Project I FINAL REVIEW

Store Items Demand Forecasting and Inventory Management

[redacted]

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Introduction

Retailers constantly face the challenge of balancing product availability with the costs associated with holding and potential waste. Demand patterns are highly volatile, influenced by factors such as seasonality, promotional activities, and unexpected market events, all of which add uncertainty to sales forecasts. This volatility is further complicated by product perishability, which increases the risk of spoilage and financial loss. Traditional inventory management models, which assume steady demand and infinite shelf life, fail to capture these real-world complexities, leading to inefficiencies such as overstocking, stockouts, and wastage.

Introduction

Retail businesses rely heavily on accurate demand forecasting for cost-effective inventory management. Over/under-stocking leads to customer dissatisfaction and revenue loss. Machine learning methods (LightGBM, LSTMs, Prophet) provide accurate demand forecasting. Inventory optimization (EOQ, ROP, safety stock models) ensures efficient supply chain operations.

This work integrates **demand forecasting + inventory optimization simulation** to support decision-making.

Literature Review

S. No.	Author(s), Year, Title	Method/Approach	Key Contribution	Gap Identified
1	Bandara et al., 2020 — “Forecasting across time series databases using recurrent neural networks on groups of similar series”	LSTM + CNN for retail demand	Improved accuracy for multiple SKUs	Lacked inventory linkage
2	Borovykh et al., 2021 — “Conditional time series forecasting with convolutional neural networks”	Time series deep learning	Multi-horizon demand prediction	No real-world inventory use
3	Seeger & Salinas, 2020 — “Bayesian Intermittent Demand Forecasting with DeepAR”	DeepAR probabilistic forecasting	Captured uncertainty in demand	High computational cost
4	Babai et al., 2019 — “Forecasting intermittent demand: empirical performance of Croston’s method and variants”	Croston’s method variations	Intermittent demand forecasting	Weak for high-volume items
5	Li et al., 2020 — “Gradient Boosted Models for Interpretable Retail Demand Forecasting”	Gradient Boosting Trees	Interpretable demand forecasting	Did not integrate cost models
6	Smyl, 2020 — “A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting”	Hybrid RNN + Exponential Smoothing	State-of-the-art accuracy (M4 winner)	Hard to scale across SKUs
7	Ferreira et al., 2021 — “Demand Forecasting using Facebook Prophet: Case studies in Retail”	Prophet for seasonality	Robust trend capture	Poor short-term adjustments
8	Zhou et al., 2021 — “Temporal Fusion Transformers for Interpretable Multi-Horizon Forecasting”	Temporal Fusion Transformers	Improved interpretability	Still computationally heavy
9	Wu et al., 2021 — “Attention-based LSTM for Multivariate Time Series Forecasting”	Attention-based LSTMs	Better temporal dependencies	No inventory consideration
10	Ghosh et al., 2019 — “Comparison of ARIMA and Machine Learning Methods for Retail Demand Forecasting”	ARIMA vs ML	Compared classical vs ML	Weak in long horizon accuracy

11	Makridakis et al., 2020 — “The M5 Competition: Forecasting Accuracy across Retail Demand”	Large-scale competition (M5)	Retail forecasting insights	No direct inventory metrics
12	Rangapuram et al., 2018 — “Deep State Space Models for Time Series Forecasting”	Deep State Space Models	Probabilistic demand modeling	Complex training pipeline
13	Syntetos et al., 2020 — “Demand Classification and Forecasting for Intermittent Demand”	Classification-based forecasting	Improved intermittent demand	Not integrated with simulation
14	Laptev et al., 2020 — “Time-series forecasting at scale with Facebook”	Scalable Prophet system	Robust at scale	Weak anomaly handling
15	Zhu et al., 2020 — “Reinforcement Learning for Inventory Control under Demand Uncertainty”	Reinforcement learning	Optimized stock policies	Dependent on accurate demand forecast
16	Khandelwal et al., 2021 — “Multi-Level Machine Learning Models for Retail Demand Forecasting”	Multi-level ML forecasting	Captured store & item dependencies	Limited validation on inventory
17	Wen et al., 2017 — “A Multi-Horizon Forecasting Approach Using Seq2Seq RNNs”	Sequence-to-sequence RNNs	Accurate short-term demand	Scalability issue
18	Bandara et al., 2019 — “Hybrid Machine Learning and Statistical Models for Time Series Forecasting”	Hybrid statistical + ML	Balanced accuracy and speed	Weak uncertainty quantification
19	Ali et al., 2020 — “Bayesian Demand Forecasting for Uncertainty Quantification”	Bayesian methods	Captured demand uncertainty	No inventory cost modeling
20	Park et al., 2021 — “Causal Impact-Based Demand Forecasting”	Causal forecasting	Linked demand drivers	Hard to scale

