Intelligent Decision Support System for Optimizing Inventory Management

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Abstract

Inventory management (InvM) is a critical aspect of supply chain management (SCM) and optimizing inventory levels can lead to significant cost savings and improved customer satisfaction. Hence, business organizations have recently worked to increase the value of their operations by utilizing modern and digital technologies such as Industry 4.0 (Ind 4.0). In the era of Ind 4.0, technologies such as the Internet of Every Thing (IoT), AI, BDA…etc. Recognizing the significance of InvM in a supply chain (SC), motivated us to volunteer technologies of Ind 4.0 as machine learning (ML) techniques to boost the decision-making (DM) process to optimize InvM. Subsequently, this study is constructed to provide an intelligent decision-support ML framework for automating the process of optimizing inventory management. Our constructed framework ensembles powerful ML prediction algorithms for inventory management, such as Artificial Neural Networks (ANNs), Random Forest (RF), and Support Vector Machine (SVM) for building robust sales regressors. The extensive experimentations on a case study of Walmart suggested that the proposed system has the potential to transform inventory management and improve supply chain performance, but further research is needed to address the challenges of data availability and quality.

Keywords: Machine Learning; Decision Support Systems; Inventory Management; Inventory Optimization

1. Introduction

In supply chain management (SCM) whether in small-medium organizations (SMO) or large organizations, Inventory management (InvM) is a crucial [1]element due to how it influences both manufacturing and price. As [2] stressed InvM is a critical process that involves the efficient management of an organization's inventory levels to meet customer demand while minimizing costs. In general [3] deciding that having too much or too little inventory can be detrimental. So, optimization of inventory is an important process for identifying the optimal inventory levels for an organization based on its sales history, market trends, and other relevant factors. This process in [4] aims to maintain optimal inventory levels that meet customer demand while minimizing the costs associated with excess inventory.

Jiang etal. [4] decided several key steps to achieve an effective InvM optimization. These steps involve accurate demand forecasting, effective inventory planning, replenishment strategies, and efficient warehouse management practices. Optimizing InvM can permit organizations to minimize stockouts, reduce carrying costs, and improve their overall profitability. Ultimately, inventory optimization gains the organization's competitive advantage by providing it with the ability to respond quickly to changing customer demands while reducing costs.

Typically [3] the accuracy of future customer demand predictions has a significant impact on how well IM functions and performs. By carefully analyzing the consumers' product expectations, the customer demand forecast may be increased. Therefore, using precise ways to determine client demand for a product becomes an increasingly prevalent subject in the disciplines of InvM in SCM. One of the most popular ways is Decision support systems (DSS). According

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to [5] the concept of DSS means an interactive computer-based system to treat ill-structured problems.

Moreover, DSS employees in various businesses for making more informed decisions. In the context of InvM optimization [6], [7], DSS is used to analyze data related to inventory levels, demand forecasting, and other relevant factors to provide insights and recommendations for decision-making (DM). Result of the importance of DSS, there are other ways to boost DSS to be more intelligent as Industry 4.0 (Ind 4.0) [8]. Ind 4.0 symbolizes a new generation of deploying a variety of technologies to improve the performance of organizations as in Fig 1. Emerging Ind 4.0 in DSS aids in the development of new and innovative business frameworks [1]. Artificial Intelligence (AI) according to Fig 1 considered one of Ind 4.0 technologies. Especially, Machine learning (ML) as a subset of AI can play a critical role in optimizing DM in InvM by analyzing large volumes of data. Also, identifying new patterns and trends that humans may not be able to detect. By leveraging ML algorithms, businesses can predict demand more accurately, optimize inventory levels, and reduce waste, leading to cost savings and increased profitability[9],[10]. For example, ML algorithms can be used to forecast demand based on historical sales data, weather patterns, and other relevant factors. These algorithms can then be used to optimize inventory levels, ensuring that the right products are available in the right quantities at the right time. ML algorithms can also be used to identify trends and patterns in customer behavior, allowing businesses to adjust their inventory management strategies accordingly. Finally, this study presents intelligent decision support based on ML (IDSML) for optimizing InvM tasks to provide more accurate, automated, and real-time decisions. Our IDSML integrates neural regressors, random forests, and support vector regressors to generate an insightful prediction about sales, which can help improve the decision-making processes in different inventory management tasks. The extensive experimentation on a case study of Walmart sales demonstrated the efficiency and effectiveness of the proposed intelligent framework.

