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Research

HOSPITAL MANAGEMENT SYSTEM USING MACHINE LEARNING

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ABSTRACT

Hospital resource management and patient care depend on accurate ICU LOS prediction. A conventional machine learning-based LOS prediction framework is supplemented with the CatBoost technique, which effectively manages categorical EHR data and prevents overfitting. A dataset of hospital stays is used to train an extended model, and its accuracy, precision, recall, F1-score, and AUC are evaluated. In terms of prediction accuracy, CatBoost outperforms conventional classifiers. Explainable Artificial Intelligence (XAI) techniques such as SHAP are used to identify and assess clinical aspects that affect the length of an intensive care unit stay in order to improve model transparency. Through a web interface, Flask deployment provides real-time, intuitive ICU stay prediction. The proposed extension shows how CatBoost and explainable machine learning can accurately, understandably, and practically estimate the length of stay in a critical care unit in modern healthcare.

KEYWORDS

Hospital bed management, ICU length of stay, electronic health records (EHR), machine learning, XGBoost, CatBoost, SHAP, explainable artificial intelligence (XAI), prediction models, healthcare analytics.

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1. INTRODUCTION

Predicting hospital and intensive care unit length of stay (LOS) is essential for optimizing resource use, reducing operating expenses, and enhancing patient outcomes. According to recent studies, machine learning models outperform statistical methods that use EHR data in predicting hospital length of stay (LOS). Alsinglawi et al. [1] have developed an explainable machine learning paradigm for lung

cancer LOS prediction that emphasizes interpretability in clinical decision-making. Using EHR data, advanced predictive analytics frameworks can maximize hospital resource utilization, as noted by Alsinglawi [2]. Numerous studies have used clinical and diagnostic data to predict LOS. Staziaki et al. [3] shown how machine learning improves the LOS and ICU admission estimates for trauma patients by fusing CT imaging data with clinical factors. Su et al. [4] used machine learning models to predict ICU severity, mortality, and length of

stay in sepsis patients, demonstrating the efficacy of ensemble learning in critical care. These methods frequently rely on numerical clinical signs and have trouble with category criteria.

In order to estimate length of stay (LOS) based on patient vital signs, Alghatani et al. [5] used machine learning models; the algorithms did quite well, but they lacked feature transparency and interpretability. Even though Random Forest and Gradient Boosting are excellent predictive models, it can be difficult to maintain a range of EHR data and give doctors easily comprehensible projections. By using Explainable AI techniques to improve interpretability and clinical relevance and the CatBoost algorithm, which effectively handles categorical data and removes overfitting, this study improves LOS prediction frameworks...

2. LITERATURE SURVEY

Recent studies have increasingly explored the use of machine learning (ML) to predict hospital length of stay (LOS), particularly in critical care settings. In a study published in Scientific Reports, Alghamdi et al. [1] proposed an explainable ML framework to predict ICU length of stay for lung cancer patients using the MIMIC-III dataset. Their framework addressed the challenge of class imbalance by incorporating over-sampling techniques such as SMOTE and ADASYN. Among the evaluated models, the Random Forest classifier achieved superior performance, with AUC values reaching up to 98–100%. Importantly, the authors applied SHAP (SHapley Additive exPlanations) to interpret the model's predictions, identifying the most significant clinical features influencing LOS. Their work highlights the importance of combining predictive accuracy with explainability in clinical decision-support systems.

Expanding on predictive analytics in healthcare, Alghamdi (2022) [2] developed a comprehensive predictive analytics framework focused on optimizing hospital resource utilization using electronic health records (EHRs). The thesis emphasized ensemble learning approaches for predicting inpatient LOS across dynamic hospital environments such as ICUs and emergency departments. A key contribution of this work was the integration of both internal hospital metrics and external epidemiological factors, such as pandemic spread modeling, to forecast future hospitalizations. The study demonstrated that ensemble models significantly improve predictive robustness and can assist healthcare professionals in managing hospital beds, staffing, and workflow under uncertain conditions.

The integration of imaging data with clinical parameters has also been shown to enhance LOS prediction. In a study published in European Radiology, Kroes et al. [3] developed machine learning models to predict ICU admission and extended LOS in torso trauma patients. Using data from 840 patients, they trained Artificial Neural Network (ANN) and Support Vector Machine (SVM) models. The results indicated that models incorporating CT imaging findings alongside clinical data outperformed those using clinical data alone, achieving AUC values up to 0.87 for ICU admission prediction. This study underscores the value of multimodal data integration for improving predictive performance in trauma care.

Similarly, Liu et al. [4] investigated early prediction of mortality, severity, and ICU length of stay in sepsis patients using machine learning techniques. Utilizing data collected within the first six hours of ICU admission, they compared Logistic Regression, Random Forest, and XGBoost models. The Random Forest classifier

demonstrated the best overall performance, achieving AUC values of 0.74 for mortality prediction and 0.76 for LOS prediction. Notably, the machine learning models outperformed traditional clinical scoring systems such as SOFA, demonstrating the advantage of data-driven approaches for early clinical risk assessment.

