Improving Hospital Supply Chain Efficiency with LSTM for Demand Forecasting

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***Abstract*—Healthcare supply chains are essential to delivering reliable patient care, yet inefficiencies are common due to fluctuating demand and resource limitations. This project proposes a Machine Learning-based approach to streamline supply chain operations, utilizing predictive models and optimization techniques focused on demand forecasting and inventory management. By addressing common challenges through data-driven methodologies, the project aims to improve resource efficiency, reduce costs, and support higher-quality patient care.**

***Index Terms*—Machine Learning, healthcare supply chain, demand forecasting, LSTM,inventory management, predictive models, hospital efficiency.**

I. Introduction

Healthcare supply chains (HSC) play a critical role in ensuring the timely availability of resources such as medical supplies and equipment. In medium-sized hospitals, supply chain inefficiencies, such as inaccurate demand forecasting and inventory shortages, can lead to higher operational costs and delayed patient care. This project employs Machine Learning (ML) and predictive analytics to address these issues, using data-driven models and optimization techniques to streamline operations. By leveraging ML algorithms, the project aims to create a supply chain model that aligns resources with demand, enhancing hospital efficiency.

II. Significance of the Project

The use of Machine Learning in healthcare supply chain management has transformative potential, offering several advantages:

- **Efficient Resource Allocation:** With demand forecasting driven by ML, hospitals can avoid both shortages and surplus inventory, ensuring essential resources are available without waste.
- **Cost Reduction:** Optimization of inventory and staffing using data-driven models minimizes unnecessary expenses, supporting hospitals with limited budgets.
- **Improved Patient Care:** By aligning resources with predicted demand, patient care can be delivered more promptly, resulting in better outcomes and higher patient satisfaction.

These benefits underscore the impact of ML-driven methods, which can streamline healthcare supply chain processes in ways that traditional approaches cannot.

III. Knowledge Gaps

Despite advancements, several knowledge gaps remain in the application of Machine Learning to healthcare supply chain management:

- **Demand Forecasting for Dynamic Needs:** Many hospitals rely on basic forecasting methods, which often fail to account for fluctuating demand patterns in healthcare, particularly during peak periods.
- **Real-Time Inventory Adjustment:** Existing inventory systems frequently lack real-time adaptability, which can lead to costly stockouts or excessive stock levels that impact patient care.

These gaps highlight the need for adaptive ML models that can improve responsiveness and resilience within healthcare supply chains.

IV. Literature Review on Healthcare Supply Chain Management

Research into healthcare supply chain management has consistently underscored several areas needing improvement, especially in resilience, inventory accuracy, and service quality. Integrating Machine Learning into these areas can help address long-standing inefficiencies.

A. Operational Resilience and Adaptability

Operational resilience is critical to healthcare, where demand can shift unexpectedly. Syahrir et al. (2015) found that most healthcare supply chain research addresses standard operational conditions, with limited focus on resilience for peak demand scenarios such as public health emergencies. ML-driven predictive models can play a key role in anticipating these variations and enhancing supply chain flexibility [1].

B. Inventory Management and Real-Time Control

Effective inventory control is central to healthcare supply chains, as shortages or surpluses directly affect patient care. Dobrzykowski et al. (2014) note that a lack of real-time data integration limits many hospitals' inventory management capabilities. Predictive ML models that dynamically adjust stock levels based on real-time usage data are still underdeveloped in this field, presenting an opportunity for improved control and accuracy [2].

C. Strategic and Service Management

Strategic planning in healthcare supply chains involves aligning resources with patient care requirements. Narayana et al. (2014) emphasize the need for strategic models that support both daily operations and emergency responses. Service management benefits significantly from predictive ML models that help anticipate demand shifts, ensuring that resources are available when needed and enhancing patient satisfaction. Further research could yield supply chain models that are better aligned with the unique demands of healthcare [3].

