Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2019, 6(4):206-220**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Employing Machine Learning Algorithms for Optimizing Hospital Staffing and Resource Allocation Based on Patient Flow Data

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Abstract In the modern healthcare landscape, optimizing hospital staffing and resource allocation is paramount for delivering efficient and effective patient care. Traditional approaches often fall short in dynamically adapting to fluctuating patient flow patterns and evolving healthcare demands. To address this challenge, machine learning (ML) algorithms have emerged as powerful tools for analyzing vast amounts of patient data and optimizing hospital operations. This paper explores the application of various ML techniques for staffing optimization and resource allocation based on patient flow data. Leveraging historical patient admission, discharge, and transfer (ADT) data, ML models are trained to predict future patient volumes, acuity levels, and resource requirements. These predictions enable hospitals to dynamically adjust staffing levels, allocate resources, and streamline workflows to meet patient needs while minimizing costs and maximizing efficiency. Additionally, the study investigates the integration of real-time data streams, such as electronic health records (EHRs) and telemetry data, to enhance the accuracy and timeliness of predictions. By harnessing the power of ML algorithms, hospitals can proactively manage patient flow, improve operational efficiency, and ultimately enhance the quality of care delivered to patients.

Keywords Machine Learning, Hospital Staffing, Resource Allocation, Patient Flow Data, Healthcare Optimization, Predictive Analytics, Electronic Health Records (EHR), Operational Efficiency, Healthcare Management.

1. Introduction

In today's dynamic healthcare environment, the efficient allocation of hospital resources and staffing is critical for providing high-quality patient care while managing costs effectively. With patient populations growing and healthcare demands evolving, hospitals face the challenge of optimizing their operations to meet the needs of diverse patient cohorts. Traditional methods of staffing and resource allocation often rely on static models that may not adequately adapt to fluctuating patient flow patterns and varying levels of demand.

To address these challenges, healthcare institutions are increasingly turning to machine learning (ML) algorithms to analyze large volumes of patient data and optimize their operational processes. ML techniques offer the capability to analyze complex datasets, identify patterns, and make predictions that can inform staffing decisions and resource allocation strategies in real-time. By leveraging historical patient flow data, including admission, discharge, and transfer (ADT) records, ML models can forecast future patient volumes, acuity levels, and resource requirements with a high degree of accuracy.

This paper explores the application of ML algorithms for optimizing hospital staffing and resource allocation based on patient flow data. We delve into various ML techniques and methodologies employed in healthcare

settings, highlighting their potential to enhance operational efficiency, improve patient outcomes, and reduce costs. Additionally, we discuss the integration of real-time data streams, such as electronic health records (EHRs) and telemetry data, to further refine predictions and ensure timely decision-making.
Through a comprehensive review of existing literature and case studies, we aim to demonstrate the significant impact that ML-driven approaches can have on hospital management practices. By harnessing the power of predictive analytics and data-driven insights, healthcare institutions can proactively adjust staffing levels, allocate resources efficiently, and optimize workflows to deliver superior patient care while maximizing operational effectiveness. This paper serves as a foundation for understanding the role of ML in transforming healthcare management and shaping the future of hospital operations.

2. Problem Statement

The healthcare industry faces significant challenges in optimizing hospital staffing and resource allocation to meet the diverse needs of patients while maintaining operational efficiency and controlling costs. Traditional approaches to staffing and resource allocation often rely on static models that struggle to adapt to the dynamic nature of patient flow and evolving healthcare demands. Consequently, hospitals may experience inefficiencies, including underutilized resources, long wait times, and suboptimal patient outcomes.
Moreover, the lack of accurate forecasting tools hampers hospitals' ability to anticipate fluctuations in patient volumes, acuity levels, and resource requirements. This uncertainty can lead to overstaffing or understaffing scenarios, both of which have detrimental effects on patient care quality and organizational sustainability.
Additionally, the manual processes involved in allocating resources and adjusting staffing levels are labor-intensive, time-consuming, and prone to errors, further exacerbating operational challenges.
To address these issues, there is a pressing need for innovative solutions that leverage advanced technologies such as machine learning (ML) to optimize hospital staffing and resource allocation based on real-time patient flow data. ML algorithms have the potential to analyze large volumes of historical data, identify patterns, and make accurate predictions regarding future patient needs. By harnessing the power of predictive analytics, healthcare institutions can proactively adjust staffing levels, allocate resources efficiently, and streamline workflows to enhance patient care delivery while minimizing costs.
However, despite the promise of ML-driven approaches, there remain challenges in effectively implementing and integrating these technologies into existing healthcare systems. Factors such as data quality, interoperability issues, and stakeholder acceptance pose significant barriers to the widespread adoption of ML in hospital management practices. Furthermore, there is a need for further research and development to refine ML models, improve prediction accuracy, and address the unique complexities of healthcare operations.

