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AI-Driven Supply Chain Demand Forecasting Using Hybrid Time-Series and Gradient Boosting Models

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***Abstract*—AI-Driven Supply Chain Demand Forecasting uses the Hybrid Time-Series and Gradient Boosting Models which was used to detect the critical challenge in supply chain management due to dynamic market conditions, seasonal variations, and un- certain customer behavior.As traditional time-series forecasting methods fails to capture business factors such as promotions, pricing changes, and sudden demand changes, which leads to inefficiencies to overcome these limitations in this project we use the AI-driven hybrid demand forecasting system that combines time-series models with gradient boosting machine learning techniques.**

This hybrid model basically divides demand forecasting into two components: base demand estimation and error correction. Time-series models such as AutoRegressive Integrated Moving Average(ARIMA) [7],Seasonal AutoRegressive Integrated Mov- ing Average (SARIMA) [2], and Long Short-Term Memory (LSTM) [3] are used to capture the real time historical data and captures the trends based on the seasonality, and temporal dependencies.However, deviations between actual demand and time-series predictions occur due to external business factors such as promotions, price changes, and holidays. To change the deviations through this we use the gradient boosting models like eXtreme Gradient Boosting(XGBoost) [4] and Light Gradient Boosting Machine (LightGBM) [5] which are trained on the residual errors produced by the time-series models.The final demand prediction is obtained by combining the time-series forecast with the adjustment of residual errors. This work facilitates the evolution of resilient supply chains, in addition to the services provided in the emerging deep reinforcement learning models.

***Index Terms*—Demand Forecasting, Supply Chain Manage- ment, Artificial Intelligence, Time-Series Analysis, Gradient Boosting, Hybrid Forecasting Model, ARIMA, LSTM, XGBoost.**

I. INTRODUCTION

Inventory management is a critical component of manu- facturing supply chains, as it directly influences operational efficiency, cost control, and customer service levels. Poor inventory decisions can result in excessive holding costs, product obsolescence, and wastage due to overstocking, while stockouts lead to delayed order fulfillment and reduced cus- tomer satisfaction. In today's competitive and globalized mar- kets, manufacturers face increasing challenges due to shorter product life cycles, fluctuating customer demand, and frequent market disruptions.

The traditional models of inventory management, namely the Economic Order Quantity (EOQ) model [5] and the Economic Production Quantity (EPQ) model [6], give an understanding of both the variables and the consequences that can be calculated in a cost-effective manner. While more advanced models accounted for stochastic demand and multi- period optimization, they are based on assumptions that are not entirely true in practice, including but not limited to a static model with a minimal product variety and a forecast provided deterministically rather than probabilistic in nature.

AI and ML developments also helped increase the accuracy of demand forecasting to a greater extent. Methods like Long Short-Term Memory networks and Gradient Boosting Machines are employed in order to address the complex and nonlinear relationships.

Furthermore, the application of Reinforcement Learning also assists in the intelligent selection of inventories through learning from a varying environment. But mostly, the related work of AI only involves the prediction part and does not take into account the associations of the above models with the cost and constraint models of inventory storage.

The IoT imporoves visibility, accuracy, and responsiveness in inventory management.IoT alone is not enough—its real benefits come when it is combined with intelligent forecasting models and optimization techniques that can convert real-time data into better decisions.

To overcome the above shortcomings, the proposed solution in the present paper is the hybrid inventory model that en- compasses the use of AI-based demand forecasting techniques, linear programming techniques for inventory optimization, and real-time IoT information. The demand forecasting results from the LSTM and GBM models will be used to formulate the inputs for the optimization model that will come up with optimal procurement plans based on the cost and capacity constraints. The real-time IoT information allows for the adjustment of the dynamic inventory policy due to the changes in the demand.

II. PROBLEM STATEMENT

Supply chain management practices have seen traditional demand forecasting methods lag behind in meeting the unpredictabilities of new market realities. Where ARIMA can be used to analyze the long-term developments in demand, this model remains "blind to real-world events such as promotional events, price changes, and shifting consumption patterns [7]." Such an absence of real-world applicability has resulted in major inefficiencies in operations that continue to hurt businesses in terms of inventory costs going to waste in stockouts.

