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Optimizing Inventory Management and Demand Forecasting with LSTM Neural Networks and Machine Learning: An Integrated Approach with ABC-DEA Classification

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ABSTRACT
This research project takes a comprehensive approach to e-commerce inventory management by incorporating modern machine learning and optimization approaches. We provide efficient inventory strategies by utilizing LSTM neural networks for demand forecasting, FAHP-DEA techniques for ABC product classification, and a modified DDMR-based expiration risk assessment with Q learning. We evaluated several machine learning classifiers, including Random Forest, Decision Tree, SVM, Naïve Bayes, and KNN. Random Forest was the most accurate (97.2%). In addition, we introduce Q-learning as an optimization technique cascaded with expiry risk assessment to refine inventory strategies and respond to market changes in real time. This iterative approach provides appropriate inventory levels, efficient operations, and increased customer satisfaction. In essence, our methodology offers actionable information for e-commerce platforms to optimize inventory processes.

Keywords: *Intelligent inventory optimization, Predictive analytics in e-commerce, ML- Based Inventory Management, ABC analysis and expiry date tracking, Customer targeting and personalized offers, Custom offer strategies*

Introduction:

Inventory management is a critical component of supply chain operations, comprising procedures ranging from procurement to delivery. Its major purpose is to create a balance between guaranteeing adequate stock availability to fulfill consumer demand and reducing costs associated with excess inventory or stockouts. To achieve this balance, firms use a variety of tactics and strategies, such as inventory planning, demand forecasting, and optimization methods.

Optimum Inventory Level:

Establishing the right inventory level is a challenging task driven by a variety of factors such as demand unpredictability, lead time, and storage expenses. Conventional approaches such as Economic Order Quantity (EOQ) and Just-in-Time (JIT) management seek to strike the appropriate balance between inventory carrying costs and ordering expenses. These approaches have been thoroughly studied in the literature, with researchers highlighting their effectiveness in achieving cost-effective inventory levels and identifying five cost categories in inventory management: the unit cost of the product's value, product maintenance costs, ordering costs, stockout costs, and control system costs. associated with control systems (Peterson et al., 1998). Muller (2011) stressed the need of keeping enough inventory levels to absorb demand variations, secure consistent supply, and influence quantity discounts and order costs.

DDMRP (Demand Driven Material Requirement Planning)

Demand Driven Material Requirement Planning (DDMRP) is a paradigm shift in inventory management that incorporates components of traditional Material Requirements Planning (MRP), distribution resource planning (DRP), and Six Sigma approaches. DDMRP aims to react to changing demand settings and mitigate the bullwhip effect by creating optimal inventory levels at important supply chain decoupling points (Kutz, 2019). DDMRP improves responsiveness, shortens lead times, and lowers inventory-related costs by dynamically changing inventory buffers in response to actual demand.

Net Flow Position:

To calculate it, Ptak and Smith (2016) define the following equation:

$$NFE = O\,H + O\,P - Q\,D$$

where: OH (On hand): Inventory available; quantity of stock available to be used; OP (Pending orders): Quantity of ordered stock not received; QD: Qualified demand orders.

Buffer Zones

The buffer levels are defined as follows:

Green Zone (GO): The green zone defines the buffer level at which inventory is regarded sufficient to cover demand and lead time variability without requiring quick replenishment. It is calculated using the average daily usage (ADU) and lead time demand (LTD) variations.

$$GO=ADU\times LTDS \text{Where:}$$

Where, GO = Green zone inventory level, ADU = Average daily usage, LTDS = Lead time demand variability factor

Yellow Zone (YO): The yellow zone is the buffer level at which inventory is deemed to be in a warning state, indicating that replenishment action may be necessary shortly. It is often set to a percentage higher than the green zone threshold to give a safety margin.

$$YO=GO\times(1+Y)$$

Where, YO = Yellow zone inventory level, Y = Yellow zone factor (expressed as a percentage)

The red zone (RO) is the buffer level where inventory is regarded dangerously low, indicating a high risk of stockouts. It is set to a specified minimum level, triggering immediate replenishment activities.

