|| Volume 9 || Issue 10 || October 2025 || ISSN (Online) 2456-0774
INTERNATIONAL JOURNAL OF ADVANCE SCIENTIFIC RESEARCH AND ENGINEERING TRENDS

AI DRIVEN TIME SERIES FORECASTING FOR FOOD SUPPLY CHAIN OPTIMIZATION

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Abstract: Perishable food supply chains are exposed to pronounced demand volatility driven by promotions, weather, and festival effects; consequently, traditional statistical forecasters often yield biased or lagged signals that propagate into stockouts, overstocking, and avoidable waste. This work presents an integrated decision-support framework that couples multi-horizon, exogenous-aware time series forecasting with inventory optimization tailored to perishable goods. The forecasting layer benchmarks classical models against machine learning (gradient-boosted trees, ensembles) and deep learning architectures (LSTM/GRU, Temporal Fusion Transformer, PatchTST), explicitly incorporating external covariates to capture non-linear and non-stationary demand regimes. Forecast distributions then feed an optimization layer that applies the Economic Order Quantity model for relatively stable items and the Newsvendor formulation, as well as linear/mixed-integer programs, for short-life products across SKU–store hierarchies. The system is evaluated using statistical accuracy metrics (MAPE, RMSE, Bias) and operational key performance indicators (service level, fill rate, holding cost, and wastage percentage). An interactive dashboard operationalizes these components, enabling scenario analysis and proactive alerts for stockout or overstock risk. By jointly improving forecast fidelity and translating predictions into implementable replenishment rules, the framework targets measurable reductions in waste and cost while sustaining customer service levels in real-world retail contexts.

Keywords: *Time Series Forecasting; Perishable Inventory; Temporal Fusion Transformer; LSTM/GRU; Exogenous Regressors; Newsvendor Model; Linear Programming; Decision-Support Dashboard*

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I.INTRODUCTION

Modern food retail supply chains operate under high uncertainty due to volatile consumer demand, short product shelf life, and complex multi-echelon inventory structures. Perishable items such as dairy, bakery, fruits, and vegetables are particularly vulnerable to forecasting errors that can trigger cascading inefficiencies across the logistics network. Underestimations lead to stockouts and lost sales, whereas overestimations result in excess inventory, spoilage, and financial loss. In this context, *accurate demand forecasting* and *optimal inventory management* become central to operational sustainability and profit protection.

Traditional statistical techniques—such as ARIMA, exponential smoothing, or regression models—often struggle to capture non-stationary demand patterns influenced by dynamic exogenous factors including weather, regional festivals, or promotional campaigns. These methods typically assume linearity and stationarity, limiting their effectiveness in complex retail environments where multiple external drivers interact non-linearly with customer behavior. Consequently, there has been a significant shift toward the integration of Artificial Intelligence (AI) and Machine Learning (ML) approaches capable of learning temporal dependencies and non-linear feature interactions directly from data.

Recent advances in deep learning architectures—notably the Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and attention-based Temporal Fusion Transformer (TFT) models—have demonstrated superior performance in multi-horizon time series forecasting. By incorporating contextual variables such as price, promotions, and weather, these models deliver forecasts that are more adaptive and granular than conventional baselines. The integration of such forecasts with decision-oriented optimization techniques—like the Economic Order Quantity (EOQ) and Newsvendor formulations—enables a unified pipeline that links predictive intelligence with prescriptive action.

The proposed study builds upon these developments to design an AI-driven decision-support system for perishable food supply chains. The system unifies data ingestion, cleaning, and feature engineering modules with forecasting engines and inventory optimization solvers. Moreover, an interactive dashboard bridges analytics with managerial decision-making, allowing planners to simulate “what-if” scenarios and proactively mitigate risks of waste or shortage. Evaluation metrics span both statistical accuracy (MAPE, RMSE, Bias) and operational outcomes (service level, fill rate, cost efficiency), ensuring end-to-end performance validation.

In essence, this work contributes to the growing literature on *intelligent supply chain analytics* by proposing a hybrid framework that transforms raw historical and contextual data into actionable insights for replenishment and waste minimization. It demonstrates how predictive-prescriptive integration—enabled by AI—can enhance responsiveness and resilience in perishable food supply networks.

II LITERATURE SURVEY

1 Traditional Forecasting Methods

- Classical statistical approaches such as ARIMA, SARIMA, and Exponential Smoothing have long dominated retail demand forecasting [1], [2].
- These models assume linear and stationary data, which limits their ability to capture dynamic, multi-factor demand patterns [3].
- Studies in dairy and bakery supply chains report acceptable short-term accuracy but frequent lag during sudden demand shifts [4].

