Advanced Predictive Model for Optimizing Inventory Management and Demand Forecasting in Smart Logistic

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Abstract: The technology is advancing very fast, and digitalization is growing at an unprecedented pace. Thus, the logistics industry has become much more dynamic than ever before. The two fundamental elements of logistics operations, inventory management and demand forecasting, have become more complex and crucial to fulfill the demands of customers and for effective operations. Traditional techniques are often inadequate to address these problems, which creates inefficiencies such as overstocking, stock outs, and incorrect order fulfillment. The goal of the research is to create a sophisticated predictive model that optimizes demand forecasting and inventory management in smart logistics by utilizing machine learning techniques. Order fulfillment rates, inventory levels, historical sales data, and operational cost data were all used. Data cleaning was done to preprocess the data, and data normalization was applied where necessary, especially for algorithms sensitive to different scales. The Efficient Honey Bee Mating model has been fused with Dynamic Random Forest to predict demand and optimize inventory management in smart logistics. EHBM determines the best replenishment strategy for the inventory and delivery routes. Comparing with the current methods, the proposed EHBM-DRF method achieved MSE 1.02 and MAPE of 0.35. The research has provided an intensive format that can be applied to enhance inventory management in smart logistics, indicating significant improvements in delivery service, stock management, and cost-effectiveness.

Keywords: Inventory Management; Demand Forecasting; Smart Logistics; Efficient Honey Bee Mating fused Dynamic Random Forest (EHBM-DRF).

Introduction

Contemporary global supply networks often present problems that are too complex for conventional optimization techniques. They are subject to complex regulations and old models. The supply chains operate in a dynamic environment with unpredictable events, diverse networks of entities, and unpredictable demand fluctuations [1]. These new kinds of data challenge traditional mathematical optimization methods especially when there are several constraints and decision factors; however, they present more opportunities for comprehension with this complexity of data. Machine learning can optimise supply chains, transportation and inventory management for the processes of pattern recognition and data-driven decision-making [2]. By evaluating both past and current data, ML algorithms might improve the organization of routes, optimize inventories, and predict demand. The capacity to manage the volatility and complexity of contemporary supply chains, ML is a vital tool for enhancing efficiency and environmental consciousness [3]. The logistics firms are primarily needed to ensure the effective delivery of various manufactured goods to shipping hubs over great distances. To provide product delivery assistance, the shipping centers' current operations are reliant on antiquated techniques.These logistical features reduce delivery efficiency in addition to raising delivery prices [4]. The smart logistics surroundings provide logistics organizations with cost-effective and efficient alternatives. Effective shipping strategies were the subject of some significant mainstream academic studies [5]. However, the effectiveness of intelligent shipping operations utilizing cutting-edge technology like artificial intelligence (AI), optimization techniques, and the Internet of Things (IoT) has not been extensively covered [6]. Consumer products and durable goods production are two examples of businesses with strong demand elasticity for income that are typically thought to be seasonal [7]. An industry is considered cyclical; it reacts to changes in the domestic and global economy. Businesses with high demand elasticity for revenue that is often considered to be seasonal include the manufacturing of consumer services and lasting products [8]. Companies can achieve scale savings, maintain supply and demand equilibrium, and avoid an oversupply and order cycle with the aid of sales administration, strategic production management, and managing inventory.Although this approach is frequently used in industry and biomedical, business administration is scarce [9]. The aim of the research is to create a sophisticated predictive model toimprove demand estimation and control of inventory in intelligent logistics. The research aims to enhance order fulfillment and optimize stock levels by combining real-time information with ML techniques. The goal of the research to optimize logistics services' performance while reducing operational expenses.

Related work

Mobile computers and technology were growing more and more significant in the healthcare industry, sensing devices but also for interaction, recording, and presentation. With its many uses, the Internet of Things (IoT) was a driving force behind data that makes it challenging to manage and assess to extract relevant data to aid in their choices. Level, the process, and transmitting time measurements of protection were used to evaluate the efficacy of the suggested and current methods. The recommended security measures for medical data were effective [10]. A rare instance was a computer that is not connected to the network. In the past, everyone used laptops to solve their problems. The software that deals with these issues was client-server programs rather than separate desktop programs. The development of the hybrid cloud offers a solution is to solve the problem. Businesses that consider security to be one of the primary concerns when moving to cloud computing utilize hybrid clouds [11]. A network of computer equipment known as the IoT was capable of sending and receiving data over a network without the need for human assistance. Because of the tremendous developments in communication software and technology over the last few years, the number of IoT devices has expanded significantly. Recently, there has been a sharp rise in threats and infections from malware on IoT devices. The suggested method's effectiveness was assessed and contrasted with several traditional approaches. According to the investigation, the suggested strategy yielded precise results and can be applied to predict and detect malware in connected devices [12].

