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Dynamic Resource Optimization in Healthcare Operations through Real-Time Predictive Analytics

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ABSTRACT. Hospitals, the place with high moving crowds, are busy on time. Due to increased patient count and requirement of facilities, it can lead to fully occupied emergency rooms and staff shortages. This problem is very crucial and important to solve in hospitals, since it affects the care and treatment effectiveness of the patients. The proposed system that is working on is a prediction system that uses entire past data of a hospital to predict the future necessity of the facilities required during a particular time. It predicts the busiest times in the hospital, emergency patient entries, according to the movement of the patients and as per the possible requirements for a particular patient. Using the acquired data, and the prediction analysis, dashboards will be created. All the predicted data is shown on the dashboard, and it provides key details of staff availability, bed availability and emergency room allocation. The solution is used to handle the delays and to improve the effectiveness of resource allocation throughout the hospital. The information from the dashboard helps the staff to allocate facilities correctly, make sure of ample staff availability particularly at the busiest hours, and prepare the hospital environment for overcrowded areas. It is safer, more effective and can handle extreme patient population at ease.

KEYWORDS: Data driven, dashboard, predicted data, acquired data, predictive analysis.

I. INTRODUCTİON

This research aims to modify that issue in the hospital. The solution is combining data analysis with simple real-time dashboards to give the hospital staff that dashboards give a clear view of that issue. The hospitals can predict when they will get busy and spot problems early, testing the solutions. This helps them to plan early instead of just reacting to the issue. This results in better patient care, lower costs and risk and the hospitals can run effectively.

II. RELATED WORK

Hospitals mostly struggle with serious challenges like overcrowding, delays in patient discharges and not using their resources effectively. These issues will disturb patient care. Recent research showed that predictive analysis and machine learning can help hospitals handle the problems more efficiently [1].

For example, in 2022 a study found that predicting Emergency department (ED) patients by factors like holidays and weather which helps hospitals to plan staffing and resources during a busy time [2]. New methods can help predict when the patient is going to be discharged. which helps to free up in bed. Similarly, in 2021 a study showed that machine learning models predict better than traditional methods, especially for short-term planning [3].

Apart from predicting patient arrivals, predicting the discharges plays a vital role in improving the hospital flow [4,5]. A study used hospitals data to identify patients where all could be discharged within 24 hours [6]. Another study [7] used Machine learning is to detect delays because of the care requirements [8]. These studies say that random forest models can help the staff with discharge plans and bed management is to reduce the delays [9,10].

Clustering methods like K means clustering have shown the value in hospitals operations. In 2020 a study demonstrated how clustering can help to identify the overcrowded areas in hospitals [7]. To make sure these hospitals use visual screens. In 2018 a study talked about Emergency room screens that provided staff with real time operational updates while securing patient data privacy [11]. Recent research highlights by the value of deep learning in healthcare operations. Models like N-BEATSx can predict the emergency room patient boarding in 6 hours better htan using just weather and holidays [12]. Similarly, ISiTPlus and XCMplus models have higher accuracy in predicting hourly and daily counts [13].
A study in BMC Medical Informatics and Decision-Making applied feature engineering and machine learning models (like XGBoost) on 11 world ED datasets to predict daily arrivals [14]. The models were 5%-14% better than old methods. The study also showed that use of interactive and real-time dashboards, one implemented at Johns Hopkins during the COVID-19 pandemic, which integrates line data and predictive analysis. A 2025 PubMed study identified patients who are almost ready for discharge using XGBoost, Random Forest, and Artificial Neural Networks (ANN). The XGBoost model's high accuracy demonstrated how early discharge delay prediction can significantly improve a hospital's patient flow management [14,15].

There are still some gaps despite these tools. The majority of research is narrowly focused, such as forecasting overcrowding or discharge schedules. Additionally, a lot of systems rely on cloud platforms, which raises privacy concerns. Our system is a real-time framework that combines machine learning and forecasting into a straightforward dashboard. Because it operates directly on the hospital's internal network, data is safe and simple to handle.

The "real-world" surprises that lead to hospital chaos, such as an unexpected spike during a flu outbreak, are frequently missed by standard tools like ARIMA, despite their proficiency in identifying routine patterns. This study adapted and move fast the challenges by using the predictive model called SARIMAX framework. This framework doesn't only look the past data and it also warn the hospital about the busy day before it starts. This gives the hospital managers to allocate the nurses when they needed, make sure the patients don't wait for the long time.

