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PREDICTING LENGTH OF HOSPITALIZATION WITH EXPLAINABLE MACHINE LEARNING TECHNIQUES

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ABSTRACT

Efficient bed management in hospitals minimizes costs and improves patient outcomes. This study presents a predictive framework for ICU length of stay (LOS) at admission, leveraging electronic health records (EHR) data. Using the hospital stay dataset from the Kaggle repository, the study evaluates various machine learning algorithms, including Logistic Regression, Random Forest, MLP, Gradient Boosting, XGBoost, and an extension with CatBoost. The algorithms are assessed based on AUC, accuracy, precision, recall, and F1 score. XGBoost achieved the highest accuracy among the traditional algorithms, while the extended CatBoost algorithm outperformed all with 98.25% accuracy. Explainable AI (XAI) methods, such as SHAP, were used to interpret feature contributions. The study demonstrates the potential of leveraging patient EHR data and advanced machine learning models to predict ICU stays, enabling better resource allocation in hospitals.

INTRODUCTION:

The duration of hospitalisation functions as a prevalent effectiveness metric in healthcare facilities. It substantially impacts resource allocation and healthcare costs. A research by the Australian National Health Performance Authority indicates that shorter hospital stays are deemed more efficient, facilitating the prompt availability of beds for incoming patients. Nevertheless, too short stays may jeopardise the quality of treatment and result in negative patient outcomes. Conversely, extended hospitalisations, often due to complications, might increase the likelihood of negative health outcomes. Delays in healthcare coordination, not pertaining to the patient's clinical state, may prolong hospitalisation periods. The survey indicated that prolonged stays may arise from delays in transferring patients to alternative care providers, such elderly care institutions, community care programs, or rehabilitation centres. Efficient management of hospital bed availability is essential for tackling ICU issues, such as patient overcrowding, infections, mortality risk, and medical complications. To mitigate these risks and enhance resource utilisation, a reduced ICU duration of stay coupled with high-quality treatment is essential, particularly in unpredictable circumstances like pandemics. This not only reduces hospital expenses but also guarantees improved patient outcomes. Thus, the provision of sufficient bed capacity and prompt patient transfers to other wards is essential for sustaining healthcare quality. The proposed system aims to develop an efficient framework for predicting ICU length of stay (LOS) using machine learning techniques, leveraging patient Electronic Health Records (EHR). The system will focus on classifying ICU stays as either "short" or "long" based on a comprehensive analysis of patient health conditions. The project will implement multiple machine learning algorithms, including

Logistic Regression, Random Forest, Multi-Layer Perceptron (MLP), Gradient Boosting, XGBoost, and an extension with CatBoost. These algorithms will be trained on patient EHR data to predict LOS and evaluated using performance metrics such as accuracy, precision, recall, F1 score, and AUC. Additionally, the system will incorporate Explainable AI (XAI) methods to interpret and identify the most significant features contributing to the predictions. By providing accurate ICU stay predictions, the proposed system can improve hospital resource management, enhance patient care, and optimize bed allocation in real-time. The proposed system integrates a wider scope of patient EHR data, including health conditions, providing a more complete analysis for ICU stay length prediction compared to systems focused solely on vital signs. It incorporates Explainable AI (XAI) techniques, enabling the identification of key features that influence predictions, significantly improving transparency and interpretability for clinicians and decision makers. The proposed system evaluates algorithms using a comprehensive set of performance metrics, including accuracy, precision, recall, F1-score, and AUC, ensuring a robust assessment of model performance across multiple dimensions. By utilizing advanced machine learning algorithms such as XGBoost and extending to CatBoost, the proposed system aims to improve prediction accuracy and resource allocation efficiency compared to traditional classifiers in existing systems.

