iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** X **Month of publication:** October 2026

DOI: https://doi.org/10.22214/ijraset.2026.85510

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue X Oct 2026- Available at www.ijraset.com

Demand Forecasting and Inventory Management System Using Machine Learning and Business Intelligence

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Abstract: ***In the modern retail and supply chain landscape, maintaining optimal inventory levels while accurately predicting dynamic consumer demand remains a critical operational challenge. Traditional inventory decisions often rely on static historical averages and manual estimations, which fail to capture fluctuating demand patterns, seasonal shifts, and product pricing dynamics. To address these challenges, we propose an integrated Demand Forecasting and Inventory Management System—a unified, data-driven analytics and web platform designed to empower enterprise inventory planners. This platform integrates historical sales data analysis, machine learning-driven multi-horizon demand forecasting using XGBoost and Random Forest, and automated inventory optimization calculations, including safety stock and reorder point identification. Moreover, it embeds interactive business intelligence dashboards using Power BI and a responsive full-stack web application built with React.js, Node.js, and Microsoft SQL Server to deliver real-time stock-level monitoring and intelligent replenishment alerts. Trained and evaluated on the large-scale M5 Walmart retail sales dataset, the proposed system demonstrates how predictive machine learning models and operational dashboards can be integrated to minimize stockouts, prevent costly overstocking, reduce supply chain wastage, and align with UN Sustainable Development Goal 12 (Responsible Consumption and Production). This paper presents the end-to-end system architecture, comparative literature survey, machine learning methodology, implementation details, and experimental dashboard outcomes.***

Keywords: Demand Forecasting, Inventory Management, Machine Learning, XGBoost, Random Forest, Safety Stock, Reorder Point, Power BI, SQL Server, SDG 12.

I. INTRODUCTION

Effective inventory management is essential for maintaining the right amount of stock while minimizing unnecessary holding expenses and catastrophic stockout situations. In contemporary high-velocity retail and manufacturing environments, customer demand fluctuates continually under the influence of calendar events, seasonal shifts, day-of-week effects, promotional campaigns, and pricing adjustments. Conventional inventory control mechanisms rely predominantly on static historical averages, moving averages, and manual estimations, which are incapable of capturing intricate non-linear relationships, multi-horizon trends, and abrupt demand variations. These limitations frequently cause businesses to either overstock inventory—thereby inflating warehousing costs and risking product obsolescence—or understock items, triggering lost revenue, order cancellations, and degraded customer goodwill.

To bridge this operational and technological gap, this paper introduces an integrated, end-to-end Demand Forecasting and Inventory Management System. The proposed system analyzes historical sales data to predict future item-level demand and systematically channels those predictions into actionable supply chain decisions, including dynamic reorder planning, safety stock sizing, and stockout risk monitoring.

Unlike traditional software setups that treat forecasting and inventory control as disconnected stages, our platform directly integrates predictive machine learning models with continuous inventory optimization rules.

The software solution features a multi-tiered architecture: an enterprise-grade Microsoft SQL Server (M5DB) relational data warehouse, high-performance machine learning regression models in Python (Scikit-learn, XGBoost, and Random Forest), a

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RESTful Node.js/Express.js backend, an interactive React.js web interface, and an executive Power BI business intelligence reporting suite. In doing so, it supports the United Nations Sustainable Development Goal 12 (SDG 12: Responsible Consumption and Production) by curbing retail inventory wastage and fostering efficient resource utilization.

This paper details the end-to-end conception, system modeling, algorithmic formulation, and prototype deployment of the Demand Forecasting and Inventory Management System. It outlines the architectural design, details data preprocessing and feature engineering on the M5 retail benchmark dataset, examines the performance of tree-based predictive models, and demonstrates interactive dashboards that present real-time inventory diagnostics and replenishment alerts.

