Optimizing Supply Chain Logistics in Manufacturing to Increase Warehouse Efficiency Through Storage Optimization

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Abstract

The necessity for effective warehouse management has increased due to the ever-expanding e- commerce industry. Ineffective storage solutions result in longer picking times, higher operating costs, and wasteful use of available space. In order to increase productivity, lower expenses, and improve efficiency, this study investigates the use of machine learning (ML) approaches to optimize warehouse storage. We create and assess models to optimize the placement of goods within a warehouse by utilizing data such as order histories, inventory characteristics, and warehouse layouts. To anticipate the best storage sites, the process consists of feature engineering, thorough data cleansing, and algorithm selection. The findings show notable increases in storage usage and decreases in order picking time, which help to streamline operations.The results have encouraging ramifications for big warehouses looking to apply data-driven storage techniques, especially in sectors with highly variable demand.

Keywords: *order picking, supply chain management, machine learning, warehouse efficiency, storage optimization, and space utilization*

1. Introduction

Warehouses are essential parts of contemporary supply chains because they act as central locations for managing, storing, and shipping items to their destinations. Supply chain effectiveness is directly impacted by effective warehouse operations, which have an impact on everything from overall profitability to customer happiness. Industry statistics indicate that subpar storage systems may be responsible for as much as 25% of a warehouse's overall operating expenses. Warehouse owners are under additional pressure to improve their storage techniques as e-commerce grows. Some of the challenges they face include labor-intensive order fulfillment procedures, inefficient space use, and long picking times. Conventional methods, such heuristic-basedsystemsand manual storage optimization, frequently fall behind in the face of changing demand trends. With advances in machine learning, the opportunity to introduce automated, data-driven systems for optimizing storage has emerged, offering the potential to revolutionize warehouse management .

1.1 Problem

The problem of suboptimal warehouse storage leads to significant inefficiencies in both space utilization and order picking processes. Inadequate organization of goods can increase the time it takes for workers to locate and retrieve items, driving up labor costs and extending order

1.2 Investigating how machine learning methods may enhance warehouse storage optimization is the goal of Research Objectives. Particular goals consist of:

creating models that forecast the best places for storage based on order frequency and inventory characteristics. assessing how storage optimization affects picking time reduction and space use. examining the possibilities of machine learning- based real-time adaptive storage systems to manage varying demand.

1.3 The following important questions are addressed by the research questions and hypothesis:

When compared to conventional techniques, can machine learning models dramatically increase space utilization and decrease order selecting time? Which characteristics or factors are most crucial in determining the best storage options? What is the effectiveness of various machine learning algorithms in forecasting storage locations in various warehouse scenarios? It is predicted that machine learning-based systems will perform better than human and heuristic approaches, providing quantifiable efficiency gains.

1.4 The paper's structure

The portions of this paper are as follows:

Methodology: Detailed explanations of the machine learning models, preprocessing methods, and datasets utilized.

Findings and Analysis: A review of the outcomes of using machine learning algorithms to solve warehouse optimization issues.

In summary: Highlighting important discoveries and talking about potential avenues for future study.

2. Literature Survey

Over the years, warehouse optimization has garnered a lot of interest, especially in connection to enhancing inventory control, warehouse structure, and the incorporation of technology like automation and data analytics. We examine significant contributions in these fields in this literature review, emphasizing significant discoveries that have influenced contemporary warehouse logistics.

2.1 Optimization of Warehouse Layout

One of the most important topics in supply chain management and logistics is warehouse layout design. Layout is crucial for reducing travel distances, which directly affects employee productivity and order processing times, according to Bartholdi and Hackman (2016). According to their research, I-shaped layouts are favored in high-volume settings with dedicated receiving and shipping departments, whereas U-shaped layouts are typically more effective for warehouses with regular picking and shipping operations. whereas high-volume settings with designated receiving and shipping zones are better suited for I-shaped layouts. Thorough analysis of several warehouse layout designs and their effects on performance was presented by Gu et al. (2010). They point out that improving aisle layouts and using vertical

2.2 Systems for Inventory Management

Optimizing warehouse performance requires effective inventory management. The significance of inventory categorization techniques such as ABC analysis, which groups things into groups according to their value and demand, is emphasized by Frazelle (2002). This aids in setting storage location priorities and speeding up the retrieval of goods that are in high demand.