LITERATURE SURVEY

1 An explainable machine learning framework for lung cancer hospital length of stay prediction: https://www.nature.com/articles/s41598-021-04608-7

ABSTRACT:

This work introduces a predictive Length of Stay (LOS) framework for lung cancer patients using machine learning (ML) models. The framework proposed to deal with imbalanced datasets for classification-based approaches using electronic healthcare records (EHR). We have utilized supervised ML methods to predict lung cancer inpatients LOS during ICU hospitalization using the MIMIC-III dataset. Random Forest (RF) Model outperformed other models and achieved predicted results during the three framework phases. With clinical significance features selection, over-sampling methods (SMOTE and ADASYN) achieved the highest AUC results (98% with CI 95%: 95.3–100%, and 100% respectively). The combination of Over-sampling and under-sampling achieved the second highest AUC results (98%, with CI 95%: 95.3–100%, and 97%, CI 95%: 93.7–100% SMOTE-Tomek, and SMOTE-ENN respectively). Under-sampling methods reported the least important AUC results (50%, with CI 95%: 40.2–59.8%) for both (ENN and Tomek- Links). Using ML explainable technique called SHAP, we explained the outcome of the predictive model (RF) with SMOTE class balancing technique to understand the most significant clinical features that contributed to predicting lung cancer LOS with the RF model. Our promising framework allows us to employ ML techniques in-hospital clinical information systems to predict lung cancer admissions into ICU.

2 Predictive analytics frameworks for electronic health records with machine learning advancements: optimising hospital resources utilisation with predictive and epidemiological models: https://researchdirect.westernsydney.edu.au/islandora/object/uws:67523/

ABSTRACT:

The primary aim of this thesis was to investigate the feasibility and robustness of predictive machine-learning models in the context of improving hospital resources' utilisation with data- driven approaches and predicting hospitalisation with hospital quality assessment metrics such as length of stay. The length of stay predictions includes the validity of the proposed methodological predictive framework on each hospital's electronic health records data source. In this thesis, we relied on electronic health records (EHRs) to drive a data-driven predictive inpatient length of stay (LOS) research framework that suits the most demanding hospital facilities for hospital resources' utilisation context. The thesis focused on the viability of the methodological predictive length of stay approaches on dynamic and demanding healthcare facilities and hospital settings such as the intensive care units and the emergency departments. While the hospital length of stay predictions are (internal) healthcare inpatients outcomes assessment at the time of admission to discharge, the thesis also considered (external) factors outside hospital control, such as forecasting future hospitalisations from the spread of infectious communicable disease during pandemics. The internal and external splits are the thesis' main contributions. Therefore, the thesis evaluated the public health measures during events of uncertainty (e.g. pandemics) and measured the effect of non-pharmaceutical intervention during outbreaks on future hospitalised cases. This approach is the first contribution in the literature to examine the epidemiological curves' effect using simulation models to project the future hospitalisations on their strong potential to impact hospital beds' availability and stress hospital workflow and workers, to the best of our knowledge. The main research commonalities between chapters are the usefulness of ensembles learning models in the context of LOS for hospital resources utilisation. The ensembles learning models anticipate better predictive performance by combining several base models to produce an optimal predictive model. These predictive models explored the internal LOS for various chronic and acute conditions using data-driven approaches to determine the most accurate and powerful predicted outcomes. This eventually helps to achieve desired outcomes for hospital professionals who are working in hospital settings.

3 Machine learning combining CT findings and clinical parameters improves prediction of length of stay and ICU admission in torso trauma:

https://link.springer.com/article/10.1007/s00330-020-07534-w ABSTRACT: Objective: To develop machine learning (ML) models capable of predicting ICU admission and extended length of stay (LOS) after torso (chest, abdomen, or pelvis) trauma, by using clinical and/or imaging data. Materials and methods: This was a retrospective study of 840 adult patients admitted to a level 1 trauma center after injury to the torso over the course of 1 year. Clinical parameters included age, sex, vital signs, clinical scores, and laboratory values. Imaging data consisted of any injury present on CT. The two outcomes of interest were ICU admission and extended LOS, defined as more than the median LOS in the dataset. We developed and tested artificial neural network (ANN) and support vector machine (SVM) models, and predictive performance was evaluated by area under the receiver operating characteristic (ROC) curve (AUC). Results: The AUCs of SVM and ANN models to predict ICU admission were up to 0.87 ± 0.03 and 0.78 ± 0.02, respectively. The AUCs of SVM and ANN models to predict extended LOS were up to 0.80 ± 0.04 and 0.81 ± 0.05, respectively. Predictions based on imaging alone or imaging with clinical parameters were consistently more accurate than those based solely on clinical parameters. Conclusions: The best performing models incorporated imaging findings and outperformed those with clinical findings alone. ML models have the potential to help predict outcomes in trauma by integrating clinical and imaging findings, although further research may be needed to optimize their performance.

