Enhancement Operations Management in Supply Chain based on Intelligent Support Techniques: A Case study.

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Abstract

The onset of the information technology revolution, economic globalization, and high customer expectations have all contributed to significant developments in businesses supply chain management (SCM). Due to the plethora of data generated throughout the entire supply chain has transformed how SCM analysis is conducted. Also, Retailers, in particular face the challenge of managing SC effectively to meet customer demands while reducing costs. Herein, we suggest an approach to optimize SCM using retail analysis techniques. As one of the most well-known artificial intelligences (AI) approaches and machine learning (ML) applications in SCM are the main goals of this study. By constructing conceptual framework, data analytics, ML, and optimization techniques are integrated to generate Intelligent Support Techniques (ISTs) for analyzing SC data and identify opportunities for improvement. We apply retail analysis techniques such as demand forecasting, inventory management, and assortment planning to optimize supply chain operations. The efficiency of our ISTs verified through employing it in a real-world case study of a large retail chain. Our results show that the suggested ISTs can lead to significant improvements in supply chain performance, including increased sales, reduced inventory costs, and improved customer satisfaction.

Keywords: supply chain management (SCM); artificial intelligences (AI); Intelligent Support Techniques (ISTs); machine learning (ML); and optimization techniques

1. Introduction

In the era of artificial intelligence (AI) and its subsets techniques, many sectors are resorted to deploy digital technologies to reduce human intervention in many businesses and reduce risks that may be exposed to. Numerous prior studies that were interested in the subject matter express artificial intelligence in numerous forms. For example, Zhou et al. in [1] invested Industry 4.0 (Ind 4.0) to advance the overall automation and digitalization process, particularly in the industrial. This is due to the fourth industrial revolution containing many artificial intelligence technologies as Big Data Analytical (BDA), Internet of Things (IoT), Cloud Computing (CC)…etc. According to the declaration of [2], the significance of AI is to support or replace decision-making processes with little interference from humans. Similarly [3] described AI as a cutting-edge type of technological digitalization that incorporates computer systems for different purposes as accumulating massive amounts of inference to address issues in decision-making situations where the most advantageous or correct solutions are either too expensive to develop or too difficult to comprehend. Also, [4] demonstrated that AI is superior to conventional information technology technologies in terms of effectiveness. As Aamer et al.[5] illustrated that In the last decade, machine learning as subset of AI, which is considered a disruptive technology, has developed quickly to enhance the effectiveness and procedure in supply chain management (SCM).

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Whilst [6], [7] described SCM as an important aspect of modern business operations, particularly in the retail industry. With in[8] the effectively and efficiently maximizing the flow of goods and services across SC, SCM focuses on providing value to the consumers.

Organizations according to[6]have been obliged to create and adopt new technologies that are able to quickly and intelligently understand a vast amount of data as a result of the exponential development in the volume of data from various SCM parts. So, Big data is an issue that the conventional decision support system cannot adequately address. Consequently, the most effective ways to address this huge data-related challenge are those that use AI techniques. Due to machine learning (ML) techniques are a popular branch of AI that automatically detect and extract patterns among variables by Using huge datasets [9]. There are other challenges facing SCM. For example, [6] demonstrated that retailers face the challenge of managing their supply chains effectively to meet customer demands while reducing costs. Therefore, retailers have turned to data analytics, machine learning, and optimization techniques to gain insights into their supply chains and improve their performance [10]

One key area of interest is the application of retail analysis techniques to optimize SCM. Retail analysis is a data-driven approach that uses statistical and machine learning techniques to analyze retail data and identify opportunities for improvement. By applying these techniques to supply chain data, retailers can gain insights into customer demand, inventory management, and assortment planning, among other areas. These insights can then be used to develop strategies for improving supply chain performance, such as reducing stockouts, minimizing overstocking, and improving product availability [11], [12]

Herein, we are suggesting an approach to optimize SCM using retail analysis techniques. As result, we are constructing a framework that invests the ability of AI in SCM according to conducted survey which we are performed for earlier studies. Subsequently, the constructed framework is based on the integration of data analytics, ML, and optimization techniques to analyze supply chain data and identify opportunities for improvement. Specifically, we are applying retail analysis techniques such as demand forecasting, inventory management, and assortment planning to optimize supply chain operations. We demonstrate the effectiveness of our approach by applying it to a real-world case study of a large retail chain. Our results show that the proposed approach can lead to significant improvements in SC performance, including increased sales, reduced inventory costs, and improved customer satisfaction.

