

“AI-POWERED SMART INVENTORY AND PROCUREMENT SYSTEM: A MACHINE LEARNING FRAMEWORK FOR PHARMACEUTICAL AND BEAUTY PRODUCT DISTRIBUTION”

Guide

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ABSTRACT

For distributors of pharmaceutical and beauty products, day-to-day efficiency and profitability depend heavily on how well inventory is managed, particularly because these product lines carry a limited shelf life, unpredictable customer demand, and suppliers whose delivery times are not always consistent. Conventional stock-control setups, built around fixed reorder thresholds and manual, spreadsheet-based tracking, generally cannot anticipate shifts in demand, factor in supplier lead time, or warn staff about products nearing expiry — gaps that translate into stock-outs, cash tied up in surplus inventory, and preventable losses from expired goods. This paper puts forward the design of an AI-Powered Smart Inventory and Procurement System that unifies machine-learning-driven demand forecasting, lead-time-sensitive reorder recommendation, automatic purchase-order generation, expiry tracking, OCR-based digitization of supplier invoices, and anomaly detection inside a single ERP-style web platform. Architecturally, the platform pairs a React.js front end with a Spring Boot back end over REST APIs, while a separate Python/FastAPI microservice houses the AI logic, all backed by a PostgreSQL database. The overall aim is to turn historical sales, stock, and purchasing records into forward-looking guidance, moving inventory decision-making away from a reactive stance and toward a proactive one.

Keywords: Artificial Intelligence, Inventory Management, Demand Forecasting, Procurement Automation, Predictive Analytics, Supplier Lead Time, Expiry Monitoring, OCR, Anomaly Detection, ERP.

1. INTRODUCTION

1.1 Background

How well a business manages its inventory largely decides whether it can consistently satisfy customer demand without tying up excessive capital in stock. This balancing act is especially difficult in pharmaceutical and beauty product distribution, since these products carry a fixed shelf life,

demand shifts with the seasons and market trends, and orders must be placed well ahead of when the stock is actually needed. Pharmaceutical distributors carry the added burden of regulatory and safety obligations that rule out dispensing expired medication, while beauty product distributors have to keep track of a large, constantly evolving catalogue in which demand varies widely from item to item.

1.2 Motivation

This work is motivated by the operational difficulties that pharmaceutical and beauty product distributors face in practice, as their catalogues keep expanding in size and variety even as demand for any single product becomes harder to predict by hand. Companies relying on purely reactive inventory practices tend to absorb repeated financial losses — from stock-outs, from money locked up in stock that moves slowly or piles up in excess, and from products that must be discarded once they expire. The manual work involved in watching stock levels, drafting purchase orders, and following up with suppliers across a large catalogue also eats into the time managers could otherwise spend on higher-value decisions. These observations point to the need for a system that forecasts demand ahead of time, proposes procurement actions on its own, and flags expiry risk before it turns into wastage.

1.3 AI-Enabled Proactive Inventory Control

Artificial Intelligence and Machine Learning offer a workable path toward a more proactive style of inventory control. A forecasting model, trained on patterns found in historical sales and stock-movement records, can estimate how much of each product will be needed in the near term; this estimate then lets the system anticipate when stock will run out and recommend how much to reorder and when, with supplier lead time taken into account. Additional AI-driven capabilities — pulling data automatically from supplier invoices, watching for products nearing their expiry dates, and picking out unusual demand or stock-movement behavior — extend this proactive approach beyond forecasting alone.

1.4 Proposed System

The AI-Powered Smart Inventory and Procurement System is put forward as a centralized, web-based, ERP-style platform aimed at pharmaceutical and beauty product distributors, wholesalers, and retail organizations.

Workflow: Historical Sales/Stock/Procurement Data → Demand Forecasting → Stock-Depletion Prediction → Lead Time-Aware Reorder Recommendation → Purchase Order Automation → Expiry Monitoring / OCR Invoice Processing / Anomaly Detection → Dashboard & Analytics.

The system is built with a React.js front end talking to a Spring Boot back end over REST APIs, while a dedicated Python/FastAPI microservice handles the AI-related work — demand prediction, reorder recommendation, OCR-based invoice processing, and anomaly detection — with PostgreSQL acting as the central data store. The main contribution of this work is bringing demand forecasting, lead-time-aware procurement automation, expiry monitoring, invoice digitization, and anomaly detection together into one coherent decision-support platform.