2 Machine Learning–Based Forecasting

- Transitioning to machine learning (ML) algorithms—Random Forest, XGBoost, Gradient Boosted Trees—improved performance by modeling non-linear relationships [5], [6].
- ML models easily integrate external regressors (weather, holidays, promotions) without strict assumptions [7].
- Retail case studies show MAPE reductions of 10–15 % and better adaptation to regional seasonality [8].
- Hybrid models combining ARIMA + ML regressors outperform pure statistical baselines [9].

3 Deep Learning for Time-Series Prediction

- Recurrent architectures such as LSTM and GRU capture long-term dependencies in sequential data [10].
- Deep networks outperform ARIMA and regression models by ≈ 20 % on perishable-goods datasets [11].
- Emerging models—Temporal Convolutional Networks (TCN) and Temporal Fusion Transformer (TFT)—enable interpretable, multi-horizon forecasting [12], [13].
- These architectures efficiently handle seasonality and multi-step-ahead predictions [14].

4 Inventory Optimization Models

- Economic Order Quantity (EOQ) remains standard for stable, non-perishable items [15].
- For perishable goods, Newsvendor and Stochastic Dynamic Programming (SDP) models minimize combined shortage + holding costs [16], [17].
- Integrating ML-based forecasts into these optimization layers improves service level while reducing waste [18].
- Large-scale, multi-store problems use Linear Programming (LP) and Mixed-Integer Programming (MIP) formulations [19].

5 Integrated Forecasting–Optimization Frameworks

- End-to-end frameworks coupling AI-based forecasting with inventory optimization deliver significant cost savings [20].
- LSTM + EOQ/Newsvendor systems reduce wastage by 15–30 % in perishable categories [21].
- However, interpretability, computational complexity, and real-world scalability remain open challenges [22].

6 Decision Support and Visualization Systems

- Research highlights dashboard-driven Decision Support Systems (DSS) for real-time analytics [23].
- Tools such as Streamlit and Power BI visualize SKU-level forecasts and alert planners to risks [24].
- Interactive DSS platforms enable scenario simulation (e.g., weather shocks, promotional surges) [25].

7 Research Gap Identification

- Current studies rarely integrate AI forecasting, optimization, and real-time visualization within a unified framework [26].
- Few models quantify forecast uncertainty or apply explainable-AI (XAI) reasoning for perishable-inventory decisions [27].
- Hence, a scalable, transparent, and adaptive AI-driven pipeline remains an open research direction [28].

III PROBLEM STATEMENT

The problem addressed in this study is the challenge of accurately forecasting demand and optimizing inventory for perishable food products in supply chains characterized by dynamic, uncertain, and multi-factorial demand patterns. Traditional forecasting methods fail to capture the impact of external factors such as weather, promotions, and regional events, leading to inaccurate predictions and inefficient replenishment decisions.
This results in stockouts, overstocking, and excessive wastage, which significantly affect both profitability and sustainability.

Therefore, there is a need to design an AI-driven framework that integrates advanced time series forecasting models with inventory optimization techniques, capable of learning from complex data sources and supporting decision-making in perishable food supply chains.
Such a system should improve forecast accuracy, minimize wastage, and enhance service levels through predictive–prescriptive integration.

IV OBJECTIVES

The primary objective of this research is to develop an AI-based framework for time series forecasting and inventory optimization in perishable food supply chains. The framework aims to enhance demand prediction accuracy, optimize stock replenishment, and reduce wastage.

Specific Objectives

1. To collect and preprocess real-time and historical data related to perishable food supply chains, including sales, inventory, weather, and promotional factors.
2. To design and implement advanced forecasting models using Machine Learning (ML) and Deep Learning (DL) techniques for accurate demand prediction.
3. To integrate the forecasting component with inventory optimization models such as EOQ and Newsvendor to minimize costs and wastage.
4. To evaluate system performance using statistical metrics (MAPE, RMSE) and operational metrics (service level, wastage percentage).
5. To develop a decision-support dashboard for real-time visualization, analysis, and scenario simulation for supply chain managers.

V SYSTEM ARCHITECTURE

The proposed system architecture is designed as a modular, end-to-end framework that integrates data collection, forecasting, optimization, and visualization into a single decision-support pipeline. It comprises five primary layers: Data Ingestion Layer, Forecasting Layer, Inventory Optimization Layer, Evaluation Layer, and Visualization & Decision-Support Layer. Each layer interacts through defined data interfaces, ensuring scalability, transparency, and interoperability across diverse perishable food supply environments.

