Predicting Length of Stay in Hospital Using Clinical Indicators Available at the time of Admission

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Submitted by

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

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CERTIFICATE

This serves as confirmation that the project titled **Predicting Length of Stay in Hospital Using Clinical Indicators Available at the time of Admission** is the authentic work of **Nagam Venkata Manoj Kumar** (Registration Number: 200905262). It was submitted as part of the fulfillment criteria for the Bachelor of Technology (B.Tech.) degree in COMPUTER SCIENCE & ENGINEERING at Manipal Institute of Technology, Manipal, Karnataka. This submission was made during the academic session of 2023-2024.

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ABSTRACT

In the dynamic landscape of healthcare, precise prediction of patients' length of stay (LOS) in hospitals is crucial. This study employs a comprehensive data-driven approach, utilizing regression analysis to uncover the intricacies of LOS prediction. By analyzing diverse patient demographics, clinical indicators, and vital signs, we aim to identify key determinants influencing LOS and develop accurate prediction models.

In our research, we utilized a diverse array of machine learning algorithms, including linear regression, decision tree, random forest, and LGBMRegressor, ultimately culminating in the implementation of the XGBoost algorithm. These methodologies were employed to optimize resource allocation and bed management while concurrently enhancing patient experience and operational efficiency within healthcare facilities. Our approach involved meticulous data acquisition, preprocessing, model selection, and training to craft robust predictive models. Moreover, we placed significant emphasis on model interpretability and conducted thorough evaluations to ensure the reliability and generalizability of our findings.

The outcomes of this research go beyond predictive accuracy, encompassing practical applications such as optimized resource allocation, streamlined patient flow, and cost savings. By elucidating the factors driving LOS and providing actionable insights, our work has the potential to drive transformative advancements in healthcare delivery, fostering improved patient care and operational excellence.

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CHAPTER 1
INTRODUCTION

1.1 *Introduction*

This chapter serves as an introduction to the research project, providing an overview of the topic, motivation, objectives, and organization of the report.

1.2 Introduction to the Area of Work

The area of work focuses on predicting the length of stay for patients in healthcare facilities using regression analysis. By leveraging machine learning techniques, we aim to develop models that can accurately estimate the duration of a patient's hospital stay based on various demographic,clinical,and contextual factors

1.3 Brief Present-Day Scenario

In the present-day healthcare landscape, optimizing hospital resource allocation and patient management is crucial for enhancing efficiency, reducing costs, and improving patient outcomes. Predicting the length of hospital stays can assist healthcare providers in resource planning, bed management, and discharge planning, ultimately leading to better patient care and resource utilization

1.4 Motivation to Do the Project Work

The motivation behind this project stems from the pressing need to address challenges in healthcare resource management and patient care. Accurate length-of-stay predictions can enable proactive decision-making, streamline operations, and enhance patient satisfaction by minimizing wait times and facilitating timely
discharge.

1.4.1 Shortcomings in Previous Work/Reference Papers

While previous studies have explored length-of-stay prediction models, many existing approaches suffer from limitations such as insufficient accuracy, narrow scope, or lack of generalizability. This project seeks to address these shortcomings by employing advanced machine learning techniques and comprehensive feature engineering strategies.

1.4.2 Brief Importance of the Work in the Present Context

In the current healthcare landscape, where hospitals face increasing demands and resource constraints, accurate length-of-stay predictions are essential for efficient resource allocation, patient flow management, and cost containment. By developing robust prediction models, this work aims to contribute to the optimization of healthcare delivery processes.

1.4.3 Uniqueness of the Methodology to Be Adopted

The uniqueness of this project lies in its comprehensive approach to length-of-stay prediction, which incorporates a wide range of patient demographics, clinical variables, and facility-related factors. Additionally, the adoption of state-of-the-art machine learning algorithms, such as XGBoost, enhances the model's predictive performance and interpretability.

1.4.4 Significance of the Possible End Result

The potential impact of this project's outcomes extends beyond academic research to real-world healthcare settings. Accurate length-of-stay predictions can empower healthcare providers with actionable insights to optimize resource allocation, improve patient flow, and enhance the overall quality of care delivery.

1.5 Objective of the work

1.5.1 Main Work Objective

The primary objective of our project is to develop a highly accurate model for predicting Length of Stay (LOS) in healthcare facilities. This objective encompasses the following key components:

1.5.1.1 Developing a Highly Accurate Prediction Model

Our primary focus is on achieving a specific target metric for predictive accuracy, such as mean squared error (MSE), R-squared, or another relevant performance measure. By leveraging advanced machine learning techniques and comprehensive feature engineering, we aim to build a model that can reliably estimate the duration of a patient's hospital stay with minimal error.

1.5.1.2 Identifying Key Demographic and Clinical Factors

In addition to predicting LOS, we seek to identify the key demographic and clinical factors that influence hospitalization duration. Through in-depth analysis of model coefficients, feature importance scores, and domain knowledge integration, we aim to gain insights into the factors driving variations in LOS and their relative importance.

1.5.1.3 Evaluating Performance of Different Regression Models

We will systematically evaluate the performance of various regression models for LOS prediction, including linear regression, decision trees, random forests, and neural networks. This comparative analysis will provide valuable insights into the strengths and weaknesses of different modeling approaches and inform our selection of the most effective predictive algorithm.