2. Earlier related studies

Based on the previous literature studies for interested areas of this study for business environment especially SCM and applied techniques for enhancing it, we concluded that there have been growing interest in the application of data analytics, ML, and optimization techniques to improve supply chain performance, in recent age.

Several researchers have demonstrated the effectiveness of these techniques in various areas such as demand forecasting, inventory management, and logistics optimization. For example, the authors of [7] contributed to the literature on supply chain management by demonstrating the effectiveness of ML techniques for demand forecasting. The authors proposed an approach through combining feature selection, model selection, and model evaluation techniques to identify the best ML algorithm for a specific forecasting problem. Also, verified their approach to a real-world case study of a manufacturing enterprise.

Others analyzed 134 articles from various academic databases [6]also, identify trends and insights into the use of big data analytics in supply chain management across different industries. The study found that the most analyzed data is related to logistics and transportation, followed by inventory and procurement data. The authors also identified several factors that influence the implementation of BDA in SCM which are represented in data quality, data integration, and data privacy and security.

The authors of [12] reviewed The dynamic modeling and control techniques for SC in [13] and categorized it into optimization-based, simulation-based, and hybrid approaches. Also, applications of these techniques in different areas of SCM are surveyed such as inventory management, production planning, and logistics.

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Other techniques are surveyed via [14] through conducting a comprehensive review for optimization methods from a ML perspective. They categorized optimization methods into four main categories: deterministic methods, stochastic methods, global optimization methods, and multi-objective optimization methods. According to earlier studies we aggregated the application of these methods in various ML areas such as neural networks (NNs), support vector machines (SVM), and ultimately DL.

Others in [15]suggested an agent-oriented approach to managing SC based on the concept of software agents, which are autonomous entities that can interact with other agents and make decisions based on their own goals and objectives. The authors argued that agent oriented SCM can provide several advantages over traditional approaches, including greater flexibility, adaptability, and responsiveness to changes in the supply chain environment. Also described several applications of agent oriented SCM, including production planning, inventory management, and logistics optimization.

Additionally [16] applied blockchain technology (BCT) as important factor in Ind 4.0 in SCM. The key features and main characteristics of BCT are provided as transparency, immutability, and decentralization. As its potential applications in different areas of SCM are discussed such as procurement, inventory management, and logistics. Also, a valuable perspective on the potential impact of BCT on SCM is provided and highlighted areas for future research in this field.

The notion of the digital supply chain (DSC) in [17] described as a "fully integrated, end-to-end supply chain that uses digital technologies to enable seamless collaboration among all stakeholders." The literature on digital technologies and their applications in different areas of SC is conducted as procurement, production, logistics, and customer service. Research framework is established and composed of four main components: understanding the impact of DT on SC, assessing the readiness of organizations to adopt DTs, evaluating the performance of DSC, and developing strategies for successful implementation.

The global investment trends in AI are analyzed by [18] and identified the key industries that are investing in this technology, including healthcare, finance, and manufacturing. Applications of AI in many areas as disease diagnosis and treatment in healthcare, fraud detection, and risk management in finance, and predictive maintenance and quality control in manufacturing are explored.

De Brito et al. [19]addressed the issue of sustainability in the fashion retail industry. And presented a case study of sustainable supply chain practices in a European fashion retailer and identify the key organizational and performance factors that contribute to a sustainable SC. Also reviewed the literature on sustainable SCM and identified the challenges and opportunities associated with implementing sustainable practices in the fashion retail industry.