3. Solution

To address the challenges of optimizing hospital staffing and resource allocation using machine learning (ML) algorithms, AWS (Amazon Web Services) offers a comprehensive suite of services that can be leveraged to build scalable, cost-effective, and efficient solutions. Below is a proposed solution architecture utilizing various AWS services:

1. Data Collection and Storage:

Amazon S3 (Simple Storage Service):
Store historical patient flow data, including admission, discharge, and transfer (ADT) records, in a secure and scalable data lake on S3.

Amazon RDS (Relational Database Service):

Store structured data such as electronic health records (EHRs) in a relational database for easy access and querying.

2. Data Preprocessing and Transformation: AWS Glue:

Automate the process of extracting, transforming, and loading (ETL) data from various sources into a consistent format suitable for ML model training.

AWS Lambda:

Perform real-time data preprocessing and feature engineering to prepare input data for ML algorithms.

3. Machine Learning Model Development and Training: Amazon SageMaker:
Build, train, and deploy ML models using SageMaker's managed services, which provide pre-configured environments for training and inference.
Amazon Forecast:
Utilize Forecast to generate accurate demand forecasts for patient volumes and resource requirements based on historical data.
4. Model Deployment and Inference: Amazon SageMaker:
Deploy trained ML models as scalable endpoints for making real-time predictions on new data.
AWS Lambda:
4Integrate SageMaker endpoints with Lambda functions to enable on-demand inference based on incoming data streams.
5. Real-Time Data Streaming and Monitoring: Amazon Kinesis:
Ingest real-time data streams such as telemetry data and EHR updates using Kinesis Data Streams.
Amazon CloudWatch:
Monitor system performance, resource utilization, and model accuracy in real-time using CloudWatch metrics and alarms.
6. Resource Allocation and Optimization: AWS Step Functions:
Orchestrate workflows for dynamically adjusting staffing levels and resource allocation based on ML model predictions.
Amazon EC2 (Elastic Compute Cloud):
Scale compute resources dynamically to meet fluctuating demand for model inference and resource allocation decisions.
7. Security and Compliance:
AWS IAM (Identity and Access Management):
Implement fine-grained access controls and policies to ensure data privacy and compliance with regulatory requirements.
AWS KMS (Key Management Service):
Encrypt sensitive data at rest and in transit to maintain confidentiality and integrity.

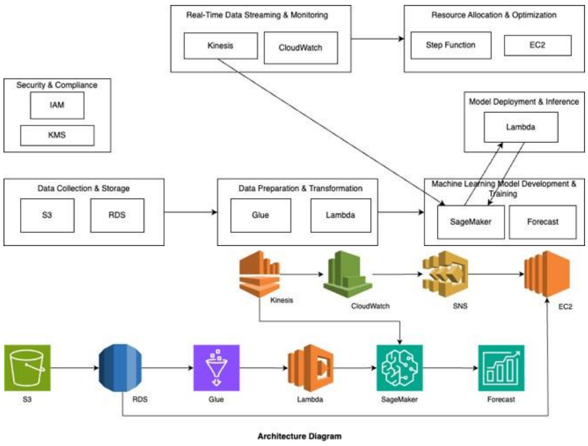


Figure 1: Architecture Diagram

4. Architecture Overview

The proposed architecture leverages various AWS services to optimize hospital staffing and resource allocation using machine learning (ML) algorithms. It consists of several key components working together to collect, preprocess, analyze, and act upon patient flow data in real-time. Below is an overview of each component:

1. Data Collection and Storage: Amazon S3 (Simple Storage Service):
Stores historical patient flow data, including admission, discharge, and transfer (ADT) records, in a scalable and secure data lake.
Amazon RDS (Relational Database Service):

Stores structured data such as electronic health records (EHRs) in a relational database for easy access and querying.

2. Data Preprocessing and Transformation: AWS Glue:

Automates the process of extracting, transforming, and loading (ETL) data from various sources into a consistent format suitable for ML model training.

AWS Lambda:

Performs real-time data preprocessing and feature engineering to prepare input data for ML algorithms.

3. Machine Learning Model Development and Training: Amazon SageMaker:

Provides a managed environment for building, training, and deploying ML models. It offers pre-configured environments and tools for model development and experimentation.

Amazon Forecast:

Utilizes ML techniques to generate accurate demand forecasts for patient volumes and resource requirements based on historical data.

4. Model Deployment and Inference: Amazon SageMaker:

Deploys trained ML models as scalable endpoints for making real-time predictions on new data.