This study is organized as follows. The literature studies are reviewed in section 2. A discussion of how our suggested framework will demonstrate optimum InvM in practical settings is given in section 3. The detailed steps involved in constructing the proposed intelligent Decision framework are in section 4. The experimental details and the results are debated in section 5. The conclusions of our work are driven in section 6.

Figure 1: Technologies of Industry 4.0

2. Literature Review

The literature on ML for optimizing inventory management has grown rapidly in recent years and has been applied to various aspects of inventory management, such as demand forecasting, stock replenishment, and order scheduling. Researchers have explored different types of ML algorithms, to improve inventory accuracy and reduce costs. Some studies have also integrated ML with other optimization techniques, such as linear programming and simulation, to further enhance InvM performance. For example, Giannoccaro et al.[2] used reinforcement learning techniques to optimize inventory management in supply chain systems that involved learning through trial and error, in which a

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multi-agent system was responsible for managing inventory at different levels of the supply chain. The study [4] proposed an approach to inventory control in a multi-agent supply chain system using case-based reinforcement learning (CBRL), which was based on learning from past experiences and using that knowledge to make better inventory control decisions. The authors highlighted the potential of CBRL for improving inventory control in complex, dynamic supply chain systems, and provided a framework for future research in this area and has the potential to significantly improve supply chain efficiency and reduce costs. The proposed approach in [11] is to solve semi-Markov decision problems (SMDPs) using average reward reinforcement learning (ARRL). SMDPs were used as a class of reinforcement learning problems where the state transitions are not necessarily Markovian, and the reward function may depend on the amount of time spent in each state. It used an ARRL-based approach to estimate g the average reward over time using a linear function approximation, whereby the policy gradient algorithm is used to learn the optimal policy in the SMDP. The study[12] proposed a warehouse management system based on the Internet of Things (IoT) for smart logistics that alleviated the reliance on manual processes, which are inefficient and prone to errors. It developed an IoT-based approach that integrated a range of IoT-enabled devices such as RFID readers, barcode scanners, and smart cameras that enable real-time monitoring of inventory levels through the use of sensors, data analytics, and real-time tracking to optimize warehouse operations. The system was applied in a real-world warehouse setting, demonstrating the effectiveness of the IoT-based approach, and the findings demonstrated that the system improves operational efficiency, reduces errors, and enhances inventory accuracy. The use of data fusion and ML techniques in [13] for industrial prognosis through the integration of these techniques to improve the accuracy and efficiency of prognostic systems, could have significant benefits for industrial applications. The paper provided an overview of the key concepts and techniques involved in data fusion and ML and discussed their application to industrial prognosis. The authors also highlighted some of the key challenges associated with integrating these techniques, such as data heterogeneity, data quality, and interpretability.

Scholars in [14] debated the use of big data analytics in the field of operations management by arguing that the increasing availability of large datasets and advances in analytical techniques have created opportunities to use big data to improve operations management practices. It presented an overview of the key concepts and techniques involved in big data analytics and discussed their application to operations management. The study [15]provided a comprehensive overview of the recent advances in robust optimization techniques as a powerful mathematical framework that provides a way to optimize solutions under uncertainty. The authors argued that advances in this area have the potential to significantly improve decision-making in a wide range of applications. They also highlighted some of the key benefits of using robust optimization, such as improved risk management, better decision-making under uncertainty, and enhanced performance in dynamic environments. a comprehensive approach in [10] proposed for solving inventory optimization problems using deep Q-learning, in which the authors focused on the well-known beer game, a simulation game that simulates a multi-echelon supply chain, to demonstrate the effectiveness of their proposed approach. The work presented an overview of the beer game and the inventory optimization problem that it represents. It also described the deep Q-network (DQN) algorithm and its implementation in the context of the beer game, in which the DQN was trained to predict the optimal inventory levels for each echelon of the supply chain, using a combination of historical data and simulated game play.

