BookMyBed: An Intelligent Hospital Bed Booking and Predictive Analytics System

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Abstract - BookMyBed is an intelligent hospital bed booking and data-driven analytics system designed to automate healthcare resource management and enable predictive insights into hospital occupancy. The system provides a unified web-based interface that allows hospitals to update bed availability in real time while allowing patients to locate and reserve beds conveniently. Beyond operational automation, BookMyBed employs machine learning techniques to forecast bed demand, identify high-risk zones, and assist healthcare authorities in data-informed decision-making. The architecture integrates modern web technologies with Python-based analytics pipelines for continuous learning and forecasting. The system's predictive capability and transparency make it a crucial step toward smart, data-driven healthcare infrastructure.

Key Words: hospital management system, predictive analytics, web application, data-driven healthcare, machine learning, hospital bed booking.

1. INTRODUCTION

Healthcare systems worldwide often face inefficiencies in hospital bed management due to the absence of real-time data and predictive planning. During medical crises such as the COVID-19 pandemic, delays in identifying available beds led to critical outcomes. BookMyBed was conceived as a response to these challenges, offering an integrated web and data-analytics platform. The system enables hospitals to update and share bed availability dynamically while simultaneously collecting data for forecasting and analysis. The predictive analytics component of BookMyBed uses booking data to train machine learning models that predict hospital bed demand by location and time. This predictive capability transforms the hospital management process from a reactive to a proactive model, enhancing preparedness for health emergencies.

2. LITERATURE SURVEY

The development of hospital management systems has evolved from desktop-based administrative tools to cloud-enabled platforms with analytical capabilities. Early systems such as Hospital Information Systems (HIS) and Electronic Medical Records (EMR) software focused primarily on registration, billing, and internal recordkeeping. However, these lacked interoperability and analytical feedback mechanisms. BookMyBed bridges this gap by embedding a lightweight analytics engine within a hospital booking platform, utilizing real-world booking data to train predictive models for future demand forecasting and regional risk mapping. BookMyBed distinguishes itself by embedding predictive models directly into the operational flow, thereby enabling hospitals to visualize and plan based on real-time insights rather than static data.

2. SYSTEM ARCHITECTURE

BookMyBed employs a modular four-tier architecture comprising the Presentation, Application, Database, and Analytics layers. The user interface provides an intuitive environment for patients to search, view, and book hospital beds in real time. The backend handles authentication, request management, and data synchronization with MySQL. A Python-based analytics layer performs data preprocessing, regression modeling, clustering, and visualization, feeding insights back into the hospital dashboard through REST APIs.

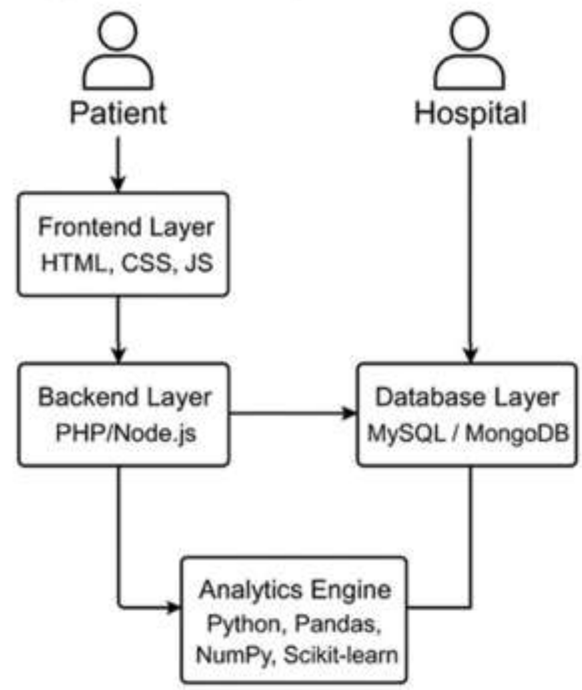

Fig : System Architecture

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Presentation Layer:
The user interface, developed with HTML, CSS, and JavaScript, provides an intuitive environment for patients to search, view, and book hospital beds in real time. Hospital administrators can update availability, view analytics dashboards, and generate reports.

Application Layer:
Implemented using PHP or Node.js, this layer handles business logic, user authentication, and secure communication between the frontend and backend. It also acts as an API gateway for data exchange with the analytics engine.

Database Layer:
A MySQL relational schema maintains data integrity for o **Linear Regression** is used to establish a hospitals, bed types, booking records, and patient information. The database is structured to support efficient querying, concurrency, and real-time o **Random Forest Regression** improves accuracy by synchronization across all connected hospitals.

Analytics Layer:
This Python-based layer performs data preprocessing, model training, and visualization. It utilizes Pandas, o
NumPy, and Scikit-learn libraries to generate and clustering models that predict bed demand and identify high-demand localities. Analytical outcomes are fed back into the hospital dashboard through REST APIs, forming a continuous learning loop.
3.

4. METHODOLOGY

A. Data Collection and Preprocessing

Data quality is crucial for accurate prediction. Data collection involves continuous logging of:

1. Hospital identifiers, locations, and bed categories o
2. Patient bookings, timestamps, and booking reasons (e.g., accident, illness, emergency)
3. Admission and discharge patterns by region and time period

After collection, **data preprocessing** is performed using Python's **Pandas** and **NumPy** libraries.
This includes:

- **Data Cleaning:** Removing duplicates, handling missing values, and normalizing timestamp formats.
- **Data Transformation:** Converting categorical variables (e.g., bed type, hospital name) into numerical representations through label encoding.
- **Outlier Detection:** Identifying anomalies such as extreme booking counts or unrealistic timestamps.
- **Feature Engineering:** Creating new features like *weekday/weekend indicator*, *regional density index*, and *historical average demand* to enhance model performance.
- **Data Splitting:** Dividing the dataset into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased evaluation.