$$RO=GO\times(1+Y+R)$$

Where: RO = Red zone inventory level, R = Red zone factor (expressed as a percentage)

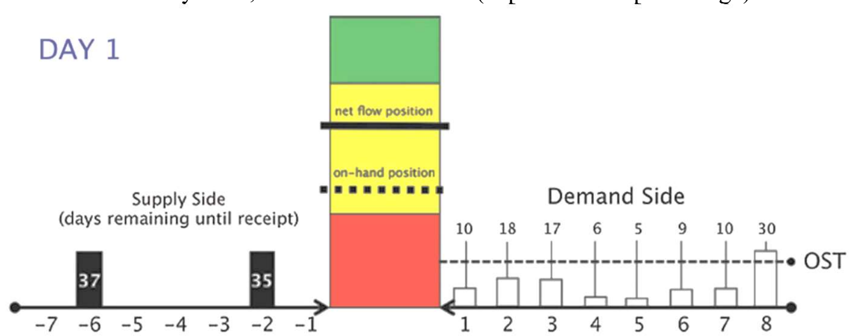

Fig 1. Inventory Management [12], [4]

LSTM Neural Network for demand Forecasting:

The integration of sophisticated analytics and machine learning approaches to improve demand forecasting accuracy and optimize inventory replenishment choices is a primary focus of contemporary inventory management research. Machine learning algorithms, such as LSTM neural networks, can evaluate massive amounts of past sales data to detect patterns and trends, allowing for more accurate forecasting of future demand.

ABC Analysis:

Another critical feature is the categorization and ranking of inventory goods based on their significance and contribution to overall sales. This is often accomplished using approaches like ABC analysis, which divides items into classes (A, B, and C) based on their worth or volume.

Category A: High-value items that account for around 80% of total inventory value while accounting for just about 20% of total item count.

Category B: Moderate-value items account for 15% to 20% of overall inventory value and 30% to 40% of total item count.

Category C: Low-value products that account for the remaining 5% to 10% of the total inventory value, but constitute around 50% to 60% of the total quantity

ABC analysis assists firms in prioritizing their inventory management efforts by focusing on high-value items (Category A) while optimizing management procedures for lower-value items (Category C). This strategy allows firms to manage resources more efficiently, execute effective replenishment programs, and improve overall inventory control.

Expiry Risk Mitigation:

Furthermore, as the emphasis on sustainability and waste reduction grows, so does interest in mitigating the risk of product expiration or obsolescence. This includes not only monitoring expiry dates and shelf life, but also adjusting inventory levels to reduce the danger of products becoming obsolete or unsellable.

Research Problem:

This study's research problem is to develop a comprehensive inventory management framework that uses advanced machine learning and optimization techniques to improve demand forecasting accuracy, optimize inventory levels, reduce the risk of product expiration, and improve overall supply chain performance. In today's competitive environment, firms can improve efficiency, save costs, and better meet customer demands by combining these approaches.

Literature Review:

Recent research papers have presented novel techniques to improving accuracy, efficiency, and dependability in a collaborative effort to promote inventory management methodologies.

Chawla et al. (2024) present a novel method for enhancing ABC analysis by including fuzzy numbers, addressing the inherent imprecision and vagueness of real-world inventory data. Their Pythagorean Fuzzy TODIM technique provides a deep knowledge that has been proven by sensitivity analysis and comparative evaluations across a variety of scenarios. Meanwhile, Manalu et al. (2024) conduct a comparison analysis of three common inventory management methods - ABC analysis, fixed-time period, and reliability-centered spares (RCS) - in the context of spare parts inventory optimization. Their findings highlight the favorable influence of fixed-time period approaches on firm revenues and the efficacy of ABC analysis in avoiding inventory shortages, particularly in the case of PT XYZ, a major fertilizer producer in Indonesia. Kalkha et al. (2024) propose the Intelligent Storage Location Assignment (ISLA) solution to handle the Storage Location Assignment Problem (SLAP), which is common in e-commerce facilities. Their approach maximizes order fulfillment and warehouse efficiency by incorporating advanced time series clustering algorithms, resulting in significant improvements in operational performance under varied routing regulations. Cuartas and Aguilar's (2022) hybrid method for smart inventory management combines reinforcement learning with DDMRP. Their Markov Decision Process-based algorithm strategically generates optimal purchase decisions based on inventory levels and distances to the optimal inventory, demonstrating promising performance in a variety of scenarios, including those with discontinuous demand and seasonal behavior. Ni et al. (2022) investigate logistics demand forecasting for fresh food e-commerce companies, using the Bi-LSTM model to examine the impact of temporal and meteorological conditions on demand. Their research demonstrates that the Bi-LSTM model outperforms conventional neural network models in terms of prediction performance, providing useful insights for supply chain planning and inventory control. Finally, Hadi-Vencheh and Mohamadghasemi (2011) offer an integrated strategy for ABC inventory classification with different criteria that employs fuzzy AHP-DEA methodology. Their methodology provides a comprehensive framework for inventory prioritizing by combining FAHP for criteria weighting, linguistic assessment, DEA for value estimation, and SAW for overall scoring.