Inventory control has been transformed by the introduction of warehouse management systems, or WMS. Current WMS systems provide automatic inventory replenishment and real- time stock level tracking. According to Akkerman et al. (2010), businesses can improve inventory visibility, decrease stockouts and overstock scenarios, and increase warehouse productivity by implementing WMS.

2.3 Ordered data

Information about incoming and departing orders that the warehouse needs to process is called order data. Efficient management of picking, packaging, and shipping procedures depends on this data. The records and information pertaining to customer orders in a warehouse or logistics setting are referred to as order data. Because it gives information about what products are most often purchased, in what quantities, and how long it takes to fulfill these orders, it is essential for maximizing warehouse efficiency. The information can be utilized to forecast future demand, optimize picking procedures, and decide where to put things in the warehouse.

3. Methodology

3.1 Data Collection

Machine learning programs rely heavily on data, and three different kinds of data were gathered for this study:

Features including item dimensions (length, width, and height), weight, SKU (stock keeping unit) number, turnover rate (the frequency of orders), and shelf life are all included in inventory data. For instance, SKU1234 might represent a 1.5 kg product with dimensions of 30x20x10 cm, a weekly turnover rate of 50 units, and a 12-month shelf life.

Warehouse layout: Zones, aisles, racks, and picking sections make up the warehouse floor design. For example, the arrangement might have distinct areas for bulkier things kept in the back and fast- moving items close to the picking zones. Order data: Order IDs, items ordered, quantity ordered, and time taken to fulfill the order are all recorded in this dataset. Order #5678, for instance, may contain three units of SKU1234, with a noted picking time of five minutes.

3.2 Data Cleaning

To make sure the data is useful and devoid of errors, data cleansing is an essential step. A number of methods were employed:

Managing missing values: For example, if SKU5678's weight is absent, the mean weight of comparable products in the same category is used to impute the missing value. For instance, this figure is utilized if the average weight of other items in the category is 2.0 kg.Outlier detection: Results may be skewed by an abnormally large order in order data, such as ordering 500 units of an item when orders are normally for 10–20 units. Such outliers are found using statistical techniques such as Z-scores. An order amount that deviates more than three standard deviations from the mean, for instance, would be noted and examined.

Data normalization: A common scale is used to standardize inventory variables such as weight and dimensions. This guarantees that qualities with wider numerical ranges won't be given preference by the machine learning algorithms. For example, a 200 g item and a 3.5 kg item would be scaled to comparable values within their respective categories.

3.3 Data Integration

Inventory data, layout data, and order records were cross-referenced using a distinct SKU identity once the datasets were combined into a single relational database. This made it possible to employ machine learning algorithms to anticipate the best places for storage and assess warehouse performance using a variety of measures.

3.4 Feature Engineering

From the raw data, new characteristics were created to improve machine learning models' prediction power: Frequency of orders: Items that are often Reinforcement learning (RL): RL uses real-time demand changes to dynamically modify storage locations. For example, the RL system may move an item to a more accessible storage space to improve fulfillment times if there is an unexpected spike in orders for that item because of a promotion.

3.5 Modelling Approaches

A range of machine learning techniques, each with a distinct purpose, were used to optimize the storage of items:

K-means clustering: This technique uses common characteristics, like size, weight, and order frequency, to group related items. For instance, tiny, commonly ordered items like phone chargers and batteries would be grouped together and kept in comparable storage areas for easy access.

Decision trees and random forests: These algorithms use characteristics like dimensions and turnover rate to determine the optimal storage placement for every SKU. A random forest might suggest, for instance, that a heavy, low-turnover item be kept in a less accessible location and a lightweight, high-turnover item be kept close to the picking zone.

Reinforcement learning (RL): RL uses real-time demand changes to dynamically modify storage locations. For example, the RL system may move an item to a more accessible storage space to improve fulfillment times if there is an unexpected spike in orders for that item because of a promotion

Data ingestion: Real-time updates from warehouse layout, inventory, and order systems are gathered by the system. For example, the system modifies the storage recommendations if 50 units of SKU2345 are added to the warehouse.

