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AI-Driven Demand Forecasting and Inventory Optimization Using Prophet-Based Time Series Modelling

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Abstract

The increasing complexity of retail operations has intensified the need for precise demand estimation and efficient inventory management. This study proposes an integrated framework that combines time-series forecasting with automated inventory decision support to enhance supply chain performance. A forecasting model based on Prophet is employed to analyse historical sales data and generate future demand predictions, while a FastAPI-based backend facilitates real-time interaction with the system. To simulate practical retail conditions, multiple product categories with varying demand patterns and promotional influences are incorporated. An intelligent decision module evaluates predicted demand against available stock levels and classifies inventory status to identify potential shortages or stable conditions. The model's performance is assessed by using standard metrics such as MAE, RMSE, and MAPE. Experimental evaluation demonstrates strong predictive performance, achieving an MAE of 5, RMSE of 5.39, and MAPE of approximately 3.55%, indicating high forecasting accuracy. The proposed approach offers a scalable and data-driven solution for improving operational efficiency in retail supply chains.

Keywords: Demand Forecasting; Inventory Optimization; Prophet Model; Time Series Forecasting; FastAPI; Retail Analytics; Machine Learning.

1. Introduction

Efficient management of inventory in modern retail systems depends heavily on the ability to estimate future product demand with reasonable accuracy. In highly competitive markets, even small errors in demand estimation can lead to excess inventory, increased holding costs, or product shortages, ultimately affecting customer satisfaction and business performance. As a result, organizations increasingly rely on data-driven approaches to support decision-making in supply chain operations.

Demand patterns in real-world retail environments are often complex and influenced by multiple factors such as seasonality, promotional activities, changing consumer preferences, and external uncertainties. Traditional forecasting approaches, while useful in controlled scenarios, may not always capture such dynamic behaviour effectively. This creates a need for models that can adapt to variations in demand while remaining practical for real-world implementation.

Over time, forecasting techniques have evolved from classical statistical methods to more advanced machine learning and deep learning approaches. While these methods offer improved capability in identifying patterns within data, they often involve higher computational requirements and increased implementation complexity. In contrast, more flexible and interpretable models that balance accuracy and usability are gaining attention for practical applications in business environments.

Alongside forecasting, inventory management remains a critical component of supply chain efficiency. However, in many existing systems, demand prediction and inventory decision-making are treated as separate processes. This separation limits the ability to translate forecasted values into timely operational actions, reducing the overall effectiveness of the system.

To address this gap, the present work introduces an integrated framework that combines demand forecasting with inventory evaluation. The proposed system utilizes a Prophet-based time-series model to generate future demand estimates and incorporates a decision-support module to assess stock conditions and recommend appropriate actions. By linking predictive analytics directly with inventory control, the framework aims to enhance responsiveness, reduce uncertainty, and support more informed decision-making in retail operations.

2. Literature Review

Demand forecasting plays a central role in retail analytics and supply chain operations, as it directly influences inventory planning and overall system efficiency. Over the years, a variety of approaches have been explored to improve forecasting accuracy and address changing demand behaviour across different market conditions. These approaches range from traditional statistical models to more advanced machine learning and deep learning techniques.

Classical time-series models, such as Auto-Regressive Integrated Moving Average (ARIMA), have been commonly applied for analysing historical demand data and identifying underlying patterns such as trend and seasonality. While these models are effective in structured scenarios, they often require careful parameter configuration and may struggle to represent complex, non-linear relationships present in real-world datasets [1].

To overcome these limitations, machine learning-based approaches including Random Forest and Support Vector Machines have been introduced for demand prediction. These methods are capable of capturing non-linear dependencies and have shown improved performance in various forecasting tasks, particularly when sufficient training data is available [2].

In recent years, deep learning models especially Long Short-Term Memory (LSTM) networks have gained prominence due to their ability to learn sequential patterns and long-term dependencies in time-series data. Despite their strong predictive capability, such models typically require large datasets and higher computational resources, which can limit their applicability in practical deployment scenarios [3].

More recently, the Prophet model has emerged as an effective and user-friendly forecasting tool. It is designed to handle key challenges such as seasonality, trend changes, and missing data with minimal preprocessing. Due to its flexibility and ease of implementation, Prophet has become increasingly suitable for real-world business applications where quick and reliable forecasting is required [4].

Alongside forecasting, inventory management remains a crucial aspect of supply chain performance. Inefficient inventory practices can lead to excessive holding costs, product shortages, and reduced profitability. However, many existing systems treat demand forecasting and inventory control as independent components, which limits their ability to support effective operational decision-making [5].

Recent studies emphasize the importance of integrating forecasting techniques with inventory decision-support mechanisms. Such integrated systems enable organizations to convert predicted demand into actionable insights, thereby improving responsiveness, reducing uncertainty, and enhancing overall supply chain efficiency [6,9–11].