The rapid growth of smart medical devices on IoMT systems has led to the adoption of a novel approach, the Internet of Medical Things (IoMT), and significant innovations in the treatment of illnesses, the modernization of healthcare operations, and the enhancement of healthcare requirements. The effectiveness of the suggested approach was examined in relation to the quantity of current strategies. Energy consumption, network lifetime, communication overload, computing time, security, and encryption productivity. The result was that the proposed approach offered better reliability and energy saving as it was reported in [13]. After recognizing regions that could opt for performance gains, the research used ML models in managing loads, inventory, optimizing routes, and predicting demand. Despite concerns over the cost of implementation and data privacy, the study demonstrated how the use of AI in logistics could extend the life of supply chains. Professional end users who plan to use AI for survival and financial benefit are benefited by the knowledge developed during the research [14]. The logistics sector was facing new difficulties as a result of international cooperation and the fusion of both offline and online channels. Technology, including (AI), computer technology, and the IoT make logistics operations more effective.This transformation attracts academics from the fields of engineering, transport, logistics, and administration.

The combination of digital and physical channels and international collaboration have created new challenges for the logistics industry. The increasing complexity and scope of logistical operations can be effectively managed using smart logistics. Future research directions were also suggested based on shortcomings in the requirements of industry practices [15]. Creating a system for inventory control that is flexible, resilient, adaptable, and dependable allows for e-commerce services, improves supply chain participants with a flow of items, and satisfies constantly shifting client needs through automation. The optimization process of the AI model required combining data for analysis and optimization with the issues faced by certain businesses. The research outlined the main procedures of the AI-predicting inventory framework and offered optimization recommendations [16]. E-commerce businesses might offer a better inventory management system to reduce overproduction or stock-outs, as well as enhance their marketing advertisement and sales tactics.

Key contribution

- The research contributes by designing a novel predictive model that combines machine learning algorithms in smart logistics.
- The model helps in reducing stock-outs and overstocking, ensuring optimal inventory levels, and improving the efficiency of order fulfilment processes.
- By leveraging data-driven insights, the research contributes to management in smart logistics systems.

Methodology

The suggested improved predictive model for optimizing the administration of inventory and projections of demand in smart logistics combines ML techniques with real-time data connectivity. The methodology makes use of hybrid optimization algorithms to improve the reliability of inventory management and demand forecasting. Figure 1 demonstrates the methodology flow.