3. Toward optimal Inventory management

This section discusses the methodology of our proposed solution for proving optimal InvM in the real world. The discussion begins by defining and analyzing the use case, and materials used to build our system. Then, the algorithmic design of the proposed system is debated and discussed in much more detail. Walmart is one of the largest retailers in the world, with an extensive network of physical stores and online marketplaces. As such, managing their inventory efficiently and effectively is a critical aspect of their business operations. Walmart uses historical sales data and other factors such as promotions, weather, and holidays to forecast demand. By accurately predicting future demand, they can optimize their inventory levels and ensure that they have the right products in stock at the right time. As a case study for optimizing inventory management, this study utilizes sales data to forecast demand and plan inventory levels accordingly. By analyzing sales materials, we can identify which products are selling well and which are not and adjust their inventory levels accordingly. This approach helps to minimize stockouts and overstocks, reduce inventory carrying costs, and maximize profitability. Additionally, we leverage data analytics to explore the elements of

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inventory management, ensuring that they can meet customer demand while minimizing waste and reducing costs. The dataset contains a total of 81 departments and 45 stores. The data contains a total of 421570 samples, which are cleaned by deleting the rows that contain wrong sales values leading to 420212. There are three different store types in the data A, B, and C. In

Fig 2, we plot the average weekly sales according to holidays by type. It is evident from the Fig that the weeks between Thanksgiving and Christmas have the greatest average sales volume. And during every holiday, Type A stores had the largest sales. Also, it is not surprising that Thanksgiving weeks account for five of the top five greatest weekly sales. Fig 3 provides a visualization of the weekly sales for each department and/or store in Walmart sales data.

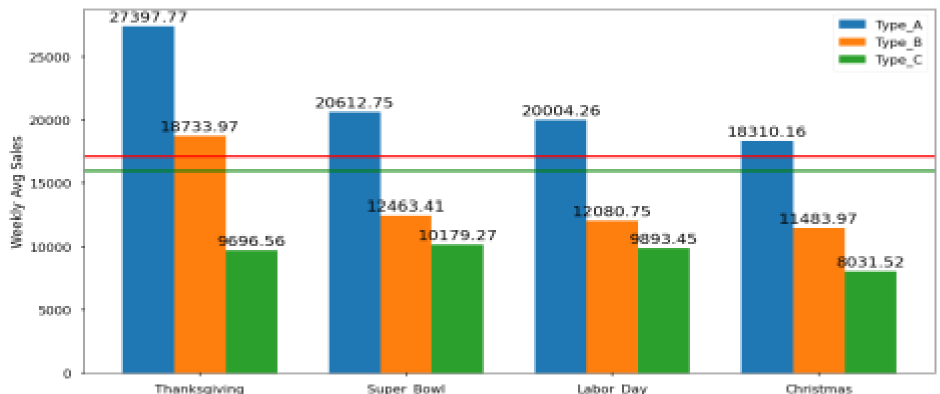

Figure 2: Illustration of the mean weekly sales on different holidays in Walmart data