The authors of [19] An integrated approach for supplier selection is suggested by [20] as well as order allocation in a green supply chain (GSC). The concept of GSC involves integrating environmental considerations into SCM decisions. Suggested integrated approach combines fuzzy multi-criteria decision-making (F-MCDM) and multi-objective programming (MOP) techniques to evaluate potential suppliers based on their environmental performance and allocate orders to suppliers in an environmentally friendly way. The suggested approach is applied on case study of a manufacturing company and showed that their proposed approach can lead to significant reductions in greenhouse gas emissions and energy consumption, as well as cost savings.

3. Intelligent Support Techniques

In this section, we describe intelligent techniques that were deployed to conduct this study. Our study aimed to investigate the effectiveness of ML techniques for retail analysis for the purpose of optimizing SCM.

To achieve this goal, we followed a systematic approach that involved several steps, including building model, training, and evaluation. Our intelligent support techniques (ISTs) were suggested to ensure the rigor and reproducibility of our research results, and to provide meaningful insights into the potential of ML technique for improving SCM.

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Long Short-Term Memory (LSTM) is applied as a type of recurrent learning technique that can capture long-term dependencies in sequential data through a memory cell and three gating mechanisms that control the flow of information through the cell [21],[14]. Our ISTs employes LSTM network to predictively model the dependency information in retail data from SC. For predicting the sales of future retail, LSTM can be trained on historical sales data, weather patterns, and other relevant variables to predict future demand for a particular product. This can help retailers optimize their inventory levels, reduce stockouts, and improve customer satisfaction.

The earliest phase in the design of LSTM network is to discover information to be excluded from the memory, using the forget gates, which generate a vector, (f_t), with values in range [0,1] related to each value of cell state, C_{t-1}.

$$f_t = \sigma\left(W_f\,[h_{t-1}, X_t] + b_f\right) \tag{1}$$

Then, we decide the chose information from retail input, X_t, to be to store in the cell state and to update the cell state. This is achieved with two linear layers with sigmoid and tanh activation. the output of them is multiplied to renew the new cell state.

$$i_t = \sigma(W_i\,[h_{t-1}, X_t] + b_i), \tag{2}$$

$$N_t = tanh(W_n\,[h_{t-1}, X_t] + b_n), \tag{3}$$

$$C_t = C_{t-1}\, f_t + N_t\, i_t. \tag{4}$$

After that, the hidden state is computed based on output cell state, where sigmoid layer is applied to select which information to the output. Next, the generated output is multiplied by the outcome of the tanh layer, with a value ranging between −1 and 1.

$$O_t = \sigma(W_o\,[h_{t-1}, X_t] + b_o), \tag{5}$$

$$h_t = O_t\, tanh(C_t). \tag{6}$$

It is important to note that LSTM is not a silver bullet and may not be appropriate for all applications in the retail data supply chain. It is important to carefully preprocess and analyze the data, and to choose appropriate hyperparameters and training techniques to ensure the accuracy and stability of the LSTM model. To this end, Genetic algorithm (GA) is applied based on inspiration from the process of natural selection to optimize the hyperparameters of LSTM models, which are set before training and can significantly affect the performance of the model, such as the number of hidden layers, the number of neurons in each layer, and the learning rate [16], [20].

The process of optimizing hyperparameters with GA involves creating a population of candidate LSTM models with different hyperparameter configurations, evaluating their performance on a validation set, and selecting the best-performing models to generate the next population. This process is repeated for several iterations until a satisfactory set of hyperparameters is found.

The first step in applying GA to optimize the hyperparameters of LSTM is to define the hyperparameter space. This involves specifying the range of values for each hyperparameter that will be considered in the optimization process. In particular, the hyperparameter space for the number of hidden layers may range from one to five, and the hyperparameter space for the number of neurons in each layer may range from 10 to 50.

Once the hyperparameter space is defined, a population of candidate LSTM models is created with randomly selected hyperparameter configurations from the space. The performance of each candidate model is evaluated on a validation set using mean absolute mean error (MAPE):

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|A_i - F_i|}{A_i}\right) \times 100\% \tag{7}$$

The best-performing models are then selected to generate the next population. This is done by applying selection, crossover, and mutation operations to the best-performing models. Selection involves selecting the best-performing

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models based on their fitness score, which is calculated based on their performance on the validation set. Crossover involves combining the hyperparameters of two or more models to create a new candidate model, while mutation involves randomly changing the hyperparameters of a candidate model.

