Optimizing Hospital Bed Allocation through Advanced Predictive Analytics and Gradient Boosting Technique

Mrs.Renuka Devi S
Professor of Artificial Intelligence and Data Science
Rajalakshmi Engineering College
Chennai, India
renukadevi.s@rajalakshmi.edu.in

Harshitha R
Artificial Intelligence and Data Science
Rajalakshmi Engineering College
Chennai, India
221801018@rajalakshmi.edu.in

Vaishnavi S
Artificial Intelligence and Data Science
Rajalakshmi Engineering College
Chennai, India
221801059@rajalakshmi.edu.in

Abstract— This research work describes a state-of-the-art hospital bed management system using predictive analytics that takes into consideration multiple challenges in patient care and resource distribution. Utilizing Gradient Boosting techniques such as XGBoost, the model shows high accuracy in predicting bed occupancy through historical data, including patient demographics, trends in admission patterns, and operational factors. The use of K-Means clustering is incorporated to categorize patients into different groups that will reflect similar needs, thus developing personalized resource management strategies for diverse patient demographics.The system included a comprehensive workflow, ranging from data pre-process and model training to deployment. Dynamic forecasting of bed demand at the predictive analytics layer culminated into intuitive insightful visualizations provided through the visualization module, which highlighted trends in bed utilization, departmental forecasts, and resource requirements, allowing administrators to react in advance to impending shortages or surges.Extensive experimentation has proven the model to effectively eliminate instances of the waiting of patients, overcrowding, and unequal workloads for staff. The real-time integration with hospital management systems ensures continuous update of predictions based on fluctuations in demand and changes in operations.This approach supports better resource allocation and enhances patient satisfaction by reducing service delay in care delivery. Future enhancement could be adaptive learning models, increased inputs of data, and integrating it more deeply with other hospital systems, such as electronic health records and supply chain management tools. The project underlines the role of AI in building a sustainable healthcare infrastructure that is patient-centered and optimizes operation and improves outcomes.

Keywords— Predictive analytics, Hospital bed management, Gradient Boosting (XGBoost), K-Means clustering, Patient segmentation, Real-time forecasting, Resource optimization, Improving patient outcomes.

I. INTRODUCTION

Good hospital bed management is critical for health service providers in delivering quality patient care while optimizing the use of available resources. Their current greatest challenges are unpredictable admission patterns, bed scarcity, and hugely variable patient needs. Overcrowding, delayed care, and resource wastage frequently result from ineffective bed allocation, which has impacts on both patient outcomes and hospital operations. Because traditional manual and reactive bed management fails to account for these complexities, it is clear that improved, data-driven solutions are needed. This project posits an integrated solution to the challenge described above by the advanced predictive analytics system utilizing the capacity of machine learning.

Being able to utilize Gradient Boosting (XGBoost) with accurate forecasting, and K-Means clustering for effective patient segmentation, the system offers relevant actionable insights pertaining to bed occupancy trends and utilization of resources. Such models base future bed demands on historical data like demographics, admission records, and seasonal fluctuations. This high accuracy bed demand forecast enables proactive resource alignment in hospitals, thus timely care for patients and better operational efficiency. The robust visualization module complements the integration of this predictive model into hospital workflows. Administrators can track real-time occupancy, identify periods of high demand, and receive alerts when potential shortages may be on the horizon. This provides healthcare providers with the ability to act quickly based on informed decisions-reducing patient wait times, avoiding overcrowding, and maximizing quality care. Another outstanding feature of this project is the application of K-Means clustering for segmentation of patients to determine different segments based on age, medical conditions, and history of admission. This segmentation can be allowed to be tailored to resource management to ensure that critical resources are there and utilized only where they are needed most. For example, patients requiring specialized care or extended stays would come first, minimizing disruption to provide a seamless flow of patients.The benefits of this system extend beyond operational improvements. By reducing inefficiencies, hospitals can lower operational costs and balance staff workloads, improving job satisfaction and overall productivity. Patients, in turn, benefit from reduced delays, personalized care, and a better overall experience, fostering trust in the healthcare system.In this changing landscape of healthcare, it is no longer optional but a need to integrate the latest technologies available such as AI and machine learning. Such a project puts forward the scope of predictive analytics in modern healthcare and gives people a new standard for future innovations in hospital management. Helping both aims of revamping patient care and optimizing resource utilization, this initiative works towards the sustainable, efficient, and patient-focused healthcare system.