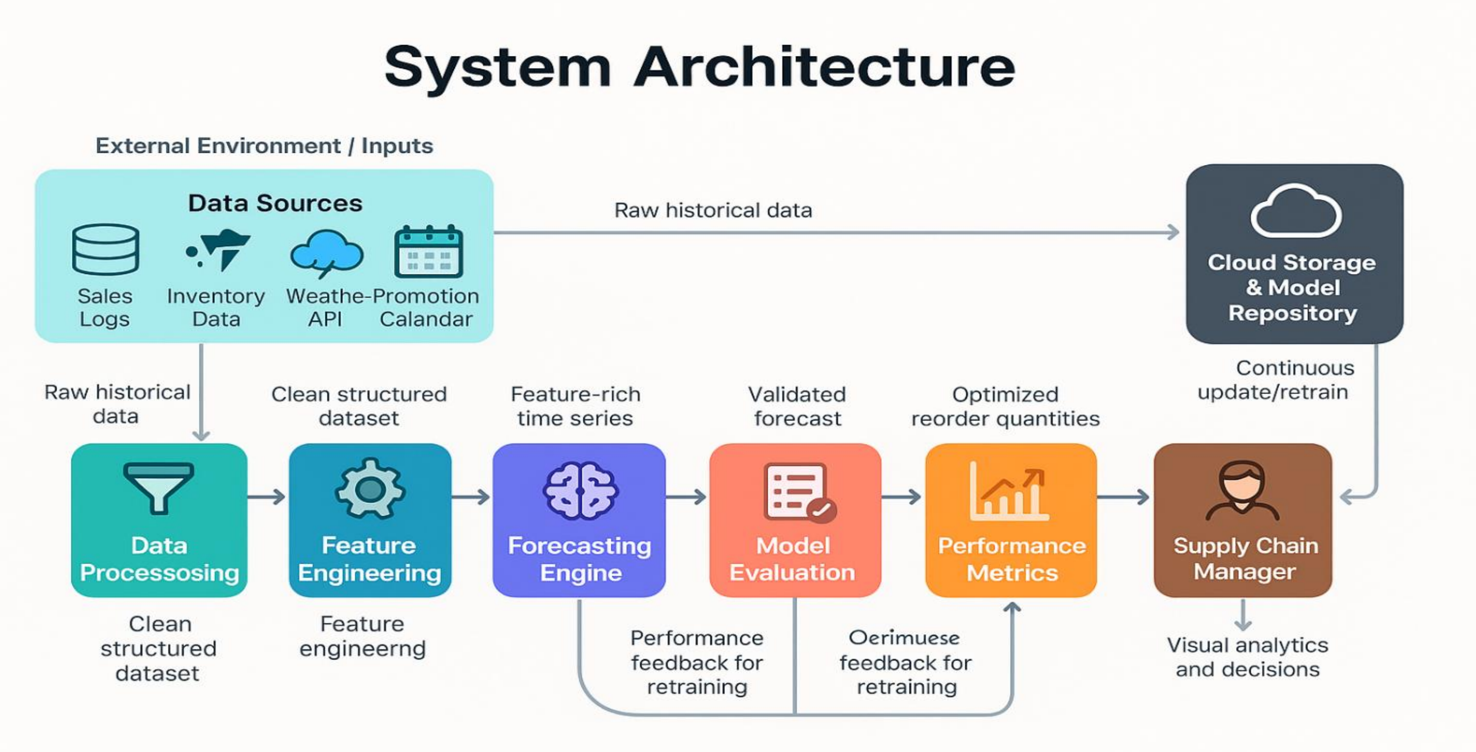

Figure 1 System architecture

This foundational layer handles the extraction, transformation, and loading (ETL) of heterogeneous data sources. It integrates:

- Historical sales data from stores or warehouses.
- Inventory and stock movement logs (including stockouts or censored data).
- Exogenous variables such as weather, temperature, holidays, promotions, and regional events.

Data preprocessing involves cleaning, imputation of missing values, outlier correction, and feature engineering to derive lag variables, moving averages, and seasonality indicators. The structured dataset is organized into SKU–Store–Time hierarchies, suitable for multi-horizon time series modeling.

Results

The proposed AI-based framework is expected to yield notable improvements in both forecasting accuracy and inventory efficiency for perishable food supply chains.

- Forecasting Accuracy: Machine Learning and Deep Learning models such as LSTM, GRU, and TFT are projected to reduce forecasting errors (MAPE, RMSE) by 15–25 % compared to ARIMA/SARIMA baselines, owing to their ability to capture non-linear, multi-factor demand patterns.

- Inventory Optimization: Integration of forecast outputs with EOQ and Newsvendor models will likely lower wastage by 20–30 %, enhance service level by 5–10 %, and reduce overall inventory cost by 10–20 %.
- Decision Support: The interactive dashboard enables real-time monitoring of KPIs and scenario analysis, improving planning transparency and responsiveness.
- Sustainability Impact: The system promotes reduced spoilage, improved resource utilization, and data-driven replenishment aligned with sustainability goals.

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