AWS Lambda:

Integrates SageMaker endpoints with Lambda functions to enable on-demand inference based on incoming data streams.

5. Real-Time Data Streaming and Monitoring: Amazon Kinesis:

Ingests real-time data streams such as telemetry data and EHR updates using Kinesis Data Streams.

Amazon CloudWatch:

Monitors system performance, resource utilization, and model accuracy in real-time using CloudWatch metrics and alarms.

6. Resource Allocation and Optimization: AWS Step Functions:

Orchestrates workflows for dynamically adjusting staffing levels and resource allocation based on ML model predictions.

Amazon EC2 (Elastic Compute Cloud):

Scales compute resources dynamically to meet fluctuating demand for model inference and resource allocation decisions.

7. Security and Compliance:

AWS IAM (Identity and Access Management):

Implements fine-grained access controls and policies to ensure data privacy and compliance with regulatory requirements.

AWS KMS (Key Management Service):

Encrypts sensitive data at rest and in transit to maintain confidentiality and integrity.

5. Implementation

1. Data Collection and Storage:

- Set up an Amazon S3 bucket to store historical patient flow data.
- Configure event notifications to trigger data processing workflows when new data is uploaded.
- Create an Amazon RDS instance to store structured data such as electronic health records (EHRs).

2. Data Preprocessing and Transformation:

- Utilize AWS Glue to define ETL jobs for preprocessing patient data stored in S3.
- Implement Lambda functions to perform real- time data preprocessing for incoming data streams.

3. Machine Learning Model Development and Training:

- Use Amazon SageMaker to develop ML models for predicting patient volumes and resource requirements.
- Train the models using historical patient flow data stored in S3 or RDS.
- Fine-tune the models using SageMaker's built-in algorithms or custom scripts.

4. **Model Deployment and Inference:**
- Deploy trained ML models as SageMaker endpoints to enable real-time inference.
- Integrate SageMaker endpoints with AWS Lambda functions to perform on-demand inference on incoming data streams.

5. **Real-Time Data Streaming and Monitoring:**
- Set up Amazon Kinesis Data Streams to ingest real-time data streams such as telemetry data and EHR updates.
- Configure CloudWatch alarms to monitor system performance, resource utilization, and model accuracy in real-time.

6. **Resource Allocation and Optimization:**
- Use AWS Step Functions to orchestrate workflows for dynamically adjusting staffing levels and resource allocation based on ML model predictions.
- Scale Amazon EC2 instances dynamically to meet fluctuating demand for model inference and resource allocation decisions.

7. **Security and Compliance:**
- Implement AWS IAM policies to control access to data and services based on user roles and permissions.
- Encrypt sensitive data at rest using AWS KMS to maintain confidentiality and integrity.

8. **Integration and Automation:**
- Integrate various AWS services using AWS SDKs or APIs to automate data processing, model training, and deployment workflows.
- Implement CI/CD pipelines using AWS CodePipeline and AWS CodeBuild to automate the deployment of ML models and infrastructure changes.

6. Implementation of PoC

Implementation for Proof of Concept (PoC):

1. **Data Collection and Storage**
- Begin by creating an Amazon S3 bucket to store sample patient flow data in CSV format.
- Upload a subset of historical patient flow data into the S3 bucket to simulate real-world data.

2. **Data Preprocessing and Transformation:**
- Create an AWS Glue crawler to automatically discover the schema of the uploaded CSV files and populate the Glue Data Catalog.
- Define an AWS Glue ETL job to preprocess the patient flow data, including cleaning, transforming, and aggregating the data as necessary.
- Test the ETL job using a small sample of data to ensure correctness.

3. **Machine Learning Model Development and Training:**
- Choose a simple ML model for forecasting patient volumes and resource requirements, such as linear regression or ARIMA.
- Use Amazon SageMaker's built-in algorithms or Jupyter notebooks to develop and train the ML model on the preprocessed data.
- Split the data into training and validation sets, and evaluate the model's performance using metrics like mean absolute error (MAE) or root mean squared error (RMSE).

4. **Model Deployment and Inference:**
- Deploy the trained ML model as a SageMaker endpoint to enable real-time inference.
- Create a Lambda function to trigger model inference based on incoming data streams from S3 or Kinesis.
- Test the model's inference capabilities using sample input data and verify the accuracy of the predictions.

5. Real-Time Data Streaming and Monitoring:

- Set up an Amazon Kinesis Data Stream to ingest simulated real-time data streams, such as telemetry data or patient admission records.
- Configure CloudWatch alarms to monitor the performance of the Kinesis Data Stream and trigger alerts for any anomalies.