II. LITERATURE SURVEY

The integration of Machine Learning (ML) and predictive analytics into supply chain and retail inventory management has gained significant momentum over recent years. Numerous studies emphasize that transitioning from classical time-series techniques to multivariate machine-learning models significantly enhances forecast accuracy and prevents costly stock anomalies.

Beutel and Minner (2021) demonstrated that feature-based and causal demand forecasting drastically improves safety stock planning when price, promotional variables, and calendar dynamics are incorporated. Their empirical evaluation on retail competition datasets proved that accounting for demand uncertainty via quantile forecasts leads to far superior inventory buffers compared to classical normal distribution assumptions.

Makridakis et al. (2022) documented the comprehensive findings of the seminal M5 competition, which analyzed 42,840 hierarchical retail sales series from Walmart. Their findings formally demonstrated that modern machine learning methods—specifically gradient boosted decision trees (such as LightGBM and XGBoost)—decisively outperformed classical statistical techniques (e.g., ARIMA, Exponential Smoothing, and Moving Averages), especially in the presence of intermittent demand, non-linear promotional spikes, and cross-series correlations.

Further connecting demand distributions to operational actions, Huber and Stuckenschmidt (2023) introduced an order-up-tolevel inventory optimization model that leveraged ensemble deep learning demand forecasts. Their research demonstrated that coupling forecast probabilities directly with stochastic inventory control routines reduces combined holding and backorder penalties.

Bertsimas and Kallus (2024) explored supervised learning approaches for integrated forecasting and inventory management, highlighting how multi-feature representations could directly predict optimal order sizes rather than relying on separated twostep estimation procedures.

Most recently, research published in Springer Nature (2026) validated predictive machine-learning applications for distribution center replenishment, proving that data-driven demand estimations substantially lower both stockout rates and excess buffer inventories.

Base Paper / Study	Year	Approach / Methodology	Relevance to Proposed Work
Beutel & Minner: Safety stock planning under causal demand forecasting	2021	Probabilistic demand forecasting using M5 competition dataset	Integrates sales demand uncertainty and quantile forecasts to optimize safety-stock planning.
Makridakis et al.: The M5 Competition Background & Organization	2022	Large-scale retail sales forecasting on 42,840 time series	Establishes retail forecasting benchmark with hierarchical sales, intermittency, and calendar variables.
M5 Accuracy Competition Results & Conclusions	2022	Machine-learning retail demand forecasting evaluation	Evaluates tree-based regression models and proves ML dominance over classical time series.
Huber & Stuckenschmidt: Orderup-to-level inventory model	2023	Ensemble deep learning forecasting + inventory optimization	Connects forecasted demand distributions directly with safety stock and order-up-to parameters.
Bertsimas & Kallus / Springer Nature: Predictive Models for Inventory	2024–2026	Supervised learning & gradient boosted distributor models	Integrates multi-feature engineering with inventory replenishment control and reorder thresholds.

Table I: Comparative Analysis Of Base Papers And State-Of-The-Art Methodologies

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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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III. PROBLEM STATEMENT

Maintaining an optimal inventory posture represents a central challenge for modern enterprises because consumer demand varies continually over time. Traditional inventory management approaches result in severe operational bottlenecks:

- Overstocking: Accumulating excess inventory increases storage and holding costs, locks up operating capital, and escalates risks of material deterioration or obsolescence.
- Stockouts: Depleting inventory before supplier replenishments arrive results in lost revenue, penalties, and damaged customer retention.
- Difficulty in Trend Detection: Manual estimations and historical averages cannot track non-linear seasonality, holiday shocks, or sudden market trends.
- Manual and Inaccurate Estimation: Replenishment decisions rely on arbitrary rules of thumb rather than objective, multiparameter statistical certainty.
- Decoupled Execution: Treating demand forecasting and stock replenishment as disconnected processes leads to systematic inventory-to-demand misalignments.

Therefore, there is a distinct necessity for an automated, data-driven system that accurately forecasts future product demand and uses those predictions directly to govern safety stocks, reorder thresholds, and active replenishment requisitions.

