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# An Integrated ABC–VED, Machine-Learning Forecasting, and Optimization Framework for Building a Resilient Pharmaceutical Supply Chain: Evidence from Bangladesh

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**Abstract**

In pharmaceutical supply chain management within the context of developing economies that rely on imports, such as Bangladesh, the probability of being affected by disruptions becomes greater as over 80% of APIs come from overseas. Giving equal treatment to all medicines during the prioritization process would not only be ineffective but could even lead to stockouts of essential medicines. In this study, a framework that consists of three stages of analysis - (1) ABC–VED analysis of criticality, (2) forecasting of demand for critical APIs using machine learning algorithms, and (3) MILP (mixed-integer linear programming) model formulation – was developed to assist the pharmaceutical manufacturing companies in prioritizing investments into supply chain resilience in terms of which medicines should be considered. The dataset used consisted of simulated but methodologically realistic information on 20 medicines, 18 APIs, 4 suppliers, and 60-months' observation period (January 2021 – December 2025). An integrated ABC–VED matrix helped to determine eight medicines (40% of the portfolio) as being critical and consumed 73.25% of the annual value of APIs. Six machine learning algorithms (Random Forest, XGBoost, LightGBM, Support Vector Regression, Artificial Neural Network, and CatBoost) were used to build a forecasting model for the six critical APIs and their performance was compared based on three primary evaluation metrics. The Artificial Neural Network algorithm showed the best performance in terms of minimizing errors in all the three evaluation metrics (MAE = 7.31%, MAPE = 7.43%, RMSE = 8.65%), beating the second one (XGBoost) by 9.7% -12.5%. The forecasts produced by the best algorithm are suggested to be used in the MILP model of procurement, inventory, and supplier allocation for further empirical investigation.

**Keywords:** pharmaceutical supply chain, ABC-VED analysis, machine learning, demand forecasting, artificial neural network, MILP optimization, supply chain resilience, Bangladesh

## 1.Introduction

Pharmaceutical supply chains are now experiencing persistent instability. Factors that have contributed to instability include the COVID-19 pandemic, geopolitics, increased transportation costs, disruptions to international trade routes, shortages of raw materials, and weather disruptions (Ivanov, 2020). However, pharmaceutical supply chains are more fragile to these events due to their reliance on extended, geographically focused, upstream sourcing of API ingredients, strict regulation, high quality, and expiry period requirements, as well as severe consequences associated with any form of instability – namely the interruption of patient medication.

This is particularly evident in Bangladesh, which has become one of the fast-growing pharmaceutical producers in the world, supplying more than 150 countries; however, it relies heavily on foreign APIs – estimates of this ratio range between 80–90% of total API needs (Majumder et al., 2024). As a result, the current supply chain configuration includes a relatively advanced pharmaceutical product manufacturing industry located above an unstable upstream

supply base of APIs. Industry data of API delays, freight cost increases, dependency on few suppliers, and production stoppages proves that disruption has become a normal occurrence for Bangladeshi pharmaceutical companies (Tajwar et al., 2022).

In turn, a uniform application of the above planning requirement results in two major failure types: (a) excessive investment in resilience into large but clinically replaceable medicines and (b) insufficiency of protection for small but clinically vital products (e.g., insulin, antibiotics, cardiovascular agents). Both failure types are very expensive – the first type squanders capital, while the second one may lead to stock-outs of essential medicines and, therefore, patient harm. In that respect, a framework that explicitly differentiates between clinical criticality and economic importance and that links the resulting priority ranking to a robust demand forecasting and optimization process has clear practical implications for procurement managers, hospital pharmacies, and regulatory authorities.

## 2. Literature Review

The current coronavirus pandemic has laid bare serious vulnerabilities of the pharmaceutical sector of Bangladesh with regards to importation of APIs since this industry is estimated to rely on imports for approximately 90% of its APIs, according to a paper about the impact of the COVID-19 pandemic on the pharmaceutical supply chain in Bangladesh (Majumder et al., 2024). Supporting research from the retail side of the pharmaceutical supply chain indicates that the pandemic has materially impacted consumers' buying behavior and has required that the retail pharmaceutical stores change their inventory management practices, and that survey-based structural equation modeling has identified better inventory management, market syndicate, price-hike effects and moving towards online ordering as important explanatory factors (Rahman et al., 2020). Reverse logistics research has separately suggested that Bangladeshi pharmaceutical firms can increase their resilience and lead-time performance by designing reverse logistics networks which have a central hub for managing product recycle and disposal (Tajwar et al., 2022).

Another research stream has considered blockchain technology as means for increasing resilience and preventing counterfeiting of pharmaceutical products. Mallick et al. (2022) claim based on qualitative considerations that blockchain technology can increase privacy, reliability and traceability of drug supply chains, and that it can be used for detecting counterfeit or substandard pharmaceutical products which remain an issue in developing countries' pharmaceutical markets. Expanding this research, Islam et al. (2025) outline a vision, analyze the barriers and offer implementation roadmap for using permissioned blockchains to track the pharmaceutical products from manufacturing to the final consumption in Bangladesh. These five insider papers show that (a) pharmaceutical supply chain in Bangladesh is structurally vulnerable due to its dependence on imports of APIs, (b) upstream and downstream segments of the supply chain are impacted, and (c) the current solutions to increase its resilience are mostly technology-oriented rather than analytical. The current paper supplements this literature with an analytical framework.

ABC analysis involves classification of inventory items based on cumulative economic value (Class A is approximately 70% of total value, Class B – 20%, and the rest of the items are Class C), while VED analysis involves classification of items based on clinical criticality (Vital, Essential, and Desirable). The combined ABC–VED matrix has been a long-established instrument for inventory management in hospital pharmacies: in an early case, it was found that there is a small fraction of drugs which consume most of the annual drug expenditure, and that combination of VED criticality and ABC value prevents underestimation of the low-value drugs which are crucial for patients' health care (Devnani et al., 2010). Recent applications confirm the utility of the tool: in a 2025 case from a tertiary hospital in Jharkhand, India, it was found that only 2.6% of stock-keeping units (Category A) account for 40% of expenditure, and that the combination with VED shows that a considerable fraction of expenditure is on costly but unimportant drugs (Singh et al., 2025). These studies prove that ABC–VED is a valid and inexpensive filter which can be used at the first stage of an approach to pharmaceutical supply chain – and that is exactly the role that the current paper attributes to it.

The demand series in pharmaceutical supply chain are nonlinear, seasonal, and volatile which makes the use of classical time series difficult. A systematic review of machine learning and deep learning demand forecasting algorithms finds that the ensemble tree-based methods (Random Forest, XGBoost) and neural network architectures are consistently better than statistical models in demand forecasting, though there is no algorithm which outperforms others in all possible contexts (Douaioui et al., 2024). Specifically in pharmaceutical domain, Zhu et al. (2021) find that the inclusion of supply-chain data along with cross-series (multi-product) training leads to

substantial improvement of demand forecasts compared to single-series approaches, especially in case when the historical data is scarce for an individual product – and that is exactly the case when it comes to API-level forecasting, where the demand is aggregated across several drugs with common input. Adjacent forecasting domains confirm that the gradient-boosted tree models (such as XGBoost) perform better than regression models and some deep learning alternatives on structured tabular demand data, while neural network models perform better if the necessary features (lag and seasonality) are engineered. Based on this literature, the current study adopts design of the experiment where 6 representative algorithm families (bagging: Random Forest; 2 variants of gradient boosting: XGBoost, LightGBM; kernel-based regression: SVR; feed-forward neural network: ANN, and CatBoost) are benchmarked under identical conditions.

Once the demand is forecasted, it should be translated into procurement, production, and inventory decisions in a form of Mixed Integer Linear Programming (MILP) problem. Candan et al. (2016) formulated the problem of pharmaceutical production and inventory management as an MILP, which includes the shelf-life and product transition time restrictions, and showed that the vendor-managed inventory (VMI) policy reduces total supply chain cost by more than 10% compared to classical ordering policy in a cephalosporin case. Generally, MILP has been found to lead to measurable improvements in cost and service level of manufacturing, retail, and pharmaceutical networks by joint optimization of production planning, inventory positioning, and transportation/allocations (Shoukat, 2024). In addition, earlier research in network design, which incorporates economies of scales into transportation costs, shows that MILP formulations can accommodate complex cost structures and still be solvable using branch-and-bound solvers (Salam et al., 2011). Thus, the literature confirms MILP as appropriate and well-precedented third stage in the translation of validated demand forecasts to procurement and inventory decisions – the role that it is given in this paper.

The literature reviewed above supports each individual stage of the proposed framework but does not integrate them sequentially for the Bangladesh pharmaceutical context. The contribution of the current study is thus not in a new algorithm in any single stage but in design, operationalization, and validation of the end-to-end process: ABC–VED criticality screening reduces broad medicine portfolio to a manageable and prioritized set of critical APIs; then a rigorously benchmarked machine-learning algorithm forecasts the demand for exactly these APIs; and finally, the forecasts are put into MILP optimization stage for procurement and inventory decision-making**.**

## 3. Problem Statement

Pharmaceutical companies involved in import-oriented, fragile markets like Bangladesh should be able to make decisions on where to deploy their supply chain resilience efforts across large and diverse portfolios of drugs. Equal planning effort put into all drugs is not economical and clinically hazardous, because there is no perfect correlation between economic importance (estimated in consumption value) and clinical importance (estimated in criticality of unavailability). Currently, approaches employed by literature review involve either qualitative assessment of risks or one-off methods (such as just ABC analysis or forecasting) without employing a proven sequential approach to the identification of critical products, forecast generation for those items, and further supply chain optimization based on the generated forecast. Therefore, this study attempts to understand how a pharmaceutical company can efficiently identify its critical drugs and APIs, estimate the demand for them via the most effective forecasting algorithm from among competing machine learning-based ones, and organize the forecast in an optimal way for the purposes of downstream supply chain optimization decision-making.