Figure 1: Tech Stacks

II. RELATED WORKS

Hospital bed management has received much attention because its optimization could lead to improvement of operational efficiencies, shorter waiting times in wards, and overall quality care at hospitals. With increasing patient volumes in emergency and critical care departments, it becomes pertinent to install advanced systems that can predict and manage bed occupancy effectively. The "Predicting Hospital Bed Utilization Using Machine Learning" study explains how algorithms, such as Random Forest, XGBoost, and Support Vector Machines (SVM), can be used to predict demand for hospital beds. Historical data and admission rates are analyzed using patient demographics and medical conditions to provide the ability to predict when beds will be occupied and when they will be available. This predictive ability allows hospital administrators to be more efficient in resource allocation, control patient flow, and minimize the number of overcrowdings-a critical challenge of many healthcare systems. However, all these models rely totally on the quality and reliability of the historical data. Inadequate data, perhaps outdated, or simply wrong data, would drastically limit the effectiveness of the predictions, making it difficult to predict abrupt alterations such as emergency admissions or unexpected conditions of patients. Another issue related to the use of these predictive models in a real-time hospital context is that significant computational resources and infrastructure may be necessary for their implementation, which would greatly inconvenience hospitals, especially those with low technological capacity.An alternative approach is through the paper "Real-Time Bed Allocation in Hospitals Using Optimization Techniques," an application based on optimization techniques using a linear programming model that dynamically allocates beds according to different factors such as patient condition severity, expected discharge times, and other departmental needs. This optimization model helps hospitals make real-time decisions about bed assignments, ensuring that the most critical patients receive appropriate care while minimizing the wait times for incoming patients. By balancing these various parameters, hospitals can optimize their bed utilization and prevent bottlenecks in care delivery. While this model is promising regarding efficiency, real-time optimization requires constant updates of data and may also be subject to unforeseen changes in patient conditions such as emergencies and unstable times of discharge. Real-time optimization can also be bound by the availability of resources such as staff and space, adding another layer to the decision-making process.

Building on these important predictive methods, the paper "Machine Learning for Predictive Bed Occupancy in Hospitals" takes it down to an even deeper dive in regards to employing deep learning algorithms-the use of artificial neural networks (ANN)-towards the analysis of massive data stored in the form of electronic health records. Deep learning models, using large-scale datasets containing patient history, admission and discharge times, and medical diagnoses, can thus learn finer patterns in the flow of patients that might be captured through simpler models. This improves the accuracy of prediction in bed occupation so that a hospital may prepare for capacity needs in advance. However, training deep learning models is very sophisticated and requires a large amount of data preprocessing as well as time to train the model, as well as computationally intensive resources. Deep learning models further also require major chunks of data to reach optimal performance and this is something smaller hospitals cannot provide or even have the infrastructure for. Another drawback is the training time for these models; thus, predictions may not be made in real-time, which might hinder them from being useful in high-pace environments of a hospital where decisions need to be made pronto.

Another novel paper is "A Hybrid Approach for Bed Management Using AI and IoT," in which the integration of machine learning with IoT technology is explored to monitor hospital bed usage in real-time. This system embeds sensors into patient rooms. It continuously observes a person's vitals and movements, and even anticipated discharge times. The IoT network feeds such real-time data into machine learning models that predict when beds are available and recommend optimal bed assignments. Such a hybrid approach is expected to streamline the operations of hospitals by providing up-to-the-minute data on bed occupancy and enabling hospital staff in informed decision-making. Although the system would offer tremendous advantages in real-time data collection, it does pose issues in managing the huge volumes of data that thousands of sensors create. Moreover, because IoT networks are exposed to potential cyber threats, the issue of security and privacy of patient data would be a key challenge as patient data should comply with health regulations. The biggest investment, however, lies in infrastructure, and maintenance and operations of such a system across large healthcare networks may not be within the bounds of smaller hospitals' budgets.