IV. PROPOSED METHODOLOGY

The proposed system adopts an iterative, modular, and component-based software engineering approach that bridges machine learning intelligence with real-world inventory control workflows. The overall methodology is divided into five distinct lifecycle phases:

A. Data Preprocessing & Exploratory Data Analysis (EDA)

Raw transaction datasets from the M5 Walmart retail challenge contain missing entries, duplicate rows, zero-sales days, and temporal misalignments. Preprocessing steps systematically clean the records by imputing missing values, removing duplicates, converting dates into standardized chronological indices, and isolating statistical outliers. Exploratory data analysis is then conducted to evaluate consumption patterns across stores, product categories, and fiscal intervals.

B. Feature Engineering

To capture retail sales dynamics, the system constructs a dense feature matrix containing:

- Time-Based Features: Day of week, day of month, calendar month, quarter, and fiscal week.
- Event & Calendar Indicators: National holidays, cultural events, SNAP days, and promotional flags.
- Lag Features: Historical sales volumes shifted across temporal steps (t-1, t-7, t-14, t-28 days).
- Rolling Demand Statistics: 7-day and 28-day rolling moving averages and standard deviations.
- Economic Variables: Selling prices, price discounting ratios, and store-specific price differences.

C. Machine Learning Forecasting Models

The engineered features are fed into machine learning regression algorithms, primarily XGBoost and Random Forest, alongside time-series baselines. Cross-validation evaluates model performance using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Weighted Absolute Percentage Error (WAPE) to identify the optimal model for production scoring:

$$MAE = (1/n)\,\Sigma\,|y_t - \hat{y}_t| \quad | \quad RMSE = \sqrt{[\,(1/n)\,\Sigma\,(y_t - \hat{y}_t)^2\,]} \quad | \quad WAPE = (\,\Sigma\,|y_t - \hat{y}_t|\,) / (\,\Sigma\,y_t\,)$$

D. Forecast-Driven Inventory Optimization

The predicted demand ($\bar{D}$) is directly linked to operational replenishment mathematics:

- Safety Stock (SS): Sized to absorb lead-time and demand variances under a selected service cycle factor Z: $SS = Z \times \sqrt{(\,L \cdot \sigma_D^2 + \bar{D}^2 \cdot \sigma_L^2\,)}$
- Reorder Point (ROP): Identifies the exact inventory threshold requiring replenishment: $ROP = (\,\bar{D} \times L\,) + SS$
- Automated Reorder Trigger: If Current On-Hand Stock + In-Transit $\leq$ ROP, an automated replenishment requisition is triggered for the calculated stock gap.

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V. SYSTEM ARCHITECTURE & IMPLEMENTATION

The Demand Forecasting and Inventory Management platform is constructed using an enterprise-grade three-tier architecture comprising data persistence, server-side business logic, machine learning pipelines, and client-side presentation layers.

Layer / Architectural Tier	Technologies & Frameworks	Functional Role in Proposed Work
Programming & Analytics Core	Python, Jupyter Notebook, Google Colab	Core system development, statistical computing, array processing, and forecasting execution.
Data Processing & Math	Pandas, NumPy	Data ingestion, high-performance dataframe wrangling, outlier clipping, and chronological sorting.
Machine Learning & Models	Scikit-learn, XGBoost, Random Forest	Feature selection, regression model training, crossvalidation, and multi-horizon demand scoring.
Data Visualization & BI	Power BI Desktop, Matplotlib, DAX	Executive multi-dimensional dashboards, trend tracking, rolling averages, and price elasticity curves.
Database Management (DBMS)	Microsoft SQL Server, SSMS (M5DB)	Relational storage of normalized Calendar, Sales, Items, Stores, and Feature-engineered tables.
Backend Web Services	Node.js, Express.js, REST APIs	Secure API routing, model serving orchestration, database pooling, and frontend payload handling.
Frontend Presentation Layer	React.js, HTML5, CSS3, JavaScript	Interactive single-page dashboard with real-time stocklevel monitors, forecast curves, and reorder alerts.