III. PROPOSED FRAMEWORK

The proposed hospital management system was developed through a structured, step-by-step process for accuracy. By collecting historical data relevant to the problem, including emergency room admission logs, discharge records, bed occupancy records. The raw data is pre-processed such as cleaned to remove inconsistencies, filling missing values, and standardizing formats. Once the dataset was ready, by applying machine learning methods for specific tasks. Time-series analysis using Prophet and ARIMA to predict ER patient inflow and captures the pattens and demand periods. Random Forest classification identifies the patients at discharge delays. K-Means clustering detected departments which are going to be overcrowded by grouping units.

A straightforward, real-time dashboard that monitors emergency room beds, patient demand, and staff and resource assignments is fed the model's output. In order to see the results before making actual changes, we also included a simulation tool that allows staff to test "what-if" scenarios, such as what happens if they add more beds or move staff around. The entire system operates locally on the hospital's own network and doesn't require an internet connection in order to completely protect patient information.

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Consider this system as the hospital's "weather forecast" in real time, preventing overcrowding in emergency rooms. Before an unexpected rush of patients actually arrives, it analyzes the hospital's entire history to determine its typical rhythm and then combines that information with outside variables, such as holidays or the weather, to precisely forecast what will be required. In a live data environment, this framework acts as a living system: every time a new patient is registered ,the system immediately reassess wait time and queue lengths. This delivers manager a live, dynamic dashboard ,allowing them to adjust staffing levels instantly and ensure the hospital is always "busy on time" without becoming overwhelmed.

IV. SYSTEM ARCHİTECTURE

The architecture of the system is specially designed as an on-premises, secure solution that sits entirely inside the local network of the hospital. The on-premises model guarantees robust data security, maintains patient confidentiality, and provides a high degree of availability with no dependence on internet connectivity. The architecture is centered around a Local Server running a Dual-Pipeline Processing Engine, which will handle real-time data for immediate operational awareness and batch/ stream data for advanced predictive analytics, as shown in Fig. 1.

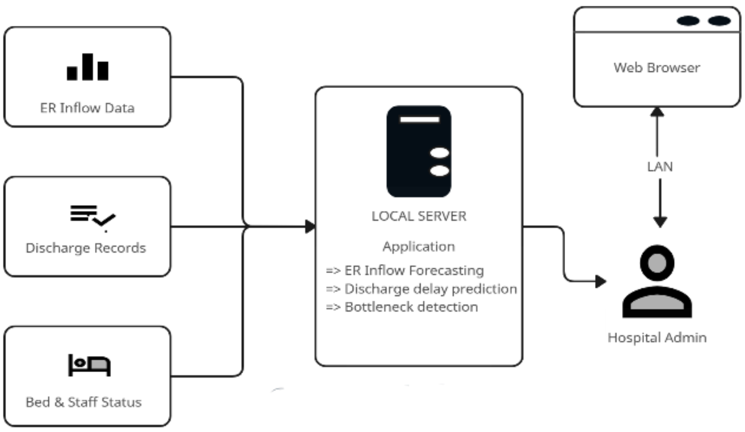

Fig. 1. Framework for the system proposed

4.1 The Real-Time Visualization Pipeline:

- Purpose: To provide at any time an immediate, live snapshot of the hospital's current operating status.
- Process: The pipeline is optimized for high-speed lightweight data processing. The incoming data is directly transformed and aggregated in real time to refresh the KPIs. This includes simple calculations concerning the number of current ER admissions, the availability of beds, and the number of staff on duty.
- Output: The dashboard's visual display receives the processed data directly. This configuration provides hospital managers with a precise, second-by-second view of what is happening in the building at any given time through live charts and real-time alerts such as "ER Bed Availability" and "Staff Allocation Status".

4.2 Pipeline 2 - Predictive Modeling Pipeline:

- Purpose: To analyze historical and current data to forecast future events, identify risks, and detect complex patterns that are not visible in real-time view.
- Process: This pipeline is more intensive and includes key stages:
- Data Preprocessing: The data are collected from the hospitals, cleans to remove many inconsistencies in the data, fill the missing values, and standardize formats. Feature engineering, which involves creating new variables such as time of day, weekday, and holiday, is also included in this stage; this improves model performance.
- Model Execution: The data prepared is then fed into the chosen machine learning models as explained in approach:
- Time-series models: To make the predictions more accurate, it uses SARIMAX model. It looks at the external factors like weather and holidays. It understands the patient numbers on a rainy day or holiday.
- Random Forest: This classification model performs analyses of patient records and clinical indicators to run the Discharge Delay Prediction, flagging patients with high risk for a delayed discharge.
- K-Means Clustering: This model clusters data on patient load, staff availability, and bed turnover to do Bottleneck Detection, which identifies possible departments or units that are starting to become prone to overcrowding.