Moreover, the absence of real-time insights into warehouse-related KPIs and inventory data hampers the organization from having the ability to formulate agile and data-informed business decisions. The absence of IoT sensor data and machine learning while considering historical data alone embeds an inflexible system in the sense that the system fails to respond and react to the short-term variations. Therefore, the need for a hybrid intelligence platform predictive model predicting the baseline demand along with the incorporation of error correction insights for external business factors is imperative.

III. LITERATURE REVIEW

Effective supply chain management requires a number of components to work together, including production scheduling, distribution, inventory, and, of course, accurate forecasting of future demand. Most studies in the past used traditional forecasting methods, including moving averages, exponential smoothing, and ARIMA models, which, while very useful, do tend to have issues when demand is not linear and stable [7]. Most, if not all, real-world supply chain data is seasonal, and is subject to the noise of promotions, market trends, economic factors, and a number of other factors which make forecasting a much more difficult task. All of this has created a demand for the use of more advanced techniques and the use of artificial intelligence.

As machine learning has advanced, more and more studies have been created focusing on the demand forecasting data driven models. Various forecasting models like neural networks, decision trees, support vector machines, and linear regression have used historical demand data as inputs [4], [5]. A lot of interest has been drawn to other ensemble learning techniques and Gradient Boosting for the fact that they have the ability to learn and mimic complex interactions, and structures. Researchers have noted that gradient boosting models are in a class by themselves when large numbers of variables and large datasets are present much more than traditional statistical techniques.

IV. PROPOSED SYSTEM

The proposed system, to address these limitations of traditional models, introduces an AI-driven hybrid intelligence framework by including LSTM and SARIMA for baseline seasonal trend capturing with XGBoost and LightGBM for residual error correction. The model makes use of real-time IoT sensor data and external business factors such as promotions and price shifts to finally come up with a high-fidelity hybrid prediction that finally goes through a linear programming engine. This provides seamless, end-to-end workflows for automating decisions on inventory replenishment, ensuring resiliency in the supply chain toward effective minimization of risks for stock-out alongside avoiding excess warehousing costs in a volatile market environment.

A. System Architecture

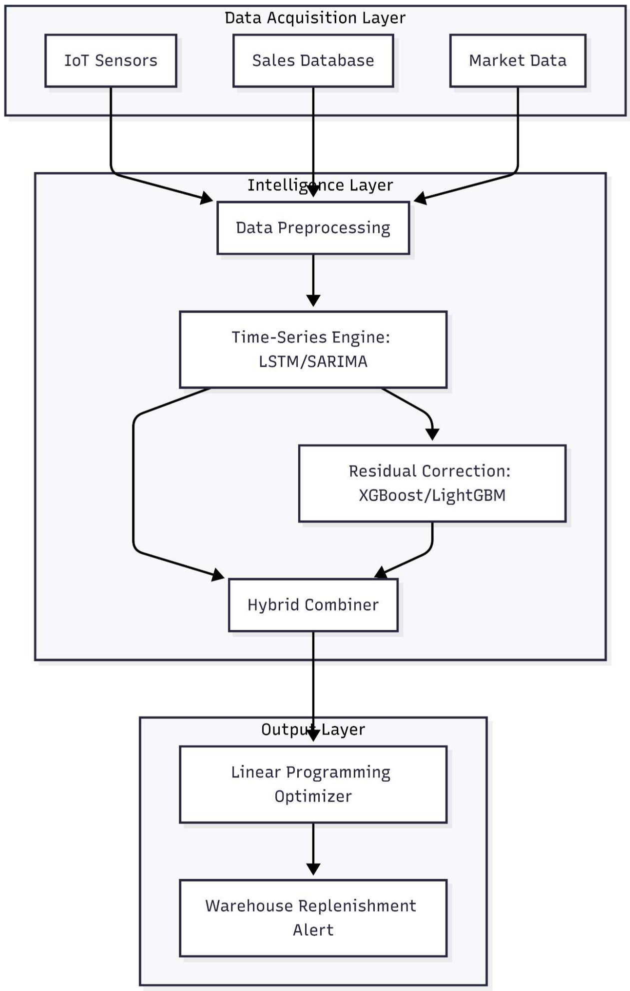

Fig. 1. System architecture of the proposed hybrid demand forecasting model

V. METHODOLOGY

The research methodology which addresses a static framework that integrates the predictive analytics into supply chain management carries profound strategic implications for diverse stakeholders and to get the real time feedback of the IOT based inventory management system.