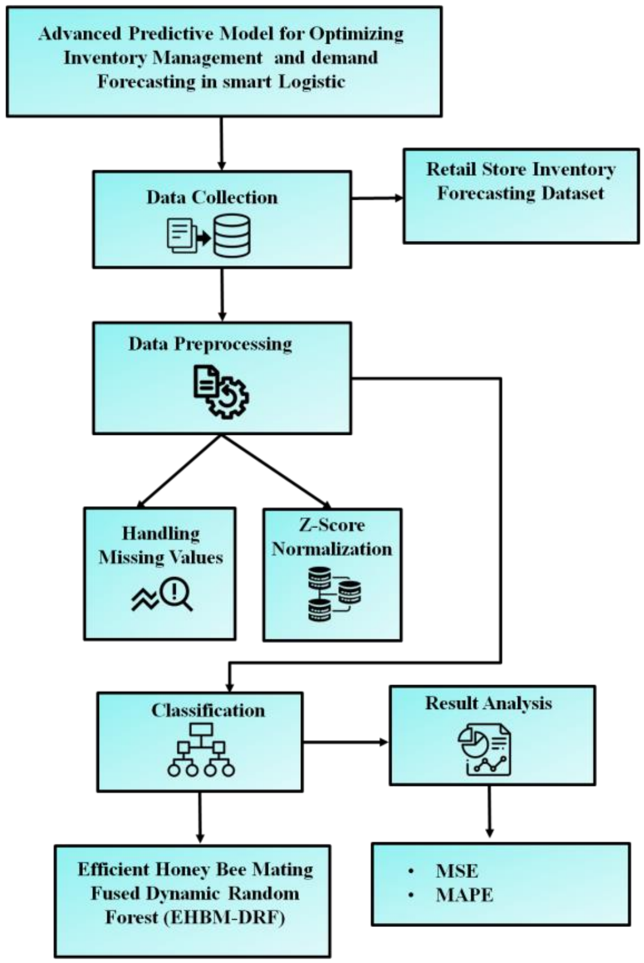

Figure 1. Structure of proposed methodology

Data collection

The open source Kaggle dataset was collected: [https://www.kaggle.com/datasets/anirudhchauhan/retail-store-inventory-forecasting-dataset.](https://www.kaggle.com/datasets/anirudhchauhan/retail-store-inventory-forecasting-dataset) The dataset provides information that is artificial realistic in the analysis and forecasting of demand for retail store inventory. It includes more than 73000 rows of information regarding various products and maintenance related to the environment, promotions, discounts, levels of inventory, price, and vacations. The perfect dataset for ML-based tasks such as inventory optimization, price optimization, and projections of demand. It enables data scientists to research time series forecasting methods, examine how weather and holidays influence sales, and design complex models that maximize the efficiency of the supply chain.

Data preprocessing

Data preprocessing for smart logistics' inventory administration and demand forecasting optimization involves cleaning the datato remove errors and duplication through handling missing values. Data normalization is used for z-score normalization to standardize features with different scales, such as lead time and demand quantity, for algorithms that are susceptible to these variations. To ensure that ML systems used for inventory optimization and predictions perform better and are more accurate.

Handling missing values

The AI algorithms to effectively optimize inventory control and predict demand in smart transportation, missing data is a significant barrier that must be appropriately addressed in the process of preprocessing In reality, several things, such as human mistakes, equipment failure, inaccurate or out-of-date information, and inconsistent data, can result in missing data. For instance, incorrect entries or inconsistent actual-time measurement yields some logistical information inaccessible. The incorrect information is removed and replaced through a data correction process, then some anomalous data like outlier values might leave some missing values. To ensure that the reliability of these prediction algorithms and accurate demands and ideal stocking levels are obtained in the intelligent logistics systems, the poor-quality information.

Z -score normalization

Z-score normalization is an essential technique that enables standardization of data to possess an average value of 0 and a regular deviation of 1. It significantly enhances demand forecasting and inventory management in smart logistics. The technique effectively minimizes the effects of differential scales in demand quantity, waiting periods, and delivery velocities of features. Normalizing data aids models to more easily notice the patterns and trends, and improve both predictions and optimizations concerning inventory. This standardizes values using Z-score, a common technique that can convert the given normal variation. With basic information set Y, the Z-score was the definition of the standardizationas shown in the equation in (1).

$$w_{ji} = Y(w_{ji}) = \frac{w_{ji} - \overline{w}_i}{\sigma_i} \tag{1}$$

By converting each attribute $\overline{w}_i$to have a mean of 0 and a standard deviation of 1, Z-score normalization standardizes the information. The sample average and variance of attribute are represented by $\overline{w}_i$and $\sigma_i$respectively. By ensuring that factors like lead times, stock amounts, and consumer demand are on a similar scale, this evolution makes forecasting techniques less inaccurate. To prevent skewing the correlations between various logistic features, Z-score normalization should be applied universally across the information set rather than with specific clusters.

Optimizing Inventory Management and Demand Forecasting in Smart Logistic using efficient honey bee mating optimization Dynamic random forest (EHBM-DRF)

The EHBM-DRFwas a hybrid optimization technique that improves demand estimation and inventory control in smart logistics by fusing DRF with the EHBM method. By fine-tuning choosing features and optimizing model settings, it increases the reliability of predictions. The approach provides a reliable solution for dynamic and intricate logistics settings by adjusting for modifications in the moment.