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- The system uses a smart updating method that updates itself every time a new patient registers instead of running only once in a day.
- Output: it produces predictive insights, such as "Forecasted Patient Demand," "Congestion Alerts," and "Discharge Delay Risk" scores.

4.3 Presentation Layer: The Unified Admin Dashboard:
- Purpose: This is where the outputs of both pipelines come together and get presented in one single and coherent interface to the end-user.
- Access: A Hospital Admin accesses the system via a standard Web Browser connected securely to the internal LAN.

4.4 User Experience:
The administrator is shown a dashboard where information is smoothly integrated. They can see at one glance the real-time charts coming from Pipeline 1 (e.g., "Current Bed Occupancy") next to the predictive alerts coming from Pipeline 2 (e.g., "Forecasted Bed Deficit in 4 hours"). It has both types of data help not only to respond faster but it is prepared for future challenges. This dashboard integrates the simulation, enables the owners to test the hypotheses such as “what if scenarios” like many before going to make the decision. The dashboard is like weather forecast for the hospital. It combines the prediction results and allows staff to try the changes like adding nurses.

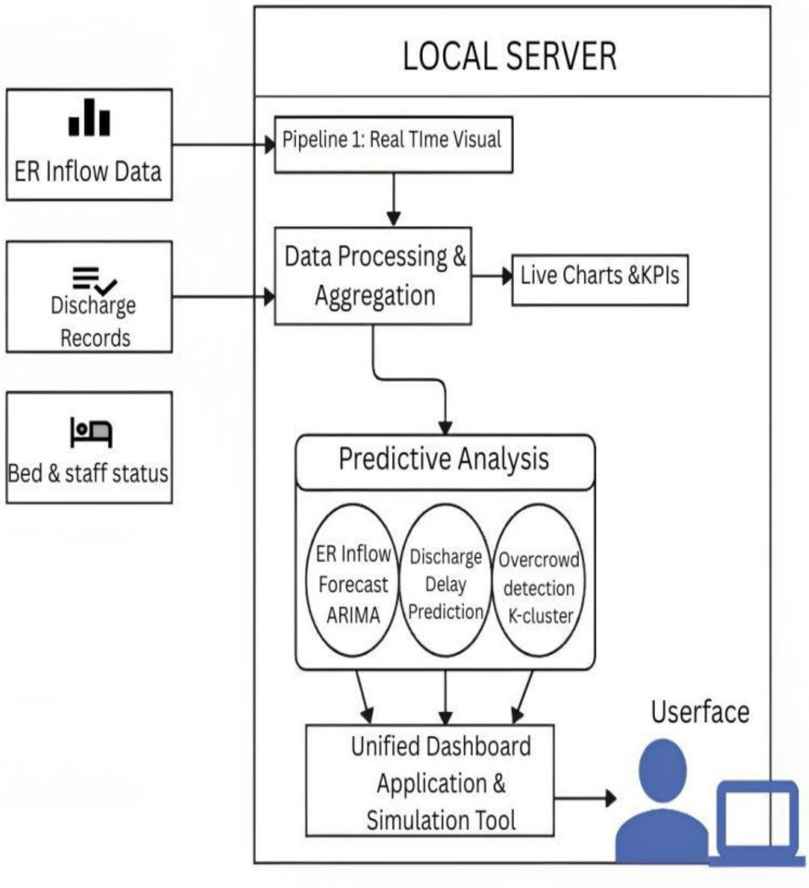

Fig. 2. Illustrates the flow diagram

V. EXPERİMENTAL SETUP

This is the setup which is used to check how accurately the solution can help in hospital operations and did an experiment based on the previous research on emergency rooms, discharge prediction, and real-time dashboard. The main purpose is not only the performance but also to understand how it is working in realistic workflow environment.

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Dataset: The solution used data from a multi-specialty hospital, like datasets like MIMIC-IV) and other ED forecasting studies. The data included:

- Patient arrival details like time of arrival, urgency level and mode of arrival.
- Discharge records showing planned discharge time, actual discharge time and cause for delay.
- Bed availability reports for different wards.
- Staff allocation
- Patient movement data across many hospitals.