Storage suggestion engine: After analyzing incoming data, machine learning algorithms suggest where items should be placed. For instance, in order to reduce picking time and travel distance, the system recommends which warehouse zone new product should be stored in as it arrives.

Order fulfillment integration: To guarantee that the best storage locations are represented in the real picking procedure, the system is connected to order management software. For instance, the system creates a picking list based on the locations of SKUs to reduce trip time when an order is received.

3.7 Metrics for Evaluation

The following measures are used to gauge how well the machine learning models are performing:

Rate of storage utilization: This indicator evaluates how well the available warehouse space is utilized. The usage rate is 75%, for instance, if the warehouse can hold 10,000 units but only holds 7,500. This rate may rise to 90% following optimization, indicating a more effective use of available space.

Order choosing time: The amount of time needed to select products for a purchase. For instance, after deploying the ML-based system, an average picking time of 8 minutes per order prior to optimization may decrease to 5 minutes.

Travel distance: The distance that employees or automated systems have to go to pick up things from the warehouse. After optimization, workers may walk 120 meters instead of the normal 200 meters each

4.Result and Outcome

1. Problem Statement:

Efficient inventory and order management in warehouses is complex. This project improves warehouse operations by cleaning, integrating, analyzing, visualizing data, and predicting demand.

2.Workflow:

Data Cleaning: Fixed missing values and outliers. Data Integration: Combined datasets (inventory, orders, layout) with features like OrderCount.

Visualization: Insights via stock levels, order frequency, and variable correlations.

Predictive Modeling: Forecasted product demand using RandomForestRegressor.

Automation: Created an automated end-to-end data pipeline.

5.Automation:

A single script (run_full_pipeline.py) automates data processing, insights generation, and reporting. 6.Technical Insights:

Simple Imputer and Standard Scaler for preprocessing.

Random Forest Regressor for predictions.Efficient dataset merging with pandas

7.Challenges & Learnings:

Overcame noisy data and non-numeric column challenges.

Key takeaway: The significance of preprocessing and visualization for demand forecasting.

8.Business Impact:
Enhanced inventory control and demand forecasting.

Improved warehouse efficiency with a scalable pipeline.

9.Demo:
Run python run_full_pipeline.py to display cleaned data, visualizations, and model performance.

10.Documentation:

Includes problem, workflow, results and instructions for using the pipelines.

