Research Article

Artificial Intelligence-Driven Inventory Management: Optimizing Stock Levels and Reducing Costs Through Advanced Machine Learning Techniques

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Abstract

This study investigates the implementation of artificial intelligence (AI) algorithms to enhance inventory management processes in small and medium-sized enterprises (SMEs) within the retail sector. Accurate inventory level determination is a critical factor in improving organizational performance. Inventory levels are subject to a wide range of influences, including seasonal fluctuations, promotional campaigns, and macroeconomic conditions, which introduce significant complexity and variability. Such complexities often render manual management approaches inefficient. This research focuses on addressing these challenges through AI-based methodologies, particularly by employing machine learning and data analytics techniques to optimize inventory control. The findings of the study contribute to the literature by highlighting the potential of AI-driven approaches in reducing inventory costs and improving supply chain efficiency.

Keywords: *Machine Learning, LSTM, AI, Inventory Management*

1. Introduction

One Small and Medium-sized Enterprises (SMEs) are key actors that shape the dynamics of economic life [1,2]. For businesses operating in the retail goods sales sector, inventory management stands out as a critical element that provides a competitive advantage. Inadequate determination of stock levels can lead to severe operational and financial challenges for these businesses. Excess inventory not only strains storage capacity and increases costs but also elevates the risk of product obsolescence. Additionally, tying up a significant portion of a company's liquidity in inventory negatively impacts cash flow. Conversely, low stock levels can result in customers being met with "out of stock" responses, leading to potential losses in sales, revenue, and reputation [2-4].

In this context, traditional enterprise resource planning (ERP) systems provide limited support to businesses in defining and managing stock threshold levels. These systems can generate alerts when inventory levels fall below a certain threshold and, through integrated solutions, can activate automated ordering processes to streamline inventory management [3-5]. However, stock thresholds are not always reliable parameters and are often influenced by economic, environmental, and business-oriented variables [6-8]. Developing an effetive inventory management solution requires a dynamic approach to the following factors:

- Macroeconomic Factors: The overall state of the national economy and market conditions.
- Seasonal and Environmental Impacts: Variations in demand driven by weather conditions and seasonal trends.
- Campaigns and Marketing Strategies: Business-specific elements such as product promotions and discount periods. [7-9]

This study explores how artificial intelligence (AI)-driven methodologies can transform inventory management processes by considering the aforementioned dynamics. AI aims to deliver a more adaptive, predictive, and efficient inventory management system by analyzing variable stock parameters.

The following significant studies have been examined based on a literature review focusing on artificial intelligence (AI) and machine learning (ML) in stock and supply chain management. These studies are analyzed regarding the contributions of AI to inventory management processes, the methodologies employed, and the outcomes achieved. The approaches and methods used in these studies serve as references for developing the foundation of this research. Lin et al. Utilized a CGAN-based machine learning model in supply chain management to reduce operational costs and enhance demand responsiveness. The model demonstrated successful predictions in procurement and inventory management [10]. Seyedan et al. Conducted order inventory optimization using deep learning methods and improved forecast accuracy with ensemble learning models. The proposed model enabled more effective stock management [11]. Hu et al. Optimized vaccine supply chain management by integrating blockchain, IoT, and machine learning, achieving real-time tracking and enhanced production efficiency [12]. Taghiyeh et al. Employed multi-stage hierarchical machine learning models to improve sales forecasts in supply chains, increasing accuracy while addressing computational costs [13]. Selukar et al. Proposed deep learning methods for managing perishable goods, reducing spoilage rates, and lowering inventory costs [14]. Mantri et al. Targeted process optimization and service quality improvement for SMEs by integrating big data analytics and AI [15]. Li et al. Optimized inventory costs using an elastic adjustment and automated learning-based model, achieving a 20% cost savings [16]. Boute et al. Offered a roadmap for inventory control using deep reinforcement learning algorithms, proposing new application areas [17]. Vidal et al. Developed a hybrid decision support model combining fuzzy logic, genetic algorithms, and artificial neural networks for inventory optimization [18]. Mediavilla et al. Analyzed AI applications in supply chain management and identified optimal demand forecasting methods [19]. Hoffman et al. Enhanced production processes by detecting waste using LSTM-based methods [20]. Peddi et al. Prevented food waste in the supply chain by integrating machine learning and FMEA techniques [21]. Moor et al. Studied the management of defective products using deep reinforcement learning, offering computational advantages [22]. Clausen et al. Developed ordering models using big data and machine learning, achieving up to 60% cost savings [23]. Deng et al. Reduced inventory costs by 25% using LSTM-based deep learning models [24]. Chandriah et al. Optimized demand forecasting in the automotive sector using RNN, LSTM, and Adam optimization, yielding successful results [25]. Naeem et al. Minimized supply chain risks and improved accuracy using fusion-based machine learning methods [26]. These studies illustrate the significant role AI and ML techniques play in enhancing efficiency in stock and supply chain management.