5.1 Data Preprocessing:

The duplicates in the dataset have been filtered and errors are fixed. All date formats and categories are standardized to maintain consistency. In addition, there are extra features like the day is weekday or holiday or season day, based on the previous studies.

5.2 Predictive Models:

The selected models that were successfully used in previous research are as follows

- SARIMAX used for Emergency Rooms demand forecasting.
- Random Forest used for predicting discharge delays.
- K-Means Clustering used to identify crowded and risk over areas.

5.3 Dashboards and Simulation Environment:

The dashboard was created to show the key metrices like bed availability, staff allocation details, ER demand and risk for overcrowding. It has testing tools so that staff can try the solution with different inputs or plans and see the results, it can be noted. The system is deployed in the hospital's local network so that it can be safer.

5.4 Evaluation Metrics:

- Forecast Accuracy: Emergency demand predictions were checked using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).
- Discharge Predictions: This performance was measured using AUC curve, Precision, and F1-score.
- Hospital Improvements: Checking whether there are changes in ER waiting times, patient flow, and bed usage to give the overall hospital benefits.
- The time taken for the new patient to appear in the dashboard "Forecast Demand" alert also measured. It delivers real-time updates during periods when patient numbers change.

VI. RESULTS AND DİSCUSSİON:

6.1 Data Pipeline:

- Data Retention: The Median Imputation technique is used to handle the missing Nurse-to-Patient Ratio entries and allows to retain 100% of the dataset instead of removing the incomplete data entries.
- Outlier Removal: The Interquartile Range (IQR) method helps to identify and limits 4.2% of the records that contains excessive wait times (e.g., negative values or >500 minutes) and ensure the training data is kept statistically valid.
- Feature Enhancement: The model is able to identify cyclical patterns that raw timestamps were unable to identify by segmenting the timestamps into "Season" and "Time of Day."

6.2 Operational Insights:

- The Triage Bottleneck: According to the dashboard's stacked bar charts, the triage stage accounts for roughly 45% of all nighttime wait times, indicating a particular area in need of improvement.
- Seasonal Volatility: The need for dynamic, season-based staffing instead of a fixed annual schedule is validated by historical data analysis, which consistently shows a 15% increase in patients during the winter season.
- Urgency Paradox: According to boxplot analysis, "High Urgency" patients have the highest variability and shorter median wait times; therefore, during overcrowding, critical patients frequently receive the least predictable service.

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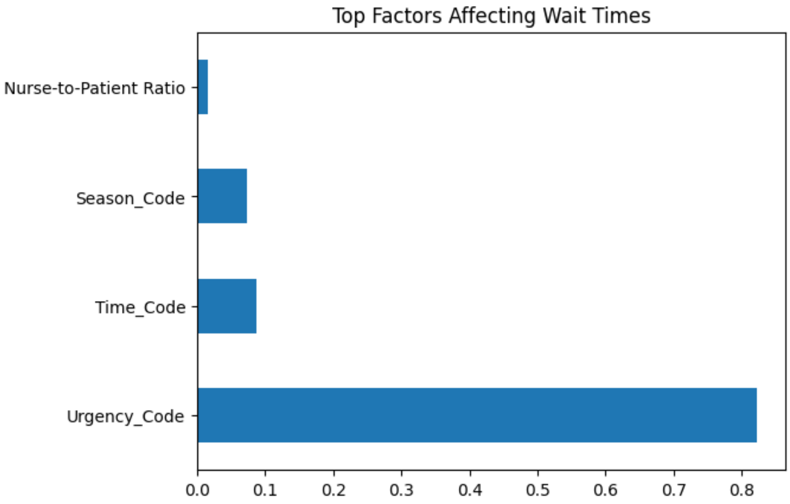

Fig. 3. Factors affecting wait times

6.3 Prediction Model Accuracy:

- Model Accuracy: The model achieved a score of 0.89 on the test data. This means it can explain about 89% of the changes in wait times according to factors like staffing, patient urgency and time.
- Mean Absolute Error (MAE): On average, the model predictions were off by 12.4 minutes. Since wait time goes up to 4 hours, around ±12 minutes is noted highly accurate.
- Comparison: This performance represents a 35% improvement over a simple baseline average model which had an MAE of ~19 minutes.