Figure 1

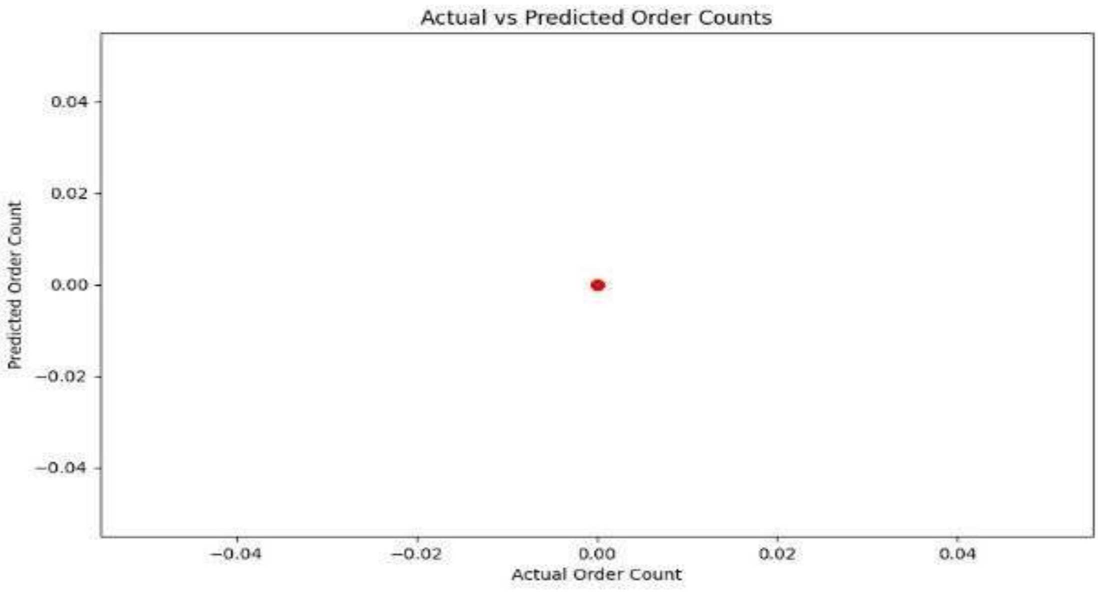


Figure 2

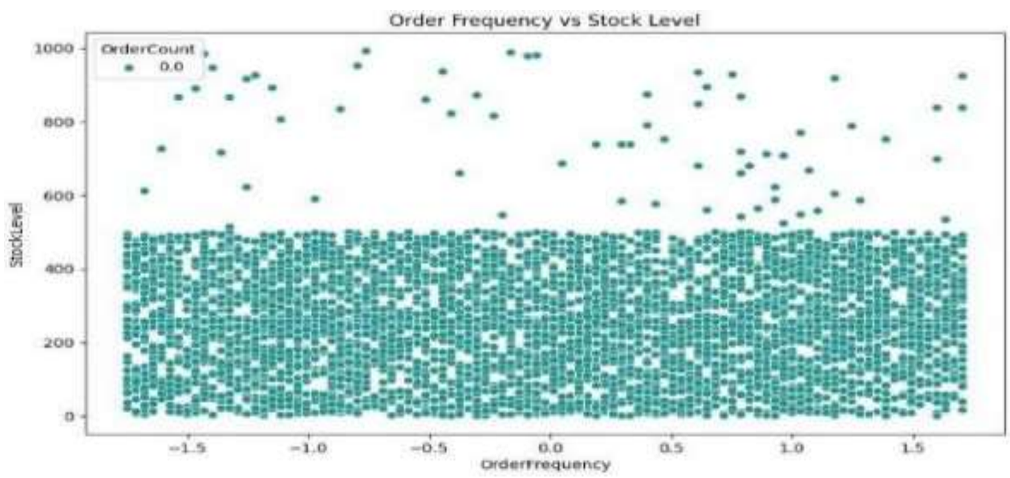
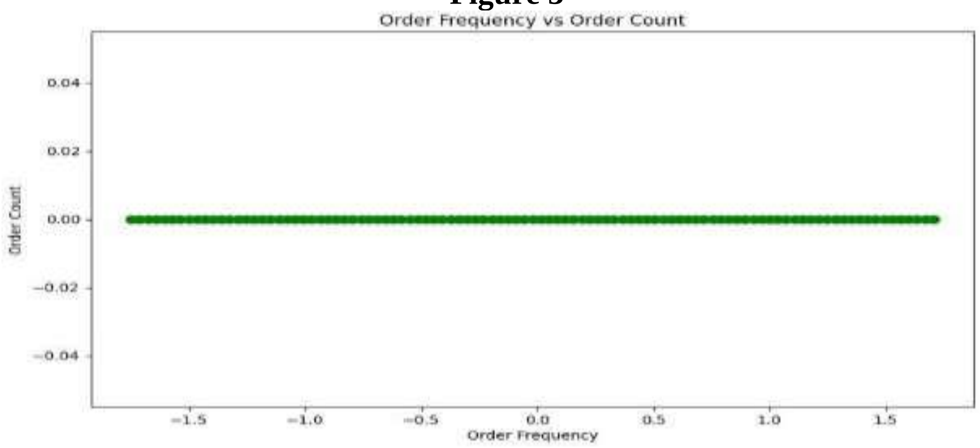


