model using hospital administrative and billing data distinguishes continuous EEG performed in acute inpatient setting from the EMU setting. The model can enable identification of acute inpatient cEEG from administrative datasets with higher accuracy, and therefore be used for comprehensive comparative effectiveness and cost effectiveness analysis. Such large epidemiologic studies can then provide further guidance for randomized trials of continuous EEG guided anti-seizure treatment in the acute setting, and refinement of continuous EEG guidelines and protocols, particularly for resource limited settings.

There has been limited prior work in the development and validation of administrative models for accurate identification of continuous EEG in the hospital setting from administrative datasets. One prior study evaluated ICD based models for accurate identification of EMU admissions from administrative datasets [22]. The authors examined three queries, with varying use of admission and primary diagnosis ICD codes in 351 admissions. They found that queries combining ICD and CPT codes for continuous EEG, with ICD codes for epilepsy, seizure, or seizure mimic codes as the admitting diagnosis had a sensitivity of 96.3%, specificity of 100.0%, positive predictive value of 98.3%, and negative predictive value of 100.0%. Models combining ICD/CPT codes for continuous EEG and ICD codes for epilepsy and seizures as principal diagnosis had sensitivity of 94.9%, specificity of 100.0%, and positive and negative predictive values of 98.8%, and 100.0% respectively. However, these queries only included elective admissions, with focus only on EMU admissions and therefore cannot be applied for identification of acute inpatient continuous EEG utilization. Additionally, our work demonstrates that a subset of EMU admissions are emergent or urgent (up to 28% in our cohort), and a subset of acute inpatient cEEG admissions are elective (up to 11% in our cohort). Urgent admissions to EMU are indicated when there are significant clinical risks for patients. These include rapid medication switches in patients experiencing adverse effects or high seizure frequency and cannot be safely titrated outpatient, seizure frequency exacerbation with unsuccessful outpatient efforts at controlling seizures, concern for non-epileptic spells occurring at a high frequency, and differentiating between new acute symptoms versus medication side effects [23]. While there is no robust data on frequency of urgent admissions to EMUs, cohort studies have shown medication adjustments account for approximately 20–30% of EMU admissions and referrals

**Table 2** Modeling performance [95% confidence intervals] of the extreme gradient boosting model evaluated in test

| Classes | AUROC | AUPRC | Sensitivity | PPV | NPV | Specificity |
|---|---|---|---|---|---|---|
| Macro average | 0.92 | 0.98 | 0.78 | 0.83 | 0.78 | 0.78 |
| | [0.91–0.94] | [0.98–0.99] | [0.75–0.81] | [0.79–0.85] | [0.79–0.85] | [0.75–0.81] |
| EMU | 0.92 | 0.66 | 0.73 | 0.61 | 0.97 | 0.96 |
| | [0.91–0.94] | [0.60–0.72] | [0.68–0.79] | [0.55–0.65] | [0.97–0.98] | [0.95–0.96] |
| cEEG | 0.92 | 0.99 | 0.96 | 0.97 | 0.61 | 0.73 |
| | [0.91–0.94] | [0.98–0.99] | [0.95–0.96] | [0.97–0.98] | [0.55–0.65] | [0.68–0.79] |