"Optimizing Hospital Bed Occupancy Using Predictive Analytics" aims to optimize hospital bed occupancy using statistical and machine learning techniques, including decision trees and gradient boosting, for the estimation of patient flow and bed occupancy. This model analyzes historical data to predict admission rates, patient severity, and discharge schedules. It may therefore allow hospitals to determine in advance when beds will become free and what departments might require supplementary supply in advance. This therefore offers an ideal approach that improves patient throughput, reduces bottlenecks in emergency departments, and minimizes wait times. In addition, predictive analytics can optimize the allocation of medical staff, equipment, and supplies into hospitals, which is fundamental in sustaining high patient care standards. It is essential to consider that the appropriateness of this model can be negatively affected when something unexpected arises-for example, a disaster or an outbreak-resulting in unanticipated spikes in patient inflow, thereby calling for an alternative approach to ensure adequate treatment during such times. This presents the challenge of real-time integration with predictive models, as hospitals need to promptly respond to dynamic fluctuations in patient conditions and bed occupancy.

Even though the outcomes of such studies are promising, there are many challenges that are still unsolved in terms of the widespread adoption of machine learning and predictive analytics in hospital bed management. For instance, predictions can only be as good as the quality of data used in compiling the models. Data inaccuracy, error, or holes can result in low forecasting accuracy that significantly depends on health environments characterized by quick changes. Real-time decision-making can also be very challenging, especially in the integration of predictive models into hospital operational activities. Many hospitals in developing countries lack the infrastructure and computational power and expertise to employ the elaborate models of machine learning at large scale. Furthermore, the implementation of predictive analytics and machine learning requires substantial investments in technology, training, and cybersecurity measures to protect patient data. There is also the challenge of integrating these technologies into existing hospital workflows and ensuring that healthcare professionals are trained to use these systems effectively. Many hospitals, especially those in resource-limited settings, may find it challenging to implement these technologies because of the financial constraints and the required long-term commitment for maintenance and updates.

However, the potential for predictive analytics and machine learning to revolutionize hospital bed management is also extremely high. As healthcare systems continue to evolve, these technologies will increasingly become critical to optimize hospital operations, improve patient outcomes, and save costs. Predictive analytics can help hospitals anticipate bed demand more accurately, reduce patient wait times, improve staff allocation, and enhance the overall patient experience. Real-time data collection through IoT technology can also provide instant insights into bed occupancy, allowing hospitals to make immediate decisions that enhance operational efficiency. Ultimately, predictive analytics, machine learning, and IoT hold the power to reshape how hospital beds are managed-and change patients' and providers' healthcare experiences. The ongoing development of these systems will likely play a crucial role in shaping the future of hospital management, leading to more efficient, patient-centered care across healthcare systems worldwide.

III. PROPOSED SYSTEM

System Overview

The Bed Allocation Optimization System architecture uses advanced predictive analytics and other machine learning models to inform the optimization of bed allocation decisions in hospitals, thereby generating forecasts that predict demand for beds and optimize their usage. The Bed Allocation Optimization System is designed to reduce overcrowding in hospitals and enhance operational efficiency in healthcare environments. It assumes three major phases: data collection, predictive analytics, and decision-making support.

Data Collection The backbone of the system is the continuous compilation of hospital data, which is available through sources like Electronic Health Records, real-time patient monitoring devices, and historical bed occupation logs. Data in this system includes patient demographics, medical conditions, admission/discharge times, and treatment progress information, as well as operational information about staffing and room availability. The system collects this information in real-time, thus keeping it updated and current. IoT devices also input to enhance the tracking of how patients' vital signs and movements are being recorded, giving real-time patient conditions, room usage patterns, and occupancy.

Predictive Analytics: The data feeds into sophisticated machine learning algorithms, such as decision trees, gradient boosting, and deep learning models like Artificial Neural Networks (ANNs). These models track the trends in historical periods, patient flow patterns, and resource utilization patterns that classify the predicted probability of future bed occupancy and demand. Forecasting where and when bed accommodations will be needed, the system allows hospital management to make proactively appropriate decisions. Predictive models point out key factors like patient severity at admission, timelines for discharge, and emergency admissions, thus providing real-time correct predictions on bed availability. Moreover, the models take into account several sources of uncertainty, such as the ad hoc nature of patient emergency arrivals, by having to update and revise on-the-fly forecasts based on the latest incoming data.