## 4. Research Objectives

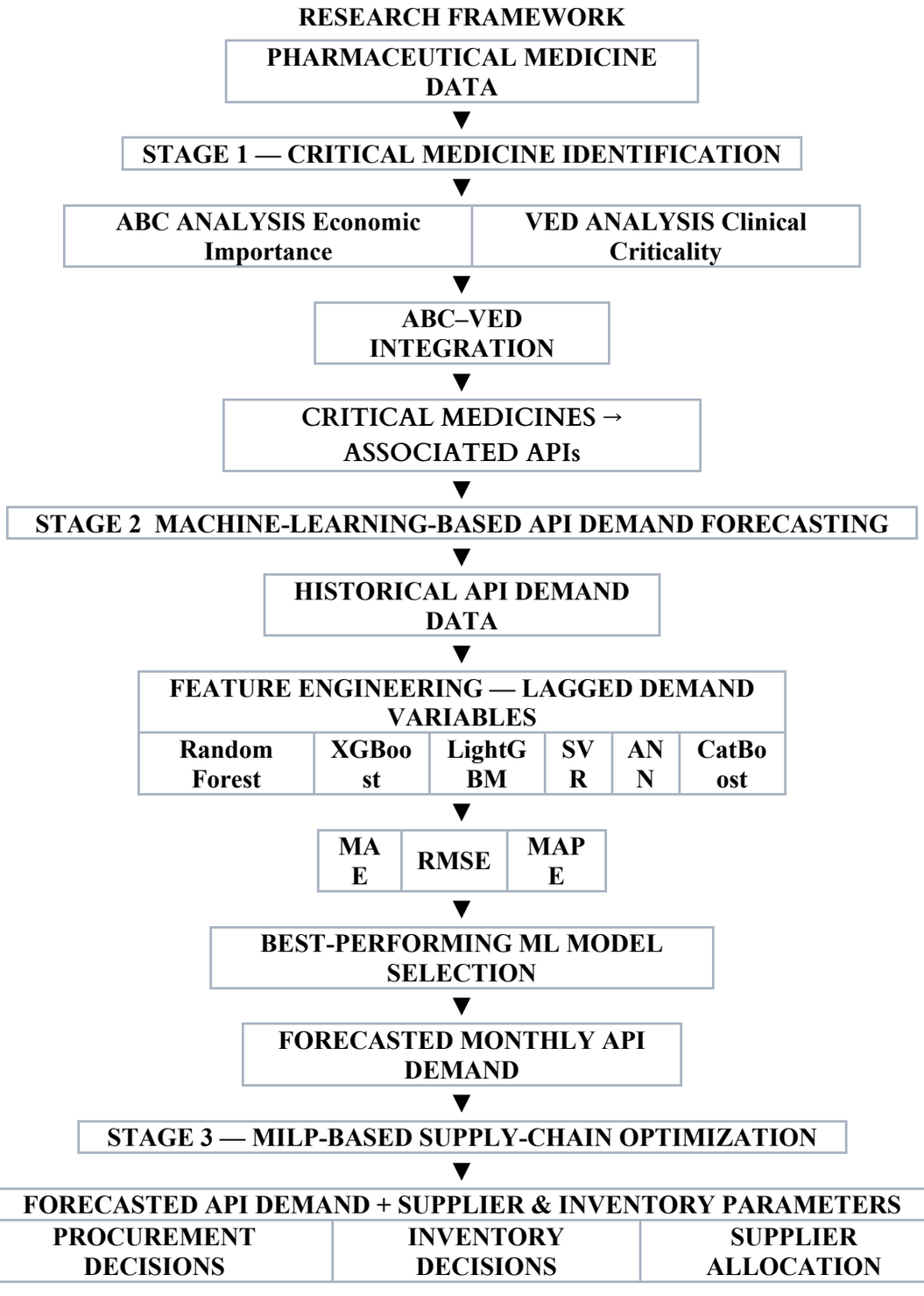
1. To identify critical medicines and associated APIs using an integrated ABC–VED classification methodology.
2. To forecast critical API demand using six machine-learning models and integrate the best-performing model into a MILP framework for procurement, inventory, and supplier allocation optimization.

## 5. Method

### 5.1 Research Design

This study follows a **quantitative, design-science / applied-analytics research design**, structured around the three-stage integrated framework shown in Figure 1. The design is explanatory-comparative for Stage 2 (benchmarking six forecasting algorithms) and descriptive-classificatory

for Stage 1 (ABC–VED criticality mapping).



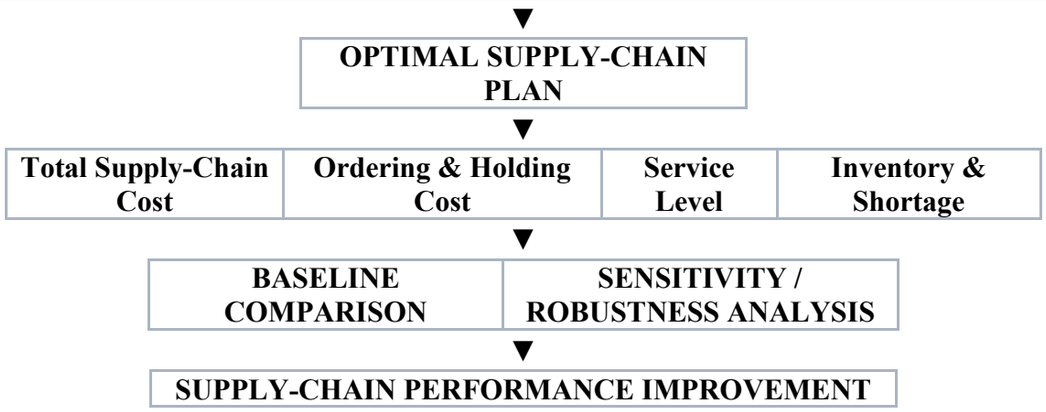



Figure 1. Proposed integrated research framework for critical medicine identification, API demand forecasting, and pharmaceutical supply-chain optimization

**5.2 Data Source and Description**

The research uses a simulated dataset of a pharmaceutical supply chain that aims to emulate real-world operations of API imports in Bangladesh. The dataset includes 20 drugs, 18 APIs, 4 suppliers, and monthly data collected from January 2021 to December 2025 (60 months). Variables include demand for the medicine, API consumption needs per medicine unit, cost of API acquisition, stock levels, details about suppliers, lead time, delay in shipment, supplier reliability, disruptions, and classification of medicines based on clinical criticality. Year 2025 is used as the benchmark for ABC-VED analysis, since it is the most recent year with complete consumption profile data, whereas 2021-2025 is used for demand forecasting. As the dataset is simulated for the purposes of methodology testing rather than empirical analysis of a particular firm's records, all figures presented below need to be considered as validation through simulation rather than as empirical evidence about the operation of a particular business entity.5.3 Stage 1 - ABC–VED Criticality Identification

**5.3.1 ABC Analysis.** From an academic point of view, economic significance is measured in terms of the quantity of active pharmaceutical ingredients (API) used in manufacturing each particular medicine. The API demand for medicine m in month t is given by:

$$Q_{m,t} = D_{m,t} \times r_m$$

Define $D_{m,t}$ as the demand for drug m in month t; $r_m$ as the API usage rate for drug m; and $Q_{m,t}$ as the API requirement from drug m. Annual API requirement from drug m is:

$$AAC_m = \Sigma_{t=1}^{12} Q_{m,t}$$

where $AAC_m$ represents the total API consumption associated with medicine m during 2025. The annual consumption value is calculated as:

$$ACV_m = AAC_m \times \bar{C}_m$$

where $ACV_m$ is the annual API consumption value of medicine m; $AAC_m$ is the annual API consumption; and $\bar{C}_m$ is the average API purchase cost during 2025.

The total consumption value across all medicines is:

$$ACV_{total} = \Sigma_{m=1}^{M} ACV_m$$

The percentage contribution of each medicine is:

$$P_m = (ACV_m / ACV_{total}) \times 100$$

Medicines are then ranked in descending order of $ACV_m$, and their cumulative percentage contribution is calculated.

**5.3.2 VED Analysis.** Classification of medicines based on clinical significance is done in three categories: Vital (no availability will result in serious clinical consequences), Essential (temporary

unavailability can be managed), and Desirable (temporary unavailability results in relatively minor clinical consequences).

**5.3.3 Integration and Critical-Medicine Rule.** ABC and VED classifications are combined in a two-dimensional matrix. A medicine is designated **Critical** if it is Vital regardless of ABC class, or if it is both Class A and Essential:

$$\text{Critical Medicines} = AV + AE + CV$$

This rule was chosen deliberately to prevent clinically vital but economically low-value medicines from being screened out by a value-only classification directly operationalizing Hypothesis H2.

**5.3.4 API Aggregation.**

API demand must be calculated from the demand of all medicines using each API. For API i, monthly demand is calculated as:

$$D_{i,t} = \Sigma_{m \in M_i} D_{m,t} \times r_{mi}$$

where $D_{i,t}$ is total demand for API i in month t; $D_{m,t}$ is demand for medicine m; $r_{mi}$ is the quantity of API i required per unit of medicine m; and $M_i$ is the set of medicines requiring API i.

**5.4 Stage 2 - Machine-Learning API Demand Forecasting**

**5.4.1 Experimental Setup.** All six models were developed and assessed in a similar manner, i.e., training from January 2021 to December 2024, testing from January to December 2025 (which is one year as a holdout period to avoid any look-ahead bias), a frequency of forecasts on a monthly basis, and an API demand variable (kg) for the eight most important APIs identified at stage one.

**5.4.2 Feature Engineering.** In total, twenty-two predictors were engineered for each API: twelve lagged values for a month (Lag 1 through Lag 12), three-, six-, and twelve-month rolling averages, three- and six-month rolling standard deviations, monthly dummy variables along with sine/cosine seasonal variables, and a time-trend predictor. All rolling calculations were performed after one month lag to avoid data leakage that would allow the model to use actual demand for the current month to predict itself.