2. PROBLEM STATEMENT

In many cases, organizations handling pharmaceutical and beauty product inventories still rely on manual or spreadsheet-driven processes to track stock, estimate demand, and coordinate procurement. Under this approach, reorder decisions typically rest on fixed minimum-stock thresholds rather than any data-driven read of near-future demand, and supplier lead time is rarely factored in systematically.

The result is that these businesses see frequent stock-outs on some items alongside excess, slow-moving inventory on others. Because purchase orders are drawn up by hand, the procurement cycle slows down and becomes more error-prone, while inconsistent tracking of expiry dates leads to wastage, added storage cost, and compliance risk. Where automation exists at all in current systems, it typically offers only limited real-time analytics and little in the way of intelligent decision support for inventory managers.

There is accordingly a clear case for an integrated, AI-powered inventory and procurement system — one that forecasts demand, predicts stock depletion, recommends and automates reordering with supplier lead time in mind, tracks procurement status, watches for expiry, and brings all of this together in a unified, real-time dashboard.

3. OBJECTIVES

The central aim of this research is to build an AI-Powered Smart Inventory and Procurement System (SIPS) that offers a

centralized, automated, and secure environment for pharmaceutical and beauty product distribution.

The specific objectives are:

1. To design an AI-driven inventory management system that can forecast future product-level demand from historical sales and consumption data.
2. To predict when stock will run out and generate reorder-quantity suggestions that factor in supplier lead time and observed consumption trends.
3. To automate the creation of purchase orders and track procurement status so as to improve replenishment efficiency.
4. To keep watch over the expiry dates of pharmaceutical and beauty products in order to cut down on wastage and the storage costs that come with it.
5. To build an OCR-based invoice-processing feature that pulls structured supplier, item, quantity, and price details from invoices, reducing manual data entry.
6. To add anomaly detection across inventory, sales, and procurement data so that unusual patterns — possible errors, fraud, or sudden demand shifts — get surfaced for review.
7. To provide an interactive, real-time dashboard that gives inventory managers analytics, alerts, and AI-based decision support.

4. LITERATURE REVIEW

Within pharmaceutical and beauty-product distribution, inventory management and procurement have become an active area of research, driven by the need to keep stock levels optimal, cut down on wastage, and ensure products stay available when needed. Traditional inventory systems built around fixed reorder points and manual oversight struggle inherently with fluctuating demand, inconsistent supplier lead times, and a finite product shelf life; this has pushed a growing body of research toward applying Artificial Intelligence and Machine Learning to inventory forecasting and procurement decisions.

Princz et al. put forward an AI-based procurement system that applied machine learning techniques — including LSTM models — to optimize material ordering amid volatile market conditions, and reported both improved ordering accuracy and roughly a four-percent cut in procurement cost [1]. Vadaga et al. carried out a systematic review of AI applications within pharmaceutical supply chains and found that AI meaningfully strengthens demand forecasting, inventory visibility, and supply chain resilience while cutting wastage [2]. David et al. built an AI-driven inventory and demand-forecasting system that also automated

communication with suppliers, reporting gains in both inventory availability and procurement efficiency [3]. In a wider-ranging review, Ni, Xiao, and Lim examined how machine learning has been used across supply chain management functions and noted that, although ML has been applied successfully to forecasting, inventory optimization, and logistics as separate problems, there remains a need for systems that bring multiple such capabilities together [4].

Supplier evaluation has drawn its own strand of research: Kohli built a supplier-evaluation model that plugs into SAP ERP using machine learning [5]; Wilson et al. used Random Forest to rank supplier performance [6]; and Srijaroon et al. introduced a supervised-learning approach to classifying suppliers within ERP systems [7]. Perishable-inventory management has likewise been examined separately from

forecasting work: Vila-Parrish, Ivy, and King proposed a simulation-based inventory model for perishable pharmaceuticals that cut wastage without hurting availability [8]. On the document-automation side, Khanchandani et al. combined OCR with large language models for automated invoice-data extraction [9], while Patel built an OCR pipeline focused specifically on pulling tables out of invoices [10]. Al-Hadidi et al. developed an automated system that detects and alerts on drug expiry to cut down medicine wastage [11]. Alghamdi and Alshammari [12] and Jebbor et al. [13] each contribute a review — the former covering AI-based inventory management broadly and the latter covering pharmaceutical drug-supply methods — while Sharma and Verma report that AI noticeably improves forecasting accuracy and inventory-management efficiency in applied settings [14].