Decision Support: In the final step, the system translates predictive understandings into actionable recommendations for hospital administrators. The system can produce alerts in real-time to alert management to potential over-occupancies of beds under projected demand. Such alerts are accompanied by optimal bed-assignment recommendations based on the patient's priority, expected discharge times, and room specialization. Resource-utilization reports in respect of occupancy trends and possible bottlenecks are also available. This empowers hospital staff to make data-informed decisions regarding bed assignments, focusing on critical patients with a significant reduction in wait times for others. The system's dynamic feedback loop allows for continuous optimization, adapting to changing patient conditions and improving overall hospital efficiency. By facilitating smoother patient flow, reducing overcrowding, and enhancing resource management, the system supports the goal of delivering timely and efficient care.

In general, the Bed Allocation Optimization System takes a mix of prediction analytics and real-time decision-making in order to optimize hospital bed management. It provides an effective solution in managing patient flow, optimizing bed usage, and overall efficiency in healthcare delivery.

System Architecture

The architecture of the Bed Allocation Optimization System is designed to streamline hospital bed management by leveraging real-time data, predictive analytics, and intelligent decision-making. It is organized into multiple interconnected modules, each serving a specific function to ensure seamless operation and accurate forecasting. The system's core architecture is composed of four primary modules: data collection, predictive analytics, decision-making support, and output generation.

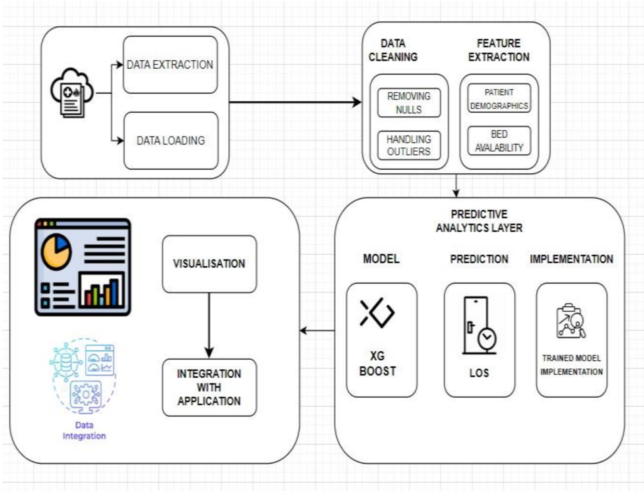


Figure 2: Architecture of the Project

The Bed Allocation Optimization System is designed to enhance hospital efficiency and patient care by leveraging predictive analytics, real-time decision-making, and an intuitive user interface.There is a data collection module that continuously collects data from sources that include EHR, real-time patient monitoring systems, and historical bed occupancy logs. IoT-enabled devices track patient-vitals and movements, providing real-time data for actual predictions. All collected data is sent to a centralized system for further analysis and in real-time updates.Predictive Analytics Module. Based on the collected data, the machine learning algorithms of decision trees, gradient boosting, and deep learning models match the patterns for patient flow, bed usage, and resource demand. The system predicts peaks in bed demand, patient discharges, emergencies admissions, and length of stay and continuously refines these predictions to adjust to changing conditions. These insights are utilized proactively in resource allocation to prevent bed shortages. For example, it has a decision-making support module that keeps hospital administrators abreast of such situations in real-time and suggests actionable recommendations such as shifting non-urgent patients, room consolidation, or streamlining new admission. The system generates detailed reports on patient flow, bed occupancy, and staffing requirements to aid administrators' data-driven decisions to optimize bed management. The module for output generation provides real-time reports, visualizations, and predictive insights for feedback to the stakeholders- that is, the staff of the hospital on bed availability, occupancy trends, and resource usage. It ensures tracking of operational strategies' effectiveness and insight into future bed demand, allowing administrators to plan accordingly. The system includes retrospective analysis, ensuring long-term improvement in bed management.

Database and Historical Data Management: All processed data is stored securely in a centralized database, providing easy access to historical data. This feature is crucial for ongoing evaluation and improving future hospital bed management strategies based on past performance.