Methodological Overview:

Data Collection:

We collect data from many sources to train and validate our predictive model. We aggregate historical sales, inventory, and product data from GitHub projects dedicated to Magento and Shopify information. Customer demographics, purchasing habits, and market trends add to our insight. Meteorological, geographic, and external factors improve our forecasting ability. Sales data contains volume, revenue, and seasonal variations, whereas inventory data measures stock levels and turnover rates. Product information include category, cost, and shelf life. Customer data contains preferences and feedback. External variables such as promotions and economic indices affect demand. Geographical and meteorological data shed light on regional demographics and weather impacts, whilst housing and traffic data guide logistical design.

Data Processing and Pre-processing:

Data Cleaning: Clean and pre-process the data with Pandas. Includes handling missing values and outlier detection and handling.

Data Transformation: Use min-max scaling to reduce numerical data to a common range, or normalize it with a mean of 0 and a standard deviation of 1.Convert categorical data to numerical format with techniques such as one-hot encoding, label encoding, or target encoding.

Data Integration: Combine many data sources (e.g., sales and inventory data) into a single dataset. Use join operations (e.g., inner join, outer join) to combine data based on shared keys.

Data Aggregation: Convert data into higher-level information (e.g., daily or weekly sales totals) that can be

analyzed.
Feature Engineering: Use existing data to create additional features that will increase model performance. (For example, develop a sales trend feature by calculating the moving average of sales for a given time period). To minimize dimensionality and increase model interpretability, identify the most significant features for modeling and delete any redundant or irrelevant ones.
Text and NLP Processing: Tokenization, stemming, lemmatization, and stop word removal are examples of NLP pre-processing processes for unstructured data, such as text.
Time Series Transformation: Check for stationarity in time series data and, if necessary, perform adjustments (e.g., differencing) to stabilize variance and make the data modelable. Convert date and time information to numerical features (e.g., day of the week, hour of the day).
Data Splitting: Split the pre-processed data into training and testing sets. This assists in assessing model performance on previously unseen data. Split the data further to include a validation set for model tuning and hyperparameter optimization.