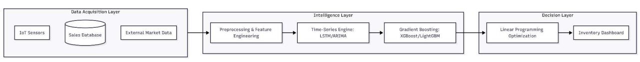

Fig. 2. Methodology workflow for hybrid demand forecasting system

Different stages of the process, including data processing, demand forecast, optimization model, and real-time optimization, have been mentioned below:

A. Data Collection & Preprocessing

- Historical sales/demand data: Transactional records of the last 24 to 36 months of monthly demand data were considered to identify the trend fluctuations.
- External factors include promotions, pricing, holidays, and weather. Events like promotional activities, changes in weather, seasonal characteristics were used as input features to capture the demand changes.

The data can also be collected through the

- Real-time IoT sensor data (inventory levels, warehouse metrics)
- Market indicators and competitor data

Data Preprocessing:

1) Data cleaning that handles the missing values, null values and duplicates
2) Feature engineering that observes the seasonal indicators and weather parameters
3) Time-based splitting (train/validation/test sets - no random split for time-series)
4) Normalization/Standardization for neural networks
5) Create residual dataset for gradient boosting training

B. Demand Forecasting

We use the ai models for forecasting. Those are time-series models and gradient Boosting Models one is for the understanding time another is for business behavior.

1) Time-Series Model: we use this for understanding of the temporal patterns, seasonality, past demand trends and predicts based on the demand
   Like Trend → Is demand increasing or decreasing? Seasonality → Weekly / monthly / yearly cycles, Auto-correlation → How past demand affects future demand
   - ARIMA / SARIMA – captures trend & seasonality [7].
   - LSTM – captures long-term dependencies [1], [4].
2) Gradient Boosting Model: It can handle the non linear relations and multiple features like promotions, price and holidays. This can learn from the errors of the time series model
   Instead of predicting demand directly, gradient boosting: Learns the errors made by the time-series model and adjusts the forecast accordingly [6].
   - XGBoost
   - LightGBM

C. Model Development

This model can be developed in three phases they are explained as

1) Phase1: Base Time-series model: we use the LSTM and ARIMA/SARIMA to train the model that generate initial demand forecasts and calculate prediction residuals