2. Materials and Methods

In this study, the following four machine learning methods will be employed to optimize inventory management in small and medium-sized enterprises (SMEs). These methods were chosen due to their proven success in the literature and their suitability for solving complex problems like inventory management.

2.1. Long Short-Term Memory (LSTM)

LSTM is a deep learning model specifically designed for analyzing time-series data. In inventory management, it is highly effective for making decisions based on time-variant data, such as demand forecasting. The primary advantage of LSTM lies in its ability to learn long-term dependencies in sequential data, making it well-suited for tasks that require understanding historical trends and predicting future outcomes.

Key Applications of LSTM in Inventory Management:

- Seasonal Demand Forecasting: LSTM can predict demand fluctuations based on historical sales data, accounting for seasonality and other time-related trends.

- Dynamic Inventory Management: By analyzing past data, LSTM forecasts future trends to determine optimal stock levels dynamically.

To make the mathematical formulation of LSTM more intuitive in the context of inventory management, the variables from the original equations are mapped to inventory-related concepts. Let's explore how LSTM operates step-by-step, considering inventory levels, demand, and other time-series data.

2.1.1. Forget Gate $f(t)$

The forget gate determines what part of the previous state (e.g., historical inventory levels) should be "forgotten" based on the new data.

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

h_{t-1} : Represents the hidden state from the previous timestep, which may include insights about prior demand or inventory fluctuations.

x_t: Current input data, such as today's demand forecast or external factors (e.g., promotions or supply chain delays).

f_t : Decides which parts of historical data (e.g., past stock levels or demand trends) are no longer relevant to the current decision-making.

2.1.2. Input Gate (i_t)

The input gate updates the cell state with new information from the current timestep, allowing the model to incorporate new inventory data (e.g., current demand or supply levels).

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

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (2)$$

$\check{C}_t$: The candidate cell state, representing potential updates to inventory levels based on new data.

i_t: Determines how much of the new information (e.g., spike in demand due to a seasonal event) should be added to the cell state.

C_t : The updated "memory" that combines past and present information. For instance, it might represent a projection of stock levels after accounting for seasonal patterns and recent demand.

2.1.3. Output Gate (o_t)

The output gate decides what part of the updated memory C_t should be passed to the next timestep or used as output (e.g., a decision on how much inventory to reorder).

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

$$h_t = o_t \odot \tanh(C_t) \tag{3}$$

o_t: Controls the relevance of the cell state for current decisions, such as determining if current trends should influence reorder quantities.

h_t : Represents the current hidden state, which can directly inform inventory decisions (e.g., setting safety stock levels or predicting the timing for replenishment).

Example Application in Inventory Management:

Let's break it down with an inventory-specific example:

Forget Gate: A sudden reduction in demand due to an economic downturn is detected, and the forget gate ensures that historical high-demand data is partially discarded when projecting future stock levels.

Input Gate: A seasonal event like Black Friday is upcoming, and the input gate ensures that the new demand spike from current data is prioritized and added to the inventory management model.

Cell State Update: Combines the adjusted historical demand trends with the new seasonal demand to update the model's "memory" (C_t), ensuring that both recent and long-term factors are balanced.

Output Gate: The model predicts optimal stock levels for the upcoming weeks, focusing on maintaining enough inventory while avoiding overstocking based on the updated trends (h_t).

By applying LSTM in this manner, inventory management systems can make informed, data-driven decisions, balancing historical patterns with real-time fluctuations for optimal stock control.

2.2. Gradient Boosting Machines (GBM) in Inventory Management

Gradient Boosting Machines (GBM) is a powerful ensemble learning method that provides high accuracy on large datasets. In inventory management, GBM effectively addresses demand forecasting and classification problems. Below is an explanation of its features, a mathematical model, and its application in inventory management.

Key Features of GBM:

Fast and Accurate Predictions: GBM increases prediction accuracy by combining the outputs of multiple weak learners (e.g., decision trees) into a single strong learner.
Inventory Optimization: It is highly suitable for demand forecasting and optimizing replenishment schedules across different product categories.