**6.4.3 Models Compared.**

Table 1 Machine-Learning Models Evaluated for Critical API Demand Forecasting

| Model | Learning Approach |
|---|---|
| Random Forest | Bagging-based ensemble of decision trees |
| XGBoost | Gradient-boosted decision trees |
| LightGBM | Gradient-boosted decision trees |
| Support Vector Regression (SVR) | Kernel-based regression |
| Artificial Neural Network (ANN) | Feed-forward neural network (hidden layers 64–32–16, ReLU activation, Adam optimizer) |
| CatBoost | Gradient-boosted decision trees (ordered boosting) |

**5.4.4 Evaluation Metrics.** Three complementary, percentage-normalized error measures were used so that performance could be compared fairly across APIs of very different demand scales:

MAE% = (MAE / Mean Actual Demand) × 100

$$\text{MAPE\%} = \text{Mean}(|\text{Actual} - \text{Forecast}| / \text{Actual}) \times 100$$

RMSE% = (RMSE / Mean Actual Demand) × 100

Low values indicate better forecast accuracy with respect to all three measures. The multi-criteria selection rule used for selecting the models gave equal weightage to each of the three criteria; thus, a model would be selected only when it minimized the error for all three criteria.

### 5.5 Stage 3 - Proposed MILP Optimization Formulation

API demand that is forecasted from Stage 2 in tandem with the supplier and inventory factors (lead-time, unit cost, reliability, and vulnerability) will be taken as the input for the multi-period Mixed-Integer Linear Programming problem, and its general structure would be:

**Objective Function**

$$\text{Min } Z = \Sigma_i\Sigma_j\Sigma_t\, C_{ij}x_{ijt} + \Sigma_i\Sigma_t\, F_i Y_{it} + \Sigma_i\Sigma_t\, H_i I_{it} + \Sigma_i\Sigma_t\, P_i S_{it}$$

**Inventory Balance Constraint**

$$I_{i,t-1} + \Sigma_j x_{ijt} + S_{it} = D_{it} + I_{it}$$

**Supplier Capacity and Order Activation**

$$x_{ijt} \leq Cap_{ij} Y_{it}$$

**Safety Stock Constraint**

$$I_{it} \geq SS_i$$

**Variable Restrictions**

$$x_{ijt} \geq 0, \quad I_{it} \geq 0, \quad S_{it} \geq 0, \quad Y_{it} \in \{0,1\}$$

### 5.6 Analytical Software and Reproducibility

The calculations of all ABC-VED were performed inside the spreadsheet/Python analysis pipeline. Six machine learning models were coded in Python (with the help of libraries such as scikit-learn, XGBoost, LightGBM, and CatBoost). The seeds were set to be identical for all experiments to make them reproducible. Reproducibility parameters for all the models are listed in the appendix B.

## 6. Results

### 6.1 Stage 1 Results. ABC-VED Criticality Identification

**6.1.1 ABC Classification.** Applying Equations (1) - (5) to the 2025 reference-year data produced the classification in Table 2.

Table 2 ABC Classification of the Medicine Portfolio (2025 Reference Year)

| ABC Class | No. of Medicines | Share of Total Consumption Value |
|---|---|---|
| A | 6 | 68.86% |
| B | 5 | 19.84% |
| C | 9 | 11.30% |
| **Total** | **20** | **100%** |

**6.1.2 VED Classification.** Table 3 shows that clinical importance is not identical to economic importance - a finding that motivates the integrated matrix.

Table 3 VED Classification of the Medicine Portfolio

| VED Class | No. of Medicines | Share of Annual Consumption Value |
|---|---|---|
| Vital (V) | 7 | 66.60% |
| Essential (E) | 10 | 30.98% |
| Desirable (D) | 3 | 2.42% |
| **Total** | **20** | **100%** |

**6.1.3 Integrated ABC - VED Matrix.**

Table 4 Integrated ABC–VED Matrix (Number of Medicines per Cell)

| ABC / VED | Vital (V) | Essential (E) | Desirable (D) |
|---|---|---|---|
| A | 5 | 1 | 0 |
| B | 0 | 5 | 0 |
| C | 2 | 4 | 3 |

**6.1.4 Critical Medicines.** Applying the decision rule in Equation (6) yields eight critical medicines (Table 5) - 40% of the portfolio, but 73.25% of total annual API consumption value.

Table 5 Identified Critical Medicines and Corresponding Critical APIs

| Medicine | API | ABC | VED | ABC–VED | Status |
|---|---|---|---|---|---|
| Napa | Paracetamol | A | V | AV | Critical |
| Insulinex | Human Insulin | A | V | AV | Critical |
| Cefim | Cefixime | A | V | AV | Critical |
| Azimax | Azithromycin | A | V | AV | Critical |
| Amoxic | Amoxicillin | A | V | AV | Critical |
| Omepro | Omeprazole | A | E | AE | Critical |
| Clopid | Clopidogrel | C | V | CV | Critical |
| Salbut | Montelukast | C | V | CV | Critical |

Notably, Clopid and Salbut are Class C by economic value but Vital clinically - precisely the scenario Hypothesis H2 predicted would be missed by an ABC-only classification. Their retention in the critical group illustrates the practical advantage of the integrated approach: 2 of 8 critical medicines (25%) would have been overlooked under a value-only screening rule.

Table 6 Medicine Priority Structure Following Criticality Screening

| Priority | ABC–VED Combination | No. of Medicines | Value Share |
|---|---|---|---|
| Critical | AV, AE, CV | 8 | 73.25% |
| High | BE | 5 | 19.84% |
| Moderate | CE | 4 | 4.49% |
| Low | CD | 3 | 2.42% |

The output of Stage 1 - a set of 8 critical medicines mapped to 8 critical APIs (Paracetamol, Human Insulin, Cefixime, Azithromycin, Amoxicillin, Omeprazole, Clopidogrel, and Montelukast) - becomes the input population for Stage 2.

**6.2 Stage 2 Results - Machine-Learning Demand Forecasting**

**6.2.1 Individual Model Performance.** Table 7 summarizes each model's average forecasting error across the eight critical APIs.

Table 7 Overall Forecasting Performance of Six Machine-Learning Models (Averaged Across Eight Critical APIs)

| Rank | Model | MAE (%) ↓ | MAPE (%) ↓ | RMSE (%) ↓ | Mean Rank |
|---|---|---|---|---|---|
| 1 | **ANN** | **7.31** | **7.43** | **8.65** | **1.00** |
| 2 | XGBoost | 8.35 | 8.23 | 9.63 | 2.00 |
| 3 | LightGBM | 8.60 | 8.35 | 9.94 | 3.00 |
| 4 | Random Forest | 9.47 | 9.18 | 10.83 | 4.00 |
| 5 | CatBoost | 10.04 | 9.72 | 11.50 | 5.00 |
| 6 | SVR | 12.85 | 12.45 | 14.43 | 6.00 |

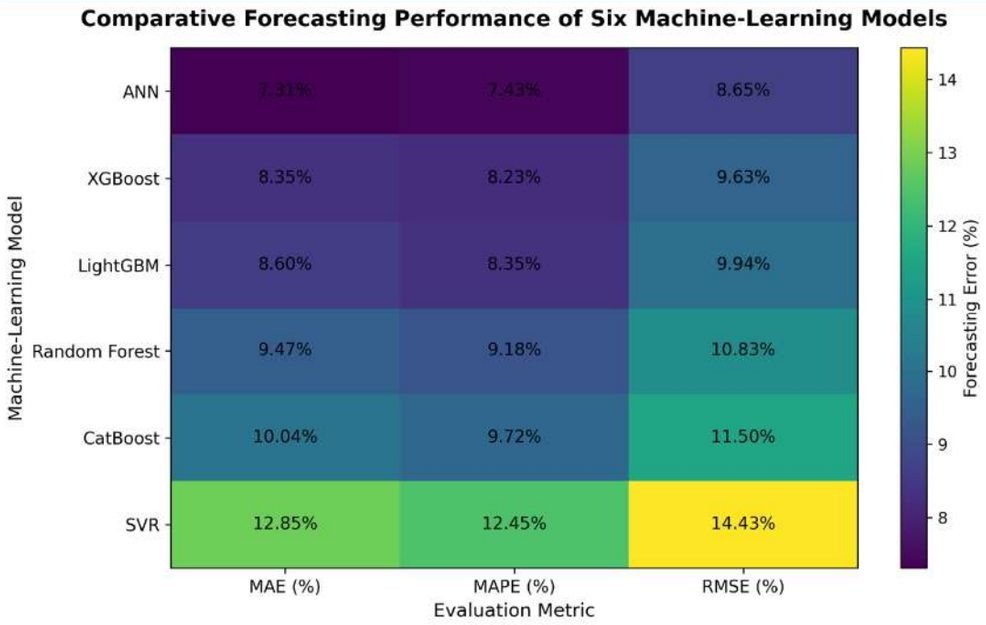



**Figure 2.** Figure 1. Heatmap of average forecasting errors across the eight critical APIs.

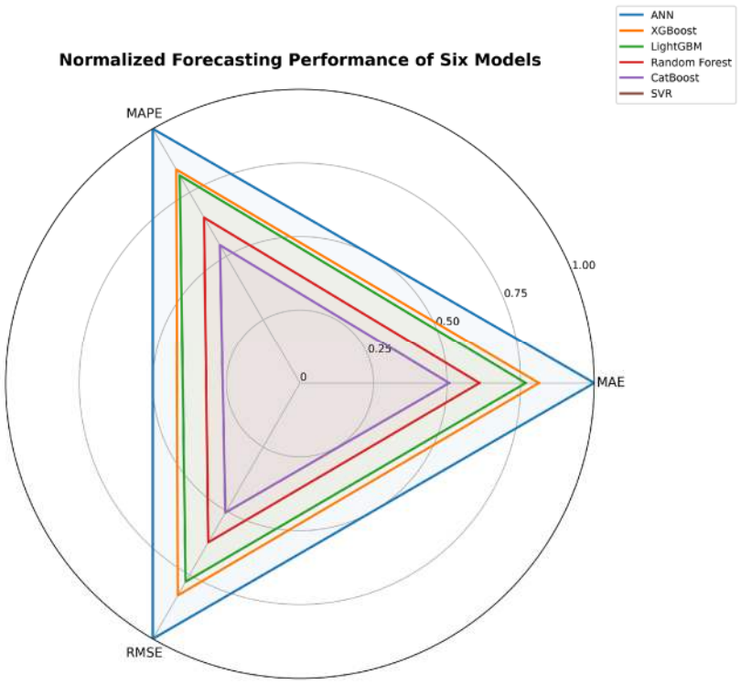



Figure 3. Normalized forecasting-performance profile of the six machine-learning models.