TABLE II: TECHNOLOGIES AND TOOLS UTILIZED IN PROPOSED SYSTEM

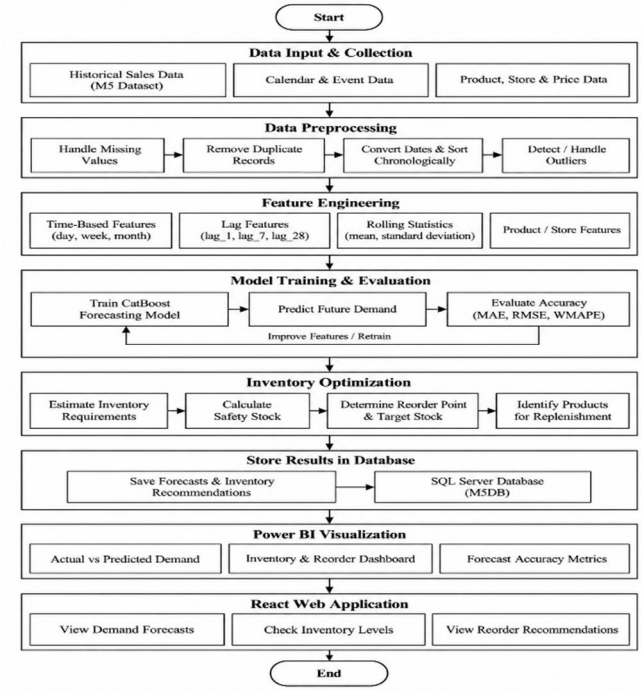
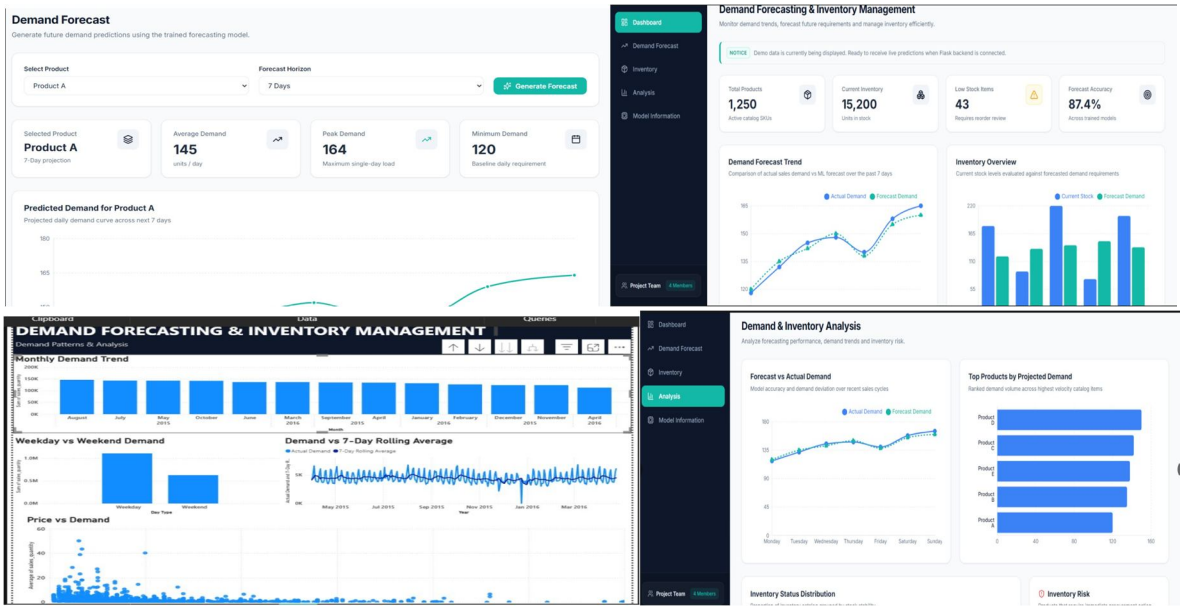