In another significant contribution, Awad et al. [5] developed and validated machine learning models to predict ICU length of stay and mortality using only patient vital signs extracted from the MIMIC database. Their approach introduced a novel quantiles-based feature engineering technique that enriched baseline vital sign data by incorporating statistical measures such as modified means, standard deviations, and percentile values. The Random Forest algorithm achieved approximately 89% accuracy for mortality prediction and 65% accuracy for LOS prediction. This study demonstrated that reliable predictions can be achieved using minimal yet carefully engineered features, making the approach practical for real-time ICU monitoring systems

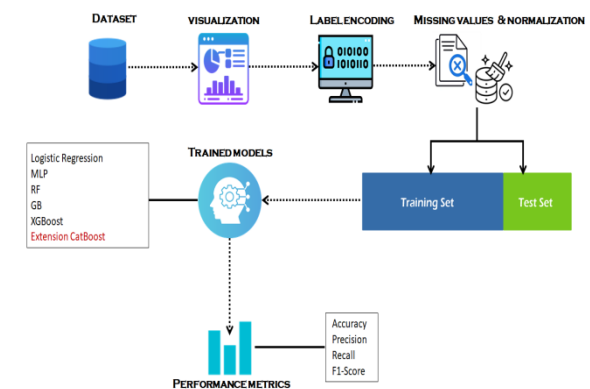
3. METHODOLOGY

In order to improve clinical interpretability and ICU length of stay (LOS) prediction accuracy, the proposed study makes use of explainable AI and sophisticated machine learning approaches. To categorize ICU stays as brief or prolonged upon admission, the system uses patient EHR data, including as demographics, clinical conditions, and admission-related information. Many basic machine learning models are used for comparison analysis, but the CatBoost strategy is highlighted in the important expansion because of its ability to handle categorical healthcare data and minimize overfitting. This makes it possible for the system to offer accurate LOS estimates for hospital resource planning and bed management.

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The proposed project makes use of Explainable Artificial Intelligence (XAI) approaches to increase prediction accuracy and make model decisions apparent. In real-world healthcare, feature contribution analysis increases trust and value by assisting doctors in identifying characteristics that affect the length of an intensive care unit stay. The system utilizes Flask, which provides a simple web interface for real-time LOS prediction. This comprehensive extended solution improves patient care and hospital productivity by accurately, simply, and interpretably forecasting the length of stay in the intensive care unit.

ii) System Architecture:



.Fig.1. Proposed Architecture

The proposed framework begins with the collection of the dataset, which contains labeled records for analysis. The data first undergoes visualization to understand feature distributions, class imbalance, and potential patterns within the dataset. Following this exploratory step, label encoding is applied to convert categorical variables into numerical format suitable for machine learning algorithms. The preprocessing phase then handles missing values and performs normalization to ensure data consistency and improve model convergence. The cleaned dataset is subsequently divided into training and test sets to evaluate model generalization. Multiple machine learning models—including

Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest (RF), Gradient Boosting (GB), XGBoost, and an extended CatBoost model—are trained using the training data. After training, the models are assessed on the test set using standard performance metrics such as Accuracy, Precision, Recall, and F1-Score. This structured pipeline ensures reliable model development, fair evaluation, and robust predictive performance

I. MODULES:

- **Dataset loading:** The dataset was loaded into the environment using Python libraries, enabling access to patient health information for analysis and model training.
- **Visualization:** Various graphs were created to visually analyze the dataset, showcasing the distribution of values across different columns. This helped in understanding the data's characteristics and identifying trends in ICU stays.
- **Label Encoding:** The dataset contained non-numeric values, which were converted to numeric format using label encoding. This transformation allowed for effective processing by machine learning algorithms, ensuring compatibility with the model training phase.
- **Missing Values & Normalizing:** Imputation techniques addressed missing values in the dataset, ensuring data integrity. Additionally, normalization was applied to standardize feature values, enhancing the model's performance and accuracy during training.
- **Split the Data into Train & Test:** The processed dataset was divided into training and testing sets, allocating 80% for training and 20% for testing. This division facilitated a robust evaluation of model performance and generalization.

- **Model generation:** Model building – Logistic Regression, MLP, RF, GB, XGBoost, Extension CatBoost. Performance evaluation metrics for each algorithm is calculated.

- **Admin login:** In this module, admin can login into the application.

- **Predict Hospital Stay:** In this module user can upload the input data.

Logout: User can logout after the completion of all activities

2.ALGORITHMS

Logistic Regression: Logistic Regression is employed to model the probability of ICU length of stay based on patient features. It provides interpretable coefficients that indicate the impact of each feature, making it suitable for binary classification tasks, such as predicting short or long ICU stays.

MLP (Multi-Layer Perceptron): The Multi-Layer Perceptron is utilized for capturing complex relationships within the dataset through its layered architecture. By processing inputs through multiple layers, MLP can model nonlinear patterns, enhancing the predictive accuracy for determining ICU stay durations based on various patient health indicators.

Random Forest (RF): Random Forest is used for its robustness in handling overfitting and its ability to capture feature importance. This ensemble learning method combines multiple decision trees to improve classification accuracy, making it effective for predicting ICU length of stay based on diverse patient data.