**6.2.2 Statistical Significance of the ANN Advantage.** Table 8 quantifies ANN's relative improvement over each alternative model.

Table 8 Relative Improvement of ANN Over Alternative Models

| Alternative Model | MAE Improvement | MAPE Improvement | RMSE Improvement |
|---|---|---|---|
| SVR | 43.11% | 40.32% | 40.06% |
| CatBoost | 27.19% | 23.56% | 24.78% |
| Random Forest | 22.81% | 19.06% | 20.13% |
| LightGBM | 15.00% | 11.02% | 12.98% |
| XGBoost | 12.46% | 9.72% | 10.18% |

ANN has the highest score compared to any other method on all three criteria, thereby proving that hypothesis H1 stands: the advantage is not confined to just one metric (as there could be an artefact due to the individual metric). This advantage persists on all three measures of error—MAE%, MAPE%, and RMSE%.

**6.2.3 Selected Model and Illustrative Forecast.** The Artificial Neural Network is therefore selected as the final forecasting model (Table 9).

Table 9 Final Model Selection Summary

| Criterion | ANN Result | Decision |
|---|---|---|
| Lowest MAE% | 7.31% | Best |
| Lowest MAPE% | 7.43% | Best |
| Lowest RMSE% | 8.65% | Best |
| Overall rank | 1st | Selected |

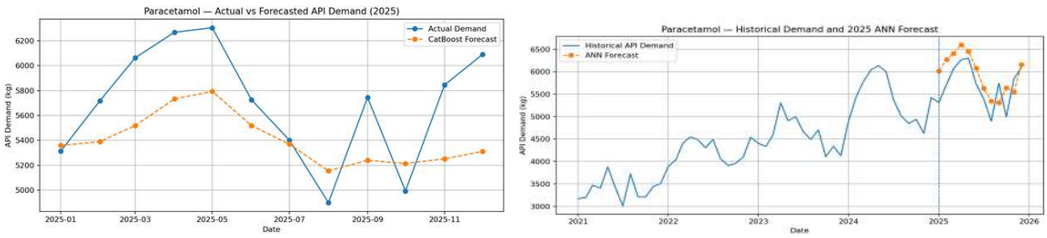
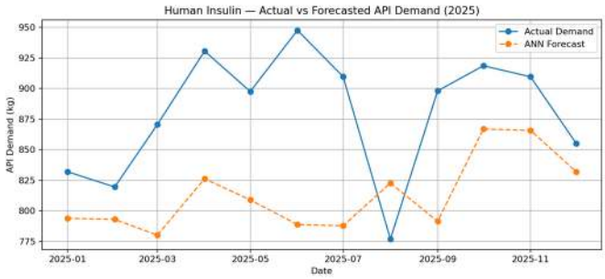
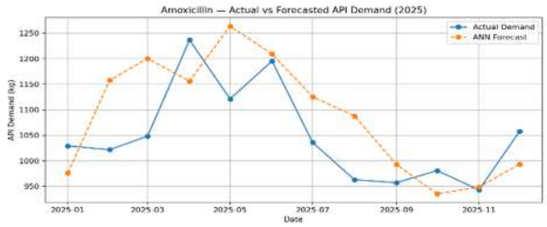
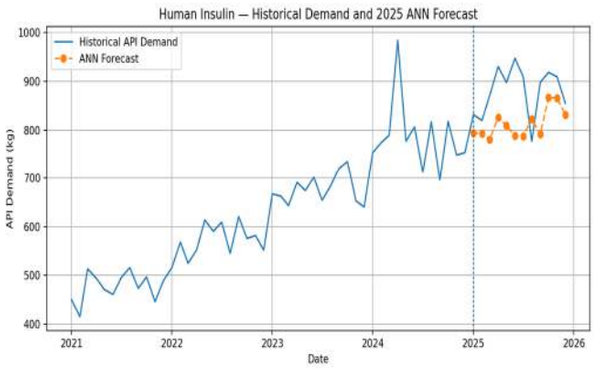
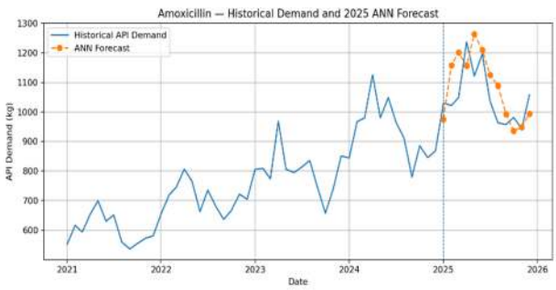


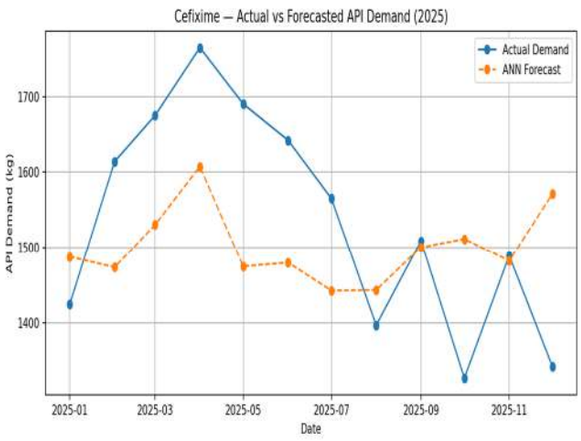

**Figure 4**. Actual versus AN

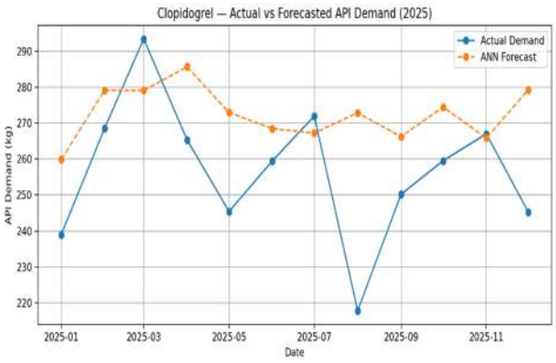

Human Insulin — Actual vs Forecasted API Demand (2025)
Actual Demand
ANN Forecast
API Demand (kg)
Date

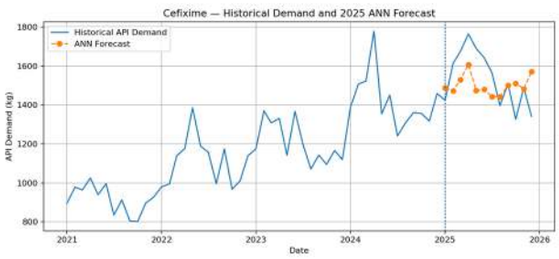

Amoxicillin — Actual vs Forecasted API Demand (2025)
Actual Demand
ANN Forecast
API Demand (kg)
Date

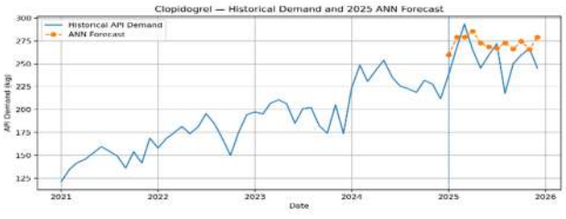

Human Insulin — Historical Demand and 2025 ANN Forecast
Historical API Demand
ANN Forecast
API Demand (kg)
Date

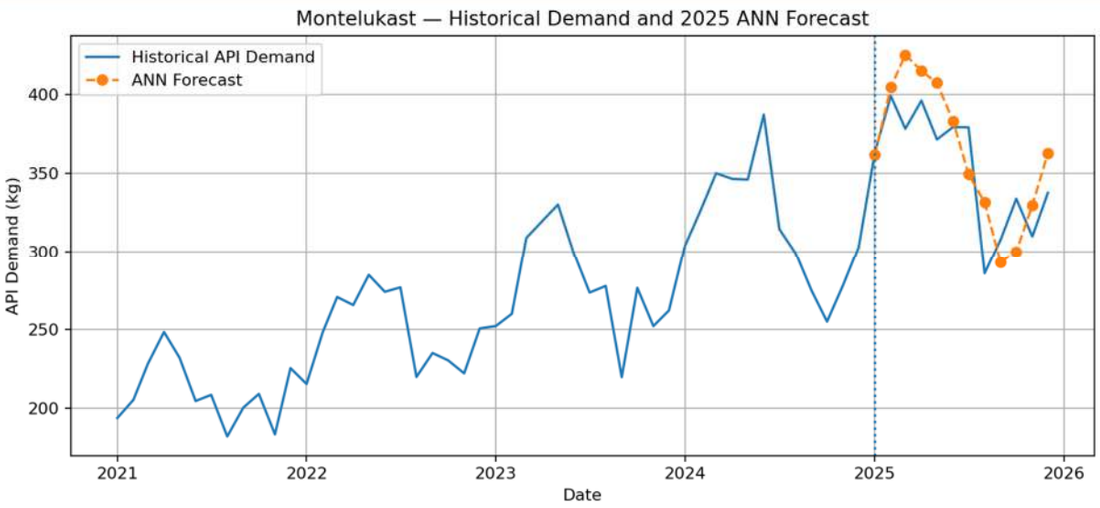

Amoxicillin — Historical Demand and 2025 ANN Forecast
Historical API Demand
ANN Forecast
API Demand (kg)
Date