V. Proposed Methodology

The goal of this project is to predict the average daily usage of key hospital supplies (Gloves, IV Drips, Surgical Masks, and Ventilators) using LSTM model to optimize inventory management and avoid shortages or overstocking.
Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) designed to handle the limitations of traditional RNNs, such as the vanishing and exploding gradient problem [4].
Unlike standard feedforward neural networks, LSTMs have feedback connections, allowing information to persist over long sequences. This capability makes LSTMs well-suited for tasks like Time Series Forecasting.
In the context of predicting hospital supply chain usage (e.g., Gloves, IV Drips, Surgical Masks, and Ventilators), LSTMs are particularly advantageous for several reasons:

- **Sequential Nature of Data:** Hospital inventory data involves daily usage patterns that are inherently sequential. LSTMs can learn from these patterns and predict future usage effectively.
- **Handling Long-Term Dependencies:** Usage patterns may depend on trends spanning weeks or months. LSTM's ability to remember long-term dependencies helps capture these trends for accurate forecasting.
- **Mitigating Noise and Irregularities:** Real-world data often contains irregularities and noise. LSTMs can handle such variability better than traditional methods.
- **Prediction Stability:** LSTMs provide stable predictions by maintaining relevant context over sequences, which is crucial for managing hospital supplies where stockouts or overstocking can significantly impact operations.

Missing values of the dataset were filled using **linear interpolation**, and the data was normalized using **Min-Max Scaling**. We split the data using **TimeSeriesSplit** to preserve temporal order. An LSTM model was designed with two LSTM layers (80 and 30 units), along with Dropout and **Batch Normalization** for regularization. The model was trained using the **Adam optimizer** and evaluated using RMSE (Root Mean Squared Error).

VI. MODEL ASSUMPTIONS

The **LSTM model** for predicting hospital supply usage operates under several key assumptions. It assumes that the time series data is stationary, meaning the statistical properties (e.g., mean and variance) remain consistent over time. The model also relies on the sequential dependency of the data, where the current usage is influenced by patterns in the previous **60 days**. Missing values are assumed to follow a linear trend, which is addressed through linear interpolation. The features used, such as **Current Stock, Min Required, Max Capacity, day of week**, and **month**, are presumed to have a meaningful relationship with **Avg Usage Per Day**. Finally, the model assumes that sufficient historical data is available to learn long-term usage patterns effectively.

VII. Model Formulation and Estimators

Given historical data sequences X_t of hospital inventory usage, the goal is to predict the **average daily usage** y_t for each supply item (Gloves, IV Drips, Surgical Masks, Ventilators) using an LSTM model.

Notations

Symbol	Description	Dimensionality
X	Input sequences	(n, T, f)
y	Target values (Avg_Usage_Per_Day)	$(n, 1)$
n	Number of sequences	Scalar
T	Sequence length (e.g., 60 days)	Scalar
f	Number of features (e.g., 6 features)	Scalar
$\hat{y}$	Predicted values	$(n, 1)$
h_t	Hidden state at time t	(n, u)
C_t	Cell state at time t	(n, u)
u	Number of LSTM units	Scalar
θ	Model parameters	-
$L(\theta)$	Loss function (Mean Squared Error)	Scalar

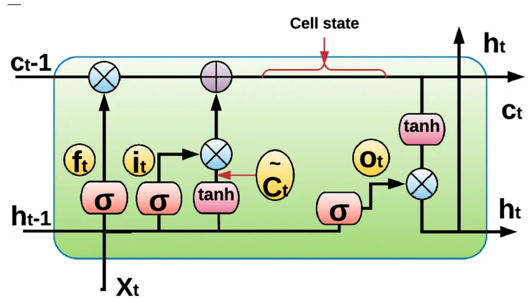


Fig. 1. LSTM Cell [4]

A. Model Formulation

a) Input Sequences: Each input sequence X is represented as:

$$X = \{x_1, x_2, \ldots, x_T\}, \quad x_t \in \mathbb{R}^f$$

where T is the sequence length and f is the number of features.

b) LSTM Equations: At each time step t, the LSTM processes the input x_t and updates the hidden state h_t and cell state C_t using the following equations:

- **Forget Gate** f_t:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- **Input Gate** i_t and Candidate Cell State $\tilde{C}_t$:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

- **Cell State Update** C_t:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