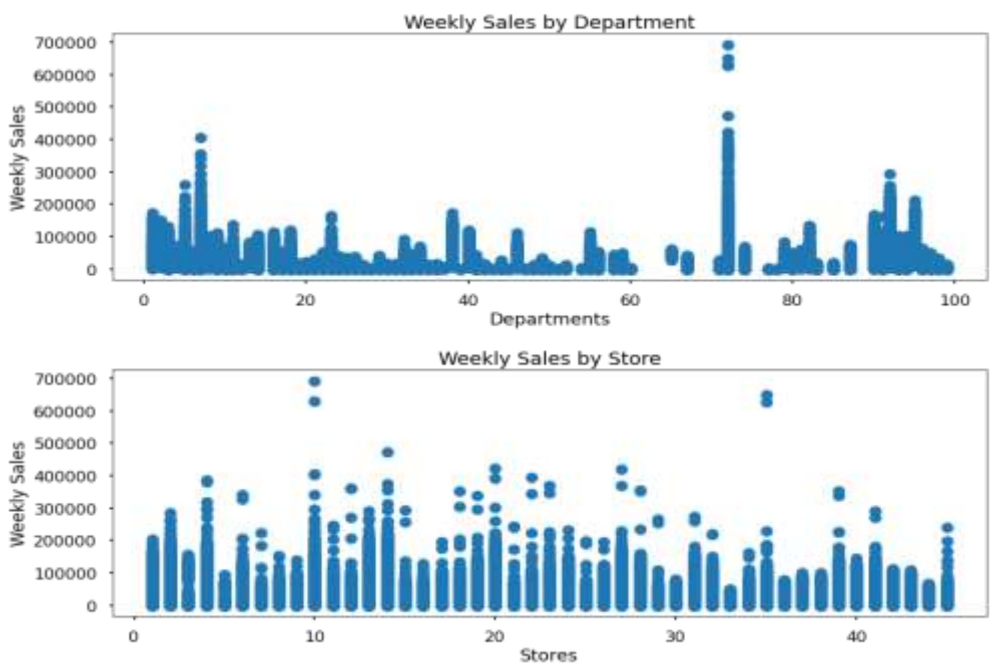

Figure 3: Illustration of the weekly sales of each department or store in Walmart data

4. Intelligent Decision Support based on ML Framework

Random forest (RF) is an ML algorithm that can be used for sales prediction in inventory management systems. The algorithm works by building a collection of decision trees, where each tree is trained on a random subset of the training data and selects a subset of features to split on at each node. To exploit RF for sales prediction in the proposed

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inventory management systems, historical sales data can be used as input to train the model. This includes data on the sales volume of various products, as well as any relevant external factors that may impact sales, such as seasonality, promotions, and economic trends. Once the model is trained, it can be used to predict future sales volumes based on input data, such as current inventory levels and upcoming promotions. These predictions can then be used to optimize inventory levels to ensure that sufficient stock is available to meet anticipated demand. RF has several advantages for sales prediction in inventory management systems. It is highly accurate and can handle large amounts of data with many features. Additionally, it can handle both categorical and continuous data, making it versatile for a range of input variables. Information gain (InfoGain) is a key concept used in decision tree-based algorithms, including RF. In our system, InfoGain is used to measure the importance of a feature in predicting the target variable (i.e., the outcome variable that the model is trying to predict). InfoGain is calculated by comparing the entropy (i.e., the degree of disorder or randomness) of the target variable before and after splitting the data based on a particular feature. The idea is that a feature with high InfoGain splits the data into groups with low entropy (i.e., more predictable outcomes) compared to the groups before the split. In RF, multiple decision trees are trained on different subsets of the data, each using a random selection of features. InfoGain is then used to rank the importance of the different features across all the trees. The idea is that features with high InfoGain across multiple trees are likely to be more important for predicting the target variable than features with low InfoGain. By using InfoGain to select the most important features for predicting the target variable, RF can reduce overfitting and improve the accuracy of the model. This can be expressed as follows:

$$Gain(T,A) = Info(T) - Info_A(T) = -\sum_{i=1}^{K} \theta_i log_2(\theta_i) - \sum_{i=1}^{K_A} \frac{|T_i|}{|T|} Info(T_i) \quad (1)$$

where θ_i denotes the fraction of examples in T that belong to a class C_i. The constraint of InfoGain is that features with the biggest values may be most elevated, leading to the GainRatio in the C4.5 process. This can be formulated as:

$$GainRatio(T,A) = \frac{Gain(T,A)}{SplitInfo(T,A) = -\sum_{i=1}^{K_A} \frac{|T_i|}{|T|} log_2 \frac{|T_i|}{|T|}.} \quad (2)$$

The Conditional Holt-Winters (CHW) model is then used as a time-series forecasting technique that extends the classical Holt-Winters model by adding a conditional component. The conditional component considers external variables that may affect the time series, allowing the model to capture more complex relationships and improve forecasting accuracy. The Holt-Winters model is a popular method that uses exponential smoothing to generate forecasts. It works by estimating the level, trend, and seasonality of the time series and using this information to forecast future values. The conditional component is added by including the external variable(s) as additional input(s) to the model. The external variables are assumed to be related to the time series in a linear way, so the model estimates the coefficients that describe this relationship. The estimated coefficients are then used to adjust the forecasts generated by the Holt-Winters model, considering the effect of the external variables. The CHW model is particularly useful in inventory management systems, where external variables such as promotions, advertising campaigns, or economic indicators can have a significant impact on demand. By incorporating these variables into the forecasting model, the CHW model can generate more accurate and reliable forecasts, which can be used to optimize inventory levels and reduce costs. In CHW, the smoothing of each predictor at time t was not just made in time, but, also by the allowance of the observations based on the Euclidean distance between x_t and $\boldsymbol{x}_i$. The weights are computed as follows:

$$v_{x_i}(x_t) = V\left(\frac{||x_t - \boldsymbol{x}_i||}{h(\boldsymbol{x}_i)}\right) \quad (3)$$