TABLE I. LITERATURE REVIEW SUMMARY

Ref.	Author/Year	Method/ Technique	Application	Key Findings	Limitations	Research Gap
[1]	Princz et al. (2025)	LSTM, CNN, ANN	Material procurement	Forecasting-driven ordering cut procurement cost by around 4%.	Focuses on procurement optimization alone; no inventory or ERP layer.	Needs pairing with a complete inventory and reorder framework.
[2]	Vadaga et al. (2025)	Systematic review	Pharmaceutical supply chain	AI strengthens demand forecasting, inventory visibility, and chain resilience.	Review-based; no working system was built.	A deployable, pharma-specific AI-ERP system is still needed.
[3]	David et al. (2026)	AI-based forecasting	Inventory and supplier communication	Historical demand patterns drove forecasts and automatic supplier notification.	Leaves out supplier analytics and expiry handling.	Needs integrated procurement analytics plus expiry tracking.
[4]	Ni, Xiao and Lim (2020)	Systematic review	Supply chain management	ML works well for forecasting, inventory optimization, and logistics.	A general review, not tied to one industry.	Points to a need for unified, multi-function AI-ERP platforms.
[5]	Kohli (2018)	Machine learning	Supplier evaluation in SAP ERP	ML sharpens supplier-selection accuracy inside an ERP setting.	Confined to the supplier-evaluation piece.	Needs linking to demand forecasting and procurement.
[6]	Wilson et al. (2020)	Random Forest	Supplier performance ranking	Random Forest ranks suppliers well using past procurement data.	No inventory or forecasting element.	A unified ERP tying supplier ranking to stock planning is needed.
[7]	Srijaroon et al. (2021)	Supervised learning	Supplier classification in ERP	Supervised classification sharpens supplier evaluation in ERP systems.	Does not consider demand-side forecasting.	Should be paired with AI-based demand forecasting.
[8]	Vila-Parrish, Ivy and King (2008)	Simulation modelling	Perishable pharmaceutical inventory	Simulation-based planning cuts wastage while keeping availability up.	No AI/ML forecasting element.	Needs an AI-based, expiry-aware demand model.
[9]	Khanchandani et al. (2025)	OCR with LLM	Invoice data extraction	Structured invoice data can be extracted automatically.	Not tied into an ERP or procurement workflow.	Needs direct linkage to procurement/inventory updates.
[10]	Patel (2025)	OCR pipeline	Table extraction from invoices	Shows structured extraction of tabular invoice data.	Narrowly scoped to table extraction only.	Requires linkage to downstream inventory updates.
[11]	Al-Hadidi et al. (2025)	Expiry detection and alerting	Pharmaceutical inventory	Automated alerts cut medicine wastage tied to expiry.	Does not address procurement planning.	Needs combining with AI-based reorder/procurement logic.
[12]	Alghamdi and Alshammari (2025)	Literature review	Inventory management	AI broadly improves forecasting accuracy and stock optimization.	Review only; no system was implemented.	A practically deployed, integrated system is still needed.
[13]	Jebbor et al. (2016)	Comparative literature review	Drug supply and inventory management	Compares inventory-management methods for pharmaceutical supply.	Does not assess AI/ML-based methods.	Needs modern AI/ML techniques applied to drug inventory.
[14]	Sharma and Verma (2025)	Applied analysis	AI in forecasting and inventory efficiency	AI meaningfully lifts forecasting accuracy and inventory efficiency.	Findings stay general rather than domain-specific.	Needs validation specific to pharma/beauty distribution.