- **Output Gate** o_t and Hidden State h_t:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

c) Output Layer: The LSTM's final hidden state h_T is passed through a Dense layer to generate the prediction $\hat{y}$:

$$\hat{y} = W_y \cdot h_T + b_y$$

B. Loss Function (Estimator)

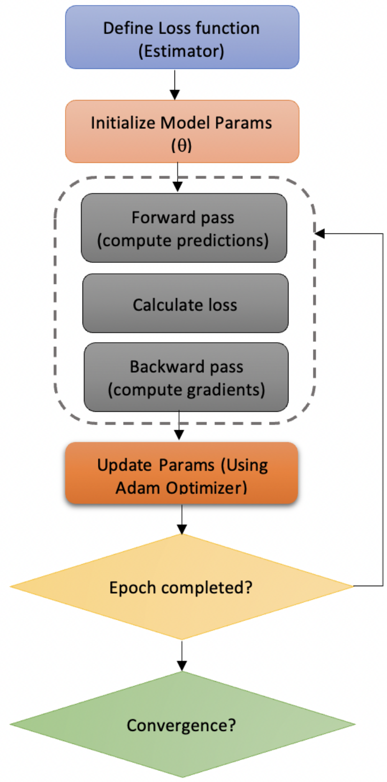
The model is trained to minimize the **Mean Squared Error (MSE)** loss function, defined as:

$$L(\theta) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where:

- y_i is the actual average usage for the i-th sample.
- $\hat{y}_i$ is the predicted average usage.
- n is the number of sequences.

VIII. Algorithm to Solve the Optimization of the Estimator



IX. Dataset Description

A. Dataset Overview

The Hospital Supply Chain dataset was taken from **Kaggle**. It consists of 500 records, each of which records daily information about the stock levels, usage, and procurement details of these supplies.

TABLE I
Dataset Description

Feature Name	Description	Data Type	Example Value
Date	Date of the record	Date	2024-10-01
Item_ID	Unique identifier for each item	Integer	105
Item_Type	Type of the item (Consumable or Equipment)	String	Consumable
Item_Name	Name of the hospital supply item	String	Ventilator
Current_Stock	Current stock level of the item	Integer	1542
Min_Required	Minimum required stock level	Integer	264
Max_Capacity	Maximum capacity of stock for the item	Integer	1018
Unit_Cost	Cost per unit of the item	Float	4467.55
Avg_Usage_Per_Day	Average daily usage of the item	Integer	108
Restock_Lead_Time	Lead time for restocking (in days)	Integer	17
Vendor_ID	Unique identifier for the vendor	String	V001

B. Input and Output Variables

TABLE II
INPUT AND OUTPUT VARIABLES

Variable Type	Feature Names
Inputs	Current_Stock, Min_Required, Max_Capacity, Unit_Cost, day_of_week, month
Output (Target)	Avg_Usage_Per_Day

C. Key Insights

- **Inputs**: The features used for prediction include stock levels, restocking constraints, and temporal information (day_of_week, month).
- **Output**: The target variable is Avg_Usage_Per_Day, representing the daily demand for each item.
- **Correlation Analysis**:
  - Stock levels and usage rates show inverse relationships.
  - Restock lead times can impact current stock availability.
  - Temporal patterns (day of the week or month) may influence usage trends, e.g., higher demand on weekdays versus weekends.

X. Training-Validation-Testing Partition

As this is a time series forecasting problem, careful partitioning of the data into training, validation, and testing sets is crucial to preserve the temporal order and prevent data leakage.
In this project, the partitioning was done using TimeSeriesSplit, which ensures that the data remains sequential. The TimeSeriesSplit method creates multiple splits, each consisting of an increasing portion of the data for training and a subsequent portion for testing. There are 3 time series split. For each split, the data is organized into sequences of 60 days.

Sequence Creation: For each split, the data is organized into sequences of **60 days**:

- **Input Sequences** (X): Each sequence contains 60 days of data for the selected features.
- **Target Values** (y): The `Avg_Usage_Per_Day` corresponding to the next day after each 60-day sequence.

Final Training, Validation, and Testing:

- **Training Set:** Used to train the LSTM model.
- **Validation Set:** Used during training to monitor the model's performance and apply **early stopping** if the validation loss does not improve.
- **Testing Set:** Held-out data used to evaluate the model's performance after training.

Sample Partition

Split	Training Data	Testing Data
Split 1	First 60% of data	Next 20%
Split 2	First 70% of data	Next 20%
Split 3	First 80% of data	Next 20%

Key Considerations

- **Preserve Temporal Order:** Data is never shuffled to ensure that the model learns sequential patterns correctly.
- **Avoid Data Leakage:** By partitioning the data chronologically, the model is only tested on future data it has not seen during training.
- **Validation for Early Stopping:** The validation set helps monitor performance during training, and **early stopping** prevents overfitting by halting training if the validation loss stops improving.

