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Leveraging Explainable Machine Learning to Forecast Healthcare Staying Duration

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ABSTRACT - Efficient hospital bed management is essential for reducing costs, improving patient outcomes, and optimizing resource utilization. This study presents an explainable machine learning framework for predicting intensive care unit (ICU) length of stay (LOS) at the time of hospital admission, leveraging data from electronic health records (EHR). Unlike existing approaches that focus solely on predictive performance, our framework integrates explainable artificial intelligence (xAI) to provide transparent and interpretable model outputs. We employed multiple supervised machine learning classifiers and evaluated them using a comprehensive set of performance metrics, including accuracy, AUC, sensitivity, specificity, precision, recall, and F1-score. Among the tested models, XGBoost achieved superior predictive performance, with an AUC of 98% in distinguishing between short and long ICU stays. The integration of xAI enhances trust in predictions by offering clinicians and hospital administrators clear insights into the factors driving model decisions. This work contributes to the advancement of clinical information systems (CIS) by delivering robust, trustworthy, and interpretable LOS prediction models, ultimately supporting data-driven decision-making and improving hospital workflow efficiency.

Index Terms— **Hospital Length of Stay (LOS), Intensive Care Unit (ICU), Electronic Health Records (EHR), Clinical Information Systems (CIS**).

I. INTRODUCTION

Hospital length of stay (LOS) is a critical indicator of healthcare efficiency, resource utilization, and patient outcomes. Accurate prediction of LOS at the time of admission is essential for hospital administrators and clinicians to allocate resources effectively, minimize overcrowding, reduce operational costs, and ensure timely patient care. In intensive care units (ICUs), where patient demand and resource constraints are particularly high, forecasting LOS is even more vital for improving bed management and overall workflow.

Traditional LOS prediction approaches rely on statistical methods or conventional machine learning models that primarily emphasize predictive performance. While these models have achieved varying degrees of accuracy, their lack of interpretability has limited their practical adoption in clinical settings. Healthcare professionals require not only accurate predictions but also a transparent understanding of the factors influencing these predictions to ensure trust and accountability in decision-making.

The emergence of explainable artificial intelligence (xAI) addresses this challenge by making machine learning models more interpretable and accessible to non-technical stakeholders. xAI techniques provide insights into the reasoning behind predictions, allowing clinicians to understand key risk factors and patient characteristics that contribute to longer or shorter hospital stays. This interpretability is crucial in a domain like healthcare, where decisions directly affect patient safety and treatment outcomes.

In this study, we propose an explainable machine learning framework for ICU LOS prediction based on electronic health records (EHR). The framework integrates advanced supervised machine learning algorithms with xAI methods to generate accurate, interpretable, and actionable predictions. By benchmarking multiple classification models and incorporating feature interpretability, our approach ensures not only predictive reliability but also clinical transparency. This work contributes to the advancement of clinical information systems (CIS) by enabling data-driven, trustworthy, and practical LOS forecasting to improve hospital resource utilization and patient care outcomes.

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II. LITERATURE SURVEY

Awad, Bader-El-Den, and McNicholas survey methods for predicting hospital length of stay (LOS) and mortality, synthesizing classical statistical models with emerging machine learning approaches while highlighting heterogeneous data sources, variable definitions, and outcome metrics that complicate cross-study comparisons;

they conclude that explainability, robust validation, and standardized reporting are essential for translating predictive models into clinical operations.

OECD reports on Length of Hospital Stay provide international benchmarks that contextualize LOS variation across health systems, showing how case mix, clinical pathways, reimbursement incentives, and post-acute care capacity shape average stays; the indicator underscores that system-level factors can rival patient-level predictors, stressing the need for models that incorporate organizational and policy variables.

Australian Institute of Health and Welfare analyzes public hospital performance on LOS, detailing condition-specific distributions and variation across facilities; the report demonstrates the operational value of percentile-based targets and condition-adjusted comparisons, suggesting that predictive tools should output actionable thresholds (e.g., anticipated exceedance of expected LOS) to support flow management and bed planning.