Legend: AUROC – area under the receiver operating characteristic curve; AUPRC – area under the precision-recall curve; cEEG – acute inpatient hospitalizations admissions class; EMU – epilepsy monitoring unit admissions class; PPV – positive predictive value; NPV – negative predictive value
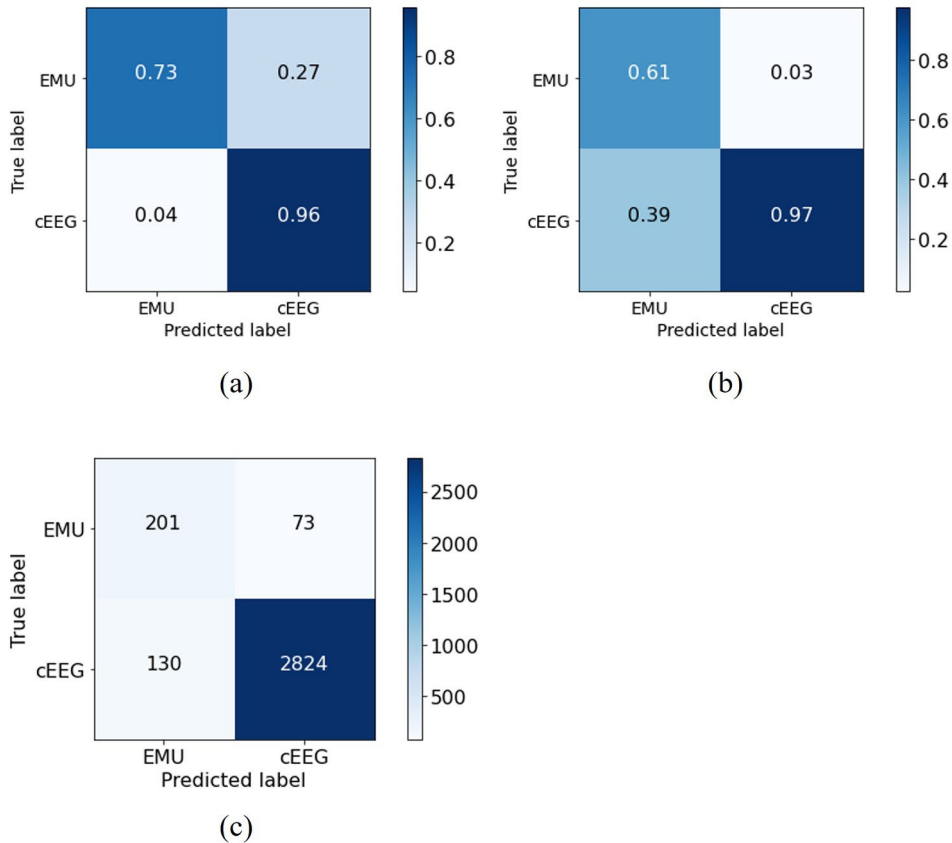


**Fig. 2** Confusion matrices normalized by (**a**) sensitivity, (**b**) positive predictive value, (**c**) without normalization. **Legend**: cEEG – acute inpatient hospitalizations admissions class; EMU – epilepsy monitoring unit admissions class

[24, 25]. Our model reduces the misclassification rate based on admission status (4% cEEGs misclassified as EMU vs. 11% using a priori stratification on the elective vs. non elective admission status). We did not see a significant change in the misclassification of EMU (27% of EMU admissions misclassified as acute inpatient cEEG vs. 28% using a priori stratification on the elective vs. non elective admission status). While elective vs. emergent and urgent admissions, continues to be the most important predictors in our model, combining them with additional ICD diagnosis, procedure and medication codes can enable identification of acute inpatient cEEGs without a priori exclusion of patients.

