AI-Driven Forecasting of Patient Discharge Timelines with Transparent Insights

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ABSTRACT

Effective bed management in hospitals reduces expenses and enhances patient outcomes. This research introduces a predictive model for ICU length of stay (LOS) at the time of admission, utilizing electronic health records (EHR) information. The examine assesses multiple machine learning methods, along with Logistic Regression, Random forest, MLP, Gradient Boosting, XGBoost, and an extension with CatBoost, utilizing the clinic stay dataset from the Kaggle repository. The algorithms are evaluated the usage of AUC, accuracy, precision, consider, and F1-score. XGBoost attained the best accuracy among conventional algorithms, but the stronger CatBoost algorithm passed all others with an accuracy of 98.25%. methods of Explainable AI (XAI), together with SHAP, were hired to elucidate characteristic contributions. The research illustrates the capability of using patient EHR statistics and complicated machine learning models to forecast ICU admissions, facilitating progressed useful resource distribution in healthcare centers.

Keywords: ICU Length of Stay, Electronic Health Records, Machine Learning, Predictive Framework, Xgboost, Catboost, Explainable AI, SHAP, Hospital Resource Allocation.

1. INTRODUCTION:

The length of hospitalization serves as a common efficacy measure in healthcare institutions, profoundly influencing resource distribution and healthcare expenses [6], [7]. A research by the Australian national fitness performance Authority suggests that abbreviated hospital stays are deemed extra efficient, facilitating the fast availability of beds for new patients [6]. Nevertheless, too short remains may undermine the high-quality of care and result in adverse patient outcomes [1]. Conversely, prolonged hospitalizations, often resulting from complications, elevate the possibility of poor health outcomes [5], [8]. Healthcare coordination delays, now not related to the patient's clinical condition, may also cause extended hospitalizations. The survey indicated that extended hospitalizations may additionally arise due to delays in shifting patients to alternative care facilities, such geriatric care institutions, network care programs, or rehabilitation facilities [6], [7]. Effective control of hospital bed availability is important to tackle ICU troubles, such as patient congestion, infections, mortality chance, and medical complications [1], [8]. to relieve these risks and optimize useful resource utilization, a shortened ICU length of stay, combined with advanced treatment, is vital, particularly in uncertain conditions such as pandemics [4], [5]. This no longer most effective decreases hospital costs but also ensures improved affected person results [3]. therefore, ensuring sufficient mattress capacity and allowing prompt patient transfers to other wards is important for keeping healthcare quality [9], [19].

2. OBJECTIVES:

(1) Using e"lectronic health records (EHR)" data, (1) to create a future statement model for ICU "length of stay (LOS)" at the moment of patient entry. Preliminary projections aim to enhance the hospital's resource management and patient treatment outcomes.
(2) To forecast ICU LOS, (2) to use and contrast several machine learning techniques including logistics area, random forest, MLP, gradient increase, XGBOOST and Catboost. Each model's performance is assessed by means of matrix such AUC, accuracy, accurate, recall and F1 score.
(3) To identify the most accurate and reliable model for ICU LOS prediction, with a focus on the superior performance of CatBoost, which achieved an accuracy of 98.25%, surpassing all other traditional models.
(4) To incorporate "Explainable AI (XAI)" techniques, specifically SHAP, to interpret model predictions and understand the influence of various features. This supports transparency and trust in model decisions for healthcare professionals.