User Interface: The system features a user-friendly and intuitive interface, enabling hospital staff to input data, observe real-time predictions, and manage alerts with minimal effort. Through its interactive dashboard, the system graphically presents key metrics so that quick decisions may be made in the fast-paced setting of the hospital. To sum it up, the Bed Allocation Optimization System uses advanced machine learning algorithms and real-time decision-making tools to optimize bed allocation, resource usage, overcrowding reduction, and improvement in overall hospital efficiency. It equips administrators with actionable insights and an effortless interface that allows them to make proactive decisions in managing bed demand, ensuring timely care of patients and all-around operational performance.

User Interface Design

The interface of "Optimizing Bed Allocation through Advanced Predictive Analytics and Gradient Boosting Technique" is intuitive, user friendly, empowering to maximize operation efficiency, and improve care. Patient admission data with a CSV file easily uploads and historical bed occupancy records can be done through use of the application on the interface. It ensures an efficient data submission process since it caters for different user preferences, with drag-and-drop functionality and traditional file selection option.

Once the data is uploaded, the system uses the latest algorithms: Gradient Boosting and K-Means Clustering to process information in real-time. This actionable insights feedback module has the potential to be designed as clear and precise about what the user might look for related to predicted patient admission rates, optimal bed distribution strategies, and insights from patient segmentation. All these outputs are presented in an organized and bite-sized manner, which can help hospital staff take action quickly.

Interactive visualizations are the heart of the interface to make complicated data easier to understand. Graphs and charts are constantly shown about bed usage, patient groups, and predicted deficits. Pie charts are used to break down patient groups and resource utilisations for administrators to see where they might have inefficiency and high demand quickly. Heatmaps and more visualization tools apply additional layers so the staff may analyze what needs attention sooner.

This makes it responsive to the user interface, thus assuring cross-device compatibility from desktops to smartphones. The level of flexibility allows on-site access for the hospital staff to ensure prompt response to dynamic situations. Designing it to be simple and clear necessarily lowers the level of learning that users have to undertake, making it accessible even to those with technically restricted knowledge.

The interface does merge real-time processing and intuitive design into rich visualization, ensuring the delivery of insights that can be used. From a standpoint of raising potential problem areas such as resource underutilization or bed shortages, the system arms administrators with measures for potential optimization of resource utilization, cost-cutting, and better patient outcomes. This is what makes such a system all the more essential for the running of nowadays modern hospital.

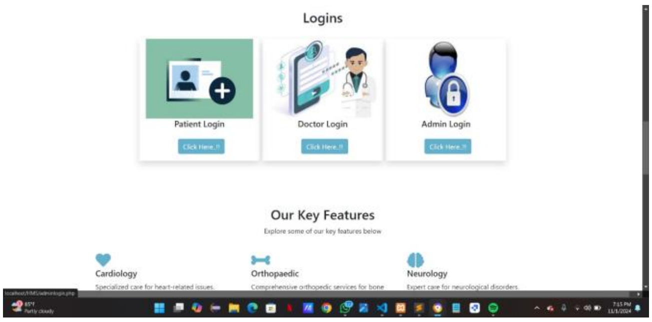


Figure 4: Login Page

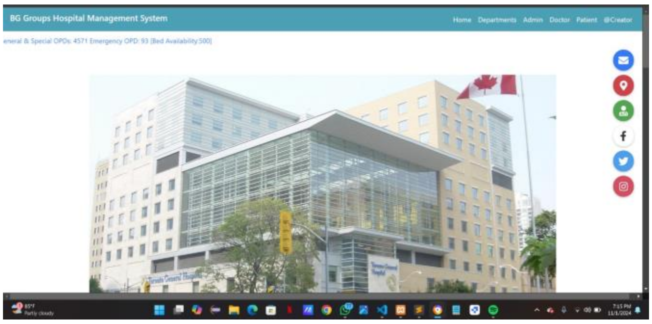


Figure 5: Home Page

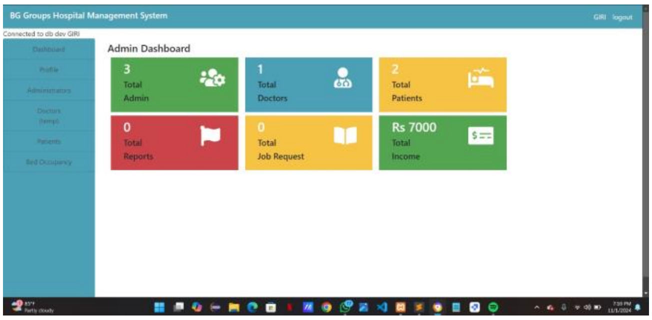


Figure 6: Dashboard

System Workflow

Data Loading and Preprocessing forms the first step of the data flow chain. This can include patient data that may involve demographics, admission records, bed occupancy rates, and other operational parameters. As a source of raw data, cleaning and preparation of this data is done using functions like normalization and transformation into the system. Applying K-Means Clustering algorithm on this preprocessed data serves to segment it, thereby associating patients who share common attributes - medical and demographic needs from them to target analysis and predictions.