1.6 Target Specifications

1.6.1 Importance of the End Result

The successful development of accurate length-of-stay prediction models holds significant importance for healthcare stakeholders, including hospitals, clinicians, administrators, and patients. By providing reliable estimates of patient length of stay, these models can facilitate more efficient resource allocation, improved patient flow, and enhanced Quality Of care.

1.7 Project Work schedule

The project work will be conducted over a specified timeline, involving phases such as data collection, preprocessing, feature engineering, model development, evaluation, and documentation. The schedule will be structured to ensure systematic progress and timely completion of Project milestones.

1.8 Organization of the project report

The project report will be organized into chapters, each addressing specific aspects of the research process. The chapters will include Introduction, Literature Review, Data Collection and Preprocessing, Methodology, Experimental Results, Discussion, Conclusion, and References.

CHAPTER 2
BACKGROUND THEORY and LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of relevant literature and background theory pertaining to the project title, "Length-of-Stay Prediction in Healthcare Settings." It examines recent developments, theoretical frameworks, and empirical findings related to length-of-stay prediction models In healthcare.

2.2 Introduction to the Project Title

The project title, "***Predicting Length of Stay in Hospital Using Clinical Indicators Available at the time of Admission***," encompasses the prediction of patients' duration of hospitalization using machine learning techniques. This chapter delves into the theoretical foundations and empirical evidence underpinning the development and application of such prediction models.

2.3 Literature review

2.3.1 Present State / Recent Developments in the Work Area

Recent developments in length-of-stay prediction encompass advancements in machine learning algorithms, feature engineering techniques, and data analytics methodologies. Studies have increasingly emphasized importance of incorporating diverse sets of patient characteristics,clinical variables,and facility-related factors Into prediction models.

2.3.2Brief Background Theory

The background theory encompasses concepts and principles relevant to length-of-stay prediction, including healthcare resource management, patient flow dynamics, predictive modeling, and statistical analysis. Understanding these theoretical frameworks is essential for designing effective prediction models and interpreting their results.

2.3.4 Literature Survey

One viable approach to addressing healthcare system sustainability involves shortening inpatient hospital stays, which is anticipated to free up bed capacity, staff time, and reduce costs associated with unnecessary hospital days [7][8]. Predicting length of stay (LOS) more accurately remains a significant challenge, crucial for improved bed planning, care delivery, and cost optimization. While traditional linear and logistic regression methods have been surpassed by machine learning (ML) and deep learning (DL) models, selecting the optimal prediction method remains complex due to variations in data sources, inclusion criteria, input variables, and evaluation metrics [7][8].

Our study found that Gradient Boosting (GB) demonstrates superior performance in LOS prediction [7]. In a recent comparison study, GB outperformed multiple linear regression, support vector machine, and Random Forest (RF) models [9]. However, another study indicated that RF slightly outperformed GB [1]. Despite Neural Networks (NN), particularly multi-layer perceptron (MLP), being commonly used as benchmarks, GB consistently outperforms NN on tabular datasets [2][3].

Efforts to accurately predict LOS have persisted for decades, yet ML applications in this area remain fragmented [7]. A systematic review identified only 21 articles on LOS prediction, highlighting various shortcomings such as inadequate inclusion criteria and insufficient demographic and clinical information [8]. In our study, we addressed these issues by providing detailed clinical and organizational data. Additionally, we categorized prolonged stays using Tukey's criterion and meticulously handled outliers [4][5].

To mitigate overfitting, we employed separate validation sets for model selection and hyperparameter tuning, along with a distinct holdout test set [6][7]. Moreover, we proposed utilizing resampling-based statistical tests for performance comparison to account for randomness in training-validation splits [11]. This approach enhances the reliability of model evaluation and guards against overfitting.

Our findings have practical implications for healthcare professionals, planners, and policymakers, particularly regarding discharge destination for elderly patients [12][13]. With an aging population, there's an urgent need to allocate resources effectively to meet the complex needs of this demographic, especially those with cognitive impairment and multiple comorbidities [14][15].

In conclusion, while challenges and limitations exist, advancements in ML, particularly with improved GB variants and explainable AI, offer promising solutions for enhancing healthcare delivery and resource management [18–21]. Additionally, the emergence of AutoML tools like AutoGluon simplifies the implementation of advanced ML models, facilitating their integration into hospital information systems to improve quality of care and operational efficiency.

2.4 Summarized outcome of the literature review

The summarized outcome of the literature review highlights common trends, emerging challenges, and gaps in existing research on length-of-stay prediction. It synthesizes key findings from the literature to inform the development of robust prediction models in this domain.

2.5 Theoretical discussions

Theoretical discussions delve into the underlying principles and assumptions guiding length-of-stay prediction modeling. Topics of discussion may include the relationship between patient demographics and length of stay, the impact of clinical interventions on hospitalization duration, and the role of predictive analytics in healthcare decision-making.

2.6 General analysis

A general analysis of the literature reviewed offers insights into the strengths, limitations, and future directions of length-of-stay prediction research. It identifies opportunities for innovation, methodological refinement, and interdisciplinary collaboration to advance the state-of-the-art in this field.