2.2.1. General Objective of GBM

GBM minimizes a loss function (L) by iteratively adding weak learners ($h_m(x)$) to the model. At each iteration, the new weak learner focuses on reducing the residual error of the previous predictions The model at iteration m is:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (4)$$

where:

$F_{m-1}(x)$: The prediction of the model at iteration *m-1,*
$h_m(x)$: The new weak learner added at iteration m
γ_m : The learning rate, which scales the contribution of $h_m(x)$

2.2.2. Loss Function

The goal is to minimize the loss function $L\ (y, F(x))$, where y is the actual value and $F(x)$ is the predicted value:

$$\arg\min_F L(y, F(x)) \quad (5)$$

In inventory management:
y: Actual demand (e.g., sales units).
$F(x)$: Predicted demand based on features such as historical sales, seasonal trends, or promotions.
Common loss functions include:

Mean Squared Error (MSE) for regression problems:

$$L(y, F(x)) = \frac{1}{N}\sum_{i=1}^{N}(y_i - F(x_i))^2 \quad (6)$$

Log-Loss for classification problems:

$$L(y, F(x)) = -\sum_{i=1}^{N} [y_i \log(F(x_i)) + (1 - y_i) \log(1 - F(x_i))] \tag{7}$$

2.2.3. Residual Computation

At each iteration m, the residuals are computed as the negative gradient of the loss function with respect to the predictions:

$$r_i^{(m)} = -\frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)} \tag{8}$$

These residuals represent the errors that the next weak learner will address.

2.2.4. Weak Learner Optimization

The weak learner $h_m(x)$ is trained to minimize the residual errors:

$$h_m(x) = \arg\min_{h} \sum_{i=1}^{N} \left(r_i^{(m)} - h(x_i) \right)^2 \tag{9}$$

Application in Inventory Management

- Demand Forecasting:

Input Features (x): Historical sales, seasonality indicators, economic trends, promotional events.
Target Variable (y): Predicted sales or demand for a product.
GBM iteratively builds a predictive model that captures complex patterns in the data.

- Stock Replenishment Optimization:

Use GBM to forecast lead times and reorder points.
Incorporate classification tasks for identifying high-priority products needing immediate restocking.

- Product Segmentation:

Apply GBM for classifying products into different categories based on turnover rates or seasonal demand variability.
By leveraging Gradient Boosting Machines in inventory management, organizations can achieve precise demand forecasts, reduce holding costs, and optimize replenishment strategies.

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2.3. Support Vector Machines (SVM) in Inventory Management

Support Vector Machines (SVM) is a supervised learning algorithm that delivers high accuracy even with limited datasets. In inventory management, SVM serves as an effective tool for stock classification and decision support processes.
Key Features of SVM:

Ability to Work with Small Datasets: Provides reliable results, especially in scenarios where only limited historical data is available.

Classification and Regression: Suitable for classifying stock categories and predicting inventory levels for different product groups.

2.4. Reinforcement Learning (RL) in Inventory Management

Reinforcement Learning (RL) is based on the concept of an agent learning to maximize rewards through trial and error within an environment. In inventory management, RL is applied to optimize decision-making processes in dynamic and variable environments.
Key Features of Reinforcement Learning:

Integrated Learning and Decision-Making: RL simultaneously evaluates demand forecasting and order decisions to optimize inventory levels.

Real-Time Adaptation: Adapts instantly to changes in demand, enhancing overall efficiency.

Hybrid Solution for Inventory Management

In the scope of this study, these methods will be integrated to create a hybrid solution. The combination of these algorithms aims to achieve flexibility, accuracy, and cost-efficiency in inventory management:
LSTM and GBM Models: Used for demand forecasting to predict future stock requirements based on historical trends and other influencing factors.
SVM and RL Algorithms: Applied to stock classification and decision support processes, enabling dynamic optimization of inventory levels and real-time adjustments.
This integrated approach is designed to enhance inventory management by providing precise forecasts, robust classification, and adaptive decision-making in ever-changing market conditions.

2.5. Experimental Studies

This section addresses the implementation of artificial intelligence algorithms, data preparation processes, and the metrics selected for comparing the performance of the tools and hyperparameter selections used in this study.

Based on evaluations conducted for the application of artificial intelligence algorithms in the project, ML.Net and machine learning libraries related to the Python programming language were chosen. The rationale for these selections is explained as follows:
ML.Net: The choice of ML.Net was influenced by the fact that Microsoft technologies were already being utilized in the project, and ML.Net's performance-oriented structure made it a suitable option.
Python and Related Libraries: Python was preferred due to its extensive community support, widespread application, and rich ecosystem of machine learning libraries (e.g., scikit-learn, TensorFlow, Keras, Pandas, NumPy, Matplotlib).
For the training and application of artificial intelligence models:

- Dataset and Parameters

The training of the model was conducted using historical data from the year 2022. The primary objective of the model is to answer the question: "What should be our sales target for the specified product in the upcoming week?" The parameters used in the dataset are as follows:

- Nationwide Price Levels: Consumer Price Index (CPI) and Producer Price Index (PPI).
- Special Days and Holiday Calendars: Seasonal variations in demand were accounted for.
- Campaign Information: Due to a lack of data, this parameter is currently excluded from the model.