According to[16], a tri-cube kernel is employed to decide the weights, as follows:

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$$V(u) = \begin{cases} (1-u^3)^3 & \text{if} u \in [0;1) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The vigorous CHW method hence contains a total of M models, for which the essence edition of the update mechanism is calculated as follows:

$$\mu_{t,i} = \mu_{t-1,i} + \alpha_{\mu}^{(\text{eff})}(t,i) g(\varepsilon_{t|t-1}, \tau) \quad (5)$$

$$S_{t,i}^{(1)} = S_{t-s_1,i}^{(1)} + \alpha_{S^{(1)}}^{(\text{eff})}(t,i) g(\varepsilon_{t|t-1}, \tau) \quad (6)$$

$$S_{t,i}^{(2)} = S_{t-s_2,i}^{(2)} + \alpha_{S^{(2)}}^{(\text{eff})}(t,i) g(\varepsilon_{t|t-1}, \tau) \quad (7)$$

5. Results and Discussions

This section encompasses the experiments conducted in this study. So, this section is divided into subsections as follows.

5.1 Correlation analysis

A correlation heatmap is a technique used to visualize the correlation between different variables in a dataset. It involves creating a matrix of values that shows the correlation coefficient between each pair of variables. In our experiments, the Pearson correlation coefficient is computed to measure the linear relationship between two variables. Fig 4 visualizes the correlation matrix in the form of a heat map that uses different colors to represent different levels of correlation. As shown, the correlation map analysis provides useful insights regarding the patterns and relationships in inventory data and can be used to guide further analysis and modeling in our system. Since the weather, the unemployment rate, and the consumer price index have little bearing on weekly sales, we ignore them. There is also a strong relationship between Markdown 4 and 5, and Markdown 1. We decide to join them in abandoning them. Potential for a multicollinearity issue to arise, hence, we shall function without them.

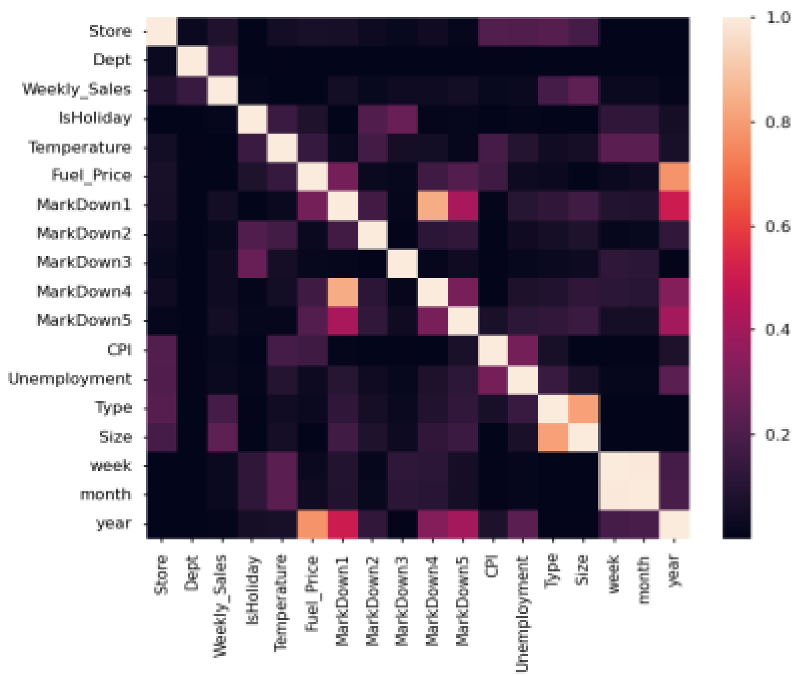

Figure 4: Visualization of the correlation map of Walmart data in the proposed system.