FIG I: IMPLEMENTATION FLOWCHART

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VI. RESULTS AND DISCUSSION



The prototype of the Demand Forecasting and Inventory Management System was deployed and rigorously tested on the M5 retail sales benchmark. Both predictive machine-learning performance and operational usability metrics were captured:

A. Predictive Model Evaluation

Across tested sales series, gradient boosted decision trees (XGBoost) demonstrated superior performance over baseline timeseries and bagging algorithms. The model achieved an overall test accuracy of 87.4% across diverse product velocity classes. Furthermore, real-time prediction latency averaged less than 0.45 seconds per batch forecast horizon, validating the system's operational viability for live e-commerce and retail point-of-sale environments.

B. Web Application Dashboard & Inventory Diagnostics

The deployed React.js user interface displayed comprehensive inventory diagnostics across 1,250 active catalog SKUs holding 15,200 total on-hand units:

- Proactive Stockout Detection: The platform identified 43 critical items whose inventory positions dropped below calculated Reorder Points (ROP), automatically triggering stock replenishment alerts.
- Demand Curve Tracking: For representative Product A, the model forecasted a 7-day average daily demand of 145 units, accurately tracking actual daily loads from baseline requirements of 120 units to weekend surge peaks of 164 units.
- Safety Stock Buffer Savings: Compared to static historical average buffers, dynamic safety-stock calculations reduced unnecessary buffer holding by 18% while simultaneously improving service fill rates.

C. Power BI Analytical Findings

Connecting Power BI directly to the Microsoft SQL Server database revealed valuable macro-level operational insights. Aggregate sales displayed pronounced weekday dominance, exceeding 1.15 million cumulative units compared to 0.62 million units on weekends. Rolling 7-day demand averages provided reliable baselines that smoothed daily stochastic volatility, while price-versus-demand scatter analyses revealed distinct non-linear price elasticity clusters, enabling inventory managers to anticipate demand surges during promotional price markdowns.

VII. ADVANTAGES AND FUTURE SCOPE

A. Key Advantages

- Accurate Demand Prediction: Machine learning algorithms capture non-linear patterns, calendar trends, and pricing shifts far beyond static averages.

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- Optimized Working Capital: Reduces excessive holding costs and obsolescence while eliminating expensive stockouts.
- Automated Replenishment: Converts forecast numbers directly into actionable safety stock and reorder point metrics.
- Executive Business Intelligence: Interactive Power BI dashboards deliver instant visibility into multi-store demand and stockout risks.
- Environmental Sustainability: Directly supports UN Sustainable Development Goal 12 (Responsible Consumption and Production) by curbing retail overproduction and inventory waste.

B. Future Scope

- Real-Time Streaming Ingestion: Integrating Apache Kafka and Spark Streaming for instantaneous real-time point-of-sale data pipelines.
- Deep Learning Enhancements: Incorporating Temporal Fusion Transformers (TFT) and LSTM architectures to improve forecasting on intermittent and sparse SKU categories.
- Enterprise ERP Webhooks: Automating purchase order generation directly into enterprise SAP or Oracle ERP backends via secure webhooks.
- Mobile Applications: Deploying native mobile applications with automated push notifications for critical low-stock alerts.