2.7 Conclusion

In conclusion, the literature review provides a comprehensive understanding of the theoretical foundations, empirical evidence, and methodological approaches relevant to length-of-stay prediction in healthcare settings. It sets the stage for the subsequent chapters by informing the development and evaluation of prediction models in this project.

CHAPTER 3
METHODOLOGY

3.1 Introduction

This chapter outlines the methodology employed in the development and evaluation of length-of-stay prediction models for healthcare settings. It discusses the approach taken, assumptions made, design considerations, modeling techniques, and tools utilized in the project.

3.2 Methodology

3.2.1 Comprehensive methodology

3.2.1.1 Data Preprocessing

Cleaning the dataset to handle missing values, outliers, and inconsistencies.

Transforming categorical variables into numerical or one-hot encoded representations.Normalizing numerical features to a common scale to facilitate model convergence.

3.2.1.2 Feature Engineering

Creating new features such as 'numberofissues' based on binary indicators of medical conditions.Selecting relevant features based on domain knowledge, statistical significance, and feature importance analysis.

3.2.1.3 Model Selection and Training

Experimenting with various regression algorithms, including XGBoost and linear regression.Performing hyperparameter tuning using techniques like grid search or randomized search.Training the selected model on the preprocessed dataset to learn the underlying patterns and relationships.

3.2.1.4 Model Evaluation

Assessing model performance using metrics such as RMSE, R-squared, and MAE. Conducting cross-validation to estimate the model's generalization error and mitigate overfitting.Visualizing model predictions and residuals to identify patterns and assess prediction accuracy.

3.2.2 Assumptions made

The dataset is assumed to be representative of the target population and free from significant biases.The relationships between predictor variables and the target variable are assumed to be consistent across different healthcare settings.

Missing data are assumed to be missing at random and are handled appropriately during preprocessing.