This process is repeated for a number of iterations, and the best-performing model is selected as the final model with optimized hyperparameters. The optimized hyperparameters can then be used to train the LSTM model on the entire dataset.

GA can be applied to optimize the hyperparameters of LSTM models by creating a population of candidate models with different hyperparameter configurations, evaluating their performance on a validation set, and selecting the best-performing models to generate the next population. This process is repeated for a number of iterations until a satisfactory set of hyperparameters is found. This approach can help improve the performance of LSTM models in retail data supply chain applications by optimizing the hyperparameters for the specific task at hand.

4. Results and Discussions

Walmart is one of the largest retailers in the world, with over 11,000 stores in 27 countries. It is also a leader in using data analytics to optimize its supply chain and retail operations. As such, Walmart's retail sales can serve as a valuable case study for our system, which aims to use an optimized LSTM for demand forecasting in the context of SCM. The data include historical sales data, type, store data, etc. This data can be used to train our IST to accurately predict demand for different products. By using our system to analyze Walmart's retail sales data, we can gain valuable insights into the potential of our solution for supply chain management in the retail industry. Table 1 showcased statistical analysis of Walmart sales data is presented to provide valuable insights into the patterns and trends in the data, which can be used for demand forecasting and inventory management.

Table 1: statistical analysis of Walmart sales.

	Count	Mean	Std	Min	25%	50%	75%	Max
Store	420212.00	22.20	12.79	1.00	11.00	22.00	33.00	45.00
Dept	420212.00	44.24	30.51	1.00	18.00	37.00	74.00	99.00
Weekly_Sales	420212.00	16033.11	22729.49	0.01	2120.13	7661.70	20271.27	693099.36
Temperature	420212.00	60.09	18.45	-2.06	46.68	62.09	74.28	100.14
Fuel_Price	420212.00	3.36	0.46	2.47	2.93	3.45	3.74	4.47
MarkDown1	420212.00	2590.32	6053.42	0.00	0.00	0.00	2809.05	88646.76
MarkDown2	420212.00	878.91	5076.93	-265.76	0.00	0.00	2.40	104519.54
MarkDown3	420212.00	468.85	5534.07	-29.10	0.00	0.00	4.54	141630.61
MarkDown4	420212.00	1083.53	3896.07	0.00	0.00	0.00	425.29	67474.85
MarkDown5	420212.00	1662.81	4206.21	0.00	0.00	0.00	2168.04	108519.28
CPI	420212.00	171.21	39.16	126.06	132.02	182.35	212.45	227.23
Unemployment	420212.00	7.96	1.86	3.88	6.89	7.87	8.57	14.31
Size	420212.00	136749.73	60993.08	34875.00	93638.00	140167.00	202505.00	219622.00

Figure 1 involves Correlation analysis to measure the strength and direction of the relationship between two or more variables. As visualized, the correlation map can be used to analyze Walmart sales data to identify the factors that are most strongly correlated with sales, such as dept, store, or fuel price. This information can be used to optimize pricing strategies and to identify the price points that maximize sales and revenue. It is notable that Temperature, unemployment, and CPI have no meaningful impact on weekly sales, thus, they can be dropped. Also, Markdown variables are highly related, thereby, two of them can be dropped.

Feature importance analysis experiment is applied to identify the most important features or variables that contribute to a particular outcome or target variable (see Figure 2). In the context