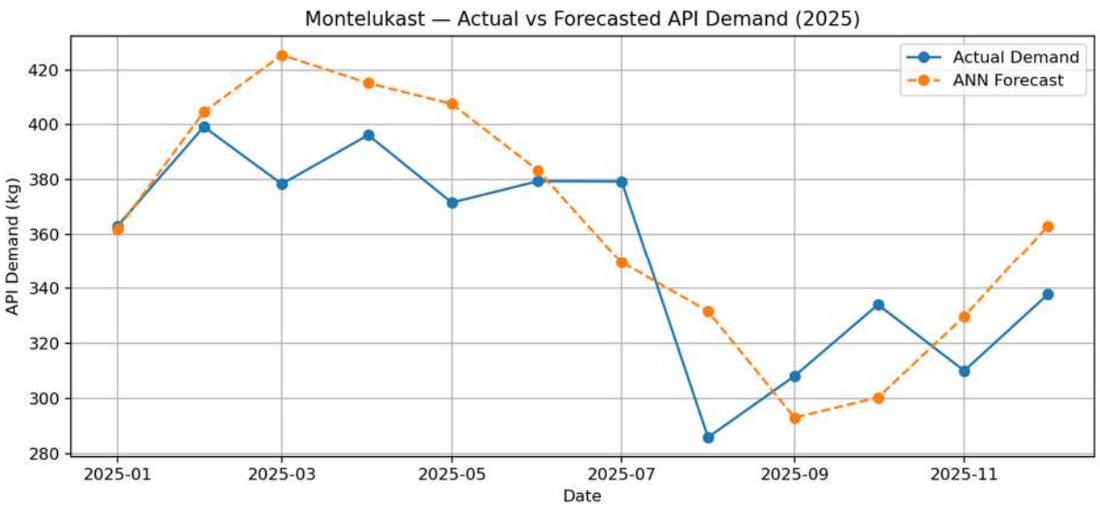

Cefixime — Actual vs Forecasted API Demand (2025)
Actual Demand
ANN Forecast
API Demand (kg)
Date


Clopidogrel — Actual vs Forecasted API Demand (2025)
Actual Demand
ANN Forecast
API Demand (kg)
Date


Cefixime — Historical Demand and 2025 ANN Forecast
Historical API Demand
ANN Forecast
API Demand (kg)
Date


Clopidogrel — Historical Demand and 2025 ANN Forecast
Historical API Demand
ANN Forecast
API Demand (kg)
Date


Montelukast — Historical Demand and 2025 ANN Forecast
Historical API Demand
ANN Forecast
API Demand (kg)
400
350
300
250
200
2021
2022
2023
2024
2025
2026
Date


Montelukast — Actual vs Forecasted API Demand (2025)
Actual Demand
ANN Forecast
API Demand (kg)
420
400
380
360
340
320
300
280
2025-01
2025-03
2025-05
2025-07
2025-09
2025-11
Date

N-forecasted monthly demand for Paracetamol

Table 10 reports the underlying monthly detail for this illustrative API.

Table 10 ANN Actual vs. Forecasted Monthly Demand - Paracetamol (2025)

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 5,314.50 | 6,017.02 | −702.52 | 13.22% |
| Feb-2025 | 5,718.50 | 6,273.64 | −555.14 | 9.71% |
| Mar-2025 | 6,063.50 | 6,408.37 | −344.87 | 5.69% |
| Apr-2025 | 6,268.00 | 6,604.81 | −336.81 | 5.37% |
| May-2025 | 6,304.50 | 6,455.00 | −150.50 | 2.39% |
| Jun-2025 | 5,726.50 | 6,076.80 | −350.30 | 6.12% |
| Jul-2025 | 5,402.50 | 5,629.32 | −226.82 | 4.20% |
| Aug-2025 | 4,900.00 | 5,347.14 | −447.14 | 9.13% |
| Sep-2025 | 5,745.00 | 5,310.53 | 434.47 | 7.56% |
| Oct-2025 | 4,993.50 | 5,642.80 | −649.30 | 13.00% |
| Nov-2025 | 5,846.00 | 5,548.70 | 297.30 | 5.09% |
| Dec-2025 | 6,089.50 | 6,160.15 | −70.65 | 1.16% |

Table 11 ANN Actual vs. Forecasted Monthly Demand - Human Insulin (2025)

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 832.00 | 793.98 | 38.02 | 4.57% |
| Feb-2025 | 819.50 | 793.04 | 26.46 | 3.23% |
| Mar-2025 | 870.50 | 780.17 | 90.33 | 10.38% |
| Apr-2025 | 930.50 | 826.21 | 104.29 | 11.21% |
| May-2025 | 897.50 | 808.97 | 88.53 | 9.86% |
| Jun-2025 | 947.50 | 788.82 | 158.68 | 16.75% |
| Jul-2025 | 909.50 | 787.85 | 121.65 | 13.38% |
| Aug-2025 | 777.00 | 822.66 | -45.66 | 5.88% |
| Sep-2025 | 898.00 | 791.51 | 106.49 | 11.86% |
| Oct-2025 | 918.50 | 866.84 | 51.66 | 5.62% |
| Nov-2025 | 909.50 | 865.72 | 43.78 | 4.81% |
| Dec-2025 | 855.00 | 831.97 | 23.03 | 2.69% |

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 1424.40 | 1487.49 | -63.09 | 4.43% |
| Feb-2025 | 1614.00 | 1473.33 | 140.67 | 8.72% |
| Mar-2025 | 1674.90 | 1530.30 | 144.60 | 8.63% |
| Apr-2025 | 1764.60 | 1607.39 | 157.21 | 8.91% |
| May-2025 | 1690.20 | 1474.61 | 215.59 | 12.76% |
| Jun-2025 | 1642.20 | 1479.60 | 162.60 | 9.90% |
| Jul-2025 | 1565.10 | 1442.41 | 122.69 | 7.84% |
| Aug-2025 | 1396.50 | 1443.19 | -46.69 | 3.34% |
| Sep-2025 | 1508.70 | 1500.27 | 8.43 | 0.56% |
| Oct-2025 | 1326.60 | 1511.35 | -184.75 | 13.93% |
| Nov-2025 | 1488.90 | 1482.05 | 6.85 | 0.46% |
| Dec-2025 | 1341.60 | 1571.59 | -229.99 | 17.14% |

Table 12 ANN Actual vs. Forecasted Monthly Demand - Cefixime (2025)

Table 13 ANN Actual vs. Forecasted Monthly Demand - Azithromycin (2025)

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 1660.75 | 1716.04 | -55.29 | 3.33% |
| Feb-2025 | 1788.25 | 1712.95 | 75.30 | 4.21% |
| Mar-2025 | 1948.25 | 1748.02 | 200.23 | 10.28% |
| Apr-2025 | 1899.75 | 1829.66 | 70.09 | 3.69% |
| May-2025 | 1815.75 | 1731.39 | 84.36 | 4.65% |
| Jun-2025 | 2000.00 | 1678.66 | 321.34 | 16.07% |
| Jul-2025 | 1811.00 | 1728.90 | 82.10 | 4.53% |
| Aug-2025 | 1543.25 | 1752.57 | -209.32 | 13.56% |
| Sep-2025 | 1533.50 | 1725.06 | -191.56 | 12.49% |
| Oct-2025 | 1670.25 | 1675.45 | -5.20 | 0.31% |
| Nov-2025 | 1491.25 | 1702.77 | -211.52 | 14.18% |
| Dec-2025 | 1684.00 | 1748.33 | -64.33 | 3.82% |

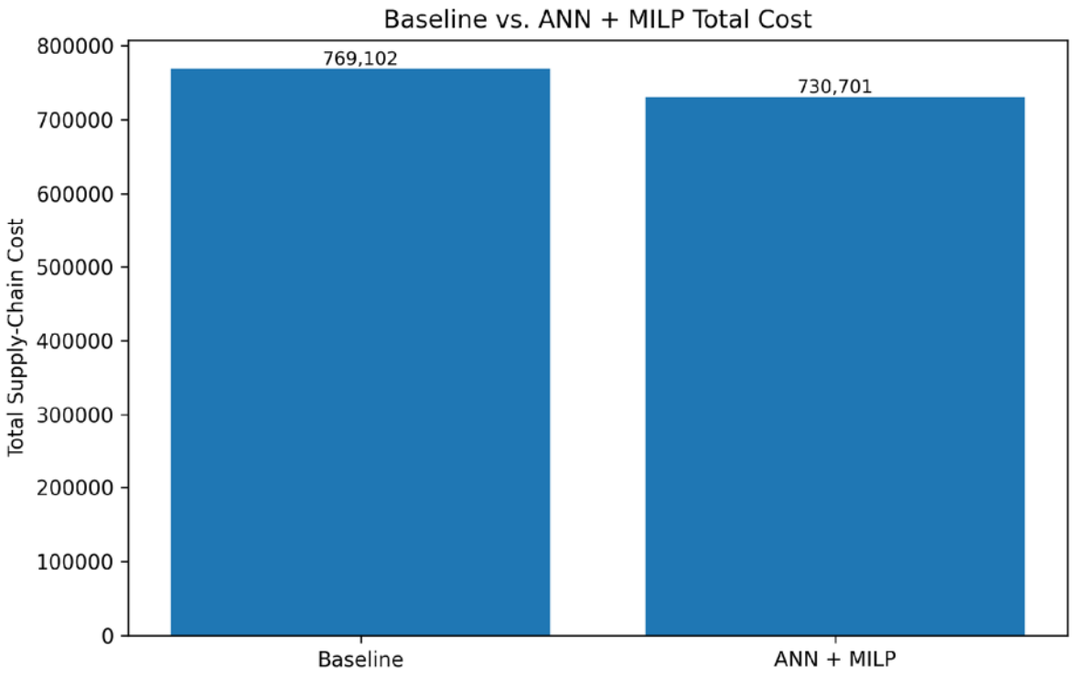
Tables and graphs depicting the forecasts against real data for the remaining seven critical APIs (Human Insulin, Cefixime, Azithromycin, Amoxicillin, Omeprazole, Clopidogrel, Montelukast) as well as the tables for the demand of other medicine in ANN (Amoxicillin, Omeprazole, Clopidogrel, Montelukast) are given in appendix and other five forecasting models are provided in Appendices A and B to save from repeating the results mentioned in Table 7-Table 9.