3.2.3 Design & Modelling, block diagrams

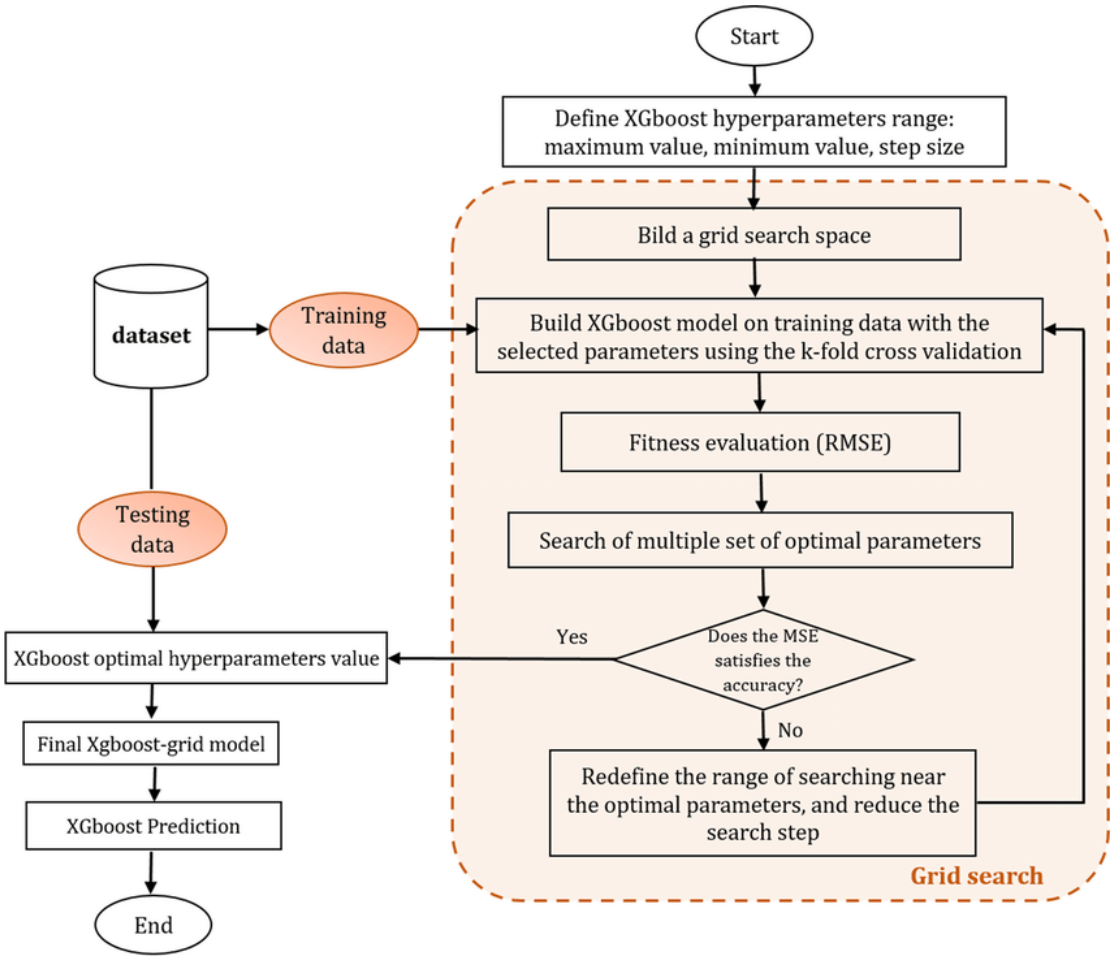


Fig-3.1 Block diagram of XGBoost

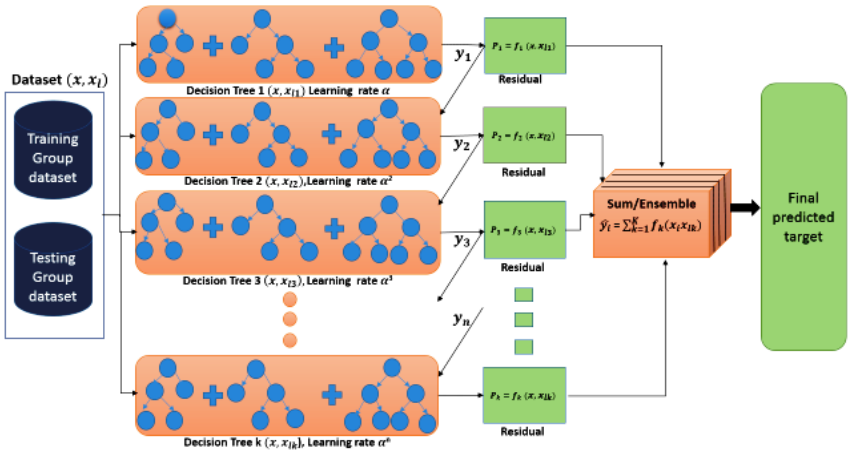


Fig-3.2 Schematic diagram of XGBoost

3.2.4 Module specifications

3.2.4.1 Data Preprocessing Module

Handles data cleaning,transformation,and normalization.

3.2.4.2 Feature Engineering Module:

Generates new features and selects relevant predictors.

3.2.4.3 Model Training Module:

Trains regression models on the preprocessed dataset.

3.2.4.4 Model Evaluation Module:

Evaluates model performance using appropriate metrics and visualization techniques.

3.2.5 Justification for your modules

Each module is designed to address specific aspects of the prediction modeling process, from data preparation to model evaluation. This modular approach promotes code reusability, maintainability, and scalability, enabling efficient experimentation and iteration.

3.3 Tools used

Programming Language : Python

Libraries : pandas, scikit-learn, XGBoost, LightGBM, matplotlib, and others.

Development Environment:Jupyter Notebook

3.4 Preliminary result analysis

3.4.1 Linear Regression

Attained an R-squared (R2) score of 0.760, suggesting a moderate level of predictive accuracy. Linear Regression is a simple yet interpretable algorithm, but it may struggle to capture nonlinear relationships in the data.

Formula

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta nXn + \epsilon$$

Where:

Y is the dependent variable (the variable you're trying to predict)

*X*1,*X*2,…,*Xn* are the independent variables (the variables used to predict the dependent variable)

*β*0 is the y-intercept (the value of Y when all the independent variables are 0)

*β*1,*β*2,…,*βn* are the coefficients (the slopes), representing the change in Y for a one-unit change in the corresponding independent variable

ϵ represents the error term (the difference between the observed and predicted values of Y).

3.4.2 Decision Tree

Achieved an R-squared (R2) score of 0.875, indicating a strong level of predictive performance. Decision Trees are capable of capturing complex interactions between variables, but they may be prone to overfitting.

Formula

$$Y = f(X) + \epsilon$$

Where:

Y is the target variable

X is the set of predictor variables

f(*X*) represents the prediction function, which is defined by the decision tree algorithm as a series of if-else conditions based on the predictor variables.

ϵ represents the error term, which captures the difference between the predicted and actual values of the target variable.

3.4.3 Random Forest

Achieved an accuracy score of 0.938, indicating a high level of predictive performance. Random Forest is known for its robustness and ability to handle complex relationships in data.

Formula

$$Y=1/N\sum i=1Nfi(X)+\epsilon$$

Where:

Y is the target variable

X is the set of predictor variables

fi(*X*) represents the prediction function of the *ith* decision tree

N is the number of trees in the forest
The symbol ϵ denotes the error term, which encompasses the variance between the predicted and observed values of the target variable.

3.4.4 LGBMRegressor

Achieved an R-squared (R2) score of 0.968, indicating high predictive accuracy.
LGBMRegressor, similar to XGBoost, is a gradient boosting algorithm known for its efficiency and accuracy.

Formula

$y\hat{}i=\sum k=1Kfk(xi)$

Where:
Y^i is the predicted value for the *ith* observation.
K is the total number of trees in the model.
fk is the prediction function of the *kth* tree.

3.4.5 XGboost

Obtained an R-squared (R2) score of 0.970, indicating excellent predictive accuracy.XGBoost is a powerful ensemble learning algorithm known for its scalability and superior performance in many machine learning tasks.

Formula

$y\hat{}i=\sum k=1Kfk(xi)$

Where:
y^i is the predicted value for the ith observation.
K is the total number of trees in the model.
fk is the prediction function of the *h*kth tree.