Dynamic random forest (DRF)

The DRF approach provides enhanced categorization accuracy, strong sensitivity against outliers and noise, and an excellent overfitting resistance property. The refinement of the splitting procedure for a decision tree node in the light of smart logistics demand forecasts and inventory management optimization was enabled through adaptive parameter choice. This advance enhances the quality of categorization-based demand and inventory forecasting that can be done to achieve more accurate and efficient projections in fluctuating logistics conditions. For the guarantee of more precise demand and stock level estimations, it is suggested that the optimal feature should be selected for node separation. It is relevant to the optimization of smart logistics in inventory management and demand forecasting. Furthermore, the linear combination of many node-splitting methods can lead to an efficient separation rule. It makes the quality selection easier during judgments and improves the accuracy of forecasting in uncertain logistical scenarios. The optimization of the node splitting process is necessary for improving demand forecasts and stock management in smart logistics. ID3 and CART are incorporated into the DRF technique. The node splitting algorithm splits the sample set X using attributes, measuring the knowledge gain and indexing two important metrics for identifying the best attribute for node dividing. The algorithm can more precisely forecast changes in demand and optimize inventory choices by utilizing these methods, which $b$improves allocation of resources and logistical effectivenessis shown in equation (2) and (3).

$$Gain(X,b) = Ent(X) - \sum_{u=1}^{U} \frac{|X^u|}{|X|} Ent(X^u) \tag{2}$$

$$Gain(X,b) = \sum_{u=1}^{U} \frac{|X|}{|X|} Gini(X^u) \tag{3}$$

As demonstrated by equations (4) and (5), X^u indicates that every situation in X with an amount of b^u on the attribute is found in the u extend cluster.

$$Ent(X) = -\sum_{l=1}^{|z|} o_l log_2 o_l \tag{4}$$

$$Gini(X) = -\sum_{l=1}^{|z|} \sum_{l' \neq l} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \tag{5}$$

The goal of node to increase the data set's following division, combining the node splitting equation and adaptive approach. The procedure for choosing variables is expressed in equation (6).

$$G = \underset{\alpha,\beta \in Q}{min} E\{X,b\} = \alpha Gini(X,b) - \beta Gain(X,b) \\ s.t \begin{cases} \alpha + \beta = 1 \\ 0 \leq \alpha, \beta \leq 1 \end{cases} \tag{6}$$

To optimize the control of inventory and projections of demand in smart logistics, the weight parameter for attribute splitting is represented by α andβwhich aims to minimize the value of G. To choose the ideal set of variables, the adaptive resource selection procedure is utilized, guaranteeing function as the most effective criteria for node segmentation. This method improves inventory segmentation and demand forecasting accuracy, which facilitates improved choice-making and resource optimization in logistics processes.Effectiveness in the experiment is gauged by the category error rate and precision rate. The sample F classification rate of errors is defined as follows by equation (7).

$$F(e;C) = \frac{1}{n} \sum_{j=1}^{n} \mathrm{II}(\mathrm{e}(w_j) = z_j) \tag{7}$$

Equation (8) defines the accuracy rate.

$$acc(e;C)\frac{1}{n}\sum_{j=1}^{n}\text{II}(\text{e}(w_j)=z_j)=1-F(e;C) \tag{8}$$

Efficient honey bee mating optimization (EHBM)

By mimicking the natural mating procedure and exploring a large solution space, EHBM can be used to optimize demand projections and management of stocks in smart logistics. By striking a balance between searching and exploiting in optimization tasks, this approach improves resource allocation and selection. EHBM enhances forecasting accuracy and optimizes inventory choices in changing logistics situations by utilizing adaptive scanning and local/global search algorithms.

- **Standard EHBM**

An aging function can be used to characterize the mating path between the princess and the drone with the highest score is shown in the equation (9).

$$Prob(R,C)=f^{\frac{-\Delta(e)}{t(s)}} \tag{9}$$

Where $\Delta(e)$represents the absolute distinction between $R\big(i.e.,e(R)\big)$fitness; The queen's speed at time s is denoted by $T(s)$while the probability of successfully mating $C\big(i.e.,e(C)\big)$ is denoted by $Prob(R,C)=f^{\frac{-\Delta(e)}{t(s)}}$. The energy, $T(s)$and speed, $E(s)$drop according to the equations (10) and (11) are expressed in follows.

$$T(s+1)=\alpha\times T(s),\ \ \alpha\in[0,1] \tag{10}$$

$$F(s+1)=E(s)-\gamma,\ \ \gamma\in[0,1] \tag{11}$$

The EHBM procedure's primary steps are as follows:

Step 1: Initial: This step includes several subroutines, including setting the EHBM algorithm's settings, creating a random population based on the optimization issue, and choosing the best response to the queen. The mating flight is when the algorithm begins, with a queen creating the optimal solution by randomly choosing drones. After that, a drone is chosen at random from this list to produce broods.