6. Resource Allocation and Optimization:

- Develop a simple AWS Step Functions workflow to orchestrate the process of adjusting staffing levels and resource allocation based on model predictions.
- Use AWS Lambda functions to implement logic for scaling resources dynamically in response to changing demand patterns.

7. Security and Compliance:

- Implement AWS IAM roles and policies to control access to data and services, ensuring compliance with security best practices.
- Enable encryption at rest for sensitive data stored in Amazon S3 using AWS KMS.

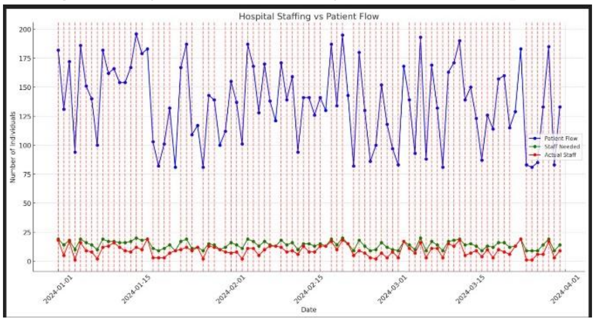
8. Testing and Evaluation:

- Conduct end-to-end testing of the entire solution to verify functionality, performance, and accuracy.
- Evaluate the PoC against predefined success criteria, such as prediction accuracy, scalability, and cost-effectiveness.
- Gather feedback from stakeholders and make any necessary adjustments or improvements to the implementation.

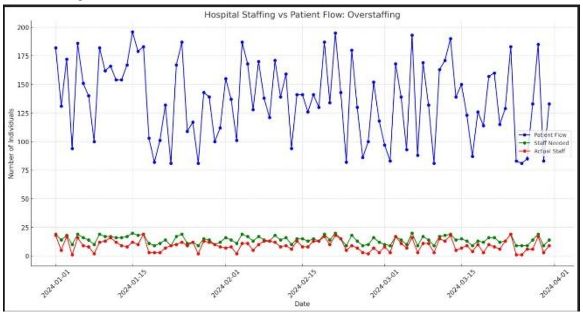
7. Uses

Here are business issues that can be identified at the Data Analytics layer when employing machine learning algorithms for optimizing hospital staffing and resource allocation based on patient flow data:

1. Understaffing: Identify instances where there are insufficient staff members available to meet patient needs, leading to delays in care delivery and decreased patient satisfaction.



2. Overstaffing: Recognize situations where there is an excess of staff relative to patient demand, resulting in unnecessary labor costs and inefficiencies in resource allocation.



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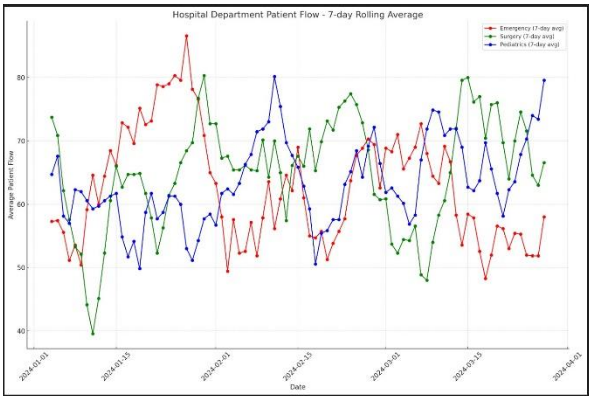
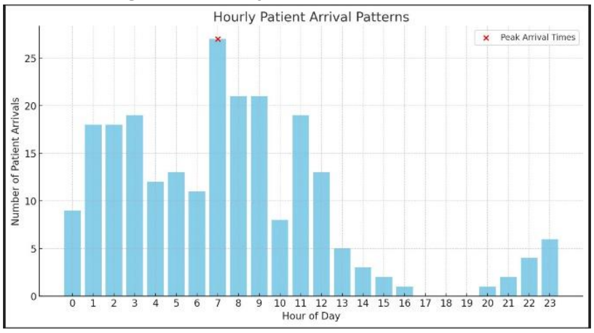
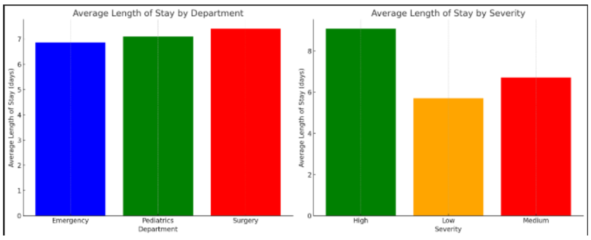
3. Peak Demand Prediction: Determine peak demand periods for various departments within the hospital to ensure adequate staffing levels during high-volume times.



