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Predicting Patient Discharge Readiness Using Machine Learning on Clinical and Operational Data

Md. Rasel Sarker
Chemistry
National University of Bangladesh
Rangpur, Bangladesh
rasel.sarker6933@gmail.com

Biswajit Sarker
Mathematics
Govt. Bangla College (7 Colleges Affiliated with University of Dhaka)
Dhaka, Bangladesh
biswajits.info@gmail.com

Iffat Rahman
Aliahat, 20 bed hospital, Shibganj, Bogura
Ministry of Health and Family Welfare
Dhaka, Bangladesh
tithij12@gmail.com

***Abstract*— The study seeks to predict the hospital length of stay (LOS) using machine learning algorithms for improved treatment strategies and resource management in healthcare. Based on a New York State Department of Health dataset, the study uses various models including Decision Tree Regressor, Random Forest Regressor, and boosting algorithms like AdaBoost and Gradient Boosting to predict LOS. Class imbalance is addressed in the study using feature engineering, encoding, and hyperparameter tuning to enhance model performance. Results indicate that Random Forest performs better than other models, leading to accurate LOS prediction and enabling better treatment planning. The study confirms the importance of clinical and operational variables, such as patient severity of illness and age, in determining LOS. The present work adds to earlier efforts by incorporating ensemble techniques and actual data, thus providing a robust and scalable model for health care facility length of stay prediction.**

Keywords—Length of Hospital Stay (LOS), Artificial Neural Networks (ANN), Regressor, K-Nearest Neighbors (KNN), Gaussian Naïve Bayes, Logistic Regression

I. Introduction

Hospital length of stay, the duration of hospital stay, is an important indicator in healthcare administration that impacts the allocation of resources, patient strategic management, and general outcomes. By offering better LOS estimations, healthcare facilities are able to benefit from increased efficiency and enhanced patient outcomes through optimized resource allocation and more timely discharges. These approaches, such as median and mean methods of LOS estimation, fail to account for patient information differences and details. For this reason, it is of great importance to develop improved prediction techniques. Most recent research has predominantly examined the application of various machine learning techniques to enhance LOS prediction.

Md. M. Rahman and others presented an efficiency-focused and privacy-preserving plan utilizing federated learning, which is highly relevant to healthcare [1]. S. Levin and others demonstrated that predictions of patient discharge times with the help of machine learning will assist team meetings and shorten hospital stays [2]. F. Jaotombo and others utilized a French health data set to demonstrate how important accurate prediction is to manage healthcare resources [3]. J. Chrusciel and others examined how unstructured data can enhance hospital stay prediction accuracy to assist hospital management [4]. X. Zeng proposed light gradient boosting machine as a suitable tool to plan with in hospitals [5], and A. J. Zeleke and others utilized a gradient-boosting technique to predict long-stay patients in the emergency department, assisting personalized decision-making [6].

The primary aim of this research is to design a model to predict the duration of stay for patients in the hospital. The research employs machine learning techniques, such as the Decision Tree Regressor, the Random Forest Regressor, and others like AdaBoost and Gradient Boosting. The research also addresses critical issues, such as class imbalance, and employs special techniques to enhance features, data format, and settings to enable the model to perform better. The research consists of some major steps, including gathering data, data preparation, model development, and model testing. Data is gathered from the hospital's inpatient discharge data set supplied by the New York State Department of Health. Data preparation included cleaning, handling missing information, variable formatting, and applying techniques to address class imbalance.

Pala [7] demonstrated how essential is the peer-review process to achieve high-quality medical informatics research. This is particularly relevant as accurate prediction models assist in decision-making in clinical practice. Multiple machine learning models have been developed and compared in terms of multiple performance metrics such as accuracy, precision, recall, and Root Mean Squared Error (RMSE). Cross-validation and hyperparameters tuning strategies have been employed to enhance the performance and utilization of the models. Zolbanin et al. [8] examined LOS prediction in chronic diseases to better utilize resources and keep them sustainable. Davoren et al. [9] examined various LOS factors in forensic hospitals, including patient safety and where patients are admitted. Turgeman et al. [10] concluded that LOS prediction by machine learning models would benefit hospital planners and resource managers.