XI. Modeling Performance

The LSTM model's performance was evaluated using the Root Mean Square Error (RMSE) for four hospital supply items. The RMSE values are as follows: Gloves (61.78), IV Drip (71.53), Surgical Masks (67.97), and Ventilators (52.55). The lowest RMSE for Ventilators suggests the model performed best for this item, while the highest RMSE for IV Drip indicates difficulties in accurately predicting its usage patterns.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

The model's predictions generally follow the overall trends of the actual test data as shown in Fig. 2. However, deviations are evident, particularly during sharp peaks and drops, reflecting the model's struggle with extreme variations. For items like Gloves and Surgical Masks, the model captures trends moderately well but misses significant fluctuations. The IV Drip data shows pronounced volatility, contributing to the highest error.

Several limitations affect the model's performance. High variability in daily usage patterns makes accurate predictions challenging. The relatively small dataset (around 500 days) limits the model's ability to learn long-term trends, potentially causing overfitting. The model also may not fully capture seasonality or periodic trends, and data noise further impacts prediction accuracy.

In summary, while the LSTM model demonstrates reasonable predictive capability, particularly for Ventilators, its effectiveness is hindered by data volatility, limited dataset size, and potential overfitting. Improvements could be made by incorporating more data, advanced features, or experimenting with alternative time series models.

XII. Validation of Results

The validation of assumptions for the model yielded favorable results in key areas. The **stationarity of the data** was confirmed through the Augmented Dickey-Fuller (ADF) test,

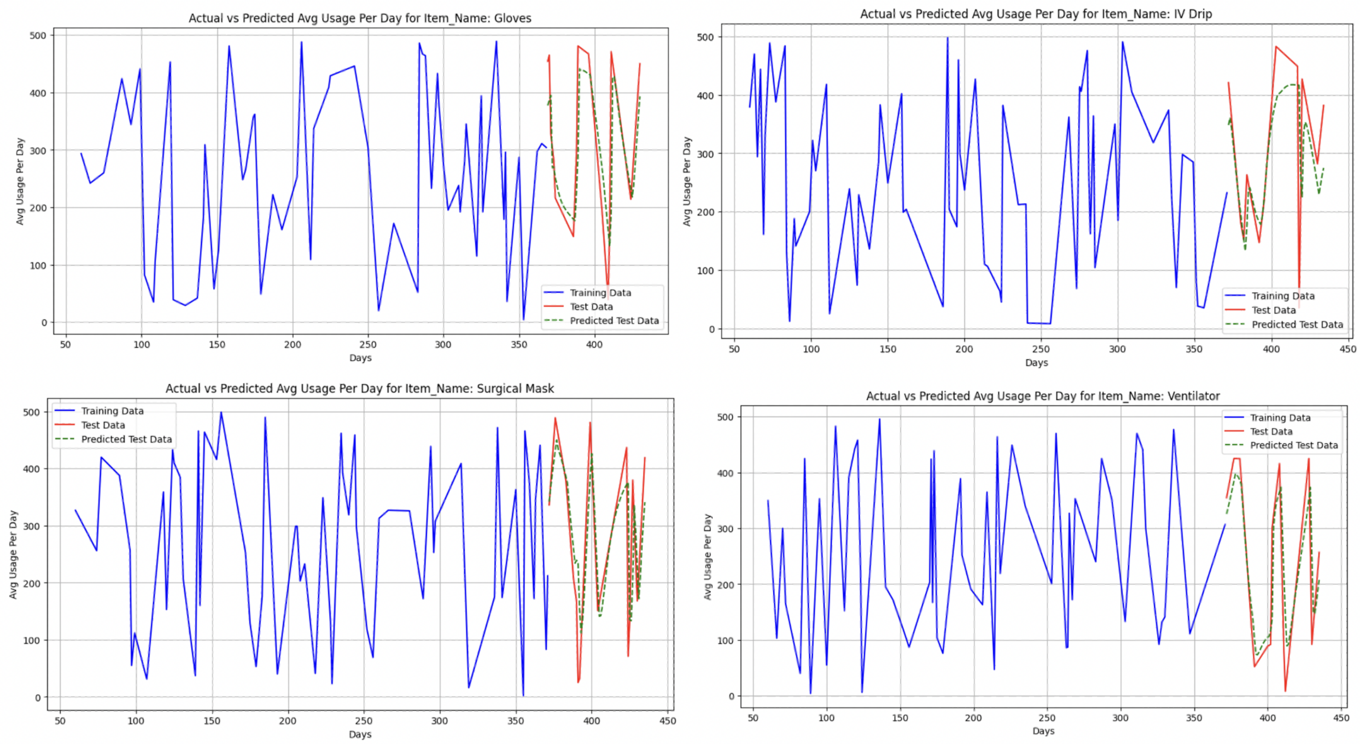


Fig. 2. Actual vs Predicted Average Daily Usage for Hospital Supply Items (Gloves, IV Drip, Surgical Masks, and Ventilators) using LSTM