3.5 Conclusion

The methodology chapter outlines the systematic approach adopted in the development and evaluation of length-of-stay prediction models. By following a structured methodology, this project aims to produce reliable and interpretable models that can assist healthcare providers in resource allocation and patient management decisions.

CHAPTER 4
RESULT ANALYSIS

4.1 Introduction

This chapter presents the analysis of results obtained from the developed length-of-stay prediction models. It includes a discussion of model performance metrics, graphical representations of predictions, and insights derived from the analysis.

4.2 Result analysis

4.2.1 Model Performance Metrics:

Evaluation of metrics such as RMSE, R-squared, and MAE to assess the predictive accuracy of the models.

RMSE(Root Mean Squared Error)

This metric is a measure of the average deviation of predicted values from the actual values in a regression problem. It calculates the square root of the average of squared differences between predicted and actual values. Lower RMSE values indicate better model performance, as it signifies that the model's predictions are closer to the actual values. RMSE provides insight into the magnitude of errors made by the model.

R-Squared(Coefficient of Determination)

This metric represents the proportion of the variance in the dependent variable (target) that is predictable from the independent variables (features) in the model. It ranges from 0 to 1.

Higher R-Squared values indicate that a larger proportion of the variance in the target variable is explained by the independent variables in the model. R-Squared provides an overall measure of how well the model fits the data.

MAE(Mean Absolute Error)

This mertic measures the average absolute difference between the predicted and actual values. It calculates the mean of the absolute differences between predicted and actual values.

MAE provides a straightforward understanding of the average magnitude of errors made by the model. Like RMSE, lower MAE values indicate better model performance, with smaller errors between predicted and actual values.

4.2.1.1 Graphical Representation

Visualizations such as scatter plots, residual plots, and feature importance plots to illustrate model predictions and interpret model behavior.

4.2.1.2 Tabulated Results:

Summary tables showcasing model performance metrics and comparative analysis across different algorithms or feature sets.

Table 4.1 Metrics of different algorithms

Model	RMSE	R-Squared	MAE
Linear Regression	1.156	0.760	0.879
Decision Tree	0.829	0.875	0.415
Random Forest	0.584	0.939	0.338
LGBM	0.416	0.968	0.306
XGBoost	0.407	0.970	0.303

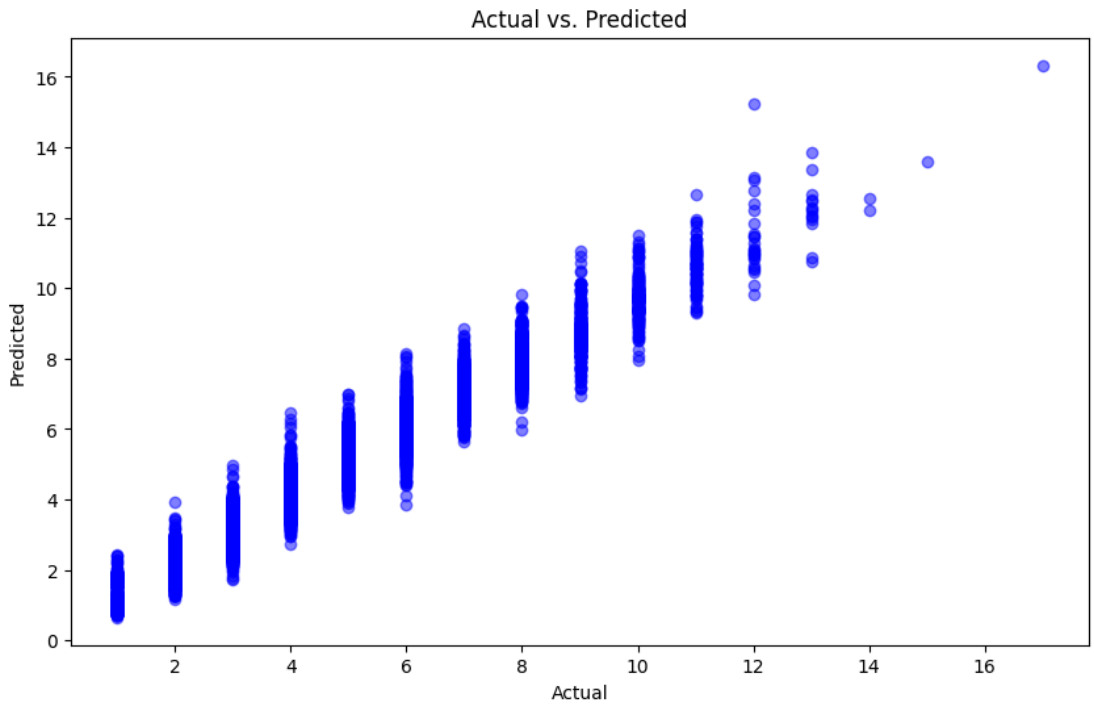
4.2.2 Explanation for the graphical / tabulated results

4.2.2.1 Scatter Plots

Visualization of predicted versus actual length of stay to assess the alignment between predicted and observed values.