This paper discusses how hospitals could work more efficiently by predicting patient stays based on how long patients will be there. The primary aim of this paper is to assist health centers to predict patient stays, and consequently, provide better patient care and optimize the usage of healthcare resources. With the application of sophisticated machine learning methods and real data analysis, in comparison to previous methods used to predict patient stays, we anticipate that upcoming studies will provide more reliable and accurate predictions. The data analyzed is available to be downloaded and is referred to as Hospital Inpatient Discharges (SPARCS De-Identified): 2021 and is available at the Department of Health, New York State [3], [5], [6], [8].

II. Methodology

A. Data Collection

The present study intends to forecast how long patients will be hospitalized. This will enhance methods of treating them and better utilize resources. To achieve this, data have been gathered from reliable sources. Some examples include inpatient discharge data by the Department of Health, New York State and a Kaggle notebook that examines length of stay prediction models. Moreover, a literature review involving a number of academic articles was carried out to gain insight into methodologies used in past studies, including machine learning, deep learning, ensemble learning methods, sophisticated data cleaning, feature engineering, feature selection, feature encoding, and dimensionality reduction methods. These sources provided both structured data, including clinical and operational parameters, and unstructured data, represented by doctor-patient stories, thereby allowing an all-encompassing strategy to model development. With the design and development of an innovative prediction model surpassing traditional median and average LOS measures, the present work intends to enhance patient care, efficiently control costs, and optimize the productivity of healthcare services. LOS prediction is critical to healthcare management, as it affects resource allocation, patient care methods, and overall cost-effectiveness. The long-term vision is to develop a powerful and dynamic hospital model that may be customized for large-scale deployment in healthcare facilities.

B. Model Development

A variety of ML algorithms is used to guess the stock prices, including:

- The analysis is carried out using supervised learning algorithms, namely DT, SVM, and RF, as they have the ability to recognize non-linear interdependencies present in the data.
- Deep Learning Methods: LSTM networks, being a subcategory under RNN, are utilized to efficiently account for the inherent temporal dependencies present in time-series data.
- Hybrid Models: These combine ANN with other technical indicators, including MACD and RSI, to enhance prediction accuracy by implementing multiple sources of data.
- Sentiment analysis techniques employ sentiment measures derived from financial and social media data using NLP techniques, including VADER and BERT, and are then combined as variables within forecast models.

C. Data Preprocessing

There are some preprocessing steps taken before training the model to prepare the dataset:

- Data Wrangling: Understanding the structure of the dataset and pre-cleaning the data to eliminate unwanted or incorrect data.
- Handling Missing Data: Imputation methods are employed to complete missing values so that the data is complete.
- Data Type Conversion: Converting the data type of various features, e.g. from string to numeric data.
- Outlier Detection & Management: Missing values are filled through imputation strategies to make sure data is full.
- Advanced Feature Encoding: Categorical features encoding into numerical values, i.e. One-Hot Encoding or Ordinal Encoding.
- Feature Engineering: New features like technical indicators and sentiment scores are developed to maximize model performance.
- Exploratory Data Analysis (EDA): Plots and graphs are used to understand the distribution, correlation, etc. of variables.
- Invalid Record Filtering: Discard invalid or unnecessary records from data to purify it.
- Normalization & Scaling: Scale input features to unit ranges so that they are compatible with ML algorithms.
- Manual Encoding and Grouping: Manually encode or group some features, e.g., Age Group or Gender.
- Data Splitting: The data is divided into test and training sets, typically an 80-20% or 70-30% split, to give a clear assessment.

D. Model Evaluation

The performance of every model is established by assessing performance metrics such as accuracy, precision, recall, F1-score, and RMSE. Cross-validation is performed to verify the generalizability of the models. Hyperparameters are optimized by performing a grid search or a random search. The models are verified for short-term hospital stay (LOS) prediction ability.

E. Performance Comparison

The performance of the ML model is compared with traditional prediction methods, such as technical analysis and statistical models, to measure the improvement in accuracy and robustness. The impact of sentiment analysis and hybrid modeling methods combined is also investigated to measure their length of hospital stay (LOS) performance. This method provides a structured framework to evaluate the performance of machine learning, DL, and EL techniques for Predicting Patient Discharge Readiness LOS effectively.