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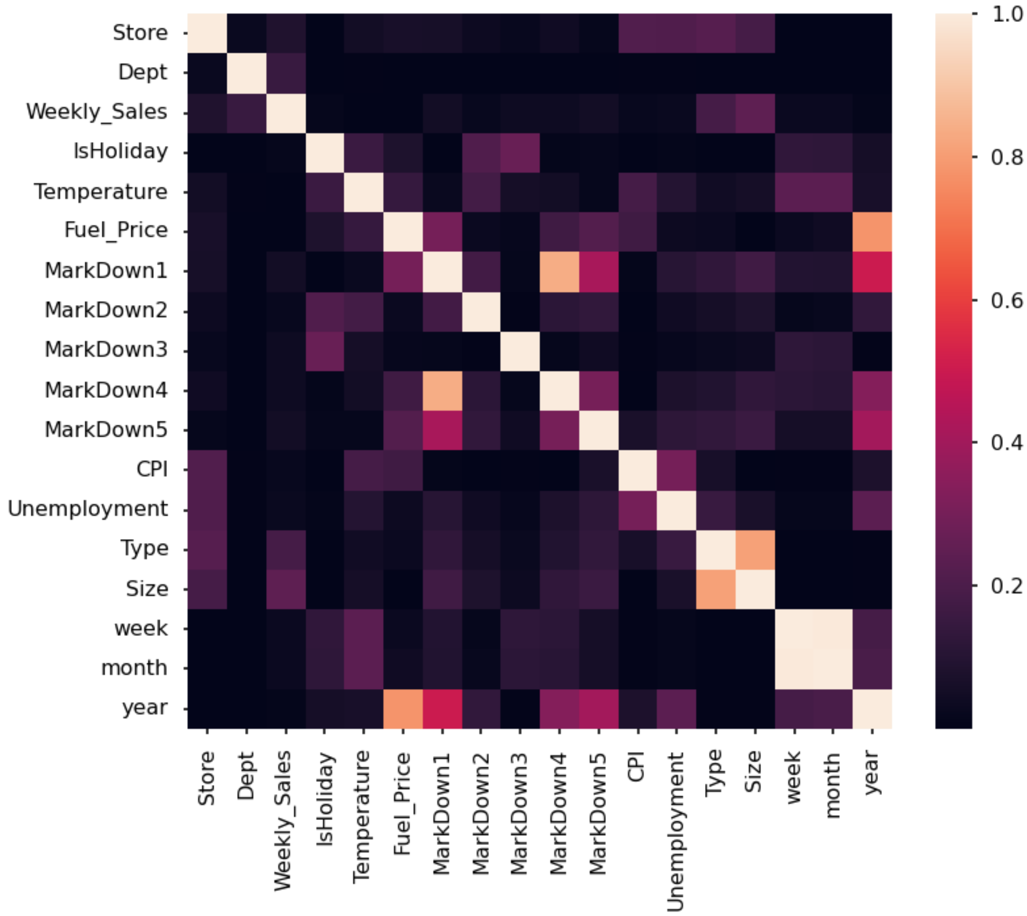

Figure 2: visualization of Pearson correlation map.