4 Early Prediction of Mortality, Severity, and Length of Stay in the Intensive Care Unit of

Sepsis Patients Based on Sepsis 3.0 by Machine Learning Models:

https://www.frontiersin.org/journals/medicine/articles/10.3389/fmed.2021.664966/full

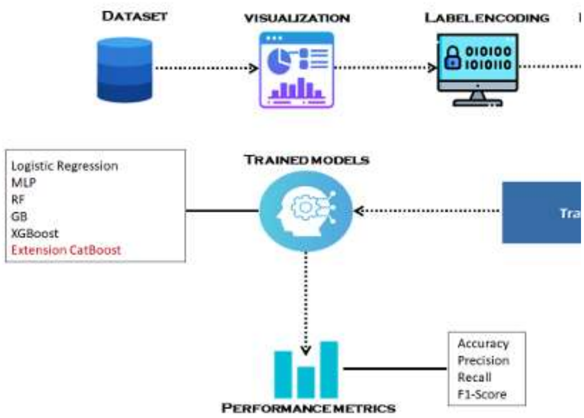
ABSTRACT: Background: Early prediction of the clinical outcome of patients with sepsis is of great significance and can guide treatment and reduce the mortality of patients. However, it is clinically difficult for clinicians. Methods: A total of 2,224 patients with sepsis were involved over a 3-year period (2016–2018) in the intensive care unit (ICU) of Peking Union Medical College Hospital. With all the key medical data from the first 6 h in the ICU, three machine learning models, logistic regression, random forest, and XGBoost, were used to predict mortality, severity (sepsis/septic shock), and length of ICU stay (LOS) (>6 days, ≤ 6 days). Missing data imputation and oversampling were completed on the dataset before introduction into the models. Results: Compared to the mortality and LOS predictions, the severity prediction achieved the best classification results, based on the area under the operating receiver characteristics (AUC), with the random forest classifier (sensitivity = 0.65, specificity = 0.73, F1 score = 0.72, AUC = 0.79). The random forest model also showed the best overall performance (mortality prediction: sensitivity = 0.50, specificity = 0.84, F1 score = 0.66, AUC = 0.74; LOS prediction: sensitivity = 0.79, specificity = 0.66, F1 score = 0.69, AUC = 0.76) among the three models. The predictive ability of the SOFA score itself was inferior to that of the above three models. Conclusions: Using the random forest classifier in the first 6 h of ICU admission can provide a comprehensive early warning of sepsis, which will contribute to the formulation and management of clinical decisions and the allocation and management of resources.

5 Predicting Intensive Care Unit Length of Stay and Mortality Using Patient Vital Signs: Machine Learning Model Development and Validation:

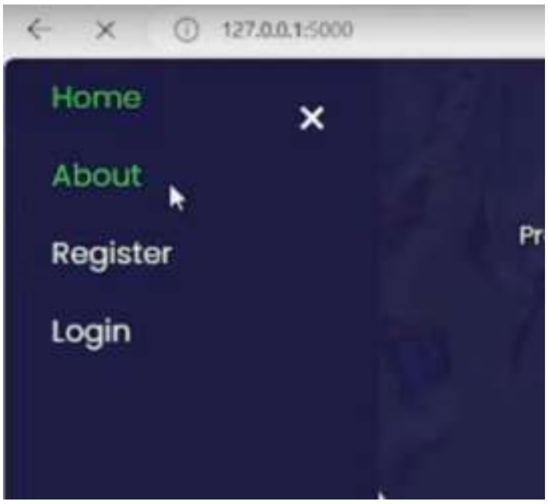
https://medinform.jmir.org/2021/5/e21347/