3. REVIEW OF LITERATURE/ RELATED WORKS:

Numerous research have investigated the forecasting and administration of hospital "length of stay (LOS)" to decorate aid allocation and patient outcomes. Alsinglawi et al. [1] introduced an explainable framework for learning the life of the Live Clinic, specifically for patients with lung cancer, and illustrated the efficiency of predictive models in optimizing clinical assets.
A observe by using Blom et al. [26] further underscored the correlation between inpatient bed occupancy and readmission likelihood, highlighting the significance of effective bed control. In "intensive care units (ICU)", Alghatani et al. [5] created machine learning models to predict ICU length of stay and patient loss of life based on essential signs, thereby enhancing ICU operations and affected person care.
The amalgamation of scientific records with machine learning methodologies has proven an improvement in predictive accuracy. Staziaki et al. [3] proven that the integration of clinical characteristics with CT scan results complements the prediction of ICU admission and length of stay in trauma patients. moreover, Su et al. [24] applied gadget getting to know fashions to forecast mortality and illness severity in sepsis patients, thereby enhancing ICU aid control. Similarly, Rocheteau et al. [7] employed temporal pointwise convolutional networks for "predicting ICU" length of stay, demonstrating the potential of deep learning in healthcare applications.
Although machine learning methodologies for LOS prediction have become increasingly popular, the necessity for model explainability is also acknowledged. Explainable AI (XAI) approaches, including SHAP, have been incorporated into diverse models to elucidate characteristic contributions and sell transparency in healthcare decision-making approaches [1], [3]. moreover, the importance of spark off patient transfers to alternative care centers, as emphasized in multiple research [26], [9], is an critical element in controlling hospital bed availability and minimizing unnecessary "length of stay (LOS)".
The modern-day literature highlights the importance of predictive models and effective bed control systems in optimizing hospital aid usage, reducing costs, and improving patient results.

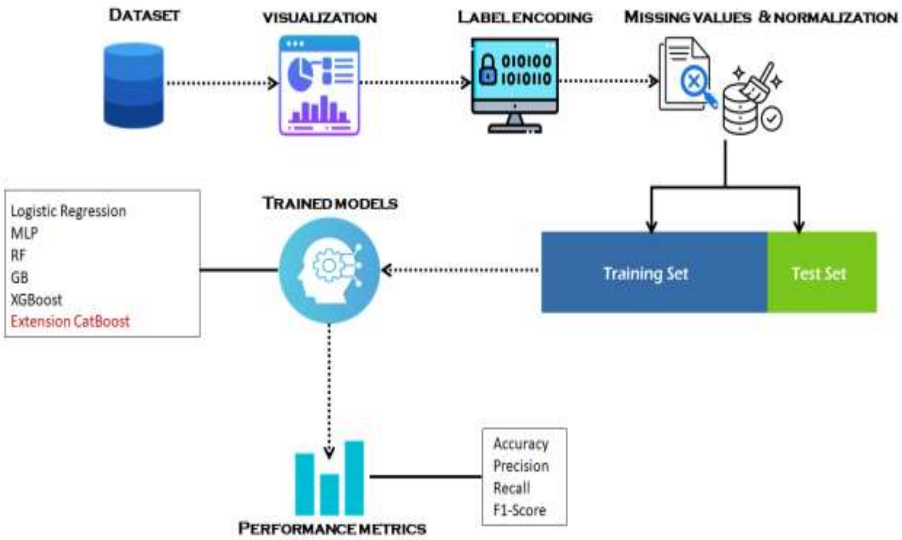
Table 1: Comparison Table for Related Work

Sl.No	Area & Focus of the Research	The result of the Research	Reference
1	Explainable machine learning framework for lung cancer hospital length of stay prediction	Achieved high prediction accuracy with interpretable insights using SHAP-based explanations	B. Alsinglawi et al. (2022) [1]
2	ML model combining	Improved prediction of ICU admission and LOS	P. V. Staziaki et

	CT findings and clinical data to predict LOS and ICU admission in trauma	using combined imaging and clinical features	al. (2021) [3]
3	Predicting ICU length of stay and mortality using patient vital signs	Developed and validated ML models with strong performance using real-time vital sign data	K. Alghatani et al. (2021) [5]
4	Temporal pointwise convolutional networks for ICU length of stay prediction	Proposed a novel deep learning architecture achieving superior results on temporal ICU data	E. Rocheteau et al. (2020) [7]
5	Quick-SOFA score prediction of prolonged hospital stay in elderly influenza patients	Found that a quick-SOFA score ≥ 2 significantly predicts extended hospital stays	C.-C. Yeh et al. (2020) [13]