Taken together, the literature shows that existing work has made solid progress on individual pieces of the puzzle — demand forecasting, supplier evaluation, procurement optimization, perishable-inventory modelling, and OCR-based invoice extraction — but mostly in isolation from one another. Few integrated solutions were found that bring together demand forecasting, lead-time-aware reorder recommendation, procurement automation, expiry monitoring, OCR-based invoice processing, and anomaly detection under a single ERP-oriented platform, and fewer still target the pharmaceutical and beauty-product distribution context specifically. The system proposed here addresses that gap by folding these capabilities into one unified, real-time decision-support platform rather than treating them as separate tools.

5. PROPOSED METHODOLOGY

5.1 Proposed System Overview

The system proposed here is a centralized, web-based ERP-style platform for AI-driven inventory and procurement management aimed at pharmaceutical and beauty product distribution. It brings inventory, demand-forecasting, procurement, expiry-monitoring, invoice-processing, and anomaly-detection activities together under one dashboard, cutting down manual effort and moving decision-making from reactive to proactive.

Workflow: Data Collection & Cleaning → Feature Engineering & Model Development → Demand Prediction → Stock-Depletion Analysis → Reorder Recommendation → Procurement Planning & Purchase-Order Generation → Supplier/Procurement Tracking → Dashboard-Based Decision Support. Expiry monitoring, OCR-based invoice processing, and anomaly detection operate as supporting components feeding the same dashboard and database layer.

5.2 System Architecture

The system is split into four layers working together: a presentation layer built in React.js that delivers the ERP-style dashboard; an application layer built in Spring Boot that exposes REST APIs for core business logic such as inventory records, supplier management, and the purchase-order workflow; a dedicated Python/FastAPI microservice that forms the AI layer, handling demand prediction, reorder recommendation, OCR-based invoice processing, and anomaly detection; and PostgreSQL, which serves as the shared relational data store for both the business-logic and AI layers.

Architecture Flow: React.js Front End → Spring Boot Back End (REST APIs) → PostgreSQL Database / Python-FastAPI

AI Microservice → Forecasts, Recommendations, Extracted Invoice Data & Anomaly Flags → Dashboard.

This layout supports scalable concurrent use, allows the AI components to be updated and retrained independently, and enforces controlled access across roles such as inventory manager and procurement staff, with all communication carried over HTTP-based REST APIs using JSON payloads.

5.3 System Modules

The system's functional modules, listed below, together cover the full inventory-and-procurement lifecycle from data ingestion through to analytics:

- **Inventory Management** — keeps records of products, stock levels, categories, and warehouses.
- **Demand Forecasting** — predicts future demand for each product based on historical consumption.
- **Stock Depletion Prediction** — estimates when current stock will drop below operating levels given forecasted demand.
- **Reorder Recommendation** — works out a suggested reorder quantity and timing from forecasted demand, current stock, and supplier lead time.
- **Supplier & Procurement Management** — keeps supplier records and lead times, and drives the procurement process through to automated purchase orders.
- **Expiry Monitoring** — keeps track of expiry dates for pharmaceutical and beauty products and raises alerts before they expire.
- **OCR Invoice Processing** — pulls structured data out of scanned or photographed supplier invoices.
- **Anomaly Detection** — flags unusual inventory, sales, or procurement activity for review.
- **Dashboard, Alerts and User/ERP Management** — shows real-time analytics and handles authentication, roles, and access control.

5.4 AI/ML Methodology

The AI forecasting component learns from historical inventory-consumption and demand patterns so that it can estimate future demand at the level of individual products. It draws on historical sales quantities, stock-movement records, and time-based features such as seasonality, and produces a short-horizon demand estimate for each product, which is then compared against current stock to work out when depletion will occur. The reorder-recommendation logic combines this forecast with supplier lead time and a

configurable safety margin to suggest a reorder quantity and a target order date. Which specific learning algorithm to use has not been settled yet; the model family will be chosen and reported once implementation and comparative testing are finished. The anomaly-detection component looks for inventory, sales, or procurement records that diverge noticeably from established patterns and flags them for manual review rather than acting on them automatically.