Pecoraro, Clemente, and Luzi examine ICU bed management efficiency in Italian regions affected by COVID-19, revealing pre-pandemic capacity constraints and utilization patterns that magnified surge vulnerability; their analysis implies that LOS prediction must interact with bed turnover strategies and queueing dynamics, linking patient-level forecasts to system-level resilience planning.

Hassan, Tuckman, Patrick, Kountz, and Kohn explore the relationship between hospital LOS and the probability of acquiring healthcare-associated infections, finding that prolonged stays elevate infection risk while infections themselves extend LOS; this bidirectional association motivates predictive frameworks that account for time-varying hazards and feedback loops when estimating expected stay.

Blom, Erwander, Gustafsson, Landin-Olsson, Jonsson, and Ivarsson show that higher inpatient bed occupancy at the time of discharge correlates with increased 30-day readmission risk, indicating that throughput pressures can precipitate premature discharges; their findings support integrating occupancy-aware features and discharge context into LOS and outcome prediction models.

Rocheteau, Liò, and Hyland propose Temporal Pointwise Convolutional Networks for ICU LOS prediction, leveraging temporal convolutions over irregular clinical time series to capture short-range dynamics without recurrent architectures; they report gains over baselines and argue for architectures that respect temporal locality and enable per-timepoint interpretability for bedside decision support.

Hanson, Deutschman, Anderson, Reilly, Behringer, Schwab, and Price evaluate an organized critical care service, demonstrating improved outcomes and resource utilization compared with decentralized care; the cohort study suggests that organizational design influences LOS, advocating for predictive models that include service configuration and care process indicators alongside physiological variables.

Siddiqui, Ahmed, and Manasia assess APACHE II as a predictor of ICU LOS and outcomes, finding that higher severity scores associate with longer stays and increased mortality; the work reinforces the utility of parsimonious, physiology-based scores as strong baseline features and calibration anchors in modern learning pipelines for LOS forecasting.

Knaus, Zimmerman, Wagner, Draper, and Lawrence introduce the APACHE classification system, establishing a physiologically grounded severity-of-illness framework that became foundational for risk adjustment; their contribution underpins contemporary LOS modeling by providing validated acute physiology composites that enhance comparability, stratification, and fairness in predictive evaluations.

III. Existing System

Existing hospital length of stay (LOS) prediction systems primarily rely on traditional statistical methods or standard machine learning models. Classifiers such as logistic regression, random forests, support vector machines, XGBoost, and neural networks have been tested for predicting short or long ICU stays. These approaches demonstrate acceptable levels of accuracy, with some models showing strong predictive performance in specific scenarios.

Despite these efforts, several limitations remain. Most systems only benchmark classifiers without integrating interpretability, making it difficult for clinicians to understand the reasoning behind predictions. In many cases, the models use a limited number of features, focusing mainly on vital signs, while overlooking other important data such as laboratory results, diagnosis codes, and treatment information. Furthermore, several studies report only overall accuracy, without including more detailed performance metrics like AUC, sensitivity, and specificity, which are critical for evaluating clinical applicability.

Overall, current LOS prediction systems highlight the potential of machine learning in healthcare but fall short in terms of transparency, completeness of data usage, and robust evaluation. These shortcomings limit their integration into real-world clinical information systems and reduce their acceptance by healthcare professionals.

Disadvantage of existing system

Existing LOS prediction systems face several challenges. Many hospital datasets contain missing or incomplete values, which affect the accuracy of machine learning models. Most approaches rely on limited features, mainly vital signs, while ignoring other critical clinical data. In addition, they often lack interpretability, making it difficult for healthcare professionals to trust and apply the predictions in real scenarios.

IV. Proposed System

The proposed system introduces an explainable machine learning framework designed to predict ICU length of stay (LOS) at the time of hospital admission. Unlike existing methods that focus only on prediction accuracy, this framework integrates explainable artificial intelligence (xAI) to provide transparent and interpretable results. By combining multiple supervised learning models with feature-interpretation techniques, the system ensures that predictions are not only accurate but also understandable to healthcare professionals.