Two prior epidemiologic studies have examined the impact of cEEG utilization in critically ill patients using the Nationwide Inpatient Sample [2, 3]. Both studies found that cEEG utilization is associated with lower in-hospital mortality, and is not associated with increased costs when compared with routine (brief) EEG [2, 3]. However, to ensure exclusion of EMU admission, the studies excluded all elective admissions. Additionally, to define a cohort of critically ill patients they only included patients that received mechanical ventilation. However, epidemiologic studies have shown that more than half of patients admitted to intensive care units do not receive mechanical ventilation [26, 27]. Moreover, our data demonstrates that approximately 60% of patients undergoing
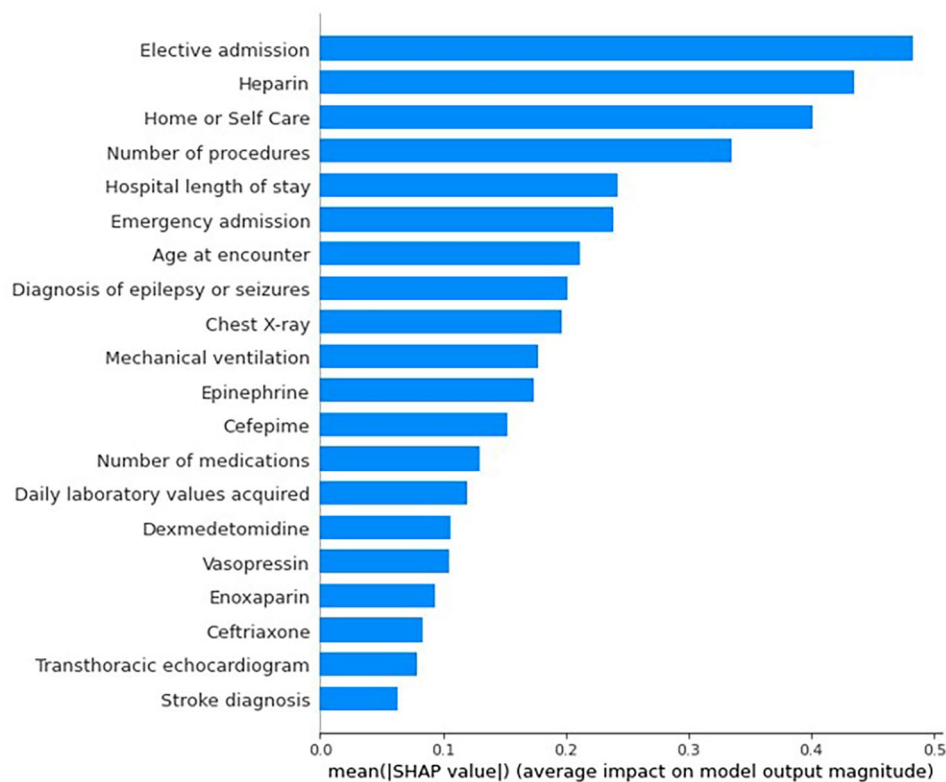
**Fig. 3** Average magnitude of the Shapley Additive exPlanations (SHAP) values for the model top 20 features. **Legend**: Positive SHAP values further from zero represent higher impact for the acute inpatient admissions class (cEEG) while negative SHAP represent higher impact for the epilepsy monitoring unit admissions (EMU) class

cEEG were not on mechanical ventilation. Therefore, a priori exclusion of patients not on mechanical ventilation potentially results in an exclusion of a large proportion of patients that are critically ill and could have undergone cEEG, resulting in potential sampling bias in the prior studies. Our model can eliminate the need for upfront inclusion and exclusion or filtering criteria based on admission status, and use of specific medical procedures such as mechanical ventilation, enabling identification of a broader more complete cohort of admissions with inpatient continuous EEG utilization from administrative datasets.

The main limitation of the study is that it is a single center study, therefore may not be generalizable. While the billing and procedure codes, medications and admission data we used in our models may not overlap with all claims datasets, the variables used are routinely available in institutional electronic health and administrative/billing data, as well as in several critical care and population based datasets (e.g. MIMIC, Premier, Nationwide inpatient sample) [28–31]. Other covariates could have been included in the model, such as free text clinical notes, including EEG reports, and discharging providers taxonomy codes, which we propose as future work, along with validation in other administrative datasets.

## Conclusions

The model developed in this study can identify continuous EEG performed in the acute inpatient setting from continuous EEG performed in the EMU setting and reduces the number of misclassifications. This model will allow the identification of continuous EEG monitoring admission in larger cohorts, thereby contributing to the scale of research of EEG utilization.

**Abbreviations**

| | |
|---|---|
| ASM | Anti-seizure medication |
| AUPRC | Area under the precision recall-curve |
| AUROC | Area under the receiver operating characteristic |
| cEEG | Continuous electroencephalography |
| CI | Confidence interval |
| CPT | Current procedural terminology |
| CT | Computerized tomography |
| EMU | Epilepsy monitoring unit |
| ICD | International Classification of Diseases |
| IQR | Interquartile range |
| LOS | Hospital length of stay |
| MGB | Mass General Brigham |
| MRI | Magnetic resonance imaging |
| NPV | Negative predictive value |
| PPV | Positive predictive value |
| SD | Standard deviation |
| SHAP | SHapley Additive exPlanations |
| TBI | Traumatic brain injury |
| XGBoost | Extreme gradient boosting model |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12913-023-10262-8.