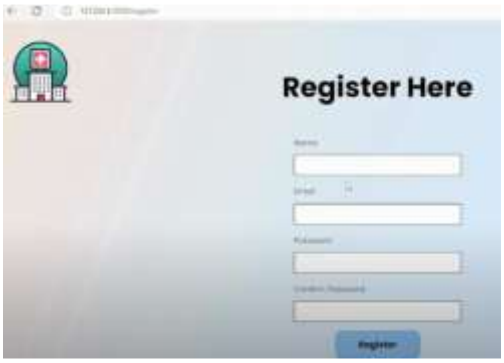
ABSTRACT: Background: Patient monitoring is vital in all stages of care. In particular, intensive care unit (ICU) patient monitoring has the potential to reduce complications and morbidity, and to increase the quality of care by enabling hospitals to deliver higher-quality, cost-effective patient care, and improve the quality of medical services in the ICU. Objective: We here report the development and validation of ICU length of stay and mortality prediction models. The models will be used in an intelligent ICU patient monitoring module of an Intelligent Remote Patient Monitoring (IRPM) framework that monitors the health status of patients, and generates timely alerts, maneuver guidance, or reports when adverse medical conditions are predicted. Methods: We utilized the publicly available Medical Information Mart for Intensive Care (MIMIC) database to extract ICU stay data for adult patients to build two prediction models: one for mortality prediction and another for ICU length of stay. For the mortality model, we applied six commonly used machine learning (ML) binary classification algorithms for predicting the discharge status (survived or not). For the length of stay model, we applied the same six ML algorithms for binary classification using the median patient population ICU stay of 2.64 days. For the regression-based classification, we used two ML algorithms for predicting the number of days. We built two variations of each prediction model: one using 12 baseline demographic and vital sign features, and the other based on our proposed quantiles approach, in which we use 21 extra features engineered from the baseline vital sign features, including their modified means, standard deviations, and quantile percentages. Results: We could perform predictive modeling with minimal features while maintaining reasonable performance using the quantiles approach. The best accuracy achieved in the mortality model was approximately 89% using the random forest algorithm. The highest accuracy achieved in the length of stay model, based on the population median ICU stay (2.64 days), was approximately 65% using the random forest algorithm. Conclusions: The novelty in our approach is that we built models to predict ICU length of stay and mortality with reasonable accuracy based on a combination of ML and the quantiles approach that utilizes only vital signs available from the patient's profile without the need to use any external features. This approach is based on feature engineering of the vital signs by including their modified means, standard deviations, and quantile percentages of the original features, which provided a richer dataset to achieve better predictive power in our models.

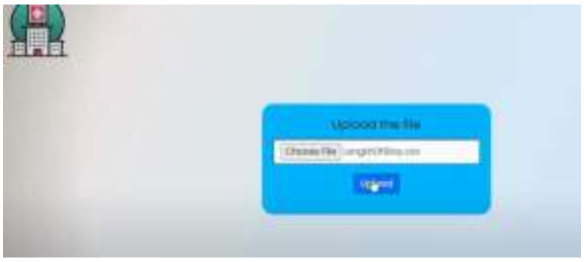
SYSTEM ARCHITECTURE:



RESULTS:







CONCLUSION

In conclusion, the proposed system successfully addresses the critical challenge of predicting ICU length of stay (LOS) using patient Electronic Health Records (EHR). By implementing various machine learning models, the study demonstrates the potential to enhance hospital resource management and patient care through accurate ICU stay predictions. Among the algorithms evaluated, the CatBoost model emerged as the top-performing method, achieving the highest accuracy of 98.25%. Its ability to handle categorical data effectively and leverage gradient boosting significantly improved the prediction results compared to other traditional models. The use of Explainable AI (XAI) techniques, such as SHAP, also added value by identifying key features that contribute to the prediction, providing transparency and insight into the decision-making process. Overall, the system highlights the importance of combining advanced machine learning algorithms and explainability to optimize ICU resource allocation, which can ultimately improve patient outcomes and hospital efficiency.

Future Scope:

In future work, the project can be further enhanced by exploring deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) for more complex feature extraction and sequence modeling from EHR data. Additionally, hybrid models and ensemble learning methods like stacking can be implemented to boost prediction accuracy. Feature engineering and dimensionality reduction techniques like PCA could be explored to optimize performance further and reduce computational complexity.

REFERENCES

[1] B. Alsinglawi, O. Alshari, M. Alorjani, O. Mubin, F. Alnajjar, M. Novoa, and O. Darwish, ''An explainable machine learning framework for lung cancer hospital length of stay prediction,'' Sci. Rep., vol. 12, no. 1, pp. 1–10, Jan. 2022.

[2] B. Alsinglawi, ''Predictive analytics framework for electronic health records with machine learning advancements: Optimizing hospital resources utilization with predictive and epidemiological models,'' Ph.D. thesis, Western Sydney Univ., Penrith, NSW, Australia, 2022. [Online]. Available: islandora/object/uws:67523/

[3] P. V. Staziaki, D. Wu, J. C. Rayan, I. D. D. O. Santo, F. Nan, A. Maybury, N. Gangasani, I. Benador, V. Saligrama, J. Scalera, and S. W. Anderson, ''Machine learning combining CT findings and clinical parameters improves prediction of length of stay and ICU admission in torso trauma,'' Eur. Radiol., vol. 31, no. 7, pp. 5434–5441, Jul. 2021.