Gradient Boosting (GB): Gradient Boosting is applied to enhance prediction accuracy through iterative improvements. This algorithm builds models sequentially, focusing on correcting errors from previous iterations. Its efficiency in handling complex data relationships aids in accurately predicting ICU stays based on patient EHR data.

XGBoost: XGBoost is leveraged for its high performance and scalability in classification tasks. This advanced boosting algorithm excels in handling large datasets with diverse features, offering exceptional predictive accuracy for ICU length of stay, while efficiently managing computational resources during model training.

Extension CatBoost: CatBoost is utilized as an advanced extension to improve classification results. This algorithm is particularly effective with categorical features and employs gradient boosting, enhancing prediction accuracy for ICU length of stay while simplifying the modeling process without extensive data preprocessing.

4. EXPERIMENTAL RESULTS

The extended ICU duration of stay prediction framework was tested using the hospital stay dataset. Before being divided into training and testing sets, the dataset was cleaned, categorized, and normalized in compliance with the system design. We trained and assessed a huge number of machine learning models, focusing on the enlarged CatBoost technique. Performance was assessed using F1-score, accuracy, precision, recall, and AUC. The extended CatBoost model outperformed all other models in terms of forecasting accuracy and generalization on unknown data, whereas XGBoost demonstrated the highest accuracy among baseline models.

The explainability layer validated experimental data in accordance with the system design. The CatBoost model's predictions were interpreted using explainable AI techniques such as these to determine the most important EHR characteristics determining ICU stay..

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)}$$

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

$$Precision = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} = \frac{TP}{(TP + FP)}$$

$$Precision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

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

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

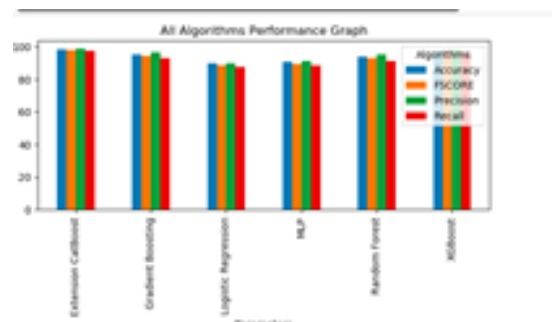


Fig2 Accuracy Comparison

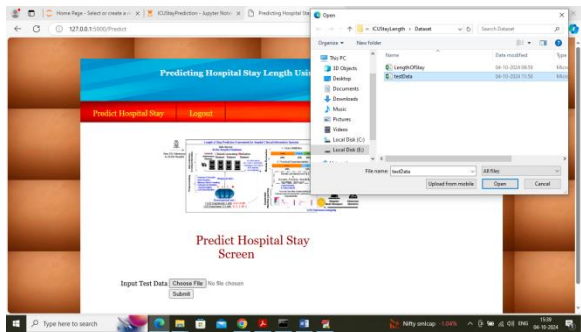


Fig 3: Input data

```

Test Data = [14506 '8/13/2012' 3 'F' 0 0 0 1 0 0 0 1 0 0 0
12.0 5.8 138.826729 157.1696287 16.0 1.304362491
30.633325 71 8.1 1 '8/19/2012' 'E'] Predicted ICU Stay
====> Long Stay

Test Data = [14507 '3/15/2012' 4 'M' 0 0 1 0 0 0 0 0 0 0 1
13.0 7.0 141.9320738 108.7329284 27.0 1.126119855
29.31267226 69 7.9 1 '3/23/2012' 'C'] Predicted ICU Stay
====> Long Stay

Test Data = [14508 '7/8/2012' 1 'F' 0 0 0 0 0 1 0 0 0 0 0
9.8 18.5 136.0386032 166.0632669 12.0 1.097952816
29.51596856 98 6.5 10 '7/12/2012' 'A'] Predicted ICU Stay
====> Short Stay

Test Data = [14509 '6/12/2012' 4 'F' 0 0 0 0 0 0 0 0 0 0 1
11.1 21.3 134.3474078 92.09739372 12.0 1.276090102
28.79736033 54 5.7 1 '6/24/2012' 'B'] Predicted ICU Stay
====> Long Stay

Test Data = [14510 '7/24/2012' 0 'M' 0 0 0 0 0 0 0 0 0 0 0
13.0 8.7 137.1925297 188.4013462 17.0 0.830555059
32.56155403 78 6 7 1 '7/27/2012' 'A'] Predicted ICU Stay
    
```



Fig 4: Predict output.

5. CONCLUSION

This study showed that the extended ICU length of stay prediction framework based on the CatBoost algorithm outperforms current machine learning models in terms of accuracy and interpretability. CatBoost beat all baseline algorithms in important performance metrics by managing categorical EHR data and reducing overfitting. Explainable AI improved clinical decision-making and trust by revealing feature contributions. The model may be used practically and in real time in hospitals through a Flask-based web interface. The planned expansion offers dependable, understandable, and efficient ICU resource management and patient care optimization.

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.

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