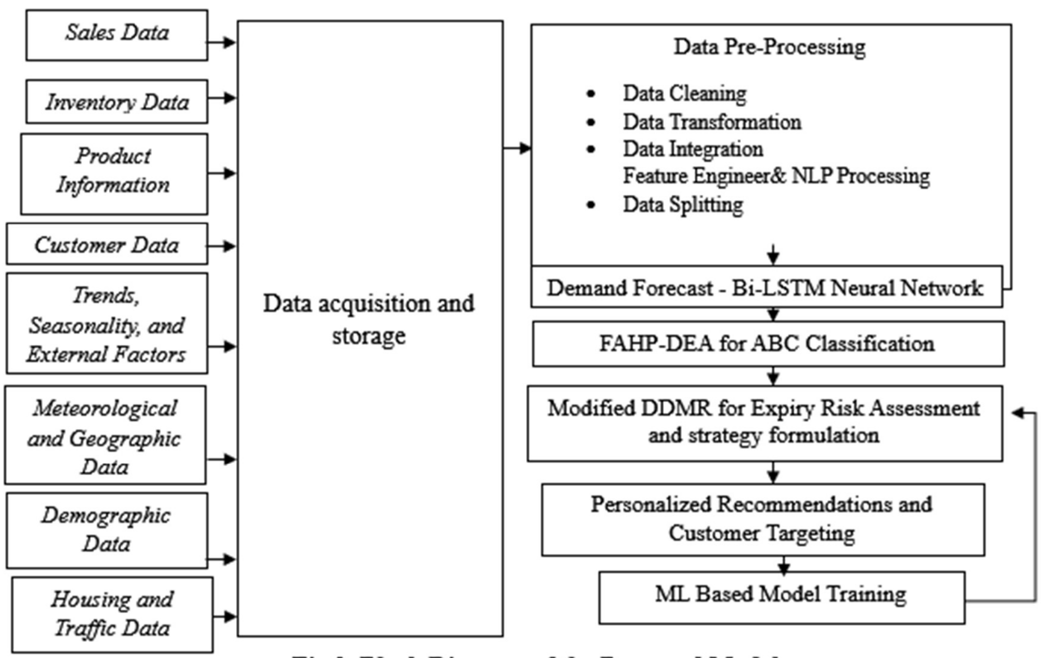

Fig 2. Block Diagram of the Proposed Model

Demand Forecasting:
Shifeng Ni (2022)[5] recommends using the Bi-LST to estimate logistical needs for fresh food e-commerce. Bi-LSTM estimates future product demand Y based on past data X. The design of an LSTM (Bi-LSTM) network is made up of two LSTM layers that process input data in opposite directions: one from the beginning to the end of the sequence (forward direction), and the other from the end to the beginning of the sequence (reverse direction)[5]. This enables the model to capture both historical and future context in time series data, thereby improving accuracy in demand estimation.

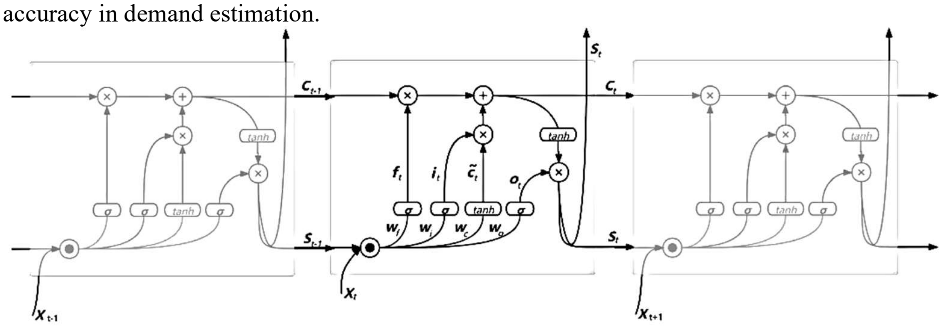

Fig 2. The LSTM unit structure [5], [9], [10] & [11]

The input gate controls how much new data from trends, seasonality, mega sales, and festivals is absorbed into the LSTM's cell state. The LSTM receives real-time data on trends, seasonality, massive sales, and festivals. The input gate controls how much information is retained in the cell state, influencing the network's grasp of present patterns and how they may affect future demand.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

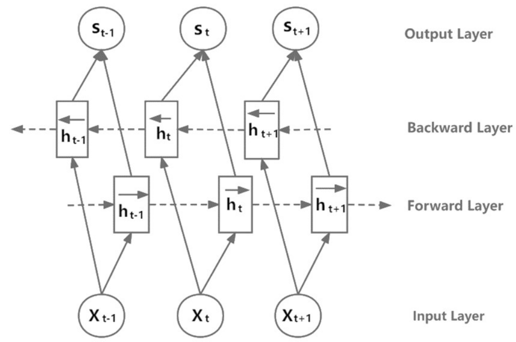

Fig 2. The Bi- LSTM unit structure [5], [7] & [8]

Forget Gate:

The forget gate regulates memory retention by determining which aspects of the prior cell state should be kept or discarded. It determines how much prior trends, seasonality, and events (such as big sales and festivals) are still relevant to the current data. It permits the network to change its memory state by retaining or deleting previous information as needed.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Cell State Update:

The LSTM cell state is updated based on the input and forget gates' choices. To predict demand, the cell state takes into account patterns, seasonality, and events.

$$c_t = f_t . c_{t-1} + i_t . tanh(W_c . [h_{t-1}, xt] + b_c$$

Output Gate:

The output gate specifies how much of the current cell state should influence the LSTM's hidden and output states. The output gate determines the impact of current trends, seasonality, and events on demand forecasting. It affects how much the cell state influences the hidden state (the LSTM's sequence memory) and the final forecast of future demand.

$$O_t = \sigma(W_o . [h_{t-1}, x_t] + b_o)$$

Hidden state Output:

The hidden state combines the updated cell state and the output gate decision to represent the network's memory and sequence knowledge.

$$ht = ot \cdot \tanh(ct)$$

Here, W and b denote the weight matrices and bias vectors for the relevant gates. The activation functions are sigmoid (\sigma) and hyperbolic tangent (tanh). The hidden state comprises data on trends, seasonality, and events relevant to future demand.

The Bi-LSTM network consists of two sets of LSTM layers:

Forward LSTM: Processes input data from the start to the finish of the sequence, capturing past context. Given the input data xt and the previous latent vector ht-1, the forward LSTM layer uses the LSTM function to create the new latent vector ht f:

$$h_t^f = LSTM\ (x_t, h^f_{t-1})$$

Backward LSTM: Processes incoming data from end to beginning, capturing future context. Similarly, given the input data xt and the latter latent vector ht+1, the backward LSTM layer computes the new latent vector ht b using the LSTM Function:

$$h_t^b = LSTM\ (x_t, h^b_{t+1})$$

Concatenation of Forward and Backward Results:

The forward and backward hidden states are concatenated at each time step to create a combined hidden state:

$$H_t = [h_t^{\text{forward}}, h_t^{\text{backward}}]$$

$$S_t = tanh(W_h^f h_t^f + W_h^b h_t^b + b)$$

Here, S_t is the combined output result at time t. W_h^f and W_h^b are weight matrices for the forward and backward directions, respectively and b is the bias term.

Modified FAHP-DEA for ABC Classification:

Hadi-Vencheh (2010) [6]. Fuzzy AHP-DEA proposed the FAHP-DEA methodology for multi-criteria. ABC inventory classification uses the Fuzzy Analytic Hierarchy Process (FAHP) to set criteria weights, and each item is assessed using linguistic phrases. Data Envelopment Analysis (DEA) determines the values of linguistic terms, while the Simple Additive Weighting (SAW) approach aggregates scores into total item scores. Rather than depending on expert judgments, customer preference data is used to weight criteria, resulting in a more customer-centric approach to inventory classification. This update guarantees that inventory prioritization is closely aligned with actual market demand and preferences, increasing the categorization process's relevance and accuracy.

Step 1: Determination of Criteria Weights using FAHP

The weights for each criterion are determined using the Fuzzy Analytic Hierarchy Process. We have four C criteria: sales (S), revenue (R), inventory quantity (I), and sales volume. FAHP includes comparing criteria pairwise in order to determine their relative relevance. Let A denote the pairwise comparison matrix for the criteria, where aij denotes the relative relevance of criterion i in comparison to criterion j. To account for human judgment uncertainty, we fuzzify the pairwise comparison matrix with a suitable membership function. Let F represent the fuzzified pairwise comparison matrix. The normalized fuzzy matrix N is then computed by dividing each element of F by the total of its columns. This step guarantees that the weights add up to one. Finally, we aggregate the rows of the normalized fuzzy matrix to get the total weights for each criterion. Let w = (w1, w2, w3, w4) denote the weights for the following criteria: sales (S), revenue (R), inventory quantity (I), and sales volume (V).