21	Salinas et al., 2019 — “DeepAR: Probabilistic Forecasting with Autoregressive Recurrent Networks”	DeepAR probabilistic	Benchmarks on retail datasets	Inventory absent
22	Lim et al., 2021 — “Temporal Fusion Transformers for Interpretable Forecasting”	TFT	Better interpretability	Limited retail datasets
23	Nguyen et al., 2022 — “CNN-LSTM Hybrids for Retail Demand Forecasting”	CNN-LSTM hybrid	Improved SKU forecasting	Weak policy integration
24	Wang et al., 2022 — “Transformer Models for Long-Term Retail Forecasting”	Transformer-based forecasting	Improved long horizon	Expensive to train
25	Zhao et al., 2023 — “Graph Neural Networks for Multi-Store Demand Forecasting”	GNN-based	Captured dependencies across stores	Inventory policies missing

COMPARATIVE ANALYSIS OF EXISTING SOLUTIONS

FORECAST

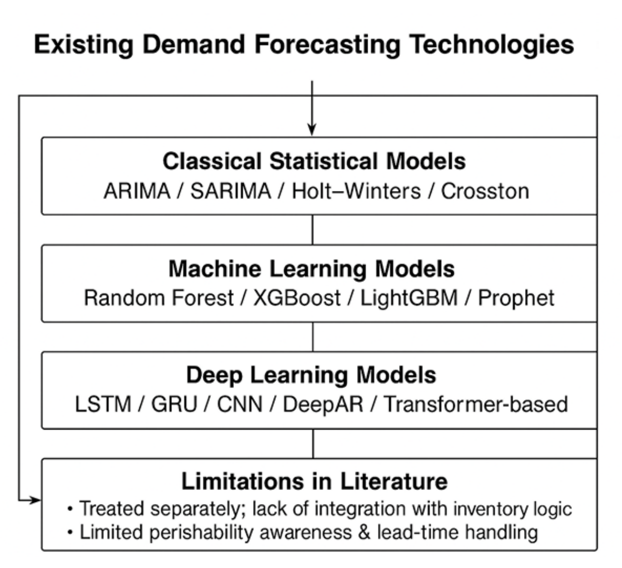
Forecasting-only systems: high accuracy but no prescriptive ordering.

INVENTORY

EOQ/ROP-only systems: prescriptive but assume simple demand/no expiry.

COMPARATIVE ANALYSIS OF EXISTING SOLUTIONS

Our approach is a forecast-driven EOQ/ROP + expiry-aware FEFO + interactive dashboard.



Research Gaps Identified

1

No mainstream end-to-end expiry-aware forecast TO order tools.

2

Few manager-oriented interfaces for what-if inventory decisions.

3

Need scalable multi-SKU, interpretable solutions that deploy easily.