The second stage of the model selection and training models uses Gradient Boosting algorithms such as LightGBM or XGBoost. These models predict an admission and bed requirement for patients over time with improvements toward accuracy through each iteration and learn from the errors of the previous ones. The training focuses on predicting the length of stay, resource demand, and the dynamically inflowing patients.

In the Prediction Logic phase, the trained model simulates real-world scenarios for hospital management. It calculates the number of additional beds required based on predicted stay durations and occupancy trends. This simulation enables hospital administrators to proactively allocate resources, minimize bottlenecks, and reduce wait times for patients. The predictions are saved in a structured Resource Allocation Database for further reference and monitoring.

The Visualization and Feedback stage provides actionable insights through dynamic charts and graphs: Overall bed utilization trends, patient cluster distribution, potential resource shortages, and other vital information are illustrated by visual tools such as bar charts and pie charts. Visualization for Hospital Staff This is how the hospital staff can very quickly identify the trends that could influence workload balancing, cost-cutting, and patient care outcomes.

The technology will link predictive analytics and machine learning with intuitive visual feedback to enable a complete solution to such complex problems as hospital bed allocation. This innovation will help the healthcare provider realize optimized resource utilization, enhanced operational efficiency, and excellent patient care and sustainability within the health system.

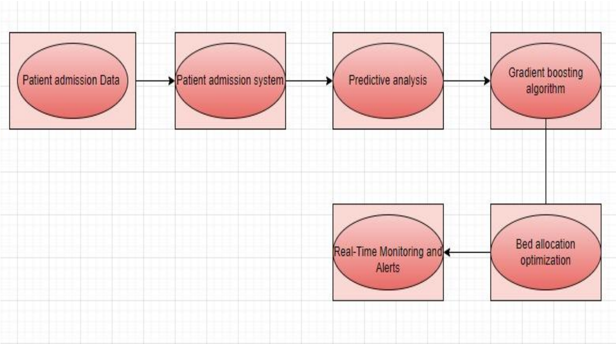


Figure 7: DFD of the Proposed System

IV. Working principle

Introduction to System Workflow

The workflow of the Hospital Bed Allocation Optimization System starts with easy upload of patient admission and operational data directly from the hospital administrators or data analysts through an intuitive web interface built on Flask, HTML, CSS, and JavaScript. This very interface provides effortless file uploads, kept entirely in the Patient Data Storage System, D1. This data would then be forwarded to the pre-processing stage, where cleaning and formatting would be done in preparation for analysis. The consistency of the data with the model's performance may be achieved through missing value imputation, normalization, and feature scaling.

Workflow Step:

Step 1: Load Data and Data Preprocessing

Step 1.1: The web interface receives hospital data submitted by users, which may include patient demographics and admission records, bed availability, or operational constraints.

Step 1.2: Data uploaded will be stored in D1: Patient Data Storage.

Step 1.3: The preprocessing completes and prepares data for analysis by the transformation of features along with removal of consistent values.

Step 2 : Segmentation through Clustering

Step 2.1: The system would also use K-Means Clustering to segment patients according to their characteristics-including demographics, medical needs, and length of stay.

Step 2.2: Such groups are used to obtain insights in planning resource allocation.

Step 3: Predictive Modeling

Step 3.1: The preprocessed and well-segmented data is fed into the Gradient Boosting Algorithm, for example, XGBoost or LightGBM.

Step 3.2: The model projects key metrics, including future patient admission rates, length of stay, and even department-specific bed demand.
Step 3.3: Iterative learning ensures the model refines predictions by minimizing errors from previous iterations.

Step 4: Analysis and Resource Use

Step 4.1: The bed requirement is determined department-wise and in total by aggregating predictions.