5.5 Dataset, OCR and Procurement Logic

The forecasting and anomaly-detection components draw on historical operational data that includes, where available, product identifiers and categories, supplier identifiers and lead times, historical stock levels, historical sales/demand records, unit price, warehouse identifiers, transaction date/time, and expiry information. Dataset size and the train/test split will be settled during implementation. The procurement logic is driven by predicted demand, current stock, consumption trend, and supplier lead time: once the projected stock-depletion date falls inside the supplier's lead-time window, the system flags that product for reorder and suggests a quantity that covers expected demand plus a safety margin, pending user approval before a purchase order is actually generated. The OCR invoice-processing component

takes in scanned or photographed supplier invoices and pulls out structured fields — supplier name, item description, quantity, unit price, and invoice date — to cut down on manual data entry; which OCR engine will be used has not been decided yet.

6. RESULTS AND DISCUSSION

6.1 Results

At this stage of the project, what has been delivered is the system design, architecture, and methodology described above. Model development for the demand-forecasting and anomaly-detection components is expected to follow a standard train/test approach, with forecasting performance judged using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), reorder-recommendation effectiveness judged through stock-out and overstock rates compared against the existing fixed-threshold policy, OCR judged by extraction accuracy against manually verified fields, and anomaly detection judged by precision and recall against labelled records. Since actual numerical results are not available yet, these criteria are laid out here as the evaluation framework to be applied once implementation wraps up, with the entries in Table II standing in as placeholders for now.

TABLE II. RESULTS TEMPLATE (TO BE COMPLETED AFTER IMPLEMENTATION AND TESTING)

Component	Evaluation Metric	Result
Demand Forecasting Model	Mean Absolute Error (MAE)	[INSERT ACTUAL MAE]
Demand Forecasting Model	Root Mean Squared Error (RMSE)	[INSERT ACTUAL RMSE]
Demand Forecasting Model	Forecast Accuracy	[INSERT ACTUAL FORECAST ACCURACY]
Reorder Recommendation	Stock-out Reduction (%)	[INSERT ACTUAL VALUE]
OCR Invoice Processing	Extraction Accuracy	[INSERT ACTUAL VALUE]
Anomaly Detection	Detection Precision/Recall	[INSERT ACTUAL VALUE]
Overall System	Average Response Time	[INSERT ACTUAL VALUE]

6.2 Discussion

These early results suggest that the proposed modular architecture gives a solid, scalable base to build on. Tying demand forecasting, lead-time-aware reordering, and automated purchase-order generation together should cut down stock-outs and excess inventory compared with a fixed-reorder-threshold baseline, while OCR-based invoice processing and anomaly detection should reduce manual effort and catch irregular records that might otherwise slip through. The main contribution of the system is bringing these pieces — demand forecasting, awareness of supplier lead time, automated procurement, expiry monitoring, invoice digitization, and anomaly detection — together into one closed-loop platform that works across both pharmaceutical and beauty-product distribution, something

most existing systems only do partially. Further evaluation, including a comparison against the current manual, spreadsheet-based baseline, will follow once implementation and testing are complete.

7. LIMITATIONS

At its current stage, the proposed system carries some limitations tied to implementation scope, evaluation, data dependency, and scalability.

7.1 Partial Implementation

The design, architecture, and methodology have been worked out, but full implementation and end-to-end integration of every module is still under way, so the system's complete functionality cannot be assessed yet.

7.2 Limited Evaluation

Actual quantitative results from model training, testing, and system-wide evaluation are not available yet. Forecast accuracy, reorder effectiveness, OCR accuracy, and anomaly-detection performance will need to be evaluated once implementation is finished.

7.3 Data Dependency

How reliable the forecasting and anomaly-detection components turn out to be depends on the availability and quality of historical inventory and sales data, and on how well seasonal and market-driven demand swings — which are hard to fully capture from historical data alone — get represented.

7.4 Supplier and OCR Variability

Variation in supplier lead times can throw off the accuracy of lead-time-aware reorder recommendations, and OCR-based invoice extraction may not perform as well on poor-quality scans or invoices that don't follow a standard format.

7.5 Scalability, Security and Integration

How the system performs at scale under heavy concurrent load across multiple warehouses hasn't been tested yet and will need dedicated load testing. It will also need to meet data-security and access-control requirements for sensitive supplier, pricing, and business information, and manage the added complexity of coordinating the React.js front end, Spring Boot back end, and Python/FastAPI AI microservice.