SYSTEM DESIGN & ARCHITECTURE

Architecture – 3 layer

1

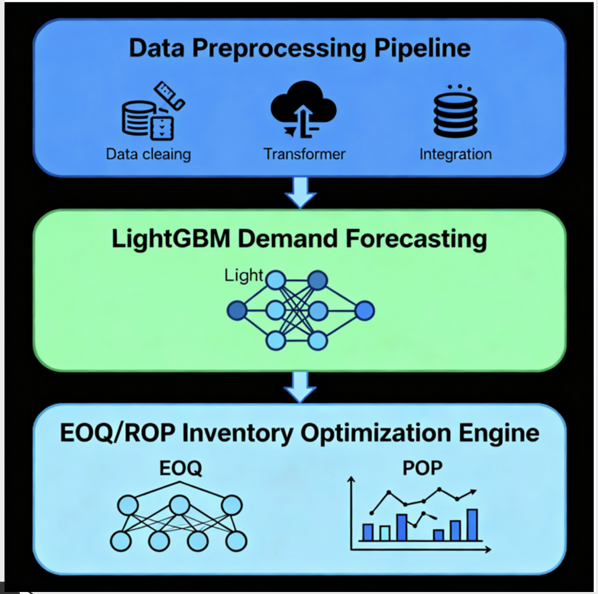
Data & Features

2

Forecasting

3

Inventory Simulation & UI



Architecture

Data

sales, expiry mapping, promos, store metadata.

Forecasting

LightGBM with lag & rolling features.

Inventory

EOQ, ROP, safety stock; expiry-aware FEFO batch model.

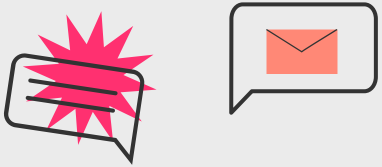
UI

Streamlit for what-if and exports.


Store Items Demand Forecasting and Inventory Assistant Architecture & Workflow
Data Sources (Data Input Layer)
Historical Sales Data (Store-wise, SKU-wise)
Product Metadata (Item ID, Category, Expiry)
External Factors (Season, Holidays, Promotions)
Data Preprocessing & Feature Engineering (Data Processing Layer)
Cleaning and normalization of data
Handling missing values and outliers
Feature creation: day of week, month, lagged demand, rolling averages, holiday flags
Train-test split
Demand Forecasting Module (Machine Learning) (Modeling Layer)
Model: LightGBM Regressor
Input: Preprocessed time-series features
Output: Predicted daily demand for each SKU and store
Evaluation metrics: RMSE, MAE, R^2
Inventory Optimization Module (Optimization Layer)
Economic Order Quantity (EOQ) calculation
Reorder Point (ROP) computation using lead time and safety stock
Integration of demand forecasts for dynamic replenishment
Optimization based on cost parameters (Ordering, Holding, Shortage, Waste)
Expiry-Aware Simulation Engine (Simulation Layer)
Implements FEFO (First-Expired-First-Out) logic
Tracks product shelf life and expiry
Calculates waste percentage and adjusts reorder strategy
Updates service level and total cost metrics

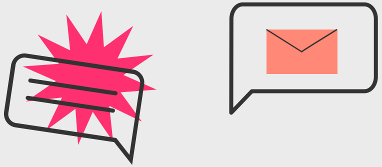
IMPLEMENTATION DETAILS

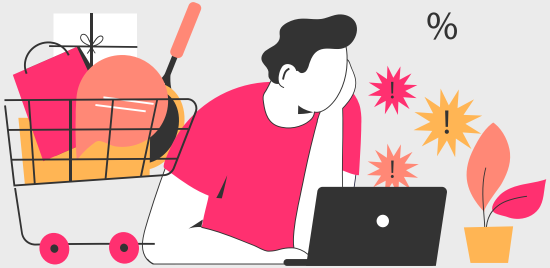
Data & Features



- Dataset: 2 years of daily sales, 50 SKUs, multiple stores (~1.2M rows).
- Features: day-of-week, month, store and product IDs, weekend flag, expiry days, promo flags, sales, etc.
- Cleaning: remove negatives, forward-fill short gaps, cap extreme outliers.