F. Equations

1. Outlier Detection and Handling:

Interquartile Range (IQR) Method:

- Compute Quartiles:

$$Q_1 = quantile(X, 0.25)$$

$$Q_3 = quantile(X, 0.75)$$

- Calculate the Interquartile Range (IQR):

$$IQR = Q_3 - Q_1$$

- Determine the Lower and Upper Bounds:

$$Lower\ Bound = Q_1 - 1.5 \times IQR$$

$$Upper\ Bound = Q_3 + 1.5 \times IQR$$

- Removing Outliers:

A data point *Xi* is considered an outlier if

$\mathrm{X}_i < Lower\ Bound$ or $\mathrm{X}_i > Upper\ Bound$

New Dataset (Filtered Data):

$$\mathrm{X}_{filtered} =$$

$$X[(X \geq Lower\ Bound\ \&\ (X \leq Upper\ Bound)]$$

2. Linear Regression Equation:

$$y = \beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \cdots + \beta_n \mathrm{X}_n + \epsilon$$

3. Logistic Regression Equation:

$$h_\theta(\mathrm{X}) = \frac{1}{1 + e^{-\theta^T}\mathrm{X}}$$

Loss Function (Binary Cross Entropy) for Logistic Regression

$$J(\theta) =$$

$$-\frac{1}{m}\sum_{i=1}^{m}[\mathrm{y_i}\log(h_\theta(\mathrm{x_i})) + (1 - \mathrm{y_i})log(1 - h_\theta(x_i))]$$

4. Random Forest Regressor (Ensemble Learning):

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{h_i}(\mathrm{X})$$

5. Mean Squared Error (MSE) - Model Evaluation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2$$

6. Confusion Matrix Formula:

$$\begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix}$$

7. Feature Encoding (One-Hot Encoding & Ordinal Encoding):

- One-Hot Encoding Formula:

$$\mathrm{X}_{encoded} = [\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \ldots, \mathrm{x}_n]$$

- Ordinal Encoding Formula:

$$\mathrm{X}_{ordinal} = [rank_1, rank_2, rank_3, \ldots, rank_n]$$

III. Result

Analysis of data for the 2,101,588 row and 33 column dataset included predicting patient discharge readiness and LOS. After excluding data on 63,824 patients who had died and unused columns, the dataset was cleaned and used in training ML models, including RF and DT, for predicting LOS on admission.

A. Exploratory Data Analysis (EDA)

- The LOS variable was right-skewed, with the majority of patients having shorter LOS. There was a class imbalance issue, particularly for longer LOS.
- Medicare patients had the highest average LOS, driven by age-related illnesses. Trauma admissions also had longer LOS.
- Patients aged 50-69 and 70+ had the longest LOS, indicating a high correlation between age and longer hospital stays.
- Patients with greater severity of illness needed longer LOS.

B. Feature Engineering and Encoding

The irrelevant columns were dropped, and the categorical variables were encoded with Ordinal Encoding to facilitate training of the model. This was particularly apt for DT and RF.

C. Model Performance and Class Imbalance

Class balancing methods were used to counter class imbalance, with the model performance better, especially on extended LOS prediction. The model was performing well with RF, with proper LOS prediction that allowed better treatment planning and resource allocation.