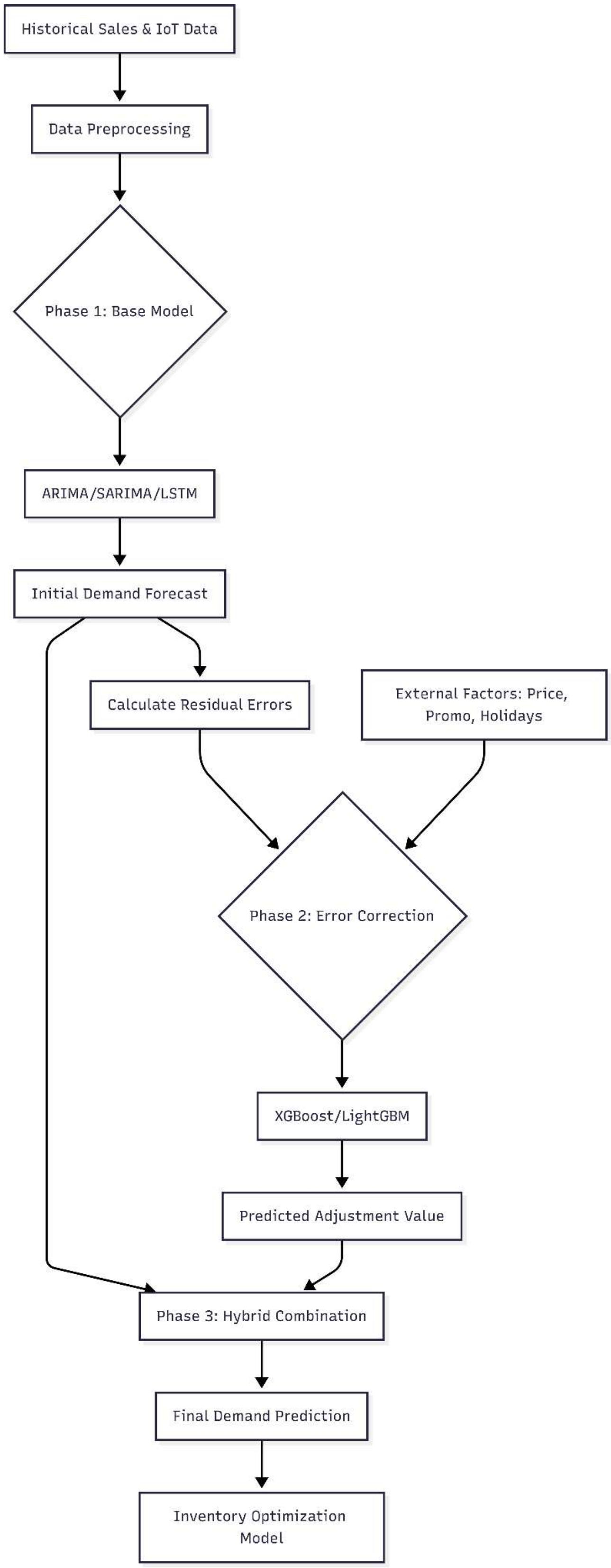

Fig. 3. Base time-series model development phase

2) Phase2: Residual Error Correction: Here we use the XGBoost and LightGBM gradient boosting models to correct the residual errors, these models take the input features as promotions, price changes, holidays, external events and learn the pattern that the time-series model misses.

3) Phase3: Hybrid model: The final stage was the combination of the base forecast using time series and residual correction. The final prediction was a hybrid model based on both models.

Final prediction = Time-Series Forecast + Gradient Boosting Adjustment

D. Real-Time Integration

Traditional supply chain strategies often operate on historical averages or static forecasts, limiting responsiveness to sudden shifts in consumer behavior or external disruptions. Predictive models, by contrast, incorporate real-time data streams—ranging from point-of-sale transactions to macroeconomic signals—to produce dynamic forecasts [1], [3].

This strategic implication of the hybrid model workflow for service providers is the opportunity to differentiate themselves in a competitive market by embedding analytics at the core of their offerings. Those who can provide not only operational efficiency but also predictive intelligence will become indispensable partners in future supply chains.

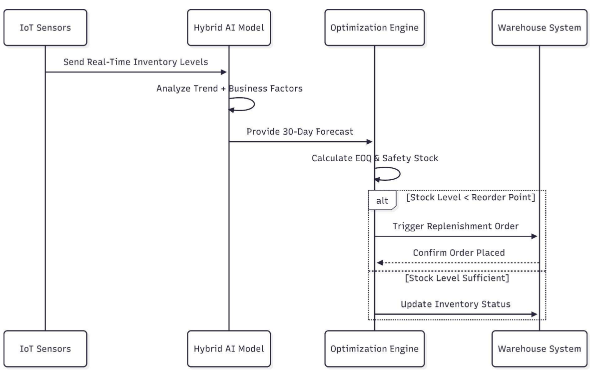

Fig. 4. Real-time integration architecture for dynamic demand forecasting

VI. RESULT

We investigated an AI-based Demand forecasting model using hybrid Time-Series and Gradient Boosting Models and a set of historical sales with their corresponding inventory and seasonality data. The objective was to analyze the most commonly employed forecasting methods and calculate their effectiveness in forecasting demand, managing inventory, and improving the entire supply chain.

We were able to achieve a significant overall improvement in demand prediction accuracy by using the hybrid forecasting approach. Time series forecasting models were able to depict the historical demand patterns and seasonal trends, while Gradient Boosting forecasting models were able to identify the more complex and nonlinear relationships that demand would have with external factors such as more competitive pricing, promotional activities, and demand fluctuations. In building models, these two were more accurate and reliable than the rest of the statistical and machine learning models, primarily due to their complementary nature.

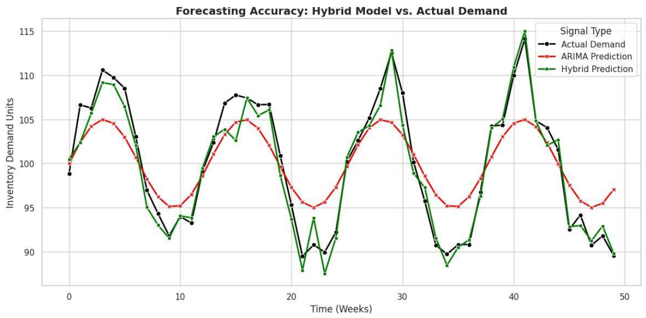

Fig. 5. Comparison of Actual Demand vs. Hybrid Model Predictions over a 50-week period