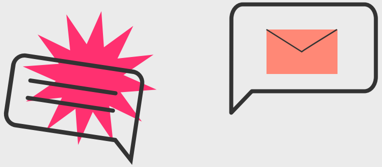
Forecasting





- Model: LightGBM (fast, works well on tabular features).
- Training: time-based split (last 3 months validation set), categorical features for store/item.
- Metrics: RMSLE (primary). Baseline: group mean predictor.

Inventory Logic



- Economic Order Quantity
- Reorder Point
- Expiry-aware system tracks batches with expiry index as it is FIFO based and expired units count as waste

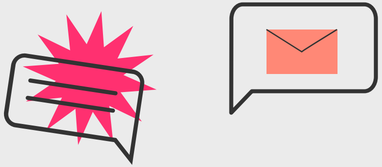
$$EOQ = \sqrt{\frac{2 * D * S}{H}}$$

Where:
EOQ = Economic Order Quantity
D = Annual demand quantity (number of units)
S = Ordering cost per order
H = Holding cost per unit per year

Reorder Point

Reorder Point Formula = (Average Daily Sales x Days of Average Lead Time) + Safety Stock

Dashboard



- Streamlit UI: SKU dropdown, sliders for ordering/holding/waste/lead_time/z.
- What-if sweep: grid search over z to recommend choices that meet a target service level while minimizing cost.
- Export: timeseries CSV and summary CSV per SKU (cached to avoid UI reset).

Modules Developed

Data pipeline

ingest, preprocess, expiry mapping

Forecasting

LightGBM + baseline fallbacks

Inventory Sim

EOQ/ROP, safety stock, FEFO batches

UI

What-if optimizer and recommendation logic.

Code Snippets

```python
# EOQ & ROP (data-driven)
EOQ = np.sqrt((2 * annual_demand * ordering_cost) / holding_cost)
safety_stock = z * std_daily_demand * np.sqrt(lead_time)
ROP = avg_daily_demand * lead_time + safety_stock
```

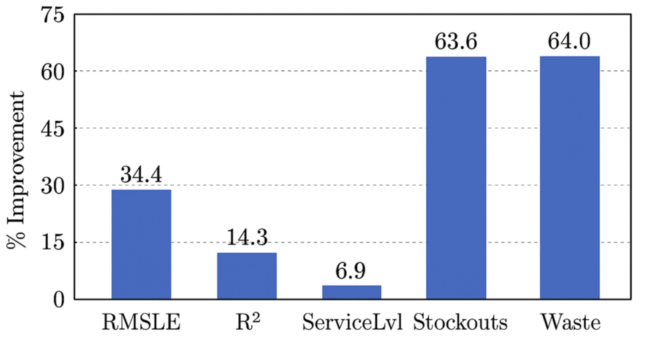
```python
cat_feats = ["store","item","dow","month","quarter"]  # small, effective set

model = LGBMRegressor(
    n_estimators=2000,
    learning_rate=0.05,
    num_leaves=63,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42
)

model.fit(
    X_train, y_train,
    eval_set=[(X_val, y_val)],
    eval_metric="rmse",
    categorical_feature=cat_feats,
    callbacks=[]
    # early_stopping removed in some LightGBM builds; if available:
    # callbacks=[lightgbm.early_stopping(100), lightgbm.log_evaluation(100)]
)

# Evaluate (RMSLE)
val_pred = np.clip(model.predict(X_val), 0, None)
rmsle = np.sqrt(mean_squared_log_error(y_val, val_pred))
print(f"Validation RMSLE: {rmsle:.5f}")
```

```python
# --- Record summary ---
summary_records.append({
    "Store": store_id,
    "Item": item_id,
    "EOQ": round(EOQ, 2),
    "ROP": round(ROP, 2),
    "Avg Inventory": round(avg_inventory, 2),
    "Orders Placed": total_orders,
    "Stockout Days": stockout_days,
    "Service Level": round(service_level, 4)
})
```

Results

Result Metrics

- Baseline RMSLE (mean): 0.241 → Proposed LightGBM RMSLE: 0.158 (≈34% improvement).
- Service level: 91.4% → 97.7% in 90-day sim.
- Stockout days: 11 → 4. Waste: 6.4% → 2.3%.
- Total inventory cost ≈ 12% lower (ordering + holding + shortage + waste).