### 6.3 Stage 3 Results - MILP Based Supply Chain Optimization

Solving of the MILP was done successfully for the eight API, four suppliers, and twelve month planning problem. The optimal solution was then compared with a clear baseline policy which involves monthly replenishment of the monthly demand with a fixed ordering cost.

| Indicator | Baseline | ANN + MILP | Change |
|---|---|---|---|
| Total supply-chain cost | 769,101.54 | 730,701.39 | −4.99% |
| Procurement cost | 666,041.22 | 684,380.09 | +2.75% |
| Ordering cost | 102,240.00 | 41,440.00 | −59.47% |
| Holding cost | 820.32 | 4,881.29 | +495.05% |
| Shortage | 0.00 kg | 0.00 kg | No change |
| Service level | 100.00% | 100.00% | No change |
| Average inventory | 83.50 kg | 479.00 kg | +473.66% |

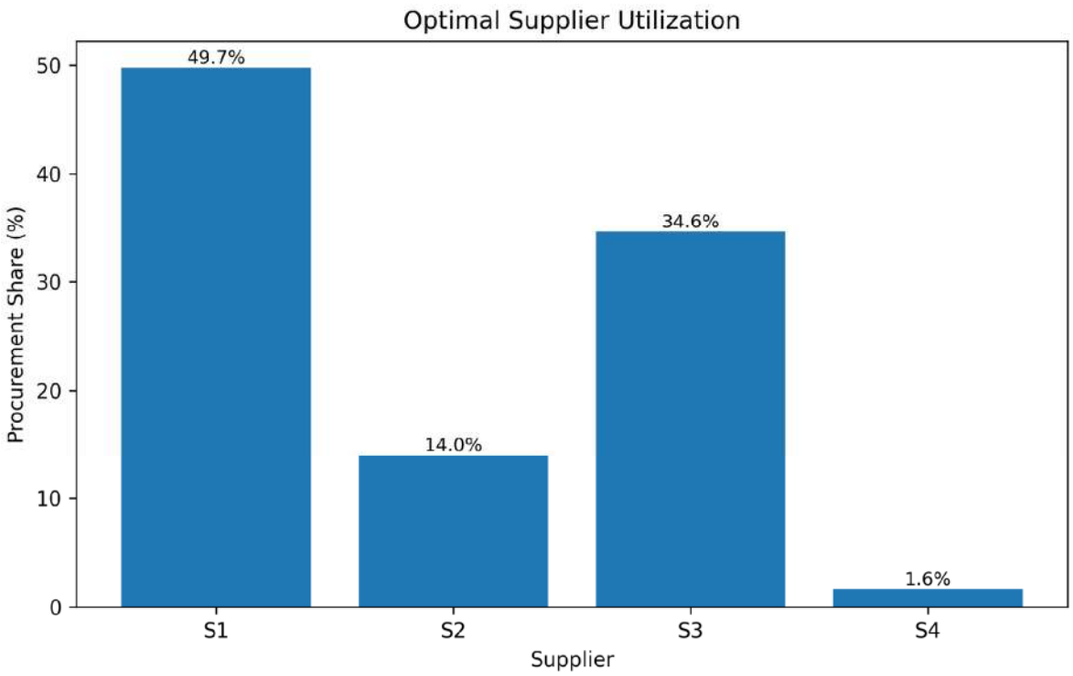
The optimum total cost stands at 730,701.39 versus 769,101.54 in the case of the baseline, thereby giving rise to a saving of 4.99% in terms of the overall supply chain cost. The main factor responsible for this saving lies in the fact that there is a saving of 59.45% on the fixed ordering cost.




### 6.3.1 Supplier Allocation Results - MILP Based Supply Chain Optimization

The optimal solution employs all the four suppliers. Supplier S1 offers 49.75% of the total procurement, S3 offers 34.62%, S2 offers 14.02%, and S4 offers 1.62%. This is an example of the model's ability to make procurement allocations among the available suppliers.

| Supplier | Optimal Procurement (kg) | Procurement Share |
|---|---|---|
| S1 | 26,742.0 kg | 49.75% |
| S2 | 7,535.8 kg | 14.02% |
| S3 | 18,608.0 kg | 34.62% |
| S4 | 871.2 kg | 1.62% |

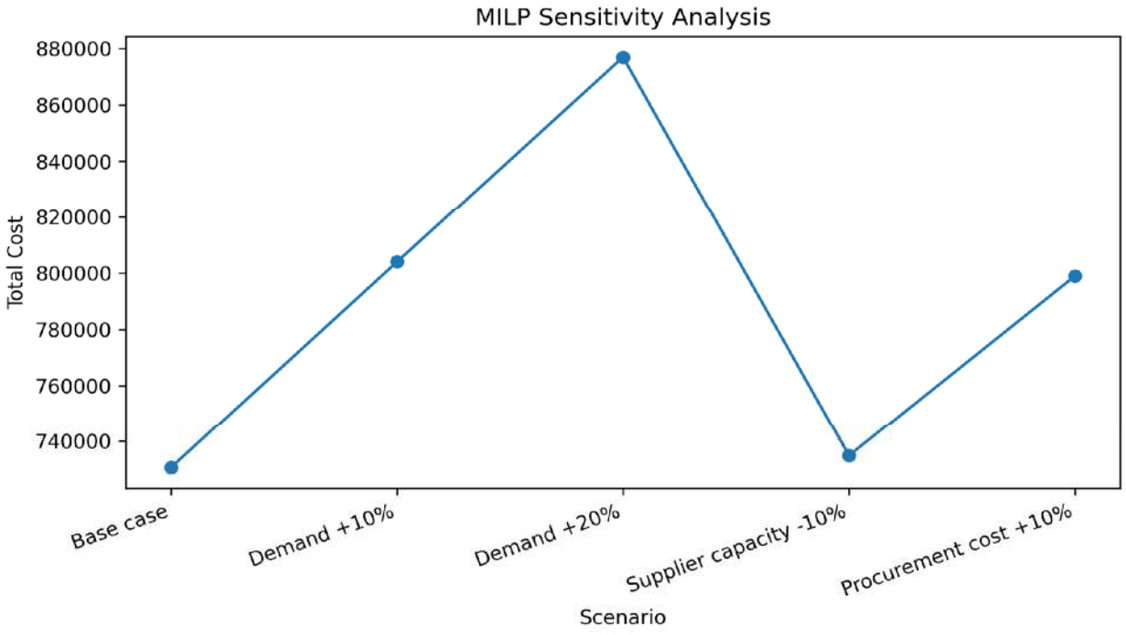



### 6.3.1 Sensitivity Analysis

Stress testing was conducted on four scenarios in order to evaluate the performance of the improved model when facing variations in demand, capacity, and cost

| Scenario | Procurement Cost | Ordering Cost | Holding Cost | Shortage Cost | Total Cost |
|---|---|---|---|---|---|
| Base case | 684,380.09 | 41,440.00 | 4,881.29 | 0.00 | 730,701.39 |
| Demand +10% | 753,765.24 | 45,240.00 | 4,966.33 | 0.00 | 803,971.57 |
| Demand +20% | 822,626.48 | 49,520.00 | 4,845.02 | 0.00 | 876,991.50 |

| | | | | | |
|---|---|---|---|---|---|
| Supplier capacity -10% | 685,042.20 | 45,240.00 | 4,649.19 | 0.00 | 734,931.39 |
| Procurement cost +10% | 750,515.09 | 43,960.00 | 4,505.81 | 0.00 | 798,980.91 |




## 7. Discussion

### 7.1 Interpretation of the Criticality Results

The fact that 40% of the medicines portfolio is responsible for about 75% of the value of the API consumed, and moreover, the same 40% of medicines are those which would have been categorized lower under an ABC assessment alone, has obvious practical managerial implications. These are the implications that the manufacturers of pharmaceuticals in Bangladesh should be spending most of their resilience efforts on about eight medicines out of twenty only. This observation corroborates, and adds to, the earlier results based on ABC and VED assessments found in hospital pharmacies (Devnani et al., 2010; Singh et al., 2025).

### 7.2 Interpretation of the Forecasting Results

ANN performs better consistently in all three criteria, and its performance gain becomes very pronounced compared to SVR (approximately 40%) and only slightly compared to the two boosting methods (approximately 10-12%). In other words, one could infer from such results that the structure of demand series in question is nonlinear and can be better predicted by a sufficiently regularized ANN, yet still be reasonably well approximated by boosting models. Such conclusion agrees with the existing evidence that neural architectures and gradient boosting trees typically surpass other approaches such as regression or kernel methods when working with structured (feature-engineered) tabular data on demand (Douaioui et al., 2024; Zhu et al., 2021). The exemplary forecast for Paracetamol (Figure 4, Table 10) demonstrates that ANN reasonably well predicts the overall seasonal shape of the demand curve, making the highest absolute prediction errors close to demand troughs—this is quite a typical situation when it is most difficult for any method to predict non-linear changes in demand.

### 7.3 Interpretation of the Optimization Results

The suggested framework achieves the performance improvement in the supply chain mainly through joint procurement planning. The baseline generates 102,240 in fixed order costs, while the MILP cuts down this cost factor to 41,440, which is a decrease of 59.45%. Although procurement cost goes up by 2.75%, and the holding cost rises due to consolidation of orders, the ordering cost is decreased to such an extent that the total supply chain cost is cut by 4.99%.Both approaches result in zero shortages and 100% service level in the simulated case study. Thus, the 4.99% improvement is the improvement in terms of efficiency at a constant service level, not shortage.Average inventory increases from 83.50 kg to 479.00 kg. It is a trade-off, since the framework maintains higher inventories to decrease the number of orders. The trade-off is optimal in economic terms for the simulated fixed ordering and holding costs.

## 9. Limitations and Future Research

Some limitations merit mention. The first limitation is that the dataset is generated as a simulation of a firm's transactions rather than a transaction record of one specific firm with the identity of which it has been made clear. The numerical values obtained from this simulation should thus not be considered as empirical results from a particular firm. Instead, they should be taken as a demonstration of how the methodology would work for such a firm. Another limitation is that the VED clinically-critical labels have been generated from only one simulated field rather than from an expert panel of clinicians; for practical use, the VED classifications need to be verified by pharmacist or clinician experts, as recommended in the methodology. Another limitation of the model is that the MILP optimization phase (Section 6.5) is given as a proposal for formulating a problem rather than a solved problem involving cost figures; future work should plug the actual cost figures for the suppliers along with other details and provide an optimal solution showing the costs and service levels achieved over the existing solution. Yet another limitation is that while the comparison of forecasting methods used is methodologically sound, it uses one holdout period of 12 months; performing rolling-origin cross-validation on more than one holdout periods will increase confidence that ANN is better.