Furthermore, research in system design and engineering highlights the value of combining analytical models with practical implementation frameworks. Aligning predictive techniques with real-world constraints can significantly improve system performance and usability [13]. Similar findings suggest that integrating optimization strategies with forecasting models leads to more robust and efficient solutions in operational environments [14].

Despite the progress made in both forecasting and inventory management, there remains a noticeable gap in developing unified systems that seamlessly combine demand prediction with real-time inventory decision-making. This study addresses this gap by proposing an integrated framework that links a Prophet-based forecasting model with an intelligent inventory decision module, enabling improved operational efficiency and data-driven decision-making.

3. Materials And Methods

3.1 System Architecture

The proposed framework is designed using a client–server model, where a user-facing interface communicates with a backend service responsible for generating demand predictions. The backend is developed using FastAPI, allowing efficient handling of requests and rapid response generation.

The process begins by loading a pre-trained forecasting model stored in a serialized format. Upon receiving a request, the system generates future time-series data and produces demand predictions for a specified duration. These predictions are then processed and delivered to the frontend along with relevant insights, including stock status and recommended actions (Figure 1).

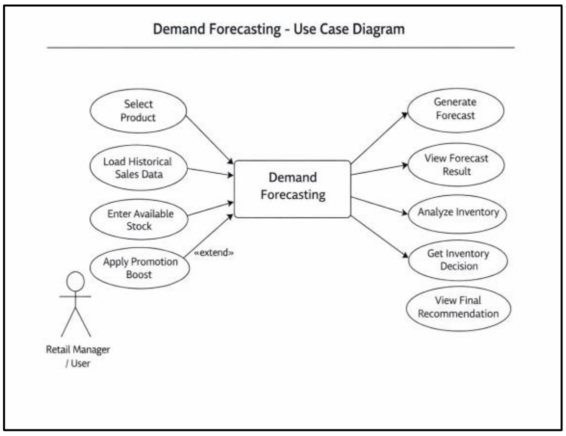

Figure 1: *System Architecture of the Proposed Demand Forecasting and Inventory Optimization System*

3.2 Forecasting Model (Prophet)

The forecasting component is based on the Prophet model, which is designed for time-series forecasting with strong seasonality and trend variations. The model is trained using historical sales data and stored in a serialized format.

During execution, the model is loaded to generate a future dataset extending 28 days beyond the existing data. The predictions are generated using components such as trend and seasonality. The output includes forecasted demand values for each time step.

3.3 API Implementation

The backend system is developed using the FastAPI framework to enable efficient communication between the frontend interface and the forecasting model. The API endpoints accept product identifiers and optional promotional parameters as inputs.

Once a request is received, the system retrieves the corresponding product configuration and performs the required data processing. It then generates demand forecasts and returns structured responses containing predicted values, inventory status, and decision-support insights. Cross-Origin Resource Sharing (CORS) is enabled to ensure smooth integration with the frontend application.

3.4 Demand Simulation and Product Profiles

To simulate real-world retail conditions, the system defines multiple product profiles with different demand characteristics. Each product is assigned a multiplier to adjust demand based on its consumption pattern.

In addition, a promotional factor is included to represent the impact of marketing activities on demand. These parameters allow the system to model various scenarios such as low-demand items, seasonal products, and high-demand goods.

3.5 Inventory Decision Logic

An intelligent decision module is incorporated to analyse inventory levels based on forecasted demand. The system computes the total expected demand over a defined time period and compares it with the currently available stock.

If the estimated demand exceeds the available inventory, the system categorizes the status as "CRITICAL_LOW" and suggests replenishment actions. Otherwise, the inventory is considered to be in a stable condition and marked as "NOMINAL." This mechanism supports proactive inventory control and minimizes the likelihood of stock shortages.

3.6 Performance Evaluation Metrics

The performance of the forecasting model is evaluated using standard accuracy metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

These metrics are used to measure prediction accuracy and assess the reliability of the model. The evaluation helps in validating the effectiveness of the proposed system for real-world applications.

4. Results

The developed AI-based demand forecasting and inventory optimization system was evaluated under multiple scenarios to assess its effectiveness in real-time inventory management. Under normal operating conditions, where inventory levels were sufficient to meet predicted demand, the system performed reliably without generating any alerts. This indicates that the system can maintain a balanced supply–demand state under stable conditions (Figure 2).

In moderate demand scenarios, slight variations in predicted demand were observed. The system successfully detected these variations and maintained appropriate inventory levels without triggering critical alerts. This demonstrates the system's ability to handle fluctuations in demand while ensuring stability (Figure 3).