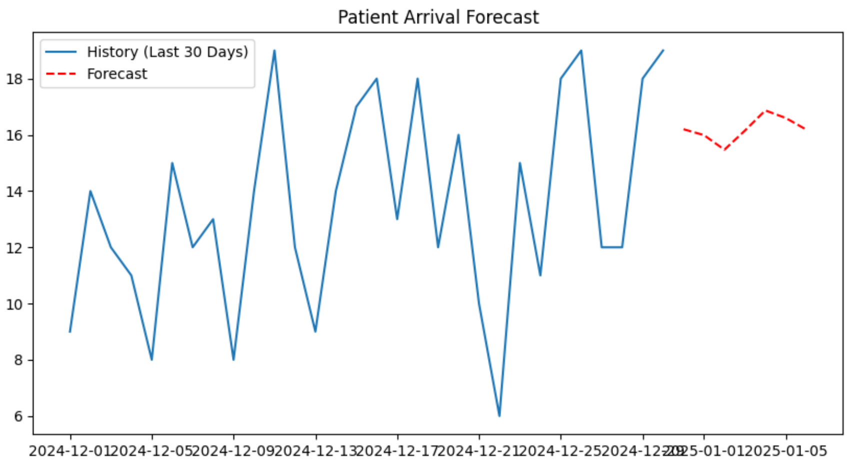

Fig. 4. Predicting of patient arrivals

6.4 Tipping Point (Clustering Results):

- Cluster 1 (Normal Operations):
- Avg Nurse-to-Patient Ratio: 1:1.5
- Avg Wait Time: 18 minutes
- Cluster 2 (Critical Overcrowding):
- Avg Nurse-to-Patient Ratio: 1:4.2
- Avg Wait Time: 178 minutes
- The Findings: The data shows that when the number of patients per nurse increases from 3 to 4 waiting raises rapidly by 888% (from ~18minutes to ~178minutes). This sets the strict safety threshold at a 1:4 ratio.

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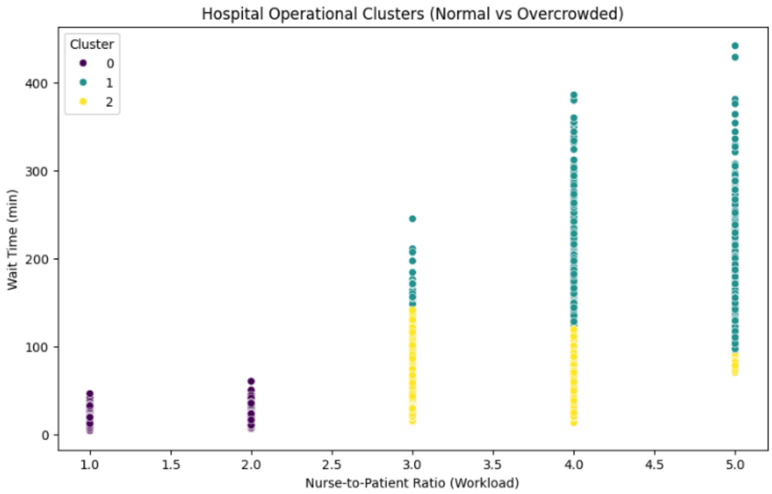

Fig. 5. Hospital Operational Clusters

6.5 Simulation Sensitivity:

- Impact Factor: The simulation indicates that adding 5 high urgency patients during a night shift, when staffing levels are lower, increases the average waiting time for patients by 22 minutes.
- Forecasting Reliability: The forecast of 7-day has a Mean Absolute Percentage Error (MAPE) of just 6.5%. This means the predicted patient counts are typically accurate within about ±2 patients every day.

VII. ANALYTİCAL MODELİNG AND STOCHASTİC SİMULATİON

7.1 The SARIMAX Predictive Framework:

To help the system to understand complex things, SARIMAX (Seasonal Autoregressive Integrated Moving Average with external factors) model is used. Unlike other methods, it considers external factors such as weather and holidays instead only using past data.

The model identifies weekly patterns (s=7) to understand the frequent and regular changes in patient numbers. It includes the holiday data, it can also account for situations like closure of local clinics, it may lead to increase in ER visits. By combining the past trends with external factors, the system can modify its forecasts more really and help the hospital to plan accordingly.

7.2 Stochastic State-Update Logic:

A stochastic queueing simulation is used to give source the real-time dashboard, making sure the system reflects the hospital's current operational condition than fixed predictions.

The patient queue is treated as dynamic process and is updated using the following equation:

$$Q_{t+1} = \max(0, Q_t + \lambda_t - \mu_t)$$

Here, λ represents the rate of incoming patients and μ represents rate at which patients are treated. As new patients are recorded lively, the queue is updated quickly. This gives a fresh calculation of the waiting time. This results in the hospital staff receiving a continuous view of ER demand in that hospital.