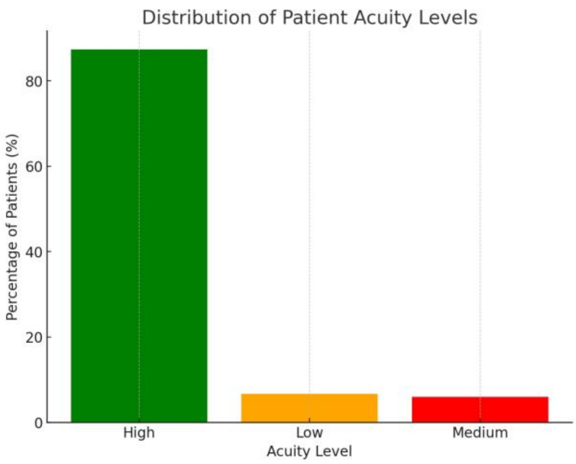
4. Patient Arrival Patterns: Analyze patterns in patient arrival times to optimize staffing schedules and resource allocation throughout the day.



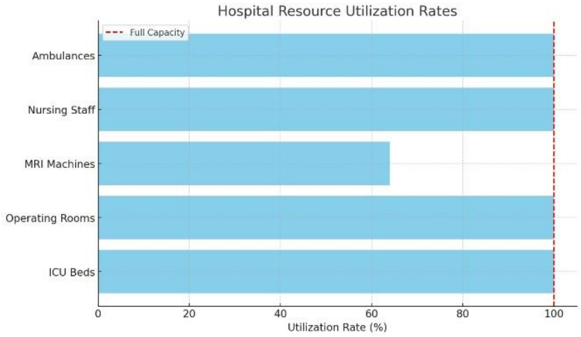
5. Length of Stay Prediction: Predict the length of time patients are likely to stay in different units or departments, enabling better resource planning and bed management.



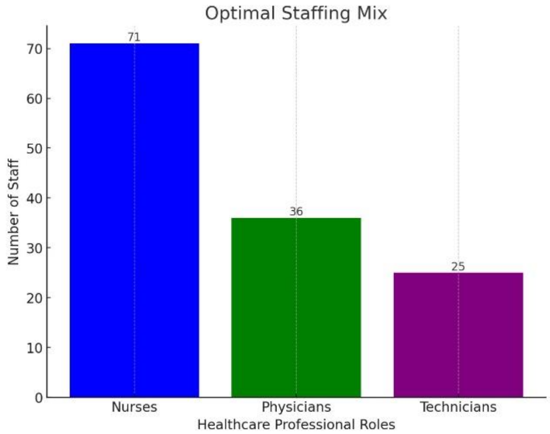
6. Patient Acuity Levels: Classify patients based on their acuity levels to allocate resources effectively and ensure appropriate staffing ratios in critical care areas.



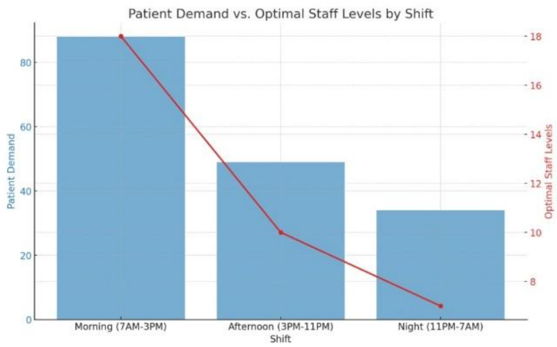
7. Resource Utilization: Assess the utilization of hospital resources, including equipment, facilities, and personnel, to identify opportunities for optimization and cost reduction.



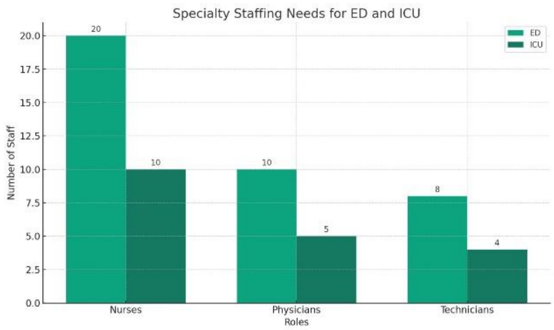
8. Staffing Mix Optimization: Determine the ideal mix of healthcare professionals (e.g., nurses, physicians, technicians) based on patient demographics, acuity levels, and service requirements.