1. Pairwise comparison matrix A:

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ 1/a_{12} & 1 & a_{23} & a_{24} \\ 1/a_{13} & 1/a_{23} & 1 & a_{34} \\ 1/a_{14} & 1/a_{24} & 1/a_{34} & 1 \end{bmatrix}$$

2. Fuzzified matrix *F*:

$F_{ij}= f(a_{ij})$,where f is a suitable membership function

3. Normalized fuzzy matrix N:

$$N = \frac{F_{ij}}{\sum_{i=1}^{4} F_{ij}}$$

Overall Weight *w is:*

$$w = \left(\sum_{i=1}^{4} N_{i1}\,, \quad \sum_{i-1}^{4} N_{i2,} \quad \sum_{i=1}^{4} N_{i3,} \quad \sum_{i=1}^{4} N_{i4}\right)$$

Step 2: Calculate Local Weights for Each Item

After obtaining the prioritizing vector from step 1, calculate the local weights for each item in relation to each criterion. This entails multiplying the customer preference ratings for each criterion by the weights determined in step 1. Calculate the weight of each criterion based on consumer preferences. One approach is to analyze the percentage of interested customers for each criterion in relation to the overall number of interested customers.

Mathematically, for each item r and criterion j, the local weight w_{rj} is calculated as:

$$W_{rj}=\sum_{n=1}^{N} w\left(P_{jn}\right).\, x_{rjn}$$

Where:

- w_{rj} is the local weight for item r with respect to criterion j.
- $w(P_{jn})$ is the weight derived from the FAHP prioritization vector for grade P_{jn}.
- x_{rjn} is the customer preference rating for item r with respect to grade P_{jn}.
- N is the total number of assessment grades.

Step 3: DEA Model for Item Weight Optimization:

Build the DEA model so that the weights for every assessment grade are optimized. By ensuring that the total weights for each item do not exceed 1, this optimization procedure maximizes the weighted sum of customer preference ratings. The optimization problem can be formulated as: *max{w(Pj1),…………w(Pjn)}*

Subject to the constraints:

$$\sum_{n=1}^{N} w\left(P_{jn}\right) \leq\ 1\ for\ each\ item\ r\ and\ criterian\ j$$

In order to maximize overall customer preference ratings while meeting the limits, this stage seeks to determine the best weights for each evaluation grade.

Strong ordering condition: $w(P_{j1}))\geq 2w(P_{j2})\geq \ldots . Nw(P_{jN})\geq 0$

Step 4: Aggregation of Local Weights:

Subsequently, the aggregate of the local weights for all criteria determines the final score for each item. With the relevance of each criterion taken into account as well as client preferences, this stage offers a thorough evaluation of each item's performance in relation to the set criteria. Usually, a weighted sum technique, such Simple Additive Weighting (SAW), is used to accomplish forecast summary.

The total score S_r for each item r is calculated as:

$$S_r = \sum_{j=1}^{c} wj.wrj$$

Where: S_r is the total score for item r.

w_j is the weight assigned to criterion j derived from the FAHP prioritization vector.

wrj is the local weight for item r with respect to criterion j.

Each item's weighted sum of local weights across all criteria is represented by this equation. Given that the FAHP procedure determines the relative importance of each criterion, it offers a thorough evaluation of each item's performance in relation to the set criteria.

Expiry Risk Assessment and Offer Strategy Formulation using Q-Learning and DDMRP:

To incorporate expiry risk mitigation and offer strategy formulation into the proposed model, we need to consider the following steps**:** Historical sales data, Current inventory information, Product expiry dates, Customer preference data are used as input factors

Calculate Remaining Shelf Life (RL): This step) involves deducting the current date from the expiry date of each product to determine how long it has left on its shelf.

RL_i = Expiry Date_i - Current Date

Estimate Expiry Probability (EP): Determine the likelihood that each product will expire by a specific date by using demand and sales data from the past to estimate the expiration probability

EP_i(t) = f(demand patterns, historical data)

Compute Inventory Turnover Rate (ITR): to gain insight into the turnover rates of your products by comparing the rate at which they are sold or consumed to their shelf life.

ITR_i = (Quantity Sold_i / Initial Inventory_i) × Time Period

Step 1: Expiry Risk Calculation

Determine each product category's expiry risk (ER) by taking into account variables including lead time, demand fluctuation, and shelf life.