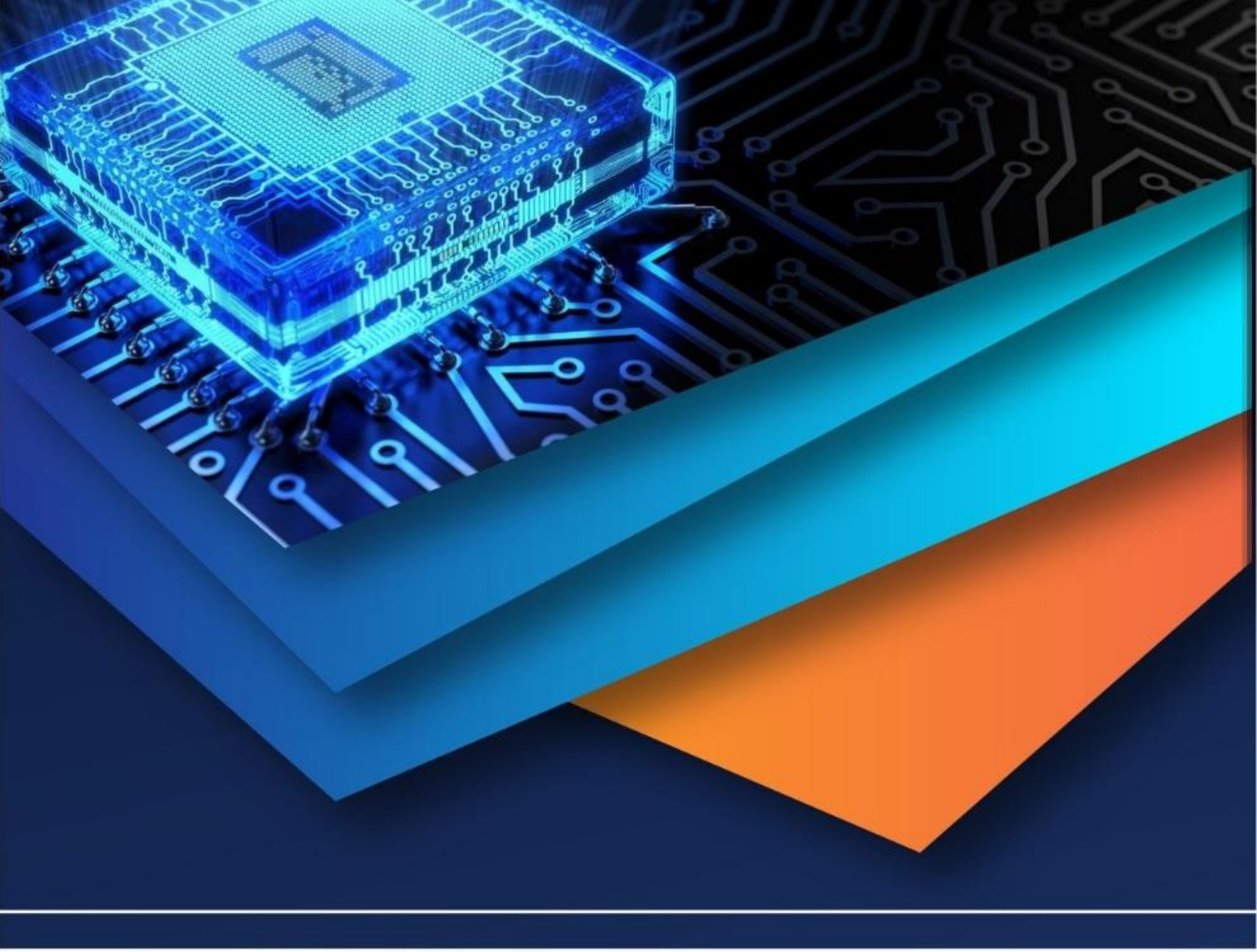
VIII. CONCLUSION

The proposed Demand Forecasting and Inventory Management System provides an effective, data-driven methodology that unifies predictive machine learning with operational inventory planning. By leveraging historical retail sales data, robust feature engineering, and high-performance regression models (XGBoost and Random Forest), the system accurately predicts future product demand across dynamic horizons. The tight integration with stochastic inventory optimization routines ensures that demand forecasts are immediately converted into actionable safety stocks, reorder points, and automated replenishment recommendations. Supported by Microsoft SQL Server warehousing, Node.js backend services, React.js web interfaces, and Power BI business intelligence dashboards, the platform empowers supply chain practitioners to minimize stockouts, prevent costly overstocking, and promote sustainable consumption in alignment with UN SDG 12.

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