Step 2: The process is started by the mating ascending, and bonding must stop when the condition is met or the queen's speed and endurance are equal.

Step 3: The current crop of adolescents:In this step, the individual receives the queen's and drones' genetics are shown in equation (12).

$$Child=Drone+\beta(Queen-Drone) \tag{12}$$

Where($\beta\in[0,1]$)the decreasing component is denoted by β.

Step 4: Adaptability of broods: mutations operators do in several ways: are applied to increase the brood population growthis shown in equation (13).

$$\begin{gathered}Brood_j^l=Brood_j^l\pm(\delta+\varepsilon)Brood_j^l\\ \delta\in[0,1],0<\varepsilon<1\end{gathered} \tag{13}$$

Step 5: Examine the requirements for dismissal: Complete the processthe requirements for termination are met; if not, replace the current queen with a new one from the present queen and goes to the second stage. Otherwise, proceed to step 2 and choose the current queen.

To optimize the handling of inventory and predict demand in smart logistic, the research suggests an effective hybrid model called EHBM-DRF, which combines DRF with EHBM. It improves DRF's effectiveness in dynamic, complicated contexts by strengthening its exploration and exploitation capabilities. The model provides more accurate predictions and optimal choices of inventory by taking into account real-time demand changes. The precision and efficacy gains over conventional methods are substantial, according to the results.

Result

The computer with the Intel Core i5 processor with 16 GB of RAM and 512 GB of SSD is part of the setup for the experiments. Python 3.8 is used to create and apply sophisticated algorithms that enhance inventory control and prediction of demand in intelligent logistics. For optimal decision-making, the system combines immediate processing of data with ML algorithms. Table 1 illustrates how the suggested EHBM-DRF approach compares to the current techniques of long short term memory (LSTM) and auto-regressive moving average (ARIMA) [17].

Table 1. Result of existing and proposed approaches

Methods	MSE	MAPE
ARIMA [17]	1.67	0.75
LSTM [17]	1.12	0.65
Proposed [EHBM-DRF]	1.02	0.35

Correlation matrix

A correlation matrix for a retail establishment's demand for goods dataset is displayed, illustrating the interactions between various variables such as sales, inventory levels, price, weather, promotions, and holidays. The inventory levels, prices, and holidays exhibit negligible connections with other parameters, whereas sales and weather exhibit a slight beneficial association. In the framework of inventory demand projections, the weak correlations imply that these factors do not substantially affect one another. This weak connection can suggest that other outside variables, which are not included here, be more important. All things considered, the research aids in locating potential areas for data refinement to enhance demand forecasts. The optimizing inventory management and demand forecasting in smart logistic correlation matrix are shown in Figure 2.

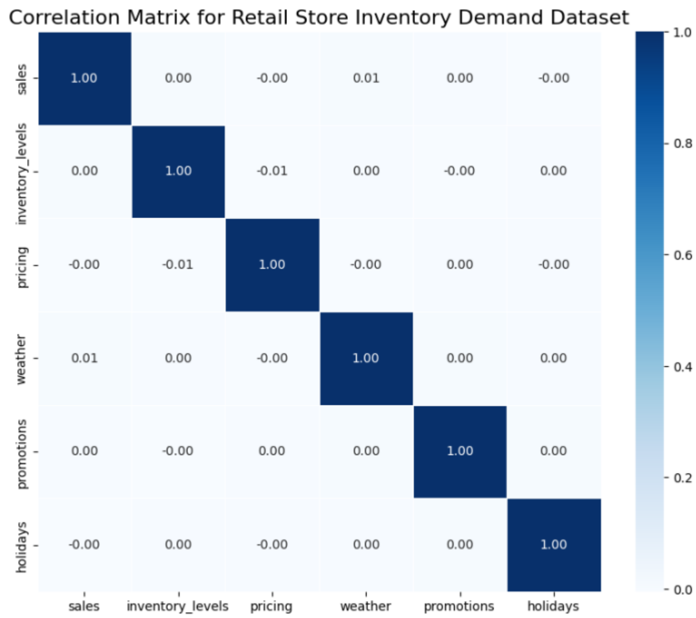

Figure 2. The correlation matrix for retail store inventory demand dataset

Mean squared error (MSE): A crucial indicator for assessing the predictive model's performance in predicting demand and inventory administration optimization in smart logistics is MSE. The model's performance is indicated by quantifying the average squared variance between the actual and projected values. Better forecast accuracy is reflected in lower MSE values, which direct logistics operations advantages.Table 1 and Figure 3is shown in comparison between the proposed EHBM-DRFmethods achieve1.02were lower than the existing method ARIMA of 1.67and LSTM of 1.12.