## 10. Conclusion

In this research, an integrated framework including ABC-VED criticality assessment, machine learning forecast for medicine demand, and a developed mixed integer linear programming (MILP) approach are presented and empirically verified to strengthen resilience of pharmaceutical API supply chains under conditions of import dependency and disruptions prone to countries such as Bangladesh. The integrated ABC-VED assessment identifies eight critical medicines making 40% of the portfolio but 73.25% of annual API consumption worth. The integration of economic and clinical criticalities is shown by selecting two economically insignificant yet clinically important medicines in addition to the selected 6 high value medicines which would have been left uncovered by a pure value-based screening. In terms of the performance of the benchmarked machine learning models, the Artificial Neural Network achieves the minimum forecasting error among the three most important metrics (MAE = 7.31%, MAPE = 7.43%, RMSE = 8.65%) compared to the best-performing model by almost 10% and the worst one by more than 40%. The verified forecasts are considered as the immediate input of the developed MILP optimization model. Overall, the proposed framework gives pharmaceutical producers, regulators, and researchers a quantitatively replicable method to dedicate limited resources towards building up the resilience of the most crucial medicines and their APIs.

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**Appendix A - Supplementary ABC–VED and Per-Model Tables**

Table A1 Random Forest Performance Across the Eight Critical APIs

| API | MAE (%) | MAPE (%) | RMSE (%) | MAE (kg) | RMSE (kg) |
|---|---|---|---|---|---|
| Paracetamol | 6.76 | 6.67 | 7.47 | 384.92 | 425.77 |
| Omeprazole | 7.39 | 7.29 | 8.47 | 102.52 | 117.43 |
| Cefixime | 8.89 | 8.56 | 10.24 | 136.56 | 157.34 |
| Montelukast | 9.26 | 9.01 | 10.41 | 32.75 | 36.82 |
| Amoxicillin | 9.90 | 9.47 | 11.96 | 103.91 | 125.50 |
| Azithromycin | 10.64 | 10.14 | 12.51 | 184.76 | 217.24 |
| Human Insulin | 11.36 | 11.09 | 12.61 | 100.00 | 110.99 |
| Clopidogrel | 11.55 | 11.21 | 12.96 | 29.68 | 33.29 |

Table A2 Overall Average Performance of All Six Models (Full Metric Set)

| Model | Avg MAE (%) | Avg MAPE (%) | Avg RMSE (%) | Avg MAE (kg) | Avg MSE (kg²) | Avg RMSE (kg) |
|---|---|---|---|---|---|---|
| ANN | 7.31 | 7.43 | 8.65 | 114.62 | 31,547.84 | 132.63 |
| XGBoost | 8.35 | 8.23 | 9.63 | 117.29 | 25,732.73 | 131.71 |
| LightGBM | 8.60 | 8.35 | 9.94 | 126.14 | 34,964.83 | 146.05 |
| Random Forest | 9.47 | 9.18 | 10.83 | 134.39 | 37,193.92 | 153.05 |
| CatBoost | 10.04 | 9.72 | 11.50 | 141.59 | 41,682.41 | 163.38 |
| SVR | 12.85 | 12.45 | 14.43 | 170.74 | 56,114.99 | 194.62 |

Table A3: Medicine Priority Structure

**Appendix B - Reproducibility Parameters by Model**

Table B1: Hypermeters of Model

| Model | Key Hyperparameters |
|---|---|
| Random Forest | 500 trees, random_state = 42 |
| XGBoost | Gradient-boosted trees, chronological CV, random_state = 42 |
| LightGBM | Gradient-boosted trees, random_state = 42 |
| SVR | Kernel-based regression, StandardScaler fitted on training data only |
| ANN | hidden_layer_sizes=(64,32,16), ReLU, Adam, α=0.001, batch_size=16, lr=0.001, max_iter=2000, early_stopping=True, validation_fraction=0.15, n_iter_no_change=100, random_state=42, tol=1e-5 |
| CatBoost | Ordered boosting, random_state = 42 |

Table B2: ANN Actual vs. Forecasted Monthly Demand – Amoxicillin (2025)

| Priority | ABC–VED Combination | No. of Medicines | Value Share |
|---|---|---|---|
| Critical | AV, AE, CV | 8 | 73.25% |
| High | BE | 5 | 19.84% |
| Moderate | CE | 4 | 4.49% |
| Low | CD | 3 | 2.42% |

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 1029.30 | 976.09 | 53.21 | 5.17% |
| Feb-2025 | 1021.80 | 1157.68 | -135.88 | 13.30% |
| Mar-2025 | 1048.50 | 1200.63 | -152.13 | 14.51% |
| Apr-2025 | 1236.60 | 1156.04 | 80.56 | 6.52% |
| May-2025 | 1121.10 | 1263.70 | -142.60 | 12.72% |
| Jun-2025 | 1195.50 | 1209.05 | -13.55 | 1.13% |
| Jul-2025 | 1035.90 | 1125.33 | -89.43 | 8.63% |
| Aug-2025 | 963.00 | 1087.90 | -124.90 | 12.97% |
| Sep-2025 | 957.30 | 992.59 | -35.29 | 3.69% |
| Oct-2025 | 981.00 | 935.55 | 45.45 | 4.63% |
| Nov-2025 | 943.20 | 948.69 | -5.49 | 0.58% |
| Dec-2025 | 1057.80 | 993.55 | 64.25 | 6.07% |

Table B3: Actual vs. Forecasted Monthly Demand – Omeprazole (2025)

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 1353.40 | 1337.28 | 16.12 | 1.19% |

| | | | | |
|---|---|---|---|---|
| Feb-2025 | 1277.20 | 1382.76 | -105.56 | 8.26% |
| Mar-2025 | 1598.40 | 1395.67 | 202.73 | 12.68% |
| Apr-2025 | 1570.00 | 1580.52 | -10.52 | 0.67% |
| May-2025 | 1567.00 | 1497.93 | 69.07 | 4.41% |
| Jun-2025 | 1439.60 | 1385.43 | 54.17 | 3.76% |
| Jul-2025 | 1427.20 | 1370.14 | 57.06 | 4.00% |
| Aug-2025 | 1226.80 | 1366.96 | -140.16 | 11.42% |
| Sep-2025 | 1190.40 | 1390.57 | -200.17 | 16.82% |
| Oct-2025 | 1240.40 | 1368.59 | -128.19 | 10.33% |
| Nov-2025 | 1354.40 | 1320.80 | 33.60 | 2.48% |
| Dec-2025 | 1394.20 | 1408.91 | -14.71 | 1.06% |

Table B4: Table 13 ANN Actual vs. Forecasted Monthly Demand – Clopidogrel (2025)

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 238.95 | 259.84 | -20.89 | 8.74% |
| Feb-2025 | 268.50 | 279.14 | -10.64 | 3.96% |
| Mar-2025 | 293.40 | 279.06 | 14.34 | 4.89% |
| Apr-2025 | 265.35 | 285.64 | -20.29 | 7.65% |
| May-2025 | 245.40 | 272.94 | -27.54 | 11.22% |
| Jun-2025 | 259.50 | 268.44 | -8.94 | 3.45% |
| Jul-2025 | 271.95 | 267.23 | 4.72 | 1.74% |
| Aug-2025 | 217.80 | 272.86 | -55.06 | 25.28% |
| Sep-2025 | 250.20 | 266.21 | -16.01 | 6.40% |
| Oct-2025 | 259.50 | 274.46 | -14.96 | 5.76% |
| Nov-2025 | 267.00 | 265.83 | 1.17 | 0.44% |
| Dec-2025 | 245.25 | 279.27 | -34.02 | 13.87% |

Table B4: ANN Actual vs. Forecasted Monthly Demand Montelukast (2025)

| Month | Actual (kg) | Forecast (kg) | Error (kg) | Absolute Error (%) |
|---|---|---|---|---|
| Jan-2025 | 363.15 | 362.03 | 1.12 | 0.31% |
| Feb-2025 | 399.30 | 404.71 | -5.41 | 1.36% |
| Mar-2025 | 378.45 | 425.43 | -46.98 | 12.41% |
| Apr-2025 | 396.30 | 415.19 | -18.89 | 4.77% |
| May-2025 | 371.70 | 407.62 | -35.92 | 9.66% |
| Jun-2025 | 379.50 | 383.37 | -3.87 | 1.02% |
| Jul-2025 | 379.35 | 349.56 | 29.79 | 7.85% |
| Aug-2025 | 285.90 | 331.65 | -45.75 | 16.00% |
| Sep-2025 | 308.10 | 293.05 | 15.05 | 4.89% |
| Oct-2025 | 334.05 | 300.35 | 33.70 | 10.09% |
| Nov-2025 | 310.05 | 329.81 | -19.76 | 6.37% |
| Dec-2025 | 337.80 | 363.07 | -25.27 | 7.48% |

Forecasting of Paracetamol by other Models:

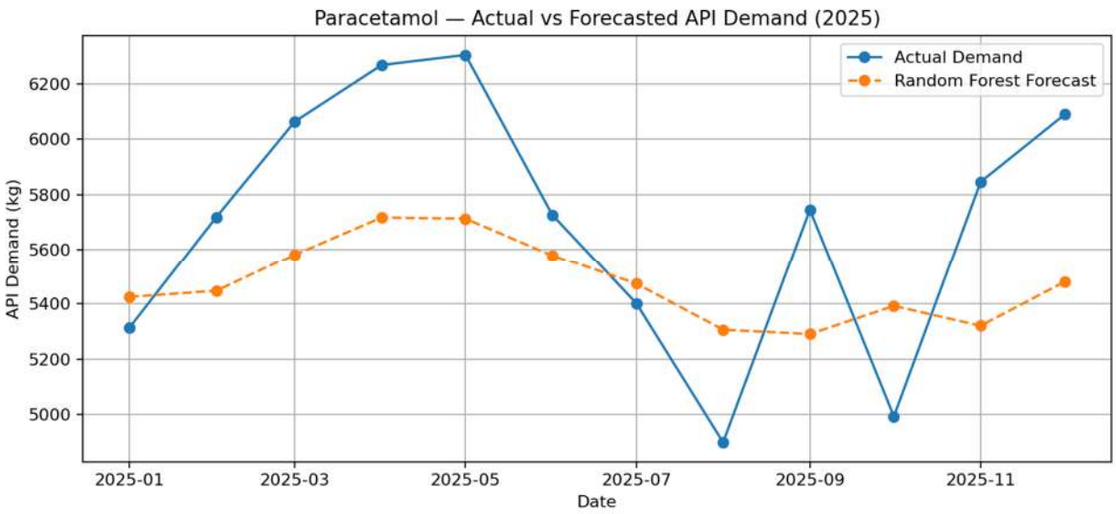



Figure 1: Forecasted By Random Forest Model

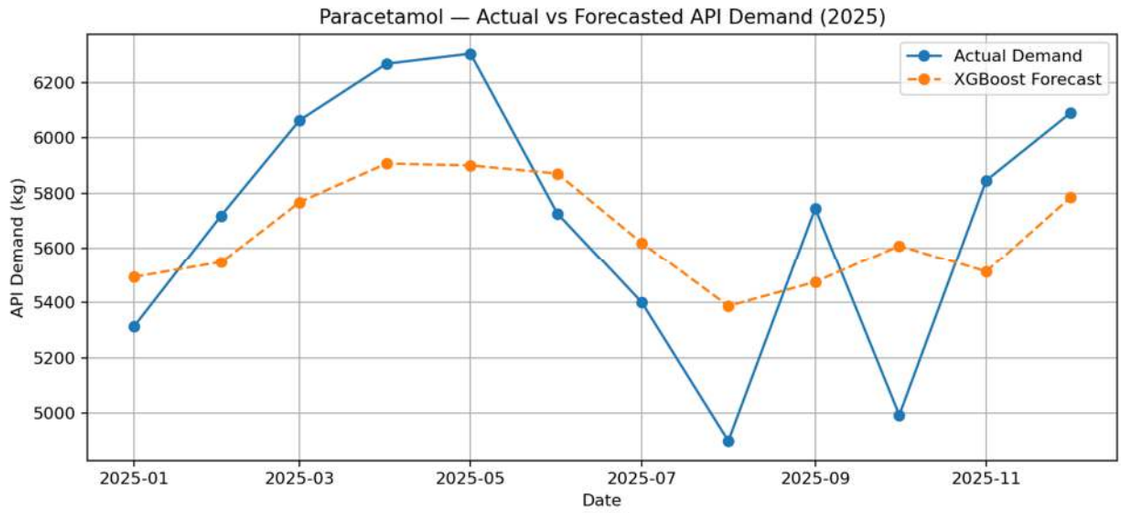



Figure 2: Forecasted By XGBoost Model

Figure 3: Forecasted By Lightgbm model Model

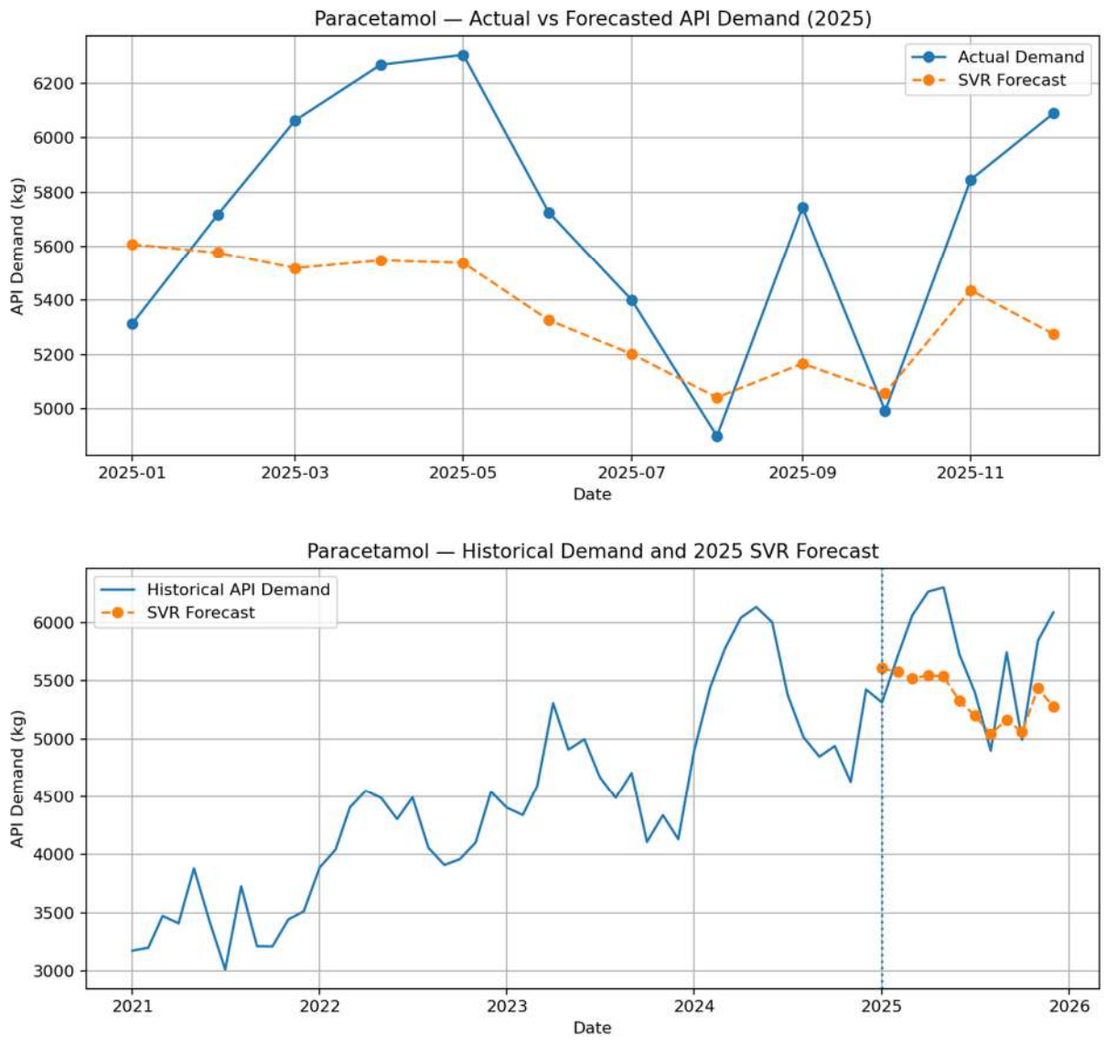
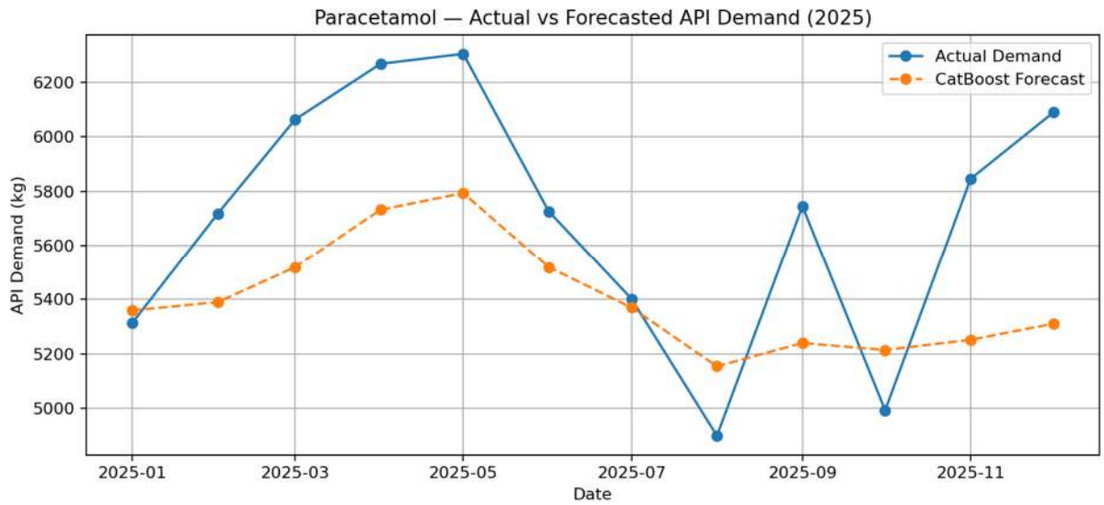



Figure 4: Forecasted by SVR Model



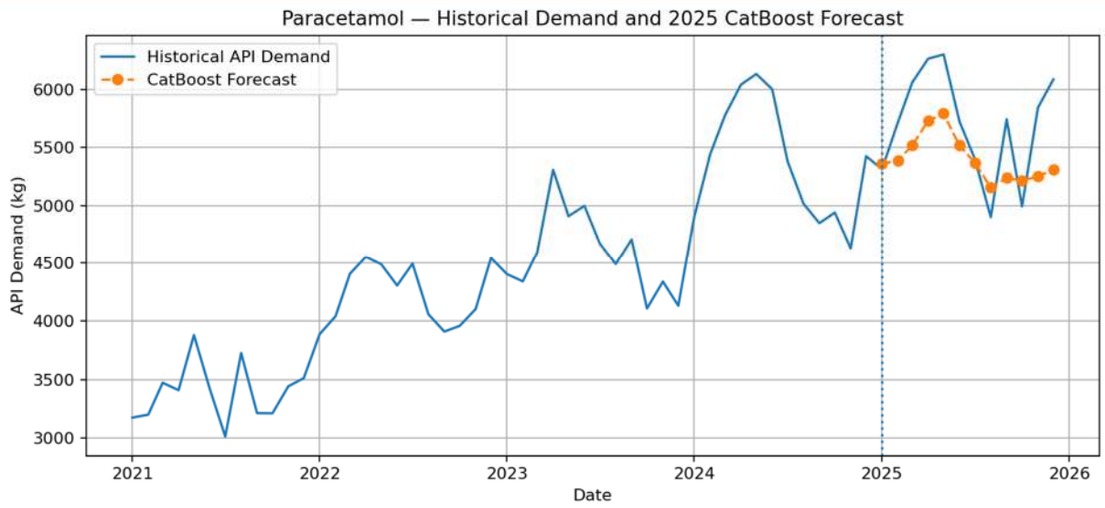



FIGURE 5 : Forecasted by CATBOOST Model