Illustrate how closely the predicted values align with the actual values. Ideally, in a perfect predictive model, all points would fall on a straight line with a slope of 1 (the diagonal line from the bottom left to the top right), indicating perfect agreement between actual and predicted values.

In Fig 4.1 plot actual values represents the values of Length of stay column



h Fig-4.1 Scatter plot

4.2.2.2 Residual Plots

Examination of residuals to identify patterns or heteroscedasticity in model errors.

Residual plots help in identifying patterns or trends in the residuals. A clear pattern in the residuals might indicate that the model has not captured all the relevant information in the data.

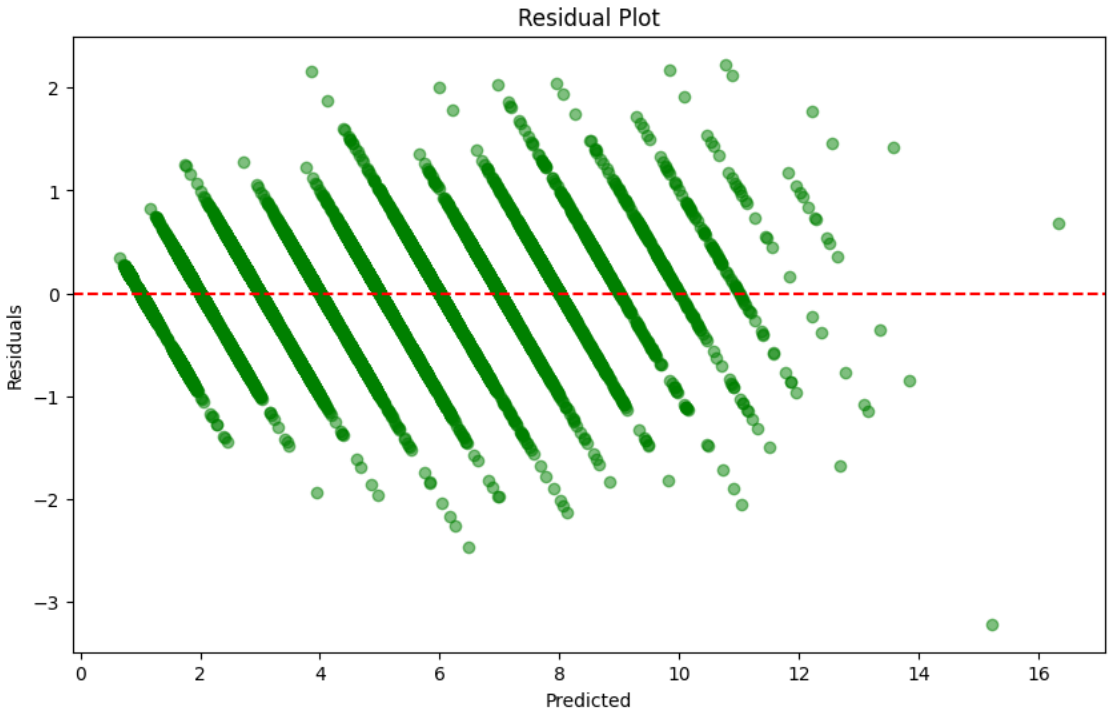


Fig-4.2 Residual Plot

4.2.2.3 Feature Importance Plots

Ranking of features based on their contribution to predicting length of stay, providing insights into the factors influencing hospitalization duration.

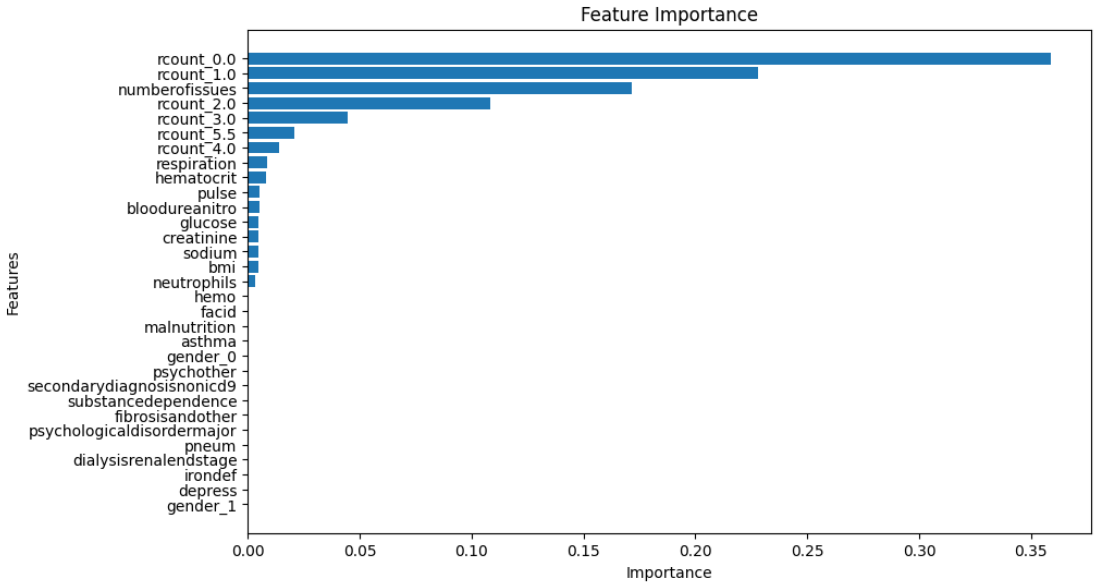


Fig-4.3 Feature Important Plot

The performance of the predictive models was evaluated using metrics such as □^2 score, mean squared error, and graphical representations. The following graph illustrates the R^2 scores obtained for each model:

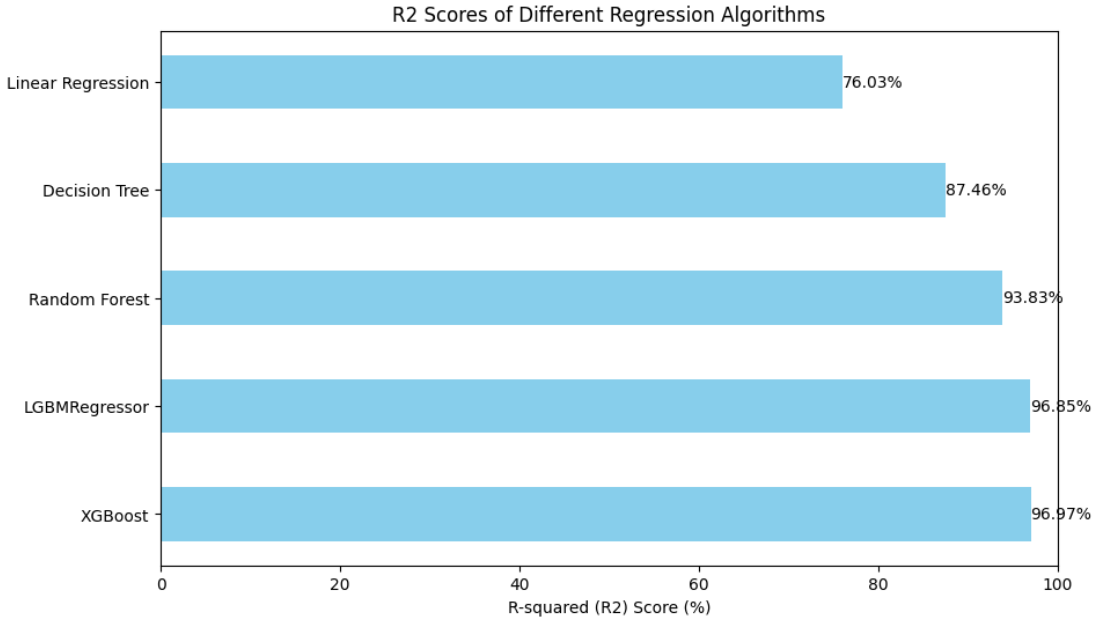


Fig-4.4 R^2 Scores of Different Regression Algorithms

4.3 Significance of the result obtained

The results obtained from the analysis are significant in several ways:

They demonstrate the efficacy of the developed prediction models in accurately estimating the length of hospital stays.They provide actionable insights for healthcare providers to optimize resource allocation, bed management, and discharge planning processes.They contribute to the advancement of predictive analytics in healthcare, fostering evidence-based decision-making and improved patient outcomes.

4.4 Deviations from the Expected Results & Its Justification

Any deviations from expected results are thoroughly examined and justified based on factors such as data quality issues, model complexity, or inherent variability in length-of-stay patterns. Sensitivity analysis may be conducted to assess the robustness of the models to different assumptions or perturbations.

4.5 Evaluation of Environmental and Societal Impact

The project solutions offer potential environmental and societal benefits by:

Optimizing hospital resource utilization, thereby reducing waste and promoting efficiency.Enhancing patient satisfaction and quality of care through streamlined processes and timely interventions.Facilitating data-driven decision-making that aligns with healthcare sustainability goals and societal needs.

4.6 Conclusion

In conclusion, the result analysis chapter provides a comprehensive assessment of the developed length-of-stay prediction models, highlighting their performance, significance, and impact. The findings underscore the importance of predictive analytics in healthcare management and underscore the potential for further research and application in this domain.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Brief summary of the work

5.1.1 Problem Statement/Objective

The primary objective of the project was to address the challenges faced by healthcare providers in effectively managing hospital resources and patient flow. By developing robust prediction models, the goal was to assist healthcare facilities in optimizing bed utilization, discharge planning, and resource allocation decisions.

5.1.2 Work Methodology Adopted, in Brief

The methodology adopted involved a systematic approach encompassing data preprocessing, feature engineering, model selection, training, and evaluation. Advanced machine learning algorithms such as XGBoost were employed, and extensive experimentation was conducted to assess model performance and generalizability.

5.2 Conclusion

In general, the research contributes to the growing body of literature on predictive analytics in healthcare, providing practical solutions to real-world challenges faced by healthcare providers. The findings highlight the importance of leveraging data-driven approaches to optimize healthcare operations and improve patient outcomes.

The results obtained from the project have significant implications for healthcare stakeholders, including hospitals, clinicians, administrators, and patients. Accurate length-of-stay predictions facilitate more efficient resource allocation, better patient flow management, and enhanced patient satisfaction, ultimately leading to improved healthcare delivery and outcomes.