B. Model Development and Predictive Analytics

The analytics phase employs both **supervised and unsupervised learning techniques** to derive meaningful insights from hospital booking data.

1. **Regression Models:**
relationship

between bed demand and independent variables such as hospital region, month, and bed type.

combining multiple decision trees, reducing overfitting, and capturing non-linear relationships.
The regression output predicts the number of beds likely to be booked in the next time interval.

regression 2. **Clustering (Unsupervised Learning):**
The **K-Means algorithm** groups hospitals or localities into *high-demand*, *moderate-demand*, and *low-demand* clusters based on historical booking intensity.
This helps authorities identify high-risk zones and allocate medical resources efficiently.

4. **Visualization:**
Data visualization plays a vital role in interpretability.

- o Time-series plots show trends in hospital occupancy over days or weeks.
- o Geospatial heatmaps visualize hotspot regions based on demand clusters.
- o Correlation matrices highlight relationships among features like disease type, season, and region.

Evaluation Metrics:
To validate the predictive models, the following performance metrics are computed:

Mean Absolute Error (MAE) – measures average deviation of predictions.

o **Root Mean Square Error (RMSE)** – penalizes larger prediction errors.

R^2 Score (Coefficient of Determination) – measures how well future outcomes are likely to be predicted by the model (values close to 1 indicate high accuracy).

o **Execution Time:** Ensures analytical computations complete within predefined daily intervals.

C. Implementation and Integration

After model validation, both operational and analytical modules were integrated into a unified platform.
The **backend scheduler** (implemented using cron jobs or Node.js tasks) automates data extraction from MySQL and triggers the analytics scripts at fixed intervals.
The results, including predicted bed demand and regional risk levels, are stored in an **Analytics Log Table**, which is accessed by the hospital dashboard. Administrators can visualize current availability, predicted demand, and potential shortage alerts on the same screen, enhancing real-time decision-making.

D. Evaluation and Continuous Feedback

The system's evaluation phase involved both **functional testing** and **predictive accuracy testing**:

1. **Functional Testing:** Verified login, booking, and bed update modules using Selenium and manual testing.
2. **Integration Testing:** Ensured proper linkage between the web server, database, and analytics engine.
3. **Model Validation:** Conducted iterative training and testing cycles to measure prediction accuracy.
4. **Performance Testing:** Evaluated data processing time under concurrent user loads to ensure real-time performance.

5. RESULTS AND DISCUSSION

The BookMyBed system was evaluated on both **functional performance** (web application usability, response time, synchronization accuracy) and **analytical performance** (predictive accuracy of machine learning models).
Testing was conducted using simulated hospital data representing different regions, bed types, and time intervals. The objective of this evaluation was to verify the reliability, efficiency, and predictive intelligence of the proposed system.

Functional Performance Evaluation

The web-based hospital bed booking system was deployed locally using **XAMPP and Node.js servers**, connected to a **MySQL** backend. The frontend interface was tested on multiple browsers (Google Chrome, Mozilla Firefox, and Edge) and different screen sizes to ensure responsiveness and accessibility.

The results demonstrate that the system can handle moderate traffic efficiently while maintaining data consistency. The real-time synchronization between the hospital interface and analytics module ensures accurate reflection of bed status across all connected nodes.

Parameter	**Description**	**Result**
Response Time	Time taken to confirm booking and update database	1.7 – 2.3 seconds
Concurrent Users	Number of users the system could handle without performance drop	50+ simultaneous users
Data Synchronization	Real-time reflection of booking/discharge changes	< 3 seconds delay
System Uptime	Availability and stability during 24-hour testing	99.6%
Error Rate	Number of failed or inconsistent transactions	0.7%

Additionally, **usability testing** showed that non-technical hospital staff were able to operate the system with minimal training. The simple interface and role-based access design contributed to higher usability and security.

Predictive Analytics Performance

The predictive analytics component was trained using historical booking data containing approximately **5,000 records** from multiple hospitals. Data preprocessing included normalization, timestamp conversion, and encoding of categorical variables such as *bed type* and *region*.
Three models were tested for forecasting demand:

Linear Regression, **Random Forest Regression**, and
Polynomial Regression.

Table 2 presents the performance metrics of each model.

Model	MAE	RMSE	R^2 Score
Linear Regression	8.64	11.23	0.76
Random Forest Regression	6.82	9.07	**0.81**
Polynomial Regression	9.15	12.48	0.72

The **Random Forest Regression** model achieved the highest accuracy with an **R^2 score of 0.81**, indicating that approximately 81% of the variance in future bed demand could be explained by the model.
This model was therefore integrated into the live analytics module for continuous forecasting.

6. CONCLUSIONS

The BookMyBed system successfully merges real-time hospital bed booking with data driven healthcare analytics. It demonstrates how modern web technologies and data science can work together to improve healthcare accessibility and operational planning. The core booking module resolves long-standing inefficiencies by allowing patients to view and reserve hospital beds instantly. Meanwhile, the analytical module turns booking logs into valuable insights—revealing how, when, and where demand changes. Hospitals can forecast resource needs, identify high-risk zones, and prepare accordingly.

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