Supplementary Material 1

## Authors' contributions
M.F. extracted the data from the hospital database, created the code for data analysis and modeling and prepared the figures for the manuscript. S.F.Z. defined the research aims and study design. Both M.F. and S.F.Z. wrote the manuscript. All authors reviewed the manuscript.

## Data Availability
The datasets used during the current study are available from the corresponding author on reasonable request.

## Declarations

### Ethics approval and consent to participate
We confirm that all methods were carried out in accordance with relevant guidelines and regulation. The need for informed consent was waived by the ethics committee/Institutional Review Board of Massachusetts General Brigham, because of the retrospective nature of the study. The research protocol was approved by the Mass General Brigham (MGB) Institutional Review Board.

### Consent for publication
Not applicable.

### Competing interests
The authors declare no competing interests.

## References
1. Herman ST, Abend NS, Bleck TP, Chapman KE, Drislane FW, Emerson RG, et al. Consensus statement on continuous EEG in critically ill adults and children, part I: indications. J Clin Neurophysiol off Publ Am Electroencephalogr Soc. 2015;32(2):87–95.
2. Ney JP, van der Goes DN, Nuwer MR, Nelson L, Eccher MA. Continuous and routine EEG in intensive care: utilization and outcomes, United States 2005–2009. Neurology. 2013;81(23):2002–8.
3. Hill CE, Blank LJ, Thibault D, Davis KA, Dahodwala N, Litt B, et al. Continuous EEG is associated with favorable hospitalization outcomes for critically ill patients. Neurology. 2019;92(1):e9–18.
4. Zafar SF, Postma EN, Biswal S, Boyle EJ, Bechek S, O'Connor K, et al. Effect of epileptiform abnormality burden on neurologic outcome and antiepileptic drug management after subarachnoid Hemorrhage. Clin Neurophysiol off J Int Fed Clin Neurophysiol. 2018;129(11):2219–27.
5. Dhakar MB, Sheikh Z, Kumari P, Lawson EC, Jeanneret V, Desai D, et al. Epileptiform Abnormalities in Acute ischemic Stroke: impact on Clinical Management and outcomes. J Clin Neurophysiol off Publ Am Electroencephalogr Soc. 2022;39(6):446–52.
6. Tabaeizadeh M, Aboul Nour H, Shoukat M, Sun H, Jin J, Javed F, et al. Burden of Epileptiform Activity predicts Discharge neurologic outcomes in severe Acute Ischemic Stroke. Neurocrit Care. 2020;32(3):697–706.
7. Kilbride RD, Costello DJ, Chiappa KH. How seizure detection by continuous electroencephalographic monitoring affects the prescribing of antiepileptic medications. Arch Neurol. 2009;66(6):723–8.
8. Rossetti AO, Schindler K, Sutter R, Rüegg S, Zubler F, Novy J, et al. Continuous vs routine Electroencephalogram in critically Ill adults with altered consciousness and no recent seizure: a Multicenter Randomized Clinical Trial. JAMA Neurol. 2020;77(10):1225–32.
9. Sivaraju A, Gilmore EJ. Understanding and managing the Ictal-Interictal Continuum in Neurocritical Care. Curr Treat Options Neurol. 2016;18(2):8.
10. Scales DC, Guan J, Martin CM, Redelmeier DA. Administrative data accurately identified intensive care unit admissions in Ontario. J Clin Epidemiol. 2006;59(8):802–7.
11. Yamana H, Matsui H, Fushimi K, Yasunaga H. Procedure-based severity index for inpatients: development and validation using administrative database. BMC Health Serv Res. 2015;15(1):261.
12. Baggs J, Fridkin SK, Pollack LA, Srinivasan A, Jernigan JA. Estimating National trends in Inpatient Antibiotic Use among US hospitals from 2006 to 2012. JAMA Intern Med. 2016;176(11):1639–48.
13. Amerineni R, Sun H, Lee H, Hsu J, Patorno E, Westover MB, et al. Using electronic health data to explore effectiveness of ICU EEG and anti-seizure treatment. Ann Clin Transl Neurol. 2021;8(12):2270–9.