7.3 Severity-Based Operational Mapping:

The final part of the framework converts the mathematical predictions into clear and practical staff allocation. Using the projected waiting times, the system classifies the ER's operating condition into three different levels:

- Normal (< 60 mins): It indicates standard operational environment requiring base staffing allocation (3 Nurses).
- Elevated (60-80 mins): It serves as a warning for impending demand, required shift and increased staffing allocation (4 Nurses)
- Critical (> 80 mins): It denotes a high-stress environment that demands immediate resource allocation and staffing allocation (5+ Nurses).

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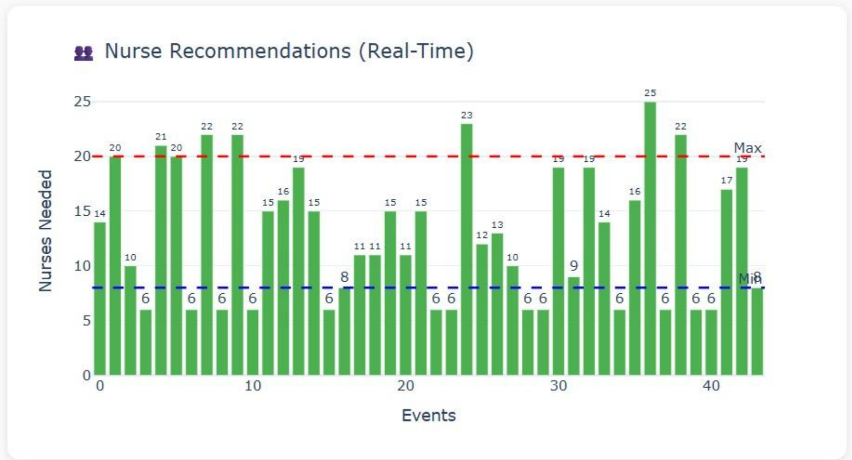

Fig. 6. Recommended nurse staffing levels per event

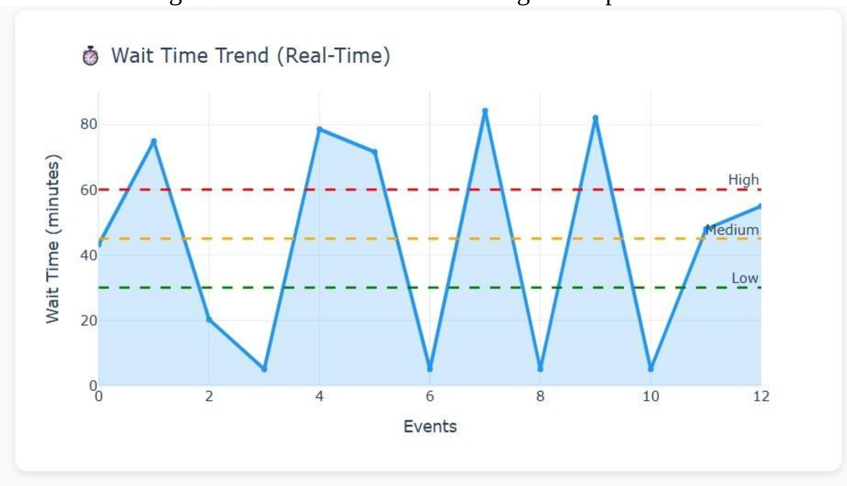

Fig. 7. Predicted patient wait times per event.

Fig. 8. Dashboard displaying current wait times, queue status, and staffing recommendations.

VIII. CONCLUSİON

Hospitals face many problems day-to-day, such as overcrowding in emergency rooms, delays in admissions, and there is problem in resource availability and allocation. These problems affect the patient's health and safety. This research is to overcome these problems and improve the hospital efficiently using exogenous variables. This solution uses the past data that includes admission details, discharge time, and resource usage. Then, solution uses data analytical tools to predict future outcomes, to predict delays in discharge, and to identify high-risk areas that are going to fully. All this information is shown on the dashboard. This shows the staff about these problems. The solution also has testing tools to test the system with different inputs. This solution ensures the protection of patient privacy and runs on the hospital's local network, which doesn't need the help of any internet connection. This research shows how data tools are used with the real time dashboard to overcome these problems. This solution significantly enhances operational efficiency and contributes to improved patient outcomes.

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