which returned a p-value of **0.0**. This result allows us to reject the null hypothesis of non-stationarity, confirming that the data is stationary, which is a critical requirement for time series modeling.

To assess multicollinearity among the features, we calculated the **Variance Inflation Factor (VIF)**. The VIF values for all features — *Current_Stock*, *Min_Required*, *Max_Capacity*, and *Avg_Usage_Per_Day* — were below the threshold of 5, with values ranging between 3.08 and 3.71. These values indicate low multicollinearity, suggesting that the features are suitable for the model without redundancy concerns.

The residual analysis shows a reasonable dispersion of residuals around the zero line, though minor patterns may suggest potential heteroscedasticity. The residuals generally not follow a normal distribution, slight deviations are present. Furthermore, the **Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)** plots show that no significant autocorrelation exists in the residuals, satisfying the assumption of independence.

In conclusion, the data supports key assumptions of stationarity and low multicollinearity. Although the residual analysis highlights slight deviations from ideal behavior, the overall model validation results suggest that the model is reasonably well-specified and performs adequately within these constraints.

XIII. Discussion of Results

The modeling outcome demonstrates the **effectiveness** of the LSTM model in predicting hospital supply chain demands, with **performance varying across items**. Ventilators achieved the **lowest RMSE (52.55)**, indicating stable and predictable demand patterns, while IV Drips recorded the **highest RMSE (71.53)**, reflecting challenges in capturing complex or variable trends. Gloves and Surgical Masks showed **moderate RMSE values** of 61.78 and 67.97, respectively, suggesting reasonable predictive accuracy.

The **justification** for these results lies in the incorporation of **temporal features** (e.g., day and month), which capture seasonality and trends, although external factors like emergencies or patient influx were not included. The model's **significance** lies in enabling **proactive inventory management**, particularly for critical items like Ventilators, where accurate forecasting is crucial for patient care.

The **TensorBoard visualizations** as shown in Fig. 3 provide clear evidence of model convergence for most items. However, there are **limitations**, such as the reliance on **linear interpolation for missing data**, fluctuations in **validation loss** (notably for Surgical Masks), and the absence of **external variables**. These findings emphasize the **potential** of LSTMs while highlighting the need for **enhanced feature engineering** and **hyperparameter tuning** to address observed gaps.