In high-demand scenarios, the system identified significant increases in predicted demand and generated alert notifications indicating potential stock shortages. For example, products such as SPF and Diet Coke showed a sharp rise in demand. The system flagged these items and recommended replenishment actions to prevent stockouts (Figure 4 and Figure 5).

In addition, the system provides visual insights through demand forecasting graphs and real-time inventory indicators. These visualizations help users understand demand trends, monitor stock levels, and make informed decisions efficiently. Overall, the results demonstrate that the proposed system effectively predicts demand patterns, maintains inventory balance, and generates timely alerts for system improvements. This contributes to improved decision-making and enhanced responsiveness in supply chain operations.

Table 1: System Response under Different Demand Scenarios

Scenario	Demand Level	System Resp.	Outcome
Normal Condition	Stable	No alert	Balanced inventory
Moderate Demand	Slight increase	No critical alert	Stable operation
Moderate Imbalance	Slight shortage	Alert generated	Restocking suggested
High Demand Surge	High increase	Critical alert	Immediate replenish-ment
Optimal Condition	Within limits	No alert	Stable system performa-nce

The table summarizes the system's behavior across different demand scenarios, highlighting its ability to generate appropriate alerts and maintain inventory balance.

4.1 System Interface and Input Controls

The system interface displays predicted demand along with current inventory levels, enabling users to quickly assess stock conditions. The visualization supports easy interpretation of demand trends and inventory status.

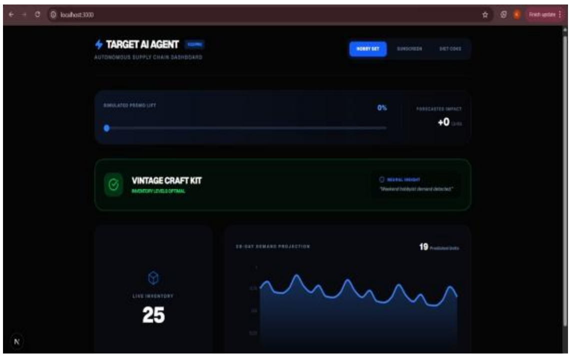

Figure 2: *Dashboard Interface Showing Product Selection and Promotional Input*

4.2 Demand Forecast under Moderate Promotion

When a promotional factor is applied, the system shows a moderate increase in predicted demand. The forecast trends remain stable, and inventory levels are maintained within acceptable limits.

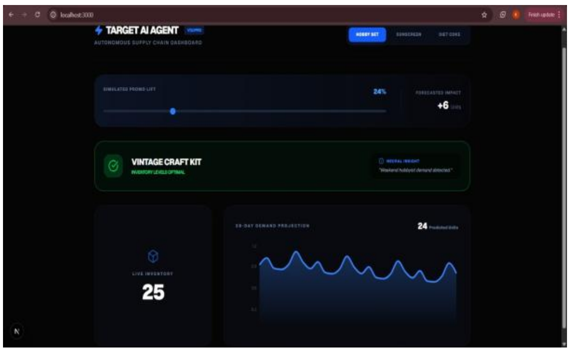

Figure 3: *Demand Forecast under Moderate Promotional Influence*

4.3 Inventory Risk Detection under Different Scenarios

4.3.1. Inventory Alert under Moderate Demand-Supply Imbalance

The system detects a mismatch between predicted demand and available inventory, generating an alert. This helps identify potential shortages and supports timely restocking decisions.

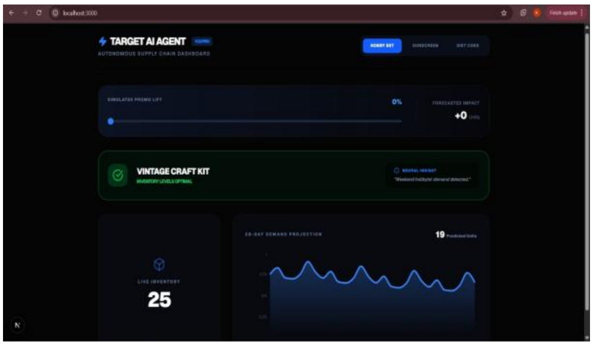

Figure 4: *Inventory Alert under Moderate Demand-Supply Imbalance*

4.3.2. Inventory Alert under High Demand Surge

Under high promotional influence, the system predicts a significant increase in demand that exceeds available inventory.

In such cases, a critical alert is generated, indicating the need for immediate replenishment.