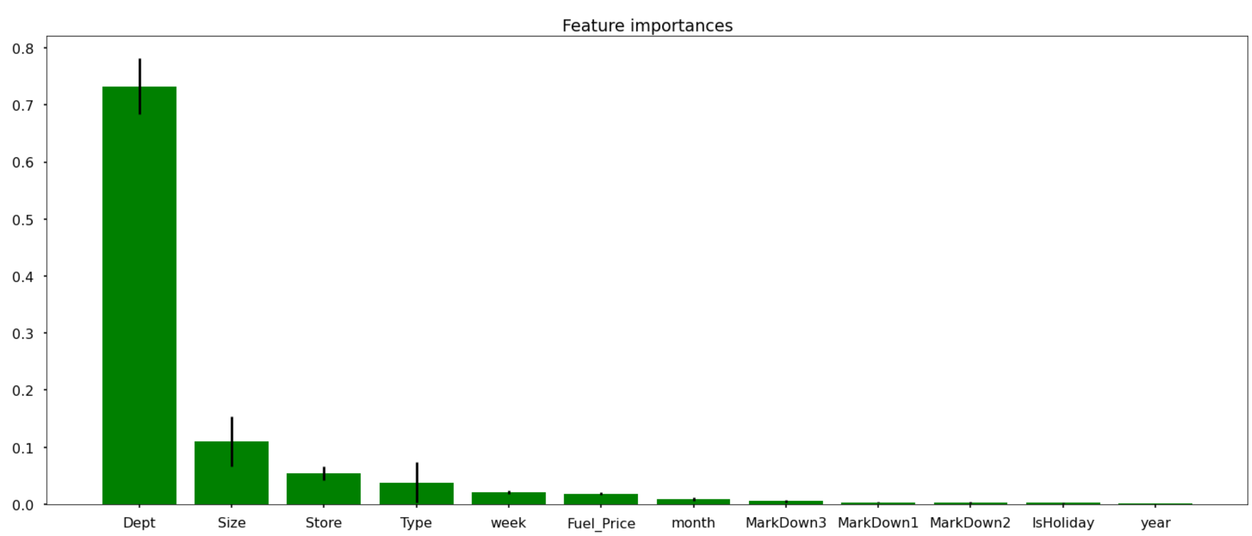

Figure 1: visualization of feature importance on our datasets.

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In the context of Walmart sales data, this imply identifying the features or variables that are most important for predicting sales. We use random forests by recursively partitioning the data according to the most important features and computing the improvement in the target variable achieved by each partition.

Experimental comparison against state-of-the-art methods is performed to evaluate the effectiveness of our system for predictive modeling of retail data in supply chain (See Figure 3). By comparing our system against existing methods, we can demonstrate the superiority of our approach and provide evidence to support its adoption in real-world settings. Our experiments include several state-of-the-art methods such as ARIMA, RNN, and Deep Neural network (DNN).

To perform an experimental comparison, we can train and evaluate our system on the same dataset and performance metrics as these existing methods. one can easily note that our system outperforms the existing methods in terms of Mean absolute percentage error (MAPE), indicating that it is more accurate in predicting sales and reducing forecasting errors.

5. Conclusion

The main objective for conducting this study is enhancing and optimizing SC 's operations. Subsequently, this study suggested ISTs for predictive modeling in retail data SC using ML technique. We have discussed the potential of

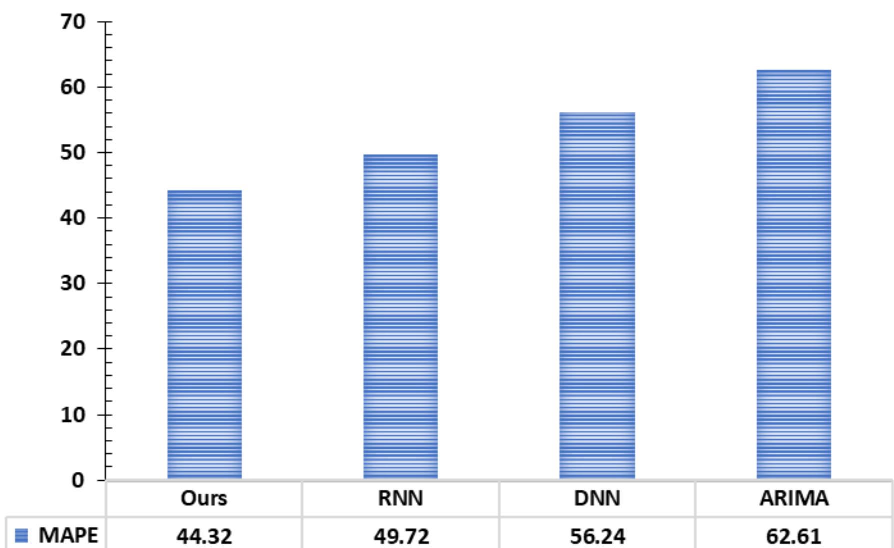

Figure 3: experimental comparison against state-of-the-art

integrating Long Short-Term Memory (LSTM) as sub technique of DL and Genetic Algorithms (GA) as optimizer algorithm for improving the predictivity of inventory management in the context of retail data SC. Our suggested ISTs applied on a case study of Walmart sales data to demonstrate the effectiveness of our suggested ISTs in a real-world setting. Compared to conventional statistical techniques, our suggested ISTs have several benefits for retail analysis. These benefits include the ability to capture long-term dependencies and patterns in the data and to optimize hyperparameters. By accurately predictive modeling for different products, our system can help retailers optimize their inventory levels, reduce stockouts, and improve our customer base.

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