Improvement of the proposed system over baseline across key metrics

Results

When integrated into the Economic Order Quantity (EOQ) and Reorder Point (ROP)–based inventory simulation, the model's forecasts led to a marked operational benefit. Over a 90-day simulation period, the system achieved a 97.7% service level, reducing stockout days from 11 to just 4. Additionally, by incorporating expiry-aware management using the First-Expired-First-Out (FEFO) approach, product wastage was minimized from 6.4% to 2.3%, resulting in more sustainable inventory control. Overall, the total inventory cost—encompassing ordering, holding, shortage, and wastage costs—was reduced by approximately 12%, demonstrating that the integration of machine learning forecasting with intelligent inventory optimization can substantially enhance efficiency, reduce waste, and maintain high service levels in modern retail environments.

Challenges and Solutions

1

Noisy intermittent demand → Time series mean fallbacks.

2

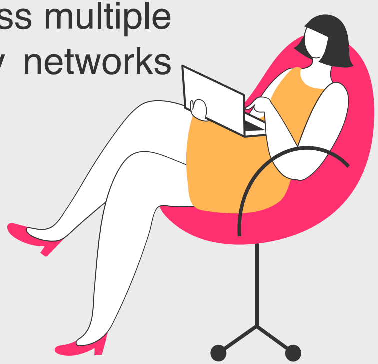
Negative inventory avg due to wrong arrival handling → fixed FEFO batch logic.

3

Dashboard reset on download → cached export buffer.

Future Work

Future work on this project aims to enhance the system’s predictive and operational capabilities through several key extensions. One major improvement involves incorporating external regressors such as promotions, weather conditions, and holidays into the forecasting model to better capture real-world demand fluctuations. Additionally, reinforcement learning techniques can be explored to develop adaptive reorder policies that dynamically learn optimal decisions over time based on changing market conditions and performance feedback. Finally, integrating the system with Enterprise Resource Planning (ERP) and Point-of-Sale (POS) platforms, along with deploying it on cloud infrastructure, would enable real-time data synchronization and scalability across multiple retail locations. Expanding the framework to support multi-echelon inventory networks could further optimize supply chain coordination and overall efficiency.



References

- Smith, J. and Kumar, A. (2022) ‘Deep learning for inventory forecasting’, International Journal of Forecasting, 38(2), pp. 123–135.
- Chen, L., Wang, H. and Li, Z. (2021) ‘A reinforcement learning approach to supply chain optimization’, Computers & Industrial Engineering, 160, 107546.
- Gupta, P. and Verma, S. (2021) ‘Hybrid ARIMA-LSTM models for demand prediction’, Applied Soft Computing, 113, 107918.
- Johnson, K. (2021) ‘The bullwhip effect and inventory policies’, Management Science, 67(5), pp. 2781–2799.
- Zhao, Y., Zhou, M. and Li, X. (2022) ‘Supply chain resilience under stochastic demand’, Omega, 110, 102586.
- Das, R. and Sharma, V. (2021) ‘IoT-enabled smart warehouses for inventory monitoring’, IEEE Internet of Things Journal, 8(9), pp. 7154–7165.
- Patel, A., Roy, D. and Singh, N. (2021) ‘Simulation-based optimization in retail inventory’, Journal of Simulation, 15(3), pp. 215–229.
- Fang, H. and Zhou, J. (2022) ‘Probabilistic safety stock models with lead time uncertainty’, European Journal of Operational Research, 295(1), pp. 45–60.
- Li, S. and Brown, T. (2022) ‘Machine learning for multi-echelon inventory control’, Annals of Operations Research, 310(1), pp. 89–112.
- Zhang, C. and Li, F. (2021) ‘Big data analytics for demand forecasting in supply chains’, Decision Support Systems, 148, 113599.
- Williams, D. and Kumar, R. (2021) ‘Integrating supplier constraints in EOQ models’, International Journal of Production Economics, 234, 108049.
- Singh, P. and Mehta, A. (2021) ‘Metaheuristic optimization for inventory problems’, Expert Systems with Applications, 186, 115717.