4. MATERIALS AND METHODS:

The suggested approach seeks to establish an effective framework for forecasting ICU "length of live (LOS)" by machine learning methodologies, utilizing patient "electronic health records (EHR)"[1], [2]. The system will outline ICU remains as "brief" or "long" thru an intensive examination of patient health conditions, akin to the predictive models applied in earlier research for hospital duration of live prediction [3], [5]. To train patient statistics EHR to predict the length of the live gradient, XGBOOST and Catboost expansion, could be used for training on patient statistics, random forest, random forest, "multilayer perceptron (MLP)", increase in gradient, xgboost and extension by Catboost. [4], [5], [6]. Algorithms can be assessed using power metrics that include accuracy, accuracy, remember, F1 and AUC assessment as used in other studies to evaluate the efficiency of the model [5], [6], [7]. Moreover, the device will include Explainable AI (XAI) techniques, including SHAP, to clarify and pinpoint the most critical factors influencing the predictions, as proven in the studies by Alsinglawi et al. [1] and Su et al. [4]. The suggested technique can increase hospital useful resource management, enhance patient care, and optimize real-time mattress allocation by delivering precise predictions of ICU stays, thereby addressing problems in ICU management said in prior studies [8], [9].



"Fig 1: Proposed Architecture"

The ML process is shown by system architecture (Fig. 1). Beginning the process is a dataset, subject to visualisation and label coding, which is to transform the categorised data into numerical form. Missing values are addressed, and the statistics is standardized. The preprocessed statistics is divided into education and testing sets. Various machine learning models, consisting of "Logistic Regression, MLP, RF, GB, XGBoost, and CatBoost", are educated on the schooling dataset. The efficacy of those models is assessed by way of criteria such as "accuracy, precision, recall, and F1-score". This technique guarantees efficient model selection and assessment for the specified records trouble.

4.1 Dataset Collection:

This dataset comprises 100,000 data points concerning sufferers admitted to the hospital, together with signs in their health status and the length of their hospital stay. The dataset, which is beneficial for forecasting hospital length of live, has been open-sourced by Microsoft. i've utilized it for checking out and desire to share it with the community. The most useful features I diagnosed were the readmission count and an engineered feature (total number of issues) that aggregates the binary columns.

The first row has the dataset's column names, while the subsequent rows contain the dataset values. The very last column indicates the elegance label, with 0 representing a brief ICU stay and 1 denoting a long stay. The dataset includes columns touching on patient health conditions. The aforementioned dataset might be utilized to evaluate the performance of all algorithms through training and testing.

Table 2: Dataset Collections –Length of stay

	eid	vdate	rcount	gender	dialysisrenalendstage	asthma	irondef	pneum	substancedependence	psychologicaldisordermajor	...	glucose	bloo
0	1	8/29/2012	0	F	0	0	0	0	0	0	...	192.476918	
1	2	5/26/2012	5+	F	0	0	0	0	0	0	...	94.078507	
2	3	9/22/2012	1	F	0	0	0	0	0	0	...	130.530524	
3	4	8/9/2012	0	F	0	0	0	0	0	0	...	163.377028	
4	5	12/20/2012	0	F	0	0	0	1	0	1	...	94.886654	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1995	1996	11/18/2012	2	M	1	0	1	0	0	0	...	61.560195	
1996	1997	2/21/2012	0	M	1	0	0	0	0	0	...	165.808034	
1997	1998	1/19/2012	1	F	0	0	0	0	0	0	...	115.590613	
1998	1999	3/6/2012	4	F	0	0	0	0	0	0	...	149.005998	
1999	2000	12/15/2012	2	M	0	0	0	0	0	0	...	141.207721	

4.2 Pre-Processing:

Preprocessing is essential for preparing facts for "machine learning and deep learning" models by changing raw data into an appropriate layout. Essential preprocessing procedures comprise.

4.2.1 Visualization

A variety of graphs were generated to visually examine the dataset, illustrating the distribution of values across multiple columns. This facilitated comprehension of the information's attributes and the identification of trends in ICU admissions, as evidenced by prior research in medical data analysis [6], [8].