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5.2 Feature analysis

Feature importance analysis is a process of identifying which features or variables in a dataset have the most significant impact on the target variable or outcome. It is an essential step in many data inventory optimization tasks, such as predictive modeling, classification, and clustering. By identifying the most important features, we can gain insights into the underlying factors that drive the outcome of interest and improve our understanding of the data. Fig 5 displays the importance of the features in Walmart data. This knowledge can be leveraged to improve and optimize decision-making in the inventory system.

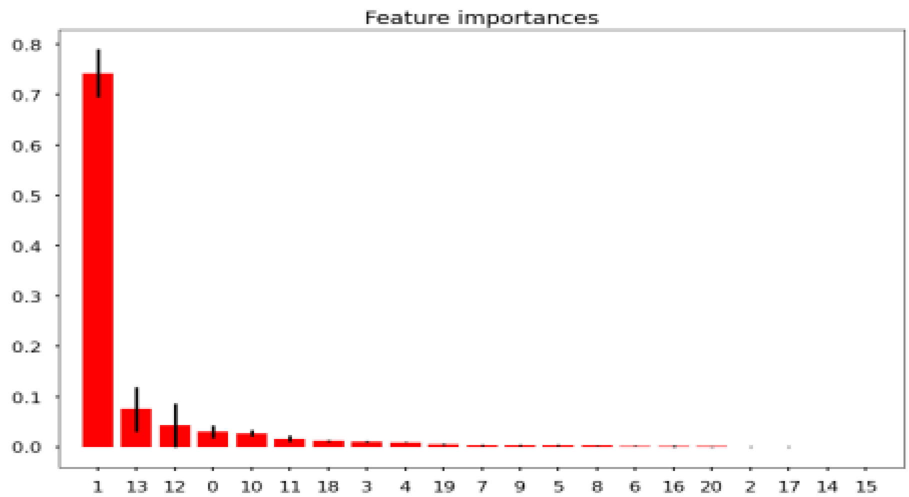

Figure 5: Visualization of the feature importance for Walmart data in the proposed framework

5.3 Comparative analysis

Comparative analysis is an essential step for evaluating and comparing the performance of different regression models in predicting a continuous numerical output based on input features. Table 1 shows the numerical comparison between the performance of the proposed model against the competing ML models on the test data. The objective of the comparative analysis is to identify the best-performing regression model that provides the most accurate and reliable predictions for optimizing inventory. This helps in making informed decisions and developing effective solutions for various tasks of inventory management. As shown, our system can provide the best prediction performance overcoming all methods.

Table 1: comparative results between the proposed model against the competing ML models

ML technique	WMAE
Support vector regressor	2150.31
Neural regressor	2013.82
Decision Tree	2102.44
RF	1623.67
CWH	1887.54
Proposed	1433.21

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Table 2: Quantitative results were obtained from the ablation experiments of the proposed system.

Model	Ablation	WMAE
V1	w/out divided holiday columns	4253.66
V2	w/out month column	3486.34
V3	Entire dataset	2161.25
V4	Entire dataset with feature selection	1801.33
V5	Entire dataset with feature selection w/out month	1433.21

5.4 Ablation analysis

Ablation analysis is performed in this part of our work to understand the contribution of different components or features of our system. It involves systematically removing or disabling one or more components or features of the system and observing the effect on the overall performance or behavior. Table 2 displays the numerical results of ablation analysis to study the effect of removing a specific feature of data or preprocessing steps. As shown, the lost prediction error can be attained under the fifth version of our model, while the highest prediction error is achieved by the first edition of the proposed system.

6 Conclusions

This study exploited the phenomena of revolution 4.0 in the industry which represents Ind 4.0 and its ability to eliminate human intervention with automation and smart. So, we merged ML techniques as a subset of AI with DSS to construct IDSML to manage and optimize InvM. ML techniques area useful approaches for accurate prediction of sales and improving inventory management. By combining the predictive power of RF and CHW, an ensemble can often provide more accurate and robust predictions than any individual model alone. With this design, our constructed framework can assist businesses in better anticipating customer demand and optimizing their inventory levels to avoid stockouts and overstocking. However, it is important to continually monitor and refine our framework over time to ensure it remains effective as market conditions and customer behaviors change. Our framework can be a valuable tool for businesses looking to improve their inventory management and optimize their operations for greater efficiency and profitability.

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