Step 4.2: The system simulates real-world scenarios by adjusting variables like total available beds to assess resource sufficiency.

Step 4.3: These results are then input into D2: Resource Allocation Database for further review and decision-making.

Step 5: Feedback and suggestions

Step 5.1: The system examines the predictions to highlight areas that might be improved

Step 5.2: Positive trends-an example would be the optimum usage of resources.
Bottlenecks, such as bed shortages in particular departments, are highlighted.

Step 5.3: This produces recommendations for balancing bed distribution, optimizing staff schedules, and improving operational efficiency for the management of the hospital.

Step 6: Visualization

Step6.1: Insights are visually presented in the form of bar charts, pie charts, and line graphs

Step 6.2: For department or patient categories, bed usage can be graphed out with a pie chart.

Step 6.3: Line graphs illustrate trends in patient admissions and bed availability over time.

Step 6.4: Such visualizations render data that is otherwise opaque usable for decision-making.

Step 7: Simulation and Interactive Features

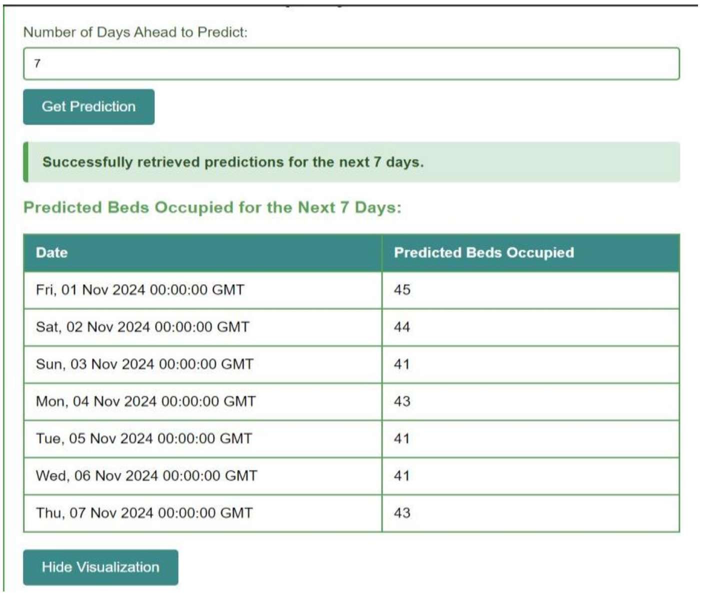
Step 7.1: Users can easily develop different scenarios based on variations such as increasing the bed capacity or changing the admission rate.

Step 7.2: Progress indicators and animations provide immediate feedback while simulations or analyses are being run.

Step 8: Results and Output

Step 8.1: The output displays the final analysis, comprising of:
Predictive metrics: bed shortages, sudden surges in demand.

Step 8.2: Actionable recommendations for optimizing hospital operations. Downloadable reports with key takeaways and visualizations for reference



Date	Predicted Beds Occupied
Fri, 01 Nov 2024 00:00:00 GMT	45
Sat, 02 Nov 2024 00:00:00 GMT	44
Sun, 03 Nov 2024 00:00:00 GMT	41
Mon, 04 Nov 2024 00:00:00 GMT	43
Tue, 05 Nov 2024 00:00:00 GMT	41
Wed, 06 Nov 2024 00:00:00 GMT	41
Thu, 07 Nov 2024 00:00:00 GMT	43