D. Visualization of Results

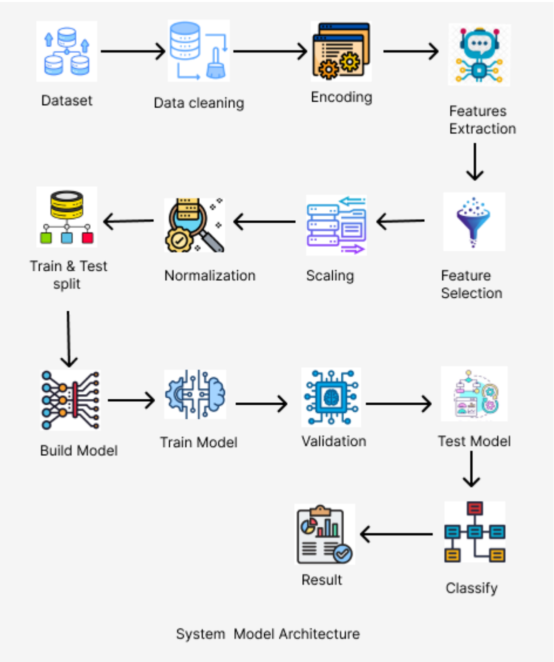

Figure 1: Architecture of the Model

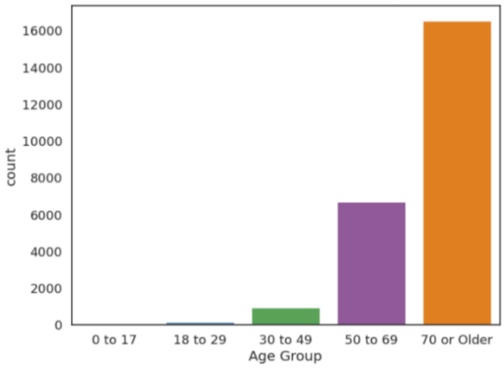

Figure 2: Number of Medicare Patients in Each Group

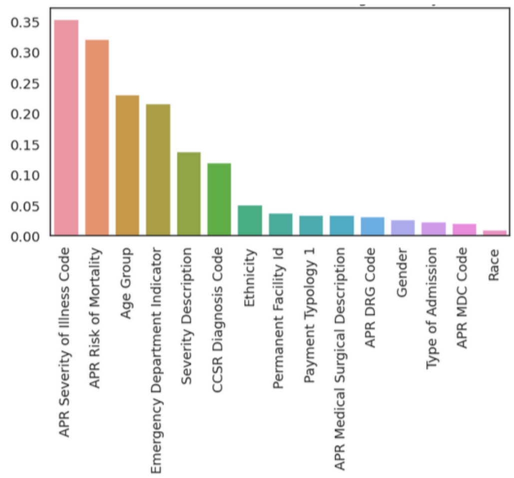

Figure 3: Correlation of Features with Length of Stay

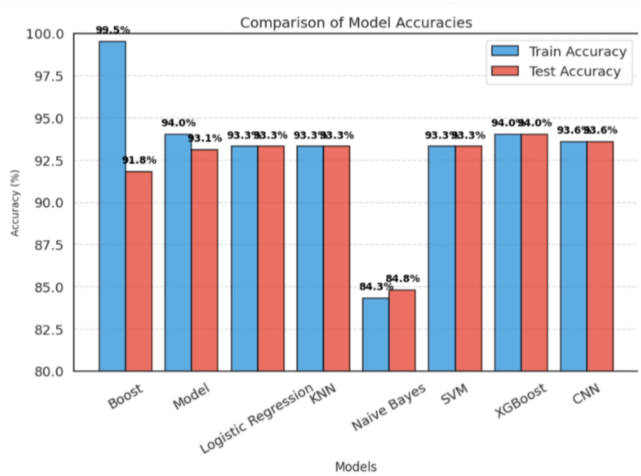

Figure 4: Comparison of Model Accuracies

Random Forest machine learning algorithms correctly predicted patient readiness for discharge and LOS. The refined model addresses class imbalance, adds important features such as severity of illness and age, improves predictive accuracy, and benefits treatment planning and resource utilization.

E. *Table*

TABLE I: Comparison of All Classifiers' Accuracies

Classifier	Accuracy	Precision	Recall	F1-score
Decision Tree	0.92	0.93	0.99	0.96
Random Forest	0.93	0.93	1.00	0.97
SVM	0.93	0.93	1.00	0.97
AdaBoost	0.91	0.94	0.98	0.96
Gradient Boosting	0.93	0.93	1.00	0.97
Logistic Regression	0.93	0.93	1.00	0.97
KNeighbors	0.93	0.93	1.00	0.97
Gaussian Naïve Bayes	0.84	0.95	0.89	0.92
XGBoost	0.93	0.93	1.00	0.96
CNN	0.93	-	-	-

IV. Discussion

The paper is highlighting the accuracy of ML algorithms, particularly RF, in predicting the hospital LOS efficiently. Overcoming class imbalance issues and applying feature engineering and hyperparameter tuning, the paper has a strong setup for predicting LOS. Important features like patient severity of illness and age have considerable influence on LOS, and ensemble methods like Gradient Boosting improve the precision of prediction. Utilization of standardized data models, such as the OMOP Common Data Model (CDM), enhances reproducibility and productivity across healthcare centers, which supports the study's relevance. As future work, addition of additional data sources, such as electronic health records (EHRs), could further enhance prediction models by being more specific about patient data.