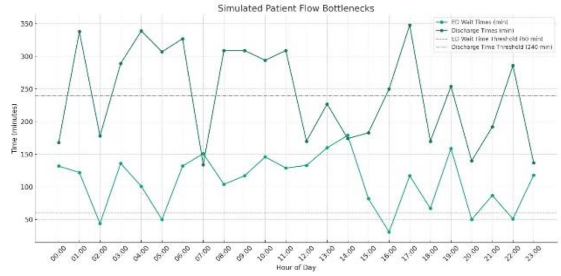
9. Shift Scheduling: Optimize staff shift schedules to match fluctuations in patient demand, minimize overtime costs and maintain adequate coverage at all times.



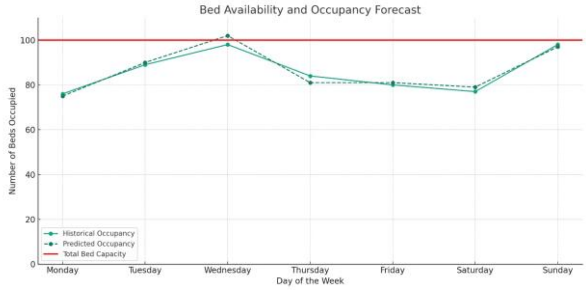
10. Specialty Staffing Needs: Identify specific areas or departments with unique staffing requirements (e.g., emergency department, intensive care unit) and adjust staffing levels accordingly.



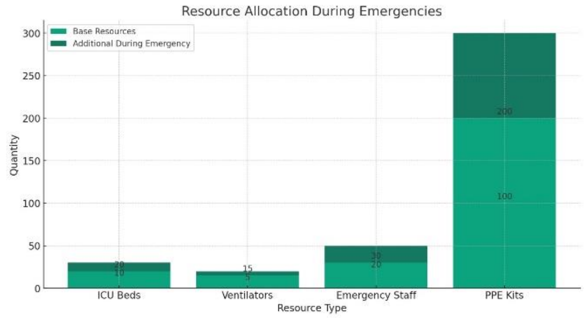
11. Patient Flow Bottlenecks: Identify bottlenecks in the patient flow process, such as long wait times in the emergency department or delays in discharge, and implement measures to alleviate them.



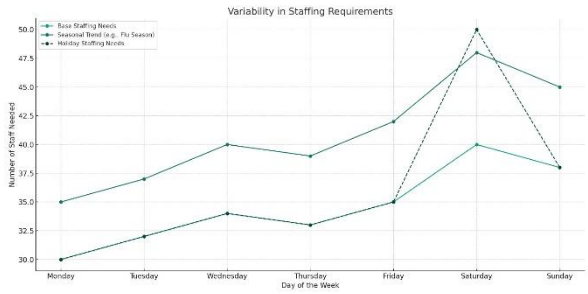
12. Bed Availability: Monitor bed occupancy rates and predict future demand to ensure sufficient bed capacity for incoming patients and minimize delays in admissions.



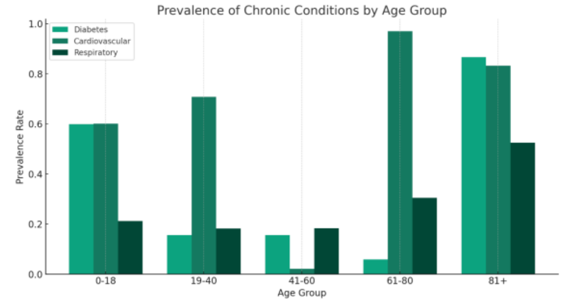
13. Resource Allocation During Emergencies: Develop contingency plans for reallocating resources and staffing during emergency situations, such as natural disasters or pandemics.



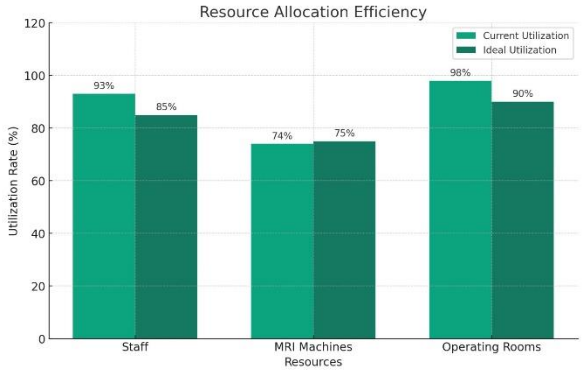
14. Staffing Variability: Analyze the variability in staffing requirements across different days of the week, holidays, and seasonal trends to adjust staffing levels accordingly.