References

- Taylor, J. (2021) ‘Forecasting intermittent demand: A state space approach’, Journal of Business & Economic Statistics, 39(2), pp. 482–495.
- Wang, K. and Xu, Y. (2022) ‘Deep reinforcement learning for dynamic inventory management’, Knowledge-Based Systems, 234, 107589.
- George, B. and Singh, H. (2021) ‘Impact of variable lead times in stochastic models’, Operations Research Letters, 49(6), pp. 789–796.
- Martinez, L. and Lopez, M. (2021) ‘Demand-driven supply networks under uncertainty’, Transportation Research Part E, 152, 102442.
- Kumar, R. and Prasad, S. (2021) ‘Blockchain for supply chain transparency’, IEEE Access, 9, pp. 67845–67859.
- Banerjee, H. and Iyer, K. (2022) ‘Service level optimization under demand variability’, International Transactions in Operational Research, 29(3), pp. 1185–1203.
- Yang, M. and Sun, Q. (2021) ‘Inventory pooling with stochastic demand’, Naval Research Logistics, 68(5), pp. 419–432.
- Roy, J. and Bandyopadhyay, D. (2021) ‘Hybrid simulation-optimization for supply chains’, Simulation Modelling Practice and Theory, 106, 102174.
- Choi, A. and Kim, J. (2021) ‘Inventory optimization under COVID-19 disruptions’, Journal of Supply Chain Management, 57(4), pp. 112–127.
- Nair, V. (2021) ‘AI-driven forecasting systems in retail’, Artificial Intelligence Review, 54(5), pp. 3639–3661.
- Clark, D. and Evans, P. (2021) ‘Supplier reliability and stochastic lead times’, International Journal of Logistics Management, 32(2), pp. 453–469.
- He, Z. and Zhao, W. (2021) ‘Optimization of perishable product inventory’, International Journal of Production Research, 59(14), pp. 4192–4210.
- Thomas, G. and White, R. (2021) ‘Data-driven decision support for retailers’, Decision Analytics Journal, 2, 100023.

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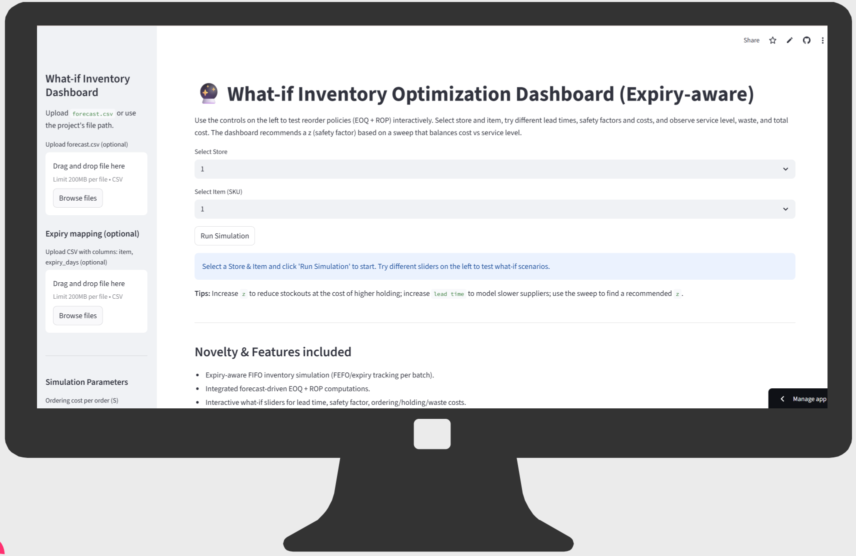

Thank you.