14. Thongprayoon C, Cheungpasitporn W, Harrison AM, Carrera P, Srivali N, Kittamongkolchai W, et al. Temporal trends in the utilization of vasopressors in intensive care units: an epidemiologic study. BMC Pharmacol Toxicol. 2016;17(1):19.
15. Han J, Pei J, Kamber M. Data Mining: concepts and techniques. Elsevier; 2011. p. 740.
16. Chen T, Guestrin C, XGBoost:. A Scalable Tree Boosting System. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining [Internet]. New York, NY, USA: Association for Computing Machinery; 2016 [cited 2022 Sep 21]. p. 785–94. (KDD '16). https://doi.org/10.1145/2939672.2939785.
17. Saito T, Rehmsmeier M. The Precision-Recall plot is more informative than the ROC plot when evaluating Binary classifiers on Imbalanced datasets. PLoS ONE. 2015;10(3):e0118432.
18. Steyerberg EW, Vickers AJ, Cook NR, Gerds T, Gonen M, Obuchowski N, et al. Assessing the performance of Prediction models: a Framework for Traditional and Novel measures. Epidemiology. 2010;21(1):128–38.
19. Sokolova M, Lapalme G. A systematic analysis of performance measures for classification tasks. Inf Process Manag. 2009;45(4):427–37.
20. Lundberg S, Lee SI. A Unified Approach to Interpreting Model Predictions [Internet]. arXiv; 2017 [cited 2022 Sep 14]. Available from: http://arxiv.org/abs/1705.07874.
21. Zepeda R, Lee Y, Agostini M, Alick Lindstrom S, Dave H, Dieppa M, et al. Emergent admissions to the Epilepsy Monitoring Unit in the setting of COVID-19 Pandemic-related, state-mandated restrictions: clinical decision making and outcomes. Neurodiagnostic J. 2021;61(2):95–103.
22. Kamitaki BK, Rishty S, Mani R, Wong S, Bateman LM, Thomas-Hawkins C, et al. Using ICD-10 codes to identify elective Epilepsy monitoring unit admissions from administrative billing data: a validation study. Epilepsy Behav EB. 2020;111:107194.
23. Shih JJ, Fountain NB, Herman ST, Bagic A, Lado F, Arnold S, et al. Indications and methodology for video-electroencephalographic studies in the Epilepsy monitoring unit. Epilepsia. 2018;59(1):27–36.
24. Gazzola DM, Thawani S, Agbe-Davies O, Carlson C. Epilepsy monitoring unit length of stay. Epilepsy Behav EB. 2016;58:102–5.
25. Izadyar S, Ewida A, Kleinhenz EM, Titoff V. Utilization of Epilepsy Monitoring Unit by General neurologists. Cureus. 2022;14(7):e27144.
26. Wunsch H, Wagner J, Herlim M, Chong DH, Kramer AA, Halpern SD. ICU occupancy and mechanical ventilator use in the United States. Crit Care Med. 2013;41(12):2712–9.
27. Esteban A, Frutos-Vivar F, Muriel A, Ferguson ND, Peñuelas O, Abraira V, et al. Evolution of mortality over time in patients receiving mechanical ventilation. Am J Respir Crit Care Med. 2013;188(2):220–30.
28. Casey JA, Schwartz BS, Stewart WF, Adler NE. Using Electronic Health Records for Population Health Research: a review of methods and applications. Annu Rev Public Health. 2016;37:61–81.
29. DeCuir J, Baggs J, Melgar M, Patel P, Wong KK, Schwartz NG, et al. Identification and description of patients with multisystem inflammatory syndrome

Fernandes *et al. BMC Health Services Research*        (2023) 23:1234

Page 9 of 9

in adults associated with SARS-CoV-2 Infection using the Premier Healthcare Database. Epidemiol Infect. 2022;150:e26.

30. Johnson AEW, Bulgarelli L, Shen L, Gayles A, Shammout A, Horng S, et al. MIMIC-IV, a freely accessible electronic health record dataset. Sci Data. 2023;10(1):1.

31. Tang OY, Pugacheva A, Bajaj AI, Rivera Perla KM, Weil RJ, Toms SA. The National Inpatient Sample: a primer for Neurosurgical Big Data Research and systematic review. World Neurosurg. 2022;162:e198–217.

**Publisher's Note**

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.