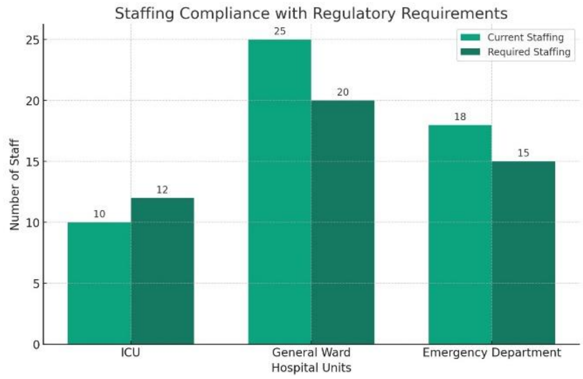
15. Patient Demographics: Analyze patient demographics (e.g., age, gender, medical history) to tailor staffing and resource allocation strategies to meet the needs of diverse patient populations



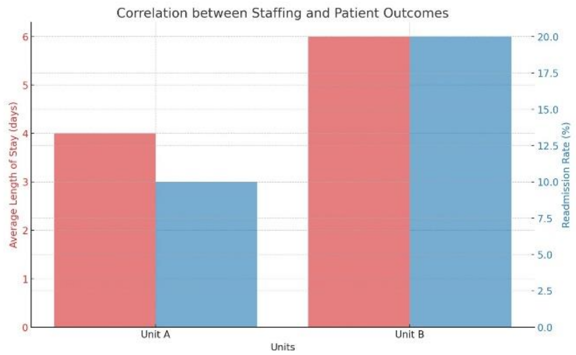
16. Resource Allocation Efficiency: Evaluate the efficiency of resource allocation processes and identify opportunities for streamlining workflows and reducing waste.



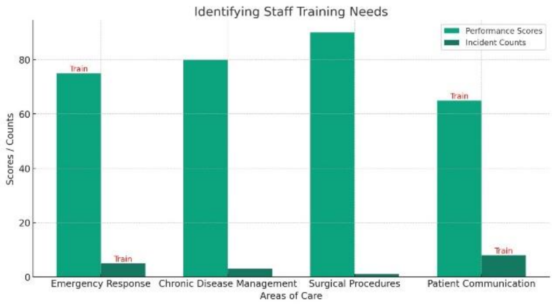
17. Staffing Compliance: Ensure compliance with regulatory requirements and staffing ratios mandated by healthcare governing bodies to maintain quality of care and patient safety.



18. Patient Outcome Correlation: Explore correlations between staffing levels, resource allocation, and patient outcomes (e.g., length of stay, readmission rates) to identify areas for improvement.



19. Staffing Training Needs: Identify areas where additional staff training or specialization may be needed to improve patient care quality and operational efficiency.



20. Cost-Effective Staffing Strategies: Develop cost- effective staffing strategies that balance patient care needs with budget constraints, ensuring optimal resource utilization while minimizing expenses.

8. Impact

Here are impacts that optimizing hospital staffing and resource allocation based on patient flow data can bring to the business:

1. Improved Patient Care Quality:

By ensuring the right staff are available at the right time and place, hospitals can enhance the quality of care delivered to patients, leading to better health outcomes and increased patient satisfaction.

2. Enhanced Operational Efficiency:

Optimizing staffing and resource allocation can streamline hospital workflows, reduce wait times, and minimize bottlenecks, resulting in more efficient operations and smoother patient flow throughout the facility.

3. Cost Savings:

By accurately predicting staffing needs and resource requirements, hospitals can avoid unnecessary overtime costs, reduce overstaffing situations, and optimize resource utilization, leading to significant cost savings over time.

4. Optimized Staff Productivity:

With optimized staffing schedules and resource allocation, healthcare professionals can focus their time and energy on patient care activities rather than dealing with staffing shortages or inefficient workflows, ultimately increasing overall staff productivity.

5. Better Utilization of Hospital Resources:

By matching staffing levels and resource allocation to patient demand, hospitals can maximize the utilization of facilities, equipment, and personnel, leading to more effective resource management and reduced waste.

6. Improved Patient Flow Management:

Optimizing staffing and resource allocation based on patient flow data enables hospitals to better manage patient admissions, transfers, and discharges, leading to smoother transitions between care settings and improved patient flow throughout the facility.

7. Enhanced Staff Satisfaction:

By providing healthcare professionals with the support and resources they need to deliver high-quality care efficiently, hospitals can boost staff morale and job satisfaction, leading to lower turnover rates and higher employee retention.