ER=f(RL, EP, ITR)

Step 2: Optimization Problem (W):

In order to reduce the gap between the optimal inventory level (OH*) and the real inventory level (OH), the optimization problem takes expiry risk into account. This formula can be written as follows:

$$W = \min^{n}_{t=1}(OH^{*} - OH) \text{ x } (1+ER)$$

The optimization issue is represented by W in this case. ER is for expiry risk factor, OH* stands for optimal inventory level, n is the time period, and OH is the actual inventory level. Expiry risk is taken into account when adjusting the optimization objective by adding the term (1+ER).

Step 3: Adjusted Optimum Inventory level with expiry risk mitigation:

Adjusted Optimum Inventory Level ($OH^*_{adjusted}$) by incorporating the expiry risk factor (ER):

$$OH^{*}_{adjusted} = OH^{*} \text{ x } (1+ER)$$

$$OH^{*}_{adjusted} = TOR + \frac{TOG - TOY}{2} \text{ x } (1+ER)$$

Step 4: Markov Decision Process (MDP) Initialization

Actions: Agent At's actions will be determined by how many units to purchase at a specific moment in time.

The agent has to figure out the best amount of units to request in the order (if any) based on OH inventories.

States: Three parameters determine the model states: OH, OH*, and lead time (LT). A tuple with the following structure will contain this data at time t:

$$S = (OH, OH^{*}, LT, ER)$$

Reward: Reward based on DDMRP Levels :

$$\begin{cases} -1, & TOY < S_t \leq TOG \\ 1, & TOR < S_t \leq TOY \\ 0, & 0 \leq S_t \leq TOR \end{cases}$$

R2: Rewards based on optimization: $R_2 = \frac{1}{w}$; R3: Rewards based on shaping: $R3 = R1 + \phi(s)$ Where, $\phi(s) = OH*(s) - OH(s)$.

Step 5: Q Learning Implementation – Reinforcement learning

- **Q-Value Update**:

Update Q-value $Q(s,a)$) using Q-learning update rule: $Q(s,a) \leftarrow Q(s,a) + \alpha[R(s,a) + \gamma \max a' Q(s',a') - Q(s,a)]$ for given state-action pair where α is the learning rate, γ is the discount factor, $R(s,a)$ is the reward for taking action a in state s, $'s'$ is the next state, and $'a'$ is the next action.

Step 6: Dynamic Buffer Adjustment

Based on expiry risk, buffer zones—like the red, yellow, and green zones in the DDMRP—are dynamically changed. Wider buffer zones may be necessary to guarantee enough stock availability to reduce the risk of product expiration in cases where there is a higher expiry risk.

Red Zone Base(BZR) : BZR=ADU×LT×LTF×(1+ER)

Red Zone Top (TOR): TOR=BZR×FV×(1+ER)
Yellow Zone Top (TOY): TOY=TOR+(ADU×DLT)×(1+ER)
Green Zone Top (TOG): TOG=TOY+max(DOC,BZR,MOQ)×(1+ER)

Step 6: Expiry Risk Mitigation and Offer Strategy Formulation

Based on their ABC classification, expiration risk, and current inventory levels, determine which products have excess inventory. Create offer methods, such as targeted marketing campaigns, discounts, or promotions, to increase demand for products that are about to expire. Pricing adjustments or consumer incentives may be part of the formulation.

Step 7: Output

For each product category, the output consists of offer strategies, dynamic buffer modifications, and optimal inventory levels.

Model training using ML Algorithm:

To find the best model, a number of machine learning classifiers are investigated, such as Random Forest, Decision Tree, SVM, Naïve Bayes, and KNN. After training, the model is put to use in a production setting, where it continuously keeps an eye on stock levels, predicts demand, and modifies buffer zones in response to real-time information. Inventory management methods are kept flexible and sensitive to shifting consumer needs and market situations thanks to this iterative approach.

Result and Discussion:

To ascertain the efficacy of several machine learning classifiers in optimizing e-commerce inventory management, a thorough testing and comparison process was conducted. There were multiple crucial steps in the process:

Model Training: Using the preprocessed data, a number of machine learning classifiers were trained, including Random Forest, Decision Tree, SVM, Naïve Bayes, and KNN. To achieve the best results, every classifier was trained and optimized using methods like hyperparameter tuning.