The dataset was divided into training and test sets:

- Training Set (70%): Used for the model's learning process.
- Test Set (30%): Reserved for evaluating the model's accuracy and generalization capability.

- Algorithms Used

The following machine learning methods were utilized for training the model and comparing the results:

Long Short-Term Memory

This model, known for its strong performance in time-series analysis, was applied for seasonal demand forecasting. After testing various hyperparameters, the following values were selected:

- Learning Rate: 0.001
- Hidden Layer Size: 50
- Number of Epochs: 100
- Optimization Algorithm: Adam

Gradient Boosting Machines

GBM was preferred to enhance the accuracy of demand forecasting. The selected hyperparameters were:

- Learning Rate: 0.1
- Maximum Depth: 6
- Number of Trees: 100

Support Vector Machines (SVM)

SVM was used as an effective classification and regression model for small datasets. The selected hyperparameters were:

- Kernel Type: RBF
- C Value: 1.0
- Gamma: 0.1

Reinforcement Learning (RL):

Applied to optimize dynamic stock levels. After tuning, the selected hyperparameters were:

- Reward Function: Includes stock holding costs and penalties for stockouts.
- Learning Rate: 0.01
- Epsilon: 0.1

The models were trained in Python using libraries such as scikit-learn, TensorFlow, and Keras, with data analysis conducted using Pandas and NumPy. Additionally, in the ML.Net environment, data processing and model training were integrated with Microsoft technologies.

The models developed in both environments were compared in terms of **accuracy**, **speed**, and **resource utilization** to assess their suitability for inventory management tasks.

3. Results and Discussions

In the study, when artificial intelligence algorithms were applied, LSTM provided the highest accuracy due to its superiority in handling time-series data. GBM demonstrated the best balance between speed and accuracy, while SVM stood out for its low resource usage. Table 1 presents the performance comparison of the modeled algorithms.

***Table 1**: Performance of Algorithms*

Algorithm	Accuracy	MAE	Computation Time	Resource Usage
LSTM	87%	0.12	35	Medium
Gradient Boosting	84%	0.15	25	Low
SVM	78%	0.18	15	Very Low
Reinforcement Learning	82%	0.14	40	High

AI has become one of the most significant trends in the tech world in recent years. The launch of generative AI technologies, especially in 2023, has further increased interest in this field. However, for traditional software companies in our country, the specific areas where AI can provide benefits remain unclear. This study aims to bridge this knowledge gap by identifying the potential advantages of integrating AI methods into business processes and exploring their application areas. The study developed a stock threshold adjustment functionality to be integrated into a rapid sales and invoicing application tailored for the retail sector. Using AI methods and dynamic parameters, this feature ensures efficient management of variables such as seasonal demand fluctuations. Through AI-based models, significant reductions in inventory and warehouse costs were achieved, offering substantial cost advantages to organizations. By better managing product shelf life, waste rates were minimized. The results of algorithms used in the study LSTM, GBM, SVM, and RL were evaluated. The LSTM model demonstrated the highest accuracy (87%) in time-series data, proving to be an effective tool for demand forecasting in the retail sector. GBM offered an ideal solution in terms of the balance between accuracy and computation time, achieving success in dynamic stock optimization. The SVM model, while excelling in low resource usage, showed limited performance in terms of accuracy. The RL model was effective in dynamic decision-making processes but incurred higher computational costs. As a result of this study, significant know-how regarding the use and training of AI methods and libraries was gained by the project team and the organization. This knowledge provides valuable guidance on determining which library is more effective for specific scenarios in different software products. Additionally, it contributes to the organization's progress toward becoming a leading technology provider in the sector. On a product basis, the dynamic parameters developed for determining ideal stock levels facilitated efficient stock tracking, positively influencing the retail software product's market image and sales. This feature stands out as a distinguishing characteristic that sets the product apart from traditional solutions, providing a competitive advantage in the market. The study has centered AI methods in the company's future software development strategies, contributing to its long-term vision. Moreover, the proposed solution serves as a guiding example for other small and medium-sized enterprises (SMEs) in the industry. Future improvements, such as incorporating campaign data into the model and integrating real-time data streams, are expected to yield even more accurate predictions. By demonstrating the transformative effects of AI-based stock management on business processes, this study establishes a reference point for other companies in the industry.

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