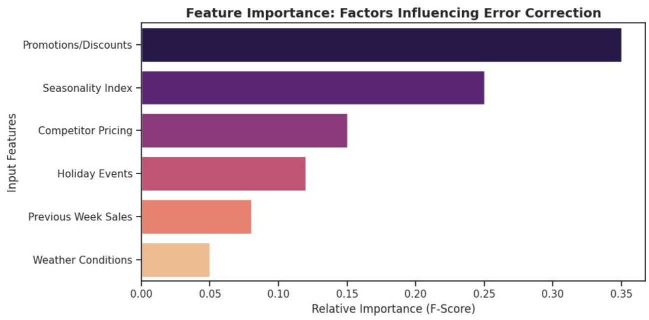

Fig. 6. Importance of external business factors in the Gradient Boosting error-correction phase

In forecasting accuracy, prediction of standard metrics such as Mean Absolute Error, Root Mean Square Error (RMSE), and Mean Absolute Percentage Error were utilized [4], [6]. A substantial drop in error values was witnessed by the hybrid model in all metrics, in comparison to base line models. This testifies the hybrid model was dominant in performing forecasting, both in the short and mid.

VII. DISCUSSION

Using time series models and gradient boosting techniques for forecasting demand in the supply chain has its practical benefits regarding this study's findings. Forecasting using the traditional methods is ineffective. Forecasting demand using historical averages and linear demand forecasting is too simplistic and will lead to failure. The proposed technique is the most effective because it accurately embodies and retains forecasting the complex and varying drivers of demand.

The assumption that this study makes is that accurate forecasting should lead to better operational decisions. The techniques that merge demand forecasting with better control of inventory reduces the mismatch of supply and demand. This

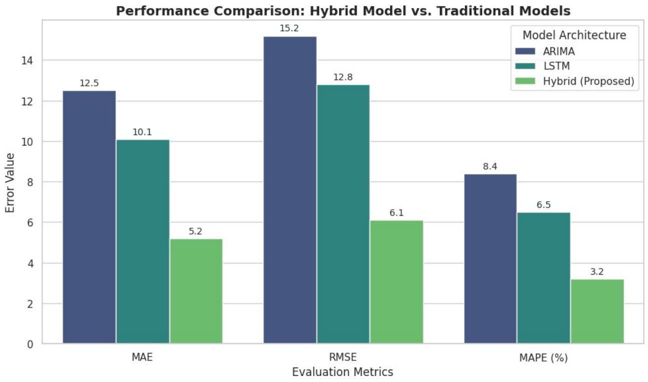

Fig. 7. Evaluation metrics (MAE, RMSE, MAPE) comparing the proposed Hybrid model against traditional ARIMA and LSTM baselines

highlights the significance of the potential of aligning analytics to the supply chain [2], [3].

The demand forecasting shifts due to revenue holidays or sudden and unexpected changes in the market/industry cycle are the critical areas that fit to gradient boosting models. The time-series models preserve seasonality and trends over the long period. Together, they provide forecasting that is accurate and in balance.

Scalability and adaptability is the most important practicality of this approach. Other users can incorporate the model easily.

VIII. CONCLUSION

This research represents a hybrid model that integrates the AI driven forecasting, linear programming optimization, and real-time monitoring for inventory control in manufacturing. This model effectively overcomes the weakness in the classical model that only depends on the historical patterns.

This method enables cost optimization, predictive precision, provides the effective use of warehouse capacity and minimizes the overstock and stockout also.This hybrid model uses AI to accurately predict product demand by combining time-series forecasting with machine learning, helping businesses reduce inventory costs and improve supply chain efficiency.

The strategic implications of predictive analytics extend far beyond operational efficiency, influencing the competitive positioning of enterprises, the service offerings of providers, and the resilience of critical supply sectors managed by policymakers. For enterprises, predictive models enhance agility, generate cost savings, and elevate customer satisfaction.

The future of predictive analytics in supply chain management is defined by the convergence of advanced technologies, the transition from predictive to prescriptive intelligence, and the increasing integration of sustainability as a core driver of procurement and inventory strategies. As global networks face persistent volatility and competitive pressures, the next wave of innovation will reconfigure how organizations forecast demand, manage inventory, and align operational decisions with broader environmental and societal goals.

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