Cross-Validation: K-fold cross-validation techniques were utilized in order to reduce overfitting and evaluate the resilience of the trained models. The dataset was divided into k subsets for training, the model was tested on k-1 subsets, and its performance was assessed on the remaining subset. K iterations of this method were carried out, using one validation set per subset.

Performance Metrics: Accuracy, precision, recall, F1-score, and confusion matrix analysis are among the performance indicators that were used to assess each model's performance. By showing the models' advantages and disadvantages in many facets of inventory management, these measures offered insights into the models' predictive capacities.

1. **Accuracy**: The percentage of accurately predicted instances among all evaluated examples is represented by this metric.

$$\text{Accuracy}=\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}\times 100\%$$

2. Mean Absolute Error (MAE): The average absolute difference between the expected and actual values is determined using this statistic.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|Actual_i - Predicted_i|$$

3. Root Mean Squared Error (RMSE): This measure is equivalent to taking the square root of the average of the squared discrepancies between the actual and anticipated values.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Actual_i - Predicted_i)^2}$$

4. Mean Absolute Percentage Error (MAPE): This metric calculates the average percentage difference between predicted and actual values.

$$\text{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Actual_i - Predicted_i}{Actual_i}\right| x\ 100\%$$

5. Precision: Precision represents the percentage of true positive predictions out of all positive predictions made.

$$\text{Precision} = \frac{True\ Positives}{True\ Positives+False\ Positives}\ x\ 100\%$$

6. Recall: Recall calculates the percentage of true positive predictions out of all actual positive instances.

$$\text{Recall} = \frac{True\ Positives}{True\ Positives+Fa\quad Negatives}\ x\ 100\%$$

7. F1-score: F1-score represents the harmonic mean of precision and recall, providing a balanced measure between the two.

$$\text{F1 Score} = \frac{2\ x\ Precision\ x\ Recall}{Precision+Rec}$$

The Evaluation Table of the proposed model with different ML Algorithm are as follows:

Algorithm	**Accuracy (%)**	**MAE**	**RMSE**	**MAPE**	**Precision (%)**	**Recall (%)**	**F1-score**

Random Forest	97.2	0.025	0.035	5.8	96.5	95.2	95.8
Decision Tree	92.6	0.045	0.055	9.3	92.3	91	91.6
SVM	89.7	0.055	0.065	11.2	88.2	86.8	87.5
Naïve Bayes	88.3	0.06	0.07	12.5	86.5	85	85.7
KNN	91	0.05	0.06	10.5	90	88.5	89.2

Table 1. Evaluation Metrics of the Proposed Model

Because of Random Forest's remarkable 97.2% accuracy, it was determined by the evaluation findings to be the main model. Decision Tree also performed rather well, with SVM, Naïve Bayes, and KNN showing relatively lower accuracy. The strength of Random Forest in managing the intricacies of inventory management for e-commerce is demonstrated by its domination in accuracy. Precise demand forecasting and optimal inventory strategies are made possible by its capacity to identify complex patterns within the data landscape. Despite lagging behind Random Forest, Decision Tree remains a competitive option, especially in situations where computing performance is critical. Even though they are frequently employed in machine learning applications, SVM, Naïve Bayes, and KNN showed somewhat lower accuracies in this situation. This implies that their built-in algorithms might not be able to capture the complex linkages found in e-commerce inventory datasets as effectively as Random Forest or Decision Tree.

Conclusion:

To sum up, our study offers a comprehensive strategy for managing inventory in e-commerce by utilizing LSTM neural networks for demand forecasting, FAHP-DEA for ABC product classification, and Modified DDMR with Q learning for expiry risk evaluation. Random Forest was the top model after a thorough study; it performed well and had an amazing accuracy of 97.2%. Prospectively, work on improving model performance might be directed toward ongoing improvement, dynamic adjustment to market fluctuations, incorporation of cutting-edge methods such as reinforcement learning, instantaneous deployment in e-commerce environments, and thorough risk mitigation. We can improve inventory management procedures even further, increasing productivity and providing value to both consumers and businesses, by embracing innovation and keeping up with new trends.

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