Deep-learning models and combined models can also enhance prediction performance, according to previous studies that suggest these are helpful in handling heterogeneous data sets. This study contributes significant insight into using machine learning for healthcare, as it indicates that accurate LOS prediction can optimize hospital operations, improve patient care, and optimize the use of resources. Incorporation of these models into clinical decision-making enables the healthcare facilities to manage their resources more effectively and reduce avoidable hospitalization.

A. *Algorithms and Methods for LOS Prediction*

- Decision Tree Regressor: Previous studies have showed the effectiveness of DT in identifying critical patterns in structured healthcare data. In this study, a DT Regressor served as a baseline model for LOS prediction. It provided interpretable results but showed overfitting issues, leading to the adoption of more robust ensemble methods.

- Random Forest Regressor: RF algorithms have been widely recognized for their ability to improve prediction accuracy by aggregating multiple decision trees. In this study, Random Forest was employed to generalize predictions and reduce overfitting, with hyperparameter tuning optimizing performance further.

- Boosting Algorithms (AdaBoost and Gradient Boosting): Boosting methods, such as AdaBoost Classifier, were applied to iteratively minimize errors from weak learners. These approaches demonstrated enhanced robustness, particularly for LOS classification tasks where categorical data bins were used.

- K-Nearest Neighbors (KNN): KNN has been explored in other research for its simplicity and efficiency. In this study, it was applied as a comparative model but did not perform as well as ensemble-based methods.

- Gaussian Naive Bayes: Leveraging its efficiency for categorical data, Gaussian Naive Bayes provided fast computations but underperformed compared to tree-based methods and ensemble models.

- Logistic Regression: Logistic regression was used as a baseline for predicting LOS bins. While interpretable, its performance highlighted the need for more sophisticated models like ensemble and boosting techniques.

B. Feature Importance and Key Predictors

The operational and clinical feature importance in the prediction of LOS cannot be overestimated. The most significant predictors were the features that were classified as such due to their impact on the models:

- APR Severity of Illness Code and APR Risk of Mortality: These were the strongest predictors, which highlight the significance of patient condition severity and the corresponding risk levels.

- APR DRG Code and CCSR Diagnosis Code: The diagnostic codes played a pivotal role in refining the accuracy of predictions by sorting out patients on the basis of clinical conditions.

- Age Group and Emergency Department Indicator: The age trends and emergency trends exerted strong effects on LOS.

- Type of Admission and Payment Typology 1: These operational dimensions provided additional insight into LOS heterogeneity.

C. Improvements Over Current Research

The present research bridges some of the gaps identified in previous studies:

- Ensemble and boosting algorithms, such as Random Forest and AdaBoost, were included, which provided better generalization and predictive power compared to traditional approaches like logistic regression.
- We employed hyperparameter tuning to enhance the parameters and avoid overfitting.
- Feature engineering included encoding categorical variables and creating LOS bins to enhance classification results.
- Using real hospital data makes it more reliable and can scale, as opposed to problems based on smaller sets or simulated data in most instances.

V. Conclusion

The research examines how effectively the machine learning algorithms, particularly the Random Forest algorithm, predict the duration a patient will spend in hospital. The research adopts methods to correct class imbalance, enhance features, and tune parameters, providing a strong foundation to predict hospital stay duration. The findings indicate that various factors such as the patient's age and the seriousness of their conditions influence how long they spend in hospital. The findings corroborate other research that indicates hospital stay duration is predictable by machine learning [11], [12].

Applying ensemble methods to real-world data has been grounded on prior work, offering a good solution to healthcare organizations. Ensemble methods, including Gradient Boosting, have been found to be helpful in LOS prediction and performed well with complex healthcare data [13], [18]. Furthermore, clinical biomarkers and structured data modeling have also been explored to enhance LOS prediction accuracy and efficiency in various healthcare environments [14], [15]. More sources of data, including electronic health records (EHRs), can be included in future studies to enhance the accuracy of predictions.

Moreover, various sophisticated deep-learning techniques and ensemble methods can be employed to enhance the accuracy and reliability of LOS predictions [16], [17]. This work would capitalize on prior machine learning work in healthcare, offering insights to provide better patient treatments and optimize the utilization of resources. In aggregate, this work illustrates how hospital operations and healthcare quality can be enhanced by accurate LOS predictions [19], [20], [21]. We will continue to refine the model to enhance prediction accuracy.

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