5.3 Future Scope of Work

While the current project has achieved promising results, there are several avenues for future research and development:

Integration of Real-Time Data : Incorporating real-time data streams and dynamic patient information could enhance the accuracy and timeliness of length-of-stay predictions, enabling proactive decision-making and intervention.

Exploration of Advanced Techniques : Further exploration of advanced machine learning techniques, such as deep learning and ensemble methods, may uncover new insights and improve prediction performance.

Validation and Deployment : Conducting external validation studies and deploying the developed models in real-world healthcare settings would validate their effectiveness and feasibility in clinical practice.

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CO and PO Mapping

NBA:

Table A1.1 Course Articulation Matrix

CO		PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3	PSO4
CSE 4299.1	Apply mathematics, science and engineering skills to identify, formulate, synthesize and solve the problems from various areas of computer science engineering.	2	1	2	2	2	1	3	2	3	2	2	2	1	1	3	1
CSE 4299.2	Have knowledge of new trends in engineering/technology by developing programmable coding in various computer programming languages.	2	3	1	2	2	3	3	3	1	2	1	1	3	3	2	2
CSE 4299.3	Use the industry standard tools to analyze, design, develop and test software engineering based applications.	1	2	3	1	1	2	2	3	3	1	1	1	2	2	2	3
CSE 4299.4	Apply theoretical knowledge to real-world engineering problems and manage complex engineering projects.	3	1	2	3	3	1	1	2	2	3	3	3	1	1	1	2
CSE 4299.5	Acquire skills of collaboration and independent learning.	2	1	3	2	2	1	1	3	3	2	2	2	1	1	1	3
CSE 4299 (Avg. correlation level)		**2**	**1.6**	**2.2**	**2**	**2**	**1.6**	**2**	**2.6**	**2.4**	**2**	**1.8**	**1.8**	**1.6**	**1.6**	**1.8**	**2.2**

PROGRAM OUTCOMES (PO)

Engineering Graduates will be able to:

1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSO)

1. Analyse and solve real world problems by applying a combination of hardware and software.
2. Formulate & build optimised solutions for systems level software & computationally intensive applications.
3. Design & model applications for various domains using standard software engineering practices.
4. Design & develop solutions for distributed processing & communication.

Table A1.2 Program Articulation Matrix

COURSE Code	Course Title	PO1	PO2	PO3	PO4	PO5	PO 6	PO7	P O8	PO9	PO 10	PO11	PO12	PS O1	PS 02	PS O3	PS O4
CSE 4299	Project Work	**Avg :2**	**Avg :1.6**	**Avg :2.2**	**Avg :2**	**Avg: 2**	**1 . 6**	**2**	**2 . 6**	**2 . 4**	**2**	**1. 8**	**1.8**	**1 . 6**	**1 . 6**	**1 . 8**	**2.2**

Table A1.3 CLO-AHEPLO Mapping

		AHEP LOs						
CLOs	**Statements**	**C8**	**C9**	**C10**	**C12**	**C15**	**C16**	**C17**
1	Apply mathematics, science and engineering skills to identify, formulate, synthesize and solve the problems from various areas of computer science engineering.	✓	✓	✓	✓	✓	✓	✓
2	Have knowledge of new trends in engineering/technology by developing programmable coding in various computer programming languages.	✓	✓	✓	✓	✓	✓	✓
3	Use the industry standard tools to analyze, design, develop and test software engineering based applications.	✓	✓	✓	✓	✓	✓	✓
4	Apply theoretical knowledge to real-world engineering problems and manage complex engineering projects.	✓	✓	✓	✓	✓	✓	✓
5	Acquire skills of collaboration and independent learning.	✓	✓	✓	✓	✓	✓	✓

AHEPS

C8	Identify and analyse ethical concerns and make reasoned ethical choices informed by professional codes of conduct
C9	Use a risk management process to identify, evaluate and mitigate risks (the effects of uncertainty) associated with a particular project or activity
C10	Adopt a holistic and proportionate approach to the mitigation of security risks
C12	Use practical laboratory and workshop skills to investigate complex problems
C15	Apply knowledge of engineering management principles, commercial context, project and change management, and relevant legal matters including intellectual property rights
C16	Function effectively as an individual, and as a member or leader of a team

C17	Communicate effectively on complex engineering matters with technical and non-technical audiences

PROJECT DETAILS

Student Details			
Student Name	**Nagam Venkata Manoj Kumar**		
Register Number	200905262	Section / Roll No	B/48
Email Address	nagammanoj1551@gmail.com	Phone No (M)	+917981614593
Project Details			
Project Title	**Predicting Length of Stay in Hospital Using Clinical Indicators Available at the time of Admission**		
Project Duration	4 months	Date of reporting	03-01-2024
Organization Details			
Organization Name	**Manipal Institute of Technology,Manipal**		
Full postal address with pin code	Department of Computer Science & Engineering, MIT Campus, Manipal 576104, Karnataka, India		
Website address	https://www.manipal.edu/mit/about/administration.html		
External Guide Details			
Name of the Guide			
Designation			
Full contact address with pin code			
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