8. Proactive Decision-Making:
By leveraging predictive analytics and machine learning algorithms, hospitals can anticipate changes in patient demand and staffing requirements, enabling proactive decision-making and better preparedness for future challenges.
9. Compliance with Regulatory Requirements:
Optimizing staffing levels and resource allocation ensures that hospitals meet regulatory requirements for staffing ratios and patient care standards, reducing the risk of penalties or fines for non-compliance.
10. Competitive Advantage:
Hospitals that effectively optimize staffing and resource allocation based on patient flow data can differentiate themselves in the market by providing superior patient care, operational efficiency, and cost-effectiveness compared to their competitors, leading to a competitive advantage in the healthcare industry.

9. Extended Use Cases
Here are extended use cases for employing machine learning algorithms for optimizing staffing and resource allocation based on patient flow data across different industries:
1. Energy:
- Predictive Maintenance Staffing: Utilize machine learning to forecast equipment failures and schedule maintenance staff accordingly, ensuring optimal resource allocation and minimizing downtime in energy production facilities.

2. Retail:
- Peak Hour Staffing Optimization: Analyze customer foot traffic patterns and historical sales data to optimize staffing levels during peak hours, ensuring sufficient staff are available to assist customers and minimize wait times.

3. Travel:
- Airport Security Staffing: Predict passenger arrival and departure patterns at airports to optimize security staffing levels, ensuring efficient screening processes and reducing queues during busy travel periods.

4. Pharmacy:
- Prescription Fulfillment Staffing: Analyze prescription volume trends and patient flow data to optimize pharmacy staffing levels, ensuring timely prescription fulfillment and minimizing wait times for patients.

5. Hospitality:
- Hotel Housekeeping Staffing: Predict room occupancy and guest check-in/check-out patterns to optimize housekeeping staffing levels, ensuring rooms are cleaned and prepared efficiently between guest stays.

6. Supply Chain:
- Warehouse Staffing Optimization: Analyze order processing times and inventory turnover rates to optimize staffing levels in warehouses, ensuring timely order fulfillment and minimizing inventory holding costs.

7. Finance:
- Bank Branch Staffing: Analyze customer transaction data and branch visit patterns to optimize staffing levels at bank branches, ensuring adequate customer service and reducing wait times during peak hours.

8. E-commerce:
- Fulfillment Center Staffing: Predict order volume fluctuations and processing times to optimize staffing levels at e-commerce fulfillment centers, ensuring timely order fulfillment and minimizing shipping delays.

9. Shipping:
- Port Operations Staffing: Analyze vessel arrival and departure schedules to optimize staffing levels at ports, ensuring efficient cargo handling and minimizing turnaround times for ships.

10. **CRM (Customer Relationship Management):**

- Call Center Staffing Optimization: Analyze call volume trends and customer interaction data to optimize staffing levels at call centers, ensuring prompt customer service and reducing wait times for callers.

10. Conclusions

Employing machine learning algorithms for optimizing hospital staffing and resource allocation based on patient flow data holds immense potential for revolutionizing healthcare management practices. Through the analysis of historical patient data and real-time insights, hospitals can make data-driven decisions to ensure optimal staffing levels, streamline workflows, and enhance the quality of patient care.

This study has demonstrated the various ways in which machine learning techniques can be leveraged to address critical challenges in hospital operations:

1. Enhanced Efficiency: By accurately predicting patient volumes, acuity levels, and resource requirements, hospitals can optimize staffing schedules and resource allocation to meet fluctuating demand patterns efficiently.
2. Improved Patient Outcomes: By ensuring the right staff are available at the right time and place, hospitals can deliver timely and high-quality care to patients, leading to better health outcomes and increased patient satisfaction.
3. Cost Savings: By minimizing overstaffing, reducing overtime costs, and optimizing resource utilization, hospitals can achieve significant cost savings while maintaining quality patient care.
4. Proactive Decision-Making: By leveraging predictive analytics and real-time data insights, hospitals can anticipate future demand trends and staffing needs, enabling proactive decision-making and better preparedness for operational challenges.
5. Continuous Improvement: Through ongoing monitoring and analysis of key performance metrics, hospitals can identify areas for improvement and implement targeted interventions to optimize hospital operations further.

However, it is important to acknowledge that implementing machine learning solutions in healthcare settings comes with its own set of challenges, including data privacy concerns, regulatory compliance, and integration with existing systems. Overcoming these challenges will require collaboration between healthcare professionals, data scientists, and IT experts to develop robust and scalable solutions that meet the unique needs of each hospital environment.

In conclusion, employing machine learning algorithms for optimizing hospital staffing and resource allocation represents a transformative approach to healthcare management that has the potential to revolutionize the way hospitals operate, leading to improved patient outcomes, enhanced operational efficiency, and cost- effective healthcare delivery. As technology continues to evolve, it is imperative for healthcare organizations to embrace innovation and leverage advanced analytics to drive continuous improvement and deliver the highest quality of care to patients.

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