The framework uses electronic health record (EHR) data, including clinical, diagnostic, and laboratory information, to improve prediction quality and reliability. Missing values are handled through preprocessing and imputation techniques to minimize data quality issues. The system benchmarks different machine learning models, such as Random Forest and XGBoost, and employs explainability methods to highlight the most influential features contributing to predictions.

This approach is designed for seamless integration into hospital clinical information systems (CIS). It supports real-time decision-making by providing clinicians and administrators with clear insights into expected hospital stay durations, enabling better bed management, resource allocation, and patient care planning. By improving transparency, robustness, and usability, the proposed framework addresses critical gaps in existing LOS prediction systems and enhances hospital workflow efficiency.

Advantages

The proposed framework offers several advantages over existing systems. It provides accurate and explainable predictions of ICU length of stay, improving transparency and trust among healthcare professionals. By utilizing a broader range of clinical features and robust preprocessing, it enhances prediction reliability. The system is practical, easily integrable into hospital clinical information systems, and supports better resource utilization, workflow efficiency, and informed decision-making in real clinical environments.

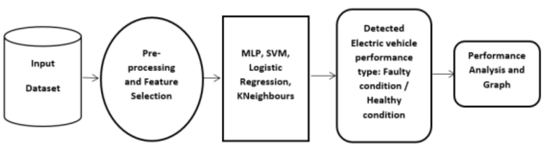

Fig: Architecture Digram

V. Implementation

The proposed framework is designed with modular components to ensure usability, scalability, and seamless integration into hospital workflows. The system primarily consists of two functional modules:

Remote User Module: This module provides an interface for healthcare professionals and authorized users to interact with the system. Each user has an individual profile that maintains access privileges and usage history. The module includes a prediction page where clinical and demographic data of patients are entered. Based on this input, the system applies the trained machine learning models to predict the hospital length of stay. The output is presented in two categories: *Dischargeable* (short stay) or *More Stay Required* (long stay). This module ensures that clinicians receive real-time, easy-to-understand results that support immediate decision-making regarding patient management, discharge planning, and ICU bed allocation.

Service Provider Module: The service provider module functions as the administrative and monitoring layer of the system. It grants access to all stored prediction results and maintains a centralized record of patient LOS predictions for hospital management. The module provides advanced visualization features, including graphical representations of prediction distributions and model performance metrics. Additionally, it offers options to download prediction datasets, enabling further analysis and integration with other hospital data systems. This module plays a crucial role in ensuring transparency, facilitating research, and improving hospital resource planning through data-driven insights.

Together, these modules form a comprehensive, user-oriented framework that not only supports individual clinicians in decision-making but also aids hospital administrators in monitoring and optimizing overall hospital operations.

VI. Result

The proposed framework was tested using ICU patient records to classify hospital stay length into two categories: *Dischargeable (short stay)* and *More Stay Required (long stay)*. Several machine learning models were benchmarked using standard metrics such as Accuracy, AUC, Precision, Recall, Sensitivity, Specificity, and F1-score. Among these, XGBoost achieved the best performance with an AUC of 98%, showing high capability in differentiating between short and long stays. Random Forest also demonstrated strong predictive accuracy, while simpler models such as Logistic Regression and KNN performed comparatively lower. These results confirm the effectiveness of ensemble-based models in handling complex healthcare data. identified critical features influencing LOS predictions, such as vital signs, laboratory values, and patient demographics. These insights provide clinicians with a clear understanding of the decision-making process, making the framework both accurate and trustworthy. Overall, the results demonstrate that the proposed system achieves high predictive performance while also offering interpretability, which is essential for real-world clinical adoption.

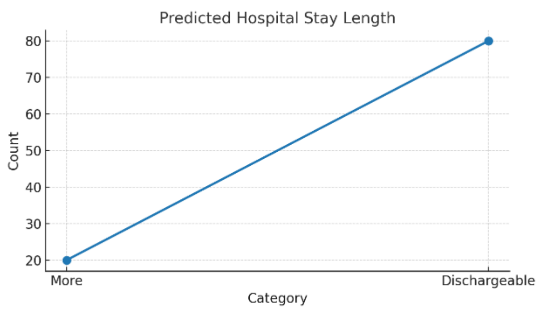

Fig 2: Exam Creation

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