AI Driven Smart Supply Chain Management System

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Abstract- *Demand forecasting plays a pivotal role in modern supply chain management, directly influencing inventory planning, logistics, and overall business decision-making. Traditional forecasting systems often rely on static machine learning models that gradually lose accuracy as market conditions evolve, leading to inefficiencies and poor resource utilization. To address these limitations, this paper proposes an AIOps-driven demand forecasting system built on the MERN stack. The system integrates machine learning models such as LSTM and Prophet with an AIOps monitoring layer that continuously tracks performance, detects data drift, and triggers automatic retraining when necessary. By combining scalable web technologies with adaptive AI, the proposed solution delivers a self- improving, real-time forecasting platform that enhances supply chain resilience, reduces stockouts, and supports intelligent business decisions.*

I. INTRODUCTION

Supply chain resilience has become increasingly important in the face of global disruptions such as pandemics, geopolitical conflicts, and fluctuating consumer behavior. Accurate demand forecasting is essential for minimizing waste, optimizing inventory, and ensuring timely delivery of goods. However, static machine learning models often fail to adapt to dynamic market conditions, resulting in declining accuracy over time. Enterprise-level solutions exist, but they are costly, complex, and inaccessible to small and medium-sized businesses. This project introduces a web-based AI system that leverages the MERN stack to provide a scalable, adaptive, and cost-effective solution. By integrating AIOps monitoring with demand forecasting, the system ensures continuous accuracy, adaptability, and transparency, making it suitable for diverse business environments.

II. LITERATURE SURVEY

Recent studies highlight the growing role of artificial intelligence in supply chain forecasting. Predictive analytics using AI and ML has been shown to reduce forecast errors by 20–50%, surpassing traditional statistical methods. Research in the manufacturing sector demonstrates that neural networks and hybrid models improve industrial demand prediction, though they remain dependent on large datasets. AIOps-based forecasting models have proven effective in detecting concept drift, thereby improving reliability in time-series predictions. Systems such as SmartStock integrate AI forecasting with web applications for MSMEs, but they lack advanced AIOps monitoring. Retail-focused models that incorporate external data sources such as social media and local events achieve higher accuracy but face challenges in data integration and scalability. These studies collectively emphasize the need for a system that combines adaptive AI forecasting with real-time monitoring and retraining.

III. PROPOSEDMETHODOLOGY

The proposed system integrates multiple layers to deliver accurate and adaptive demand forecasting. The **frontend**, built with React.js, provides interactive dashboards that visualize sales data and forecasts using Chart.js. The **backend**, developed with Node.js and Express, manages APIs, business logic, and system integration. A **MongoDB database** stores historical sales data, user details, and retraining logs. The **machine learning layer** employs LSTM and Prophet models to analyze historical sales patterns, seasonality, and external factors, generating forecasts ranging from 7 to 90 days. The **AIOps layer** continuously monitors model performance using metrics such as MAPE and RMSE, detects data drift through statistical tests, and triggers automatic retraining when accuracy falls below thresholds. Real-time insights are delivered via WebSocket updates, ensuring that businesses receive timely alerts and actionable recommendations.

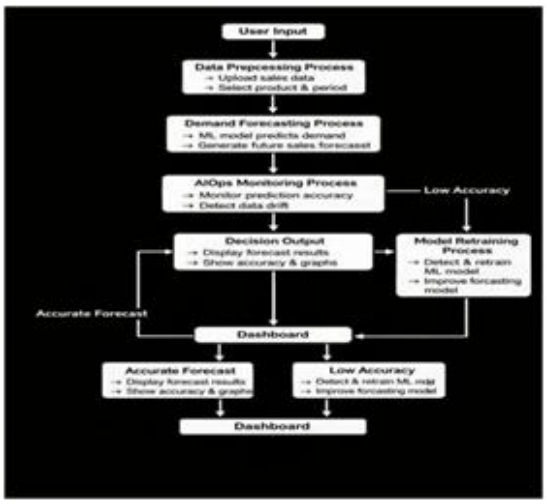

Figure 1 : Dataflow diagram of our proposed module

IV. SYSTEM PROCESS FLOW

1. Data Acquisition:

Users provide input through historical sales data uploads in CSV or similar formats.

2. Preprocessing & Data Cleaning:

Raw data is cleaned by removing missing values and noise, then normalized to improve model performance.

3. Demand Forecasting:

The processed data is analyzed using ML algorithms to identify trends and predict future demand for selected products.

4. AIOps Monitoring:

The system continuously tracks accuracy metrics (MAPE/RMSE) and detects data drift.

5. Model Retraining:

If drift is detected or accuracy falls below a threshold, the system triggers automated retraining on fresh data.

6. Result Visualization:

The output is presented via an interactive dashboard displaying forecast results, probability scores, and trend graphs.

V. RESULT AND DISCUSSIONS

The prototype system was tested using historical sales datasets to evaluate accuracy and adaptability. Forecasting performance was measured using MAPE and RMSE, demonstrating consistent accuracy across multiple test scenarios. The AIOps layer successfully detected data drift exceeding 10% and triggered retraining, ensuring that the model remained reliable over time. User testing confirmed that the interactive dashboards were intuitive and accessible, even for non- technical users. Compared to static ML systems, the proposed solution maintained accuracy over extended periods, reducing stockouts and improving inventory planning. These results validate the effectiveness of integrating AIOps with demand forecasting in a web-based environment.

VI. CONCLUSION

This paper presents an AI-driven supply chain management system that integrates demand forecasting with AIOps monitoring and retraining. By leveraging the MERN stack, the system offers scalability, real-time insights, and adaptability to dynamic market conditions. Unlike traditional forecasting methods, the proposed solution ensures continuous accuracy through automated drift detection and retraining. Future enhancements include integrating external data sources such as social media and IoT sensors, deploying cloud-based scalability with Kubernetes, and extending functionality to predictive logistics and route optimization. Overall, the system represents a significant step toward intelligent, adaptive, and accessible supply chain management.

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