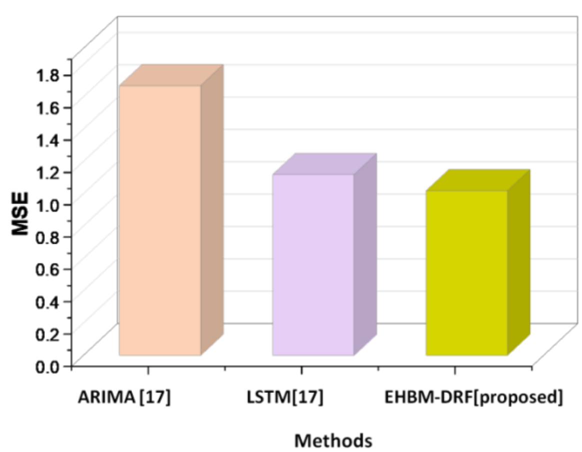

Figure 3. Graphical representation of MSE

Mean Absolute Percentage Error (MAPE): By calculating an average amount of difference between expected and actual requirement values, MAPE is a statistic used to assess the precision of demand projection models in smart logistics. It helps improve the administration of inventory by giving an unmistakable sign of predicting inaccuracies. Better predictive accuracy and more accurate demand forecasts are indicated by a lower MAPE number. Table 1 and Figure 4as shown in the comparison between the proposed EHBM-DRFmethods 0.35were lower than the existing method ARIMA of 0.75and LSTM of 0.65.

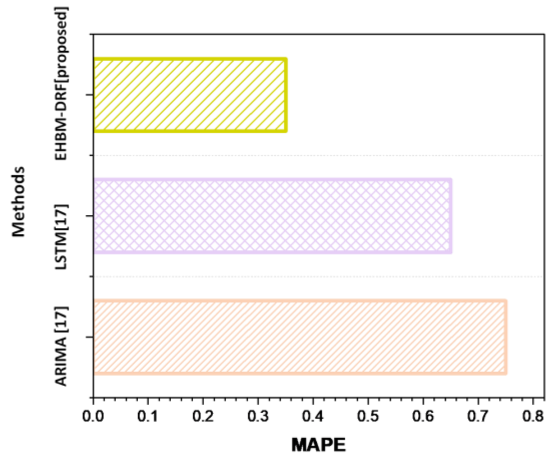

Figure 4. The outcome of the MAPE

Discussion

The intricate, non-linear connections and dynamic fluctuations found in smart logistics data are difficult for the current approaches, ARMA and LSTM, to adequately capture. Although ARIMA works well for predicting linear time series, those contain several limits with the extremely volatile or irregular data that is common in logistics. Despite its strength in processing sequential information, LSTM frequently struggles with sustainability and training performance when working with big datasets. By fusing the advantages of both approaches with cutting-edge hybrid optimization techniques, the suggested EHBM-DRF approach gets over these drawbacks and improves its ability to identify complex patterns and trends regarding demand and data from inventories. EHBM-DRF improves accuracy and computational effectiveness by combining dynamic regression foundations with evolving heuristic-based simulations, offering a more reliable approach to managing inventory and forecasting in intelligent logistics networks.

Conclusion

The advanced predictive model, combined with ML algorithms and data, significantly enhances demand estimation and stock management in smart logistics. Optimized demand estimates result in a reduction of surplus inventory, minimization of stockouts, and higher efficiency in overall logistical activities. By employing hybrid optimization techniques and learning from past and present data, the model offers a scalable, adaptive solution for various logistics scenarios. The capability to revolutionize logistics procedures in the era of intelligent technology is evident in the increased accuracy and productivity of operations. Compared to the existing methods, the suggested method obtained the lowest MAE of 1.02 and MAPE of 0.35. Further research should explore more sophisticated DL approaches to enhance the optimization of demand prediction in unpredictable logistics systems, such as those employing reinforcement educations. Furthermore, more detailed current information from other IoT devices can increase the precision and adaptability of the representation. The flexibility and efficacy of the model can be improved when its use is extended to international supply chains.

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