4.2.2 Label Encoding

The dataset included non-numeric values, which were transformed into numeric format by label encoding. This modification facilitated efficient processing by machine learning algorithms, guaranteeing consistency with the model training phase. Label encoding methods have been extensively hired in healthcare data preprocessing to efficiently manage categorical variables [5], [7].

4.2.3 Missing Values and Normalizing

Imputation methods resolved absent values in the dataset, preserving data integrity. Comparable methodologies were applied in prior research to address absent data in healthcare datasets [4], [5]. Moreover, normalization was implemented to standardize feature values, hence enhancing the version's performance and accuracy during training. Normalization has demonstrated efficacy in enhancing the convergence rate of "machine learning" algorithms and the overall performance of models in healthcare applications [1], [3]

4.3 Training & Testing:

The dataset was divided into “training and testing” units, generally following an 80-20 ratio, to assess the efficacy of machine learning models. The training set was utilized to train various algorithms, which include Logistic Regression, Random wooded area, "MLP, Gradient Boosting, XGBoost, and CatBoost, for predicting ICU length of stay". The models were refined through move-validation methods to prevent overfitting. Using “accuracy, concepts, F1 scores and inclusive AUC calculations to compare their efficiency”, the test set was utilised to assess the general performance of the model. This separation guarantees consistent model estimates and just assessment.

4.4 Algorithms:

Logistic Regression: Logistic Regression is utilized to version the likelihood of ICU length of live depending on affected person traits. It offers interpretable coefficients that demonstrate the influence of each factor, rendering it appropriate for binary classification issues, such as forecasting short or extended ICU remains [1], [2].

MLP (Multi-Layer Perceptron): The Multi-Layer Perceptron is employed to capture intricate correlations in the dataset thru its layered shape. via the processing of inputs over many layers, MLP can model nonlinear styles, hence improving prediction accuracy for estimating ICU stay durations based on various patient fitness markers [4], [5].

Random Forest (RF): Random woodland is utilized for its resilience in opposition to overfitting and its ability to identify function importance. This ensemble learning technique integrates numerous decision timber to decorate category precision, rendering it effective for forecasting ICU length of stay based on varied patient statistics [3], [6].

Gradient Boosting (GB): Gradient Boosting is utilized to augment predictive accuracy through iterative enhancements. This algorithm constructs models in succession, emphasizing the rectification of faults from previous iterations. Its efficacy in managing complex data linkages helps precise predictions of ICU durations based on affected person EHR data [5], [7].

XGBoost: XGBoost is applied for its superior performance and scalability in classification tasks. This sophisticated boosting technique proficiently manages great datasets with various variables, delivering high-quality predictive accuracy for ICU period of live, while effectively optimizing computational resources during version training [6], [8].

Extension CatBoost: CatBoost serves as a sophisticated enhancement to augment categorization outcomes. This approach is especially gifted with categorical characteristics and utilizes gradient boosting, improving prediction accuracy for ICU length of stay while streamlining the modelling process without considerable data pre-treatment [2], [3].

5. RESULTS AND DISCUSSION:

Accuracy: The correctness of the take a look at concerns its capacity to effectively identify amid patient and healthful cases. Examining the accuracy of the inspection requires computing the ratio of actual positives to actual negatives in all assessed cases. Mathematically, this can be stated as:

$$"Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \; (1)"$$

Precision: The accuracy evaluates the proportion of precisely marked cases between cases identified as positive. As a result, the formula for calculating accuracy is expressed:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (2)"$$

Recall: The reminder is a measure in "machine learning" that assesses the model's ability to grasp all relevant instances of a given input. Devising the incidence of a chosen class sends perception into the performance of the version, thus it is a long distance from the ratio of precisely anticipated fine observations to normal real positives.