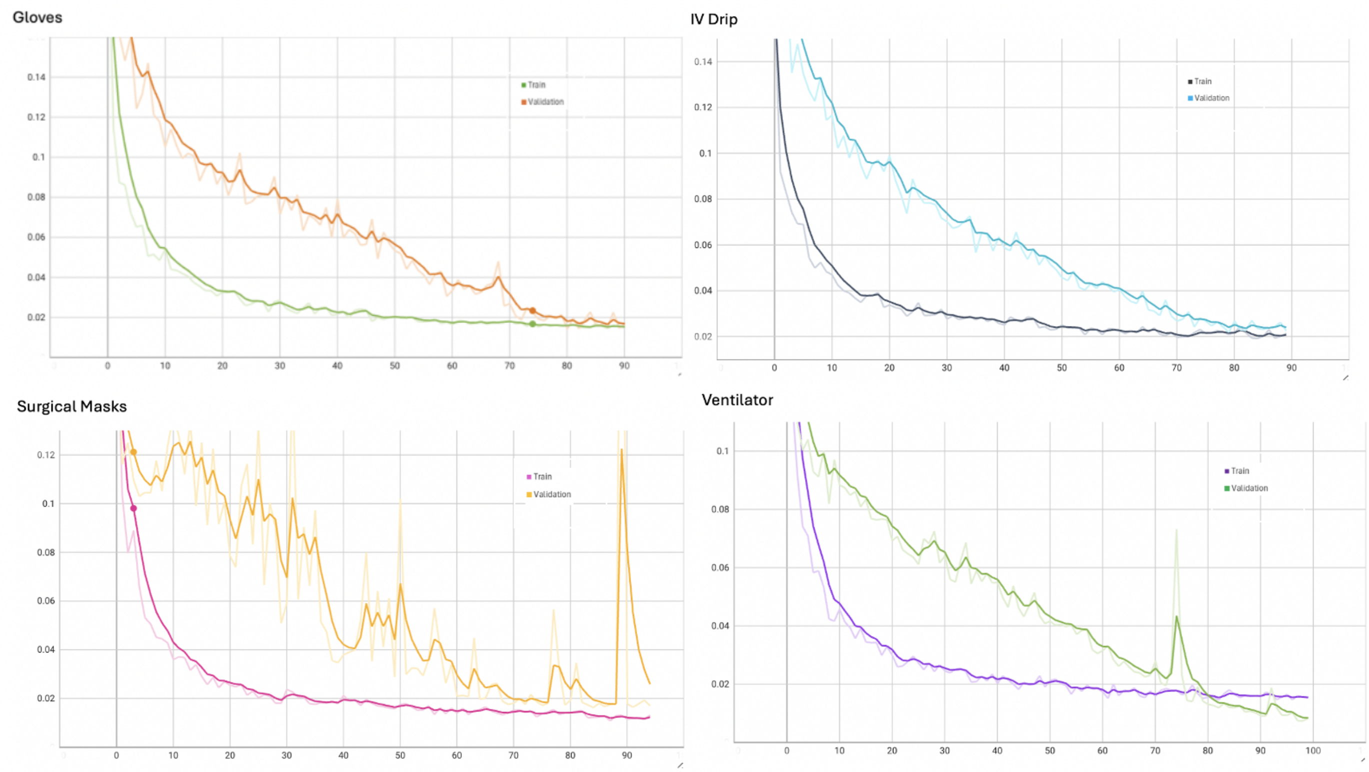


Fig. 3. Training and validation loss over epochs, demonstrating model convergence and generalization performance for Hospital Supply Items (Gloves, IV Drip, Surgical Masks, and Ventilators)

XIV. Conclusions and Future Work

In this study, we developed a predictive model to forecast the average daily usage of key medical supplies (Gloves, IV Drips, Surgical Masks, and Ventilators) within a hospital setting. Our results demonstrate that the model performs reasonably well, as indicated by the Root Mean Square Error (RMSE) values ranging between 52.55 and 71.53. The residual analysis shows that the model captures most of the trends in the data, but certain deviations suggest potential areas for improvement.

The model's strengths lie in its ability to handle time-series data, with stationarity confirmed through statistical tests. The Variance Inflation Factor (VIF) results indicate no significant multicollinearity between features, reinforcing the robustness of the predictor variables. However, the residual diagnostics also reveal patterns that may point to limitations, such as unmodeled seasonal trends or autocorrelation. These findings are consistent with challenges identified in similar supply chain forecasting studies [5], [6].

Future work will aim to address these limitations by incorporating more sophisticated forecasting techniques like Prophet which are particularly suited for capturing temporal dependencies [7]. Additionally, integrating external factors such as patient inflow, seasonal variations, and supplier lead times could enhance the model's predictive accuracy.

To further validate the model's performance, testing it on larger datasets from different hospitals and incorporating real-time data streams will be valuable. These enhancements could ultimately support hospitals in minimizing shortages and optimizing inventory levels, improving overall healthcare resource management.

XV. Contributions

This project's contributions will be both practical and methodological:

- **Applicational Contribution:** The ML-driven approach will improve resource allocation, cost efficiency, and patient care in healthcare settings. This framework may be adapted by other facilities for similar improvements.
- **Methodological Contribution:** Integrating time-series forecasting, optimization, and predictive ML models offers a comprehensive and innovative approach to healthcare supply chain management.

XVI. Broader Impacts

The broader impacts of this ML-based project could extend across healthcare and other sectors:

- **System-Wide Efficiency:** If effective, this framework could be scaled across healthcare networks, improving efficiency on a larger scale.

- **Cross-Industry Relevance:** Methods such as ML-driven demand forecasting and inventory optimization could benefit other sectors with similar supply chain structures, including manufacturing and retail.
- **Sustainability and Resource Conservation:** Optimized resource allocation and reduced waste align with sustainability goals, which are increasingly important in healthcare and beyond.

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