[4] L. Su, Z. Xu, F. Chang, Y. Ma, S. Liu, H. Jiang, H. Wang, D. Li, H. Chen, X. Zhou, N. Hong, W. Zhu, and Y. Long, ''Early prediction of mortality, severity, and length of stay in the intensive care unit of sepsis patients based on sepsis 3.0 by machine learning models,'' Frontiers Med., vol. 8, p. 883, Jun. 2021

[5] K. Alghatani, N. Ammar, A. Rezgui, and A. Shaban-Nejad, ''Predicting intensive care unit length of stay and mortality using patient vital signs: Machine learning model development and validation,'' JMIR Med. Informat., vol. 9, no. 5, May 2021, Art. no. e21347.

[6] M. C. Blom, K. Erwander, L. Gustafsson, M. Landin-Olsson, F. Jonsson, and K. Ivarsson, ''The probability of readmission within 30 days of hospital discharge is positively associated with inpatient bed occupancy at discharge—A retrospective cohort study,'' BMC Emergency Med., vol. 15, no. 1, pp. 1–6, Dec. 2015.

[7] E. Rocheteau, P. Liò, and S. Hyland, ''Temporal pointwise convolutional networks for length of stay prediction in the intensive care unit,'' 2020, arXiv:2007.09483.

[8] C. W. Hanson, C. S. Deutschman, H. L. Anderson, P. M. Reilly, E. C. Behringer, C. W. Schwab, and J. Price, ''Effects of an organized critical care service on outcomes and resource utilization: A cohort study,'' Crit. Care Med., vol. 27, no. 2, pp. 270–274, Feb. 1999.

[9] S. Siddiqui, S. Ahmed, and R. Manasia, ''Apache II score as a predictor of length of stay and outcome in our ICUs,'' J. Pakistan Med. Assoc., vol. 55, no. 6, p. 253, 2005.

[10] W. A. Knaus, J. E. Zimmerman, D. P. Wagner, E. A. Draper, and D. E. Lawrence, ''APACHE—Acute physiology and chronic health eval uation: A physiologically based classification system,'' Crit. Care Med., vol. 9, no. 8, pp. 591–597, Aug. 1981.

[11] A. Knaus, D. P. Wagner, E. A. Draper, J. E. Zimmerman, M. Bergner, P. G. Bastos, C. A. Sirio, D. J. Murphy, T. Lotring, A. Damiano, and F. E. Harrell Jr., ''The APACHE III prognostic system: Risk prediction of hospital mortality for critically Ill hospitalized adults,'' Chest, vol. 100, no. 6, pp. 1619–1636, 1991. [12] M. T. Keegan, O. Gajic, and B. Afessa, ''Comparison of APACHE III, APACHE IV, SAPS 3, and MPM0III and influence of resuscitation status on model performance,'' Chest, vol. 142, no. 4, pp. 851–858, Oct. 2012.

[13] C.-C. Yeh, Y.-A. Chen, C.-C. Hsu, J.-H. Chen, W.-L. Chen, C.-C. Huang, and J.-Y. Chung, ''Quick-SOFA score ≥ 2 predicts prolonged hospital stay in geriatric patients with influenza infection,'' Amer. J. Emergency Med., vol. 38, no. 4, pp. 780–784, Apr. 2020.

[14] C. Li, L. Chen, J. Feng, D. Wu, Z. Wang, J. Liu, and W. Xu, ''Prediction of length of stay on the intensive care unit based on least absolute shrinkage and selection operator,'' IEEE Access, vol. 7, pp. 110710–110721, 2019.

[15] M. M. Islam, T. N. Poly, and Y.-C. Li, ''Recent advancement of clinical information systems: Opportunities and challenges,'' Yearbook Med. Informat., vol. 27, no. 1, pp. 83–90, Aug. 2018.

[16] E. Levesque, E. Hoti, D. Azoulay, P. Ichai, D. Samuel, and F. Saliba, ''The implementation of an intensive care information system allows shortening

theICUlengthofstay,’’J.Clin.Monitor.Comput.,vol.29,no.2, pp. 263–269, Apr. 2015.

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