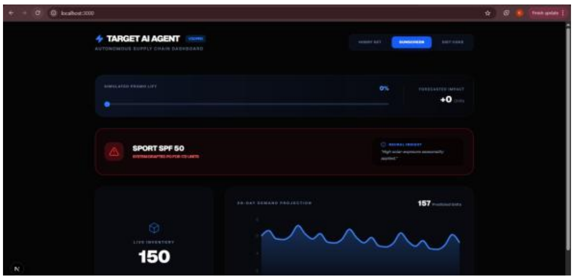

Figure 5: *Inventory Alert under High Demand Surge*

4.4 Visualization of Forecasted Demand and Inventory

The system also identifies scenarios where inventory levels are sufficient to meet predicted demand. In such cases, no alerts are generated, indicating a stable supply–demand condition (Figure 6).

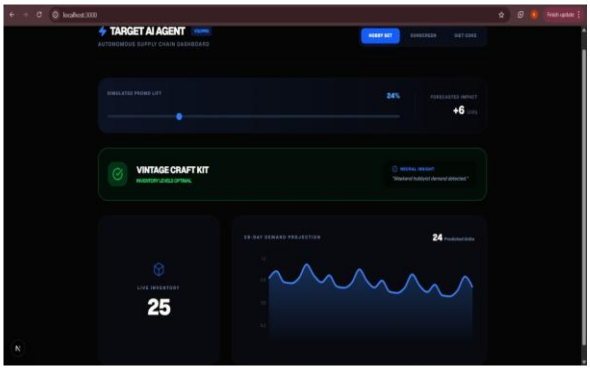

Figure 6: *Dashboard Showing Optimal Inventory Condition*

5. Performance Evaluation

The performance of the proposed demand forecasting system is evaluated using standard accuracy metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are widely used to assess the accuracy and reliability of forecasting models [12].

The evaluation is based on the comparison between actual demand values and predicted demand values generated by the system.

5.1 Evaluation Metrics

The performance metrics are calculated as follows:

$$MAE = \left(\frac{1}{n}\right)\sum |Actual - Predicted|$$

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right)\sum (Actual - Predicted)^2\right]}$$

$$MAPE = \left(\frac{1}{n}\right)\sum\left(\frac{|Actual - Predicted|}{Actual}\right) \times 100$$

Absolute values of errors are used in the calculation of MAE and MAPE to ensure that both overestimation and underestimation are treated equally, while RMSE considers squared errors to emphasize larger deviations.

For example: If the actual demand is 100 units and the predicted demand is 95 units:

MAE = |100 − 95| = 5

RMSE = $\sqrt{(5^2)}$ = 5

MAPE = (5 / 100) × 100 = 5%

These calculations demonstrate how prediction errors are measured and validate the accuracy of the forecasting model.

5.2 Sample Data for Evaluation

Table 2: Actual vs Predicted Demand Values

Day	Actual Demand	Predicted Demand	Absolute Error
1	120	115	5
2	135	143	8
3	150	144	6
4	160	156	4
5	170	168	2

The above table shows a comparison between actual and predicted demand values generated by the system. The differences between these values are used to calculate performance metrics such as MAE, RMSE, and MAPE.

From Table 2:

- Total Absolute Error = 5 + 8 + 6 + 4 + 2 = 25
- Number of observations (n) = 5

MAE Calculation

$$\boldsymbol{MAE = \frac{25}{5} = 5}$$

RMSE Calculation

$$RMSE = \sqrt{\frac{(5^2+8^2+6^2+4^2+2^2)}{5}} = \sqrt{29}$$

$$\boldsymbol{RMSE = 5.39}$$

MAPE Calculation

$$MAPE = \frac{1}{5} \times \left(\frac{5}{120} + \frac{8}{135} + \frac{6}{150} + \frac{4}{160} + \frac{2}{170}\right) \times 100$$

$$\boldsymbol{MAPE \approx 3.55\%}$$

5.3 Interpretation of Results

The calculated values indicate that the forecasting model produces low prediction errors across the evaluated data points. The MAE and RMSE values are consistent, indicating stable error distribution, while the low MAPE value (approximately 3.55%) reflects high prediction accuracy.

These results demonstrate that the proposed system is effective in capturing demand patterns and can be reliably used for real-time inventory decision-making.

6. Conclusion

The study introduces an integrated approach that combines demand prediction with inventory decision-making to address practical challenges in retail operations. By linking forecasting outputs directly with stock evaluation, the system enables more informed and timely inventory control.

The use of the Prophet model allows the framework to effectively interpret variations in demand under different conditions, ensuring that changes in consumption patterns are identified with consistency. This, in turn, supports more accurate and responsive inventory actions across multiple scenarios.

In addition, the incorporation of a decision module strengthens the system by converting predicted values into actionable insights, reducing the likelihood of both excess stock and shortages. The backend implementation using FastAPI further enhances the system by enabling efficient processing and real-time interaction.

Overall, the proposed solution demonstrates a practical and scalable method for improving demand forecasting and inventory management. By supporting data-driven decisions and enhancing operational responsiveness, the framework contributes to more efficient and reliable supply chain performance.

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