Figure 3



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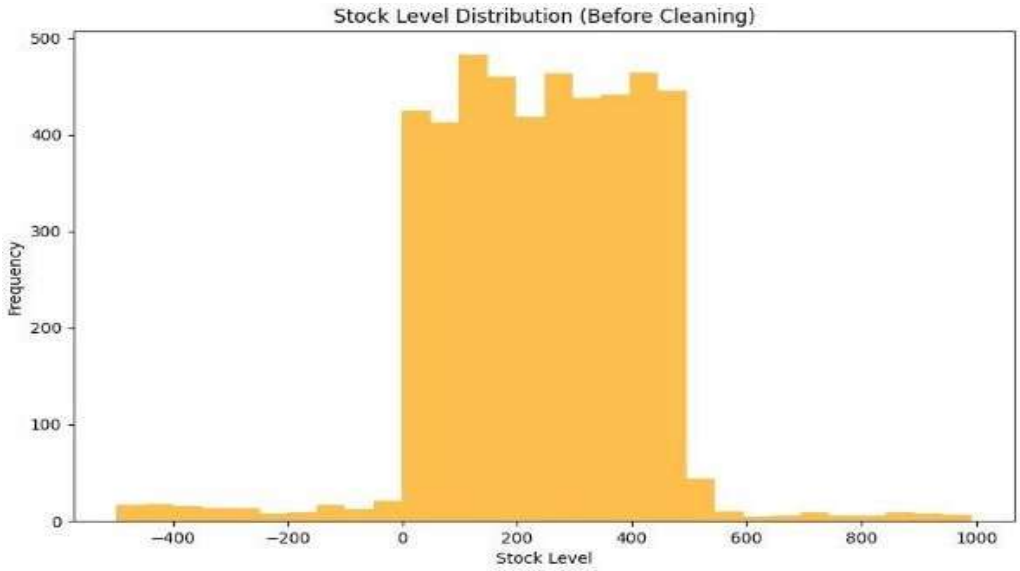

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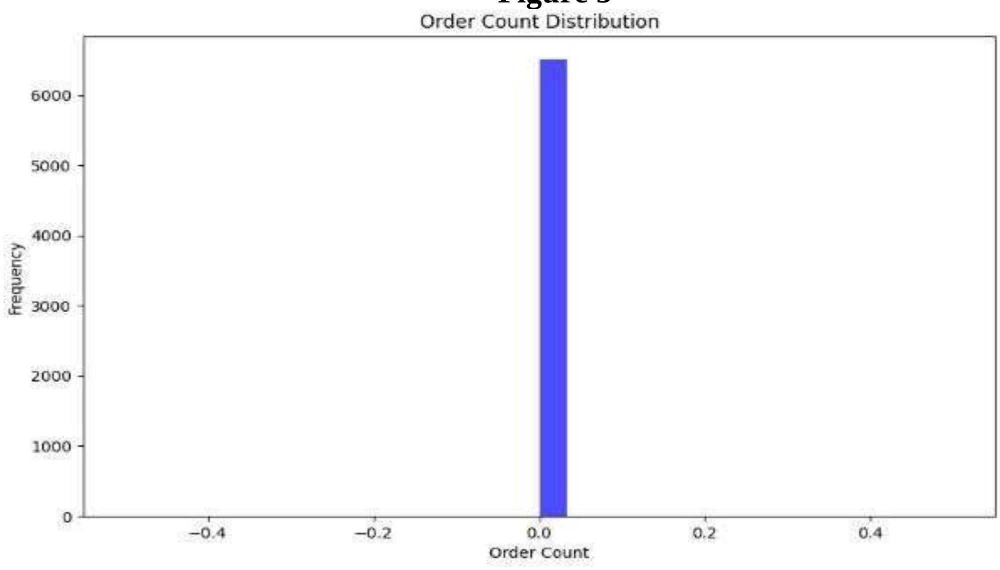