Figure 8: Bed Occupancy Prediction

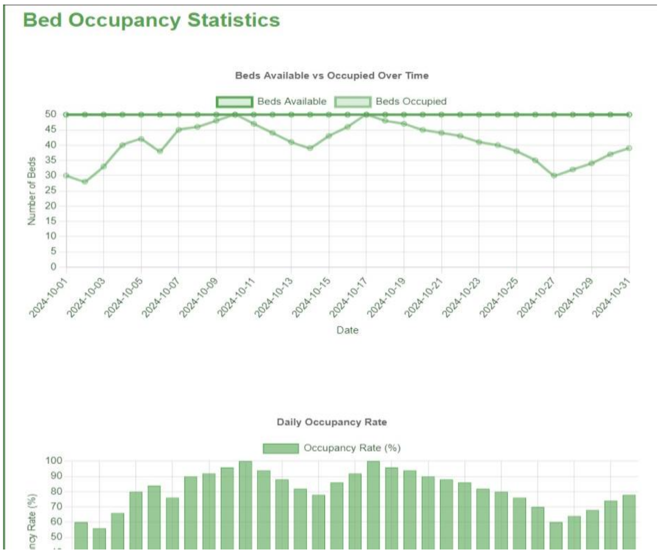


Figure 9: Prediction Analysis

V. RESULT AND CONCLUSION

Output

The hospital data is uploaded, computed by the system, and finally generates a comprehensive analysis that outlines the forecasts of patient admissions and the optimal bed sharing across all the departments. Then the findings are best articulated through a detailed pie chart to clearly break down metrics such as bed usage per department and patient categories. It would, for instance, show that 40% of the beds are used by emergencies, 30% by surgeries, and the remaining 30% by general admissions. In addition to graphical output, the system provides actionable feedback with strategy on balancing resources, reduction of waiting times among the patients, and optimal staff allocation. Administrators will also get a comprehensive report of the analysis, providing predictions and actionable recommendations, making sure data-driven decisions opt for optimizing hospital operations and patient care.

Conclusion

By and large, this project depicts a genuine step toward the implementation of hospital resources management using advancements in predictive analytics and machine learning capabilities. The system thus equips the healthcare administrators with insightful recommendations about the number of patients that should come in and optimizes bed allocation using Gradient Boosting and K-Means Clustering. Real-time analysis and visualization tools will overcome the traditional challenges associated with manual resource planning so that healthcare administrators may proactively make decisions. Thus, through this approach, patient outcomes could be improved in terms of a reduction in wait times and overcrowding with optimal resource utilization. The system also offers a foundation for the broader investigation in healthcare analytics, which extends to the most diversified application such as optimal staff workload and inventory management. Specifically, the answer should also benefit hospital operation and lead toward the eventual attainment of 'sustainable, patient-centered healthcare delivery'.

REFERENCES AND RESOURCES

[1] Adan, I., Bekkers, J., Dellaert, N., Vissers, J., & Yu, X. (2009). "Patient Mix Optimization and Stochastic Resource Requirements: A Case Study in Cardiothoracic Surgery Planning," *Health Care Management Science*, 12(2), 129-141.

[2] Ahmed, M. A., & Alkhamis, T. M. (2009). "Simulation Optimization for an Emergency Department Healthcare Unit in Kuwait," *European Journal of Operational Research*, 198(3), 936-942.

[3] Aboagye-Sarfo, P., Mai, Q., Sanfilippo, F. M., Preen, D. B., Stewart, L. M., & Fatovich, D. M. (2015). "A Comparison of Multivariate and Univariate Time Series Approaches to Modelling and Forecasting Emergency Department Demand in Western Australia," *Journal of Biomedical Informatics*, 57, 62-73.

[4] Chen, T., et al. (2016). "Gradient Boosting Decision Trees for Predicting Patient Outcomes in Healthcare," *Proceedings of the IEEE International Conference on Healthcare Informatics*, 121-130.

[5] Majzoubi, F., Bai, L., & Heragu, S. S. (2012). "An Optimization Approach to Dispatching and Relocating EMS Vehicles," *IIE Transactions on Healthcare Systems Engineering*, 2(3), 211-223.

[6] Nezamoddini, N., & Khasawneh, M. T. (2016). "Modeling and Optimization of Resources in Multi-Emergency Department Settings with Patient Transfer," *Operations Research for Healthcare*, 10, 23-34.

[7] Thomas, S., & Jayaraman, S. (2020). "Predicting Bed Allocation Using Gradient Boosting Techniques," *Journal of Healthcare Resource Management*, 18(4), 345-356.

[8] White, A. L., & Greenfield, R. (2019). "The Role of Clustering Techniques in Optimizing Hospital Resources," *Journal of Applied Data Science*, 27(3), 112-129.

[9] Liu, X., et al. (2018). "Real-Time Analytics for Resource Allocation in Hospitals Using Machine Learning," *IEEE Transactions on Learning Technologies*, 11(2), 142-151.

[10] Cao, Y., et al. (2017). "A Survey on Hospital Bed Allocation Optimization Techniques," *Journal of Operational Research in Healthcare*, 14(5), 230-246.