7.6 Future Scope and Overall Limitation

Planned next steps include IoT-based smart shelves for sensor-driven stock updates, RFID tagging for tracking at the item level, blockchain-based record-keeping across the supply chain, more advanced deep-learning forecasting models, real-time analytics on supplier performance, cloud deployment across multiple warehouses, a companion mobile app, and ongoing automated model retraining. These limitations reflect where the project currently stands; once the remaining modules are completed, integrated, and thoroughly tested, a full evaluation of the system's functionality, security, evaluation accuracy, performance, and scalability will be possible.

8. References

- [1] G. Princz, F. Reisacher, and S. Erol, "AI-based Procurement System: Optimization of Material Ordering and Inventory Management in Volatile Markets," *Procedia CIRP*, vol. 134, pp. 873–878, 2025.
- [2] A. K. Vadaga, U. R. Dokuburra, H. Nekkanti, A. K. A. E. Reddy, S. D. V. S. R. A. R. M. Sekhar, and A. P. D. N. Ram, "Digital transformation in pharmaceuticals: The impact of AI on supply chain management," *Intelligent Healthcare Systems*, vol. 1, Art. no. 100008, 2025.
- [3] D. Stalin David, N. Siva Virhush, V. Ajay, H. Kalai Selvan, and S. Manikandan, "AI-Driven Inventory and Demand Forecasting System with Automated Supplier Communication and Trend Analysis," *IJERT*, vol. 15, no. 4, pp. 576–582, 2026.
- [4] D. Ni, Z. Xiao, and M. K. Lim, "A Systematic Review of the Research Trends of Machine Learning in Supply Chain Management," *Intl. J. Machine Learning and Cybernetics*, vol. 11, no. 7, pp. 1463–1482, 2020.
- [5] M. Kohli, "Supplier Evaluation Model on SAP ERP Application Using Machine Learning Algorithms," *Intl. J. Engineering & Technology*, vol. 7, no. 2.28, pp. 306–311, 2018.
- [6] V. H. Wilson, A. Prasad N. S., A. Shankharan, S. Kapoor, and J. Rajan A., "Ranking of Supplier Performance Using Machine Learning Algorithm of Random Forest," *IJARET*, vol. 11, no. 5, pp. 298–308, 2020.
- [7] P. Srijaroon, P. Chiadamrong, and S. Krittanai, "A Supervised Learning-Based Supplier Classification Model for Supplier Performance Evaluation Problem in SAP ERP," *Thai J. Operations Research*, vol. 9, no. 2, pp. 43–58, 2021.
- [8] A. R. Vila-Parrish, J. S. Ivy, and R. E. King, "A Simulation-Based Approach for Inventory Modeling of Perishable Pharmaceuticals," in *Proc. 2008 Winter Simulation Conference*, pp. 1532–1538, 2008.
- [9] K. Khanchandani, A. Thakur, A. Shetty, C. Reddy, and R. Behera, "Automated Invoice Data Extraction: Using LLM and OCR," *arXiv:2511.05547*, 2025.
- [10] P. D. Patel, "Design and Implementation of an OCR-Powered Pipeline for Table Extraction from Invoices," *arXiv:2507.07029*, 2025.
- [11] A. A. Al-Hadidi, M. Al-Momani, and M. Alshurideh, "Automated Drug Expiry Detection and Alert System via Email Notifications," *American J. Networks and Communications*, vol. 14, no. 1, pp. 1–9, 2025.
- [12] A. A. Alghamdi and M. A. Alshammari, "A Review of Artificial Intelligence in Inventory Management," *IJACSA*, vol. 16, no. 10, pp. 822–834, 2025.
- [13] S. Jebbor, A. El Afia, R. Chiheb, and F. Ouzayd, "Comparative Analysis of Drug Supply and Inventory Management Methods: Literature Review," in *Proc. LOGISTQUA 2016*, pp. 194–199, 2016.
- [14] P. K. Sharma and R. Verma, "The Transformative Impact of AI on Forecasting Accuracy and Inventory

Management Efficiency,” IJFMR, vol. 7, no. 3, pp. 1–9, 2025.