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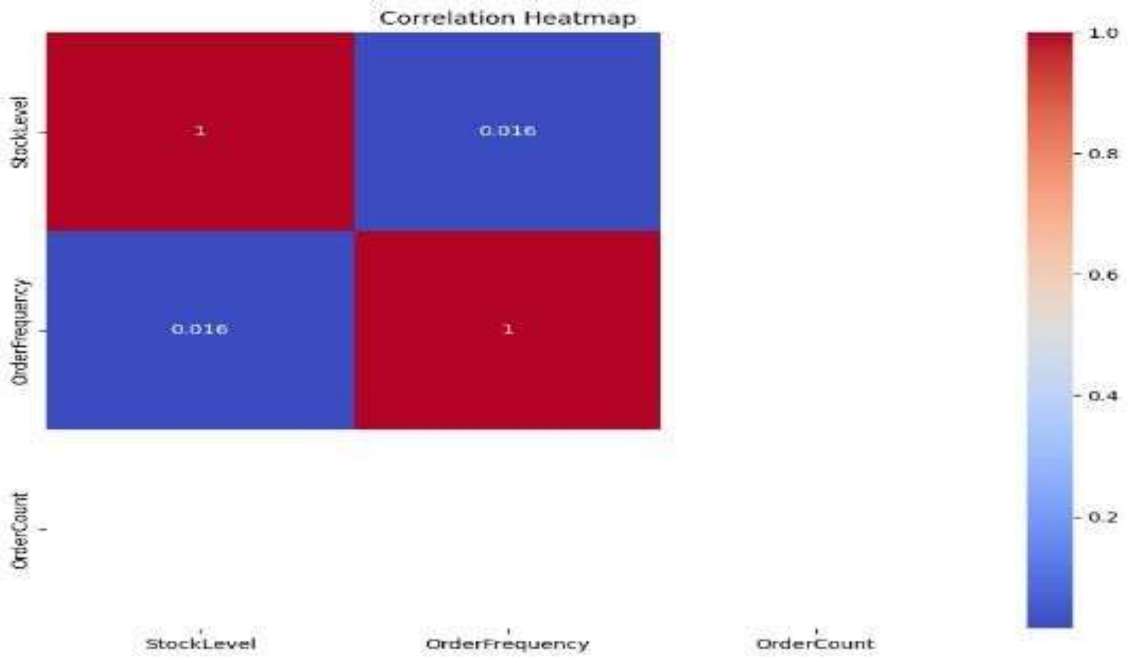

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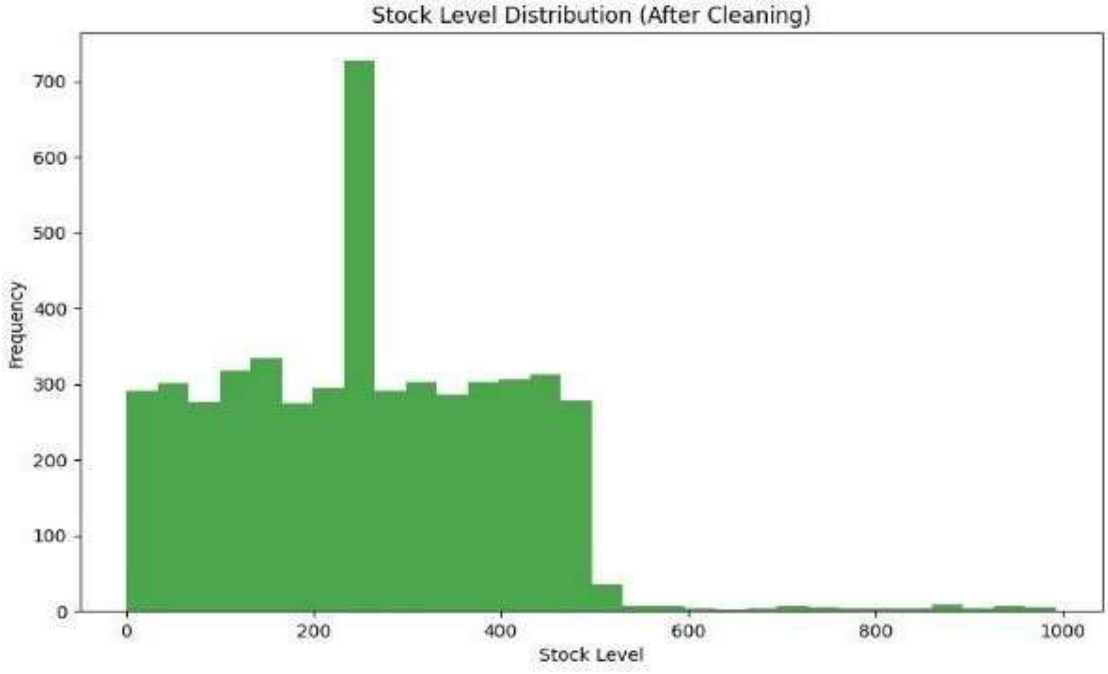

5. Conclusion

This report highlights the critical role of supply chain logistics in manufacturing, demonstrating that effective management of logistics processes can lead to significant cost savings and improved service levels. The optimization strategies implemented at ABC Manufacturing resulted in substantial improvements in inventory management, order fulfillment, and supplier coordination.

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