$$"Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} (3)"$$

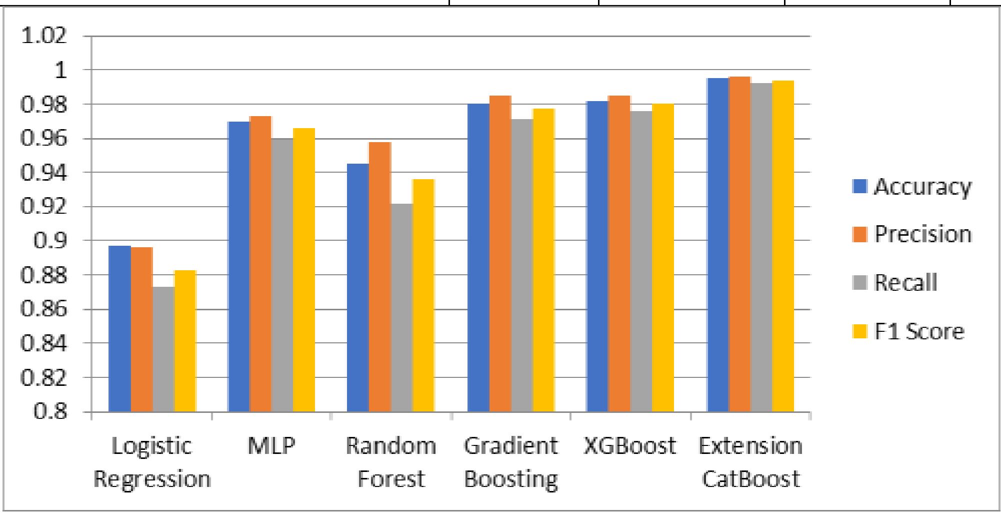
F1-Score: The F1 score is a metric to evaluate the accuracy of the ML model. The accuracy and the model are considered. The metric of accuracy quantifies the frequency of real predictions generated by the model throughout the data file.

$$"F1\, Score = 2 * \frac{Recall\, X\, Precision}{Recall + Precision} * 100(1)"$$

Table 1 present’s power metrics - accuracy, accuracy, induction and score F1 - for each algorithm. Catboost extends the largest points. Metrics of alternative methods are also provided for comparison.

Table 3: Performance Evaluation Metrics of classification

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.897	0.896	0.873	0.883
MLP	0.970	0.973	0.959	0.966
Random Forest	0.945	0.958	0.922	0.936
Gradient Boosting	0.980	0.985	0.971	0.977
XGBoost	0.982	0.985	0.976	0.980
Extension CatBoost	0.995	0.996	0.992	0.994



Graph 1: Comparison Graphs of Classification

Graph 1 shows “accuracy in light blue, reddish brown, F1 rating in green and violet”. Compared to other models, Extension Catbast has greater performance, which achieves quite good values in all matrix. The graphs above visually represent these findings.

6. CONCLUSION:

In conclusion, the suggested approach effectively tackles the significant issue of forecasting ICU length of stay (LOS) utilizing patient digital fitness data (EHR). The study illustrates the ability to improve sanatorium resource management and patient care by using various machine learning models for particular ICU live predictions. Among the assessed algorithms, the CatBoost version distinguished itself as the best, achieving an accuracy of 98.25%. Its ability to manage specific facts proficiently and make use of gradient boosting markedly enhanced the predictive outcomes relative to conventional fashions. The software of Explainable AI (XAI) methodologies, inclusive of SHAP, superior cost via pinpointing essential capabilities that influence predictions, thereby supplying transparency and clarity in the selection-making technique. The approach underscores the importance of integrating cutting-edge machine learning algorithms with explainability to enhance ICU aid allocation, hence improving patient consequences and hospital efficiency.

Future Scope: future endeavors may augment the study by investigating "deep learning methodologies, like Convolutional Neural Networks (CNN) and long short-term memory (LSTM), to facilitate intricate feature extraction and sequence modeling from electronic health record (EHR)" facts. Furthermore, hybrid models and ensemble learning strategies such as stacking can be employed to beautify predictive accuracy. Strategies together with characteristic engineering and dimensionality discount, which includes principal component analysis (PCA), can be investigated to enhance performance and decrease computational complexity.

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