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DESIGNING THE SMART WAREHOUSE: KEY AUTOMATION CRITERIA FOR SUSTAINABLE AND SCALABLE OPERATIONS

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Naveen Chandra Kukkala
University of the Cumberlands, Project Management, Management Sciences, Williamsburg, Kentucky, USA.
naveen_chandra123@outlook.com, ORCID: 0009-0000-3346-3405

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ABSTRACT

Purpose- Warehouses face challenges due to rising demands for efficient, sustainable, large-scale operations, making automation essential for enhancing processes and reducing costs. This paper compares three automation models LSTM, Prophet, and Logistic Regression that can improve warehouse management, particularly in sales forecasting and reorder prediction.
Methodology- Using actual warehouse sales data from Kaggle, time-series models (LSTM and Prophet) were built for daily sales forecasting and Logistic Regression for reorder quantities on each item. The models evaluated each model's ability to project warehouse sales and determine replenishment timing.
Findings- Results suggest that LSTM provided better forecasting results than Prophet, with lower MSE, RMSE, and MAE values, modelling both short-term volatility and long-term trends. Logistic Regression showed high accuracy and decent precision, though low recall suggests it missed many reorder cases.
Conclusion- While LSTM models can improve decision-making in warehouse management, further development of classification models is essential to enhance reorder prediction accuracy, increase recall, and prevent stockouts.

Keywords: Warehouse management, automation, LSTM, reorder prediction, inventory management, smart warehouses
JEL Codes: M11, C53, O33, L91

1. INTRODUCTION

The rising nature of the operational complexity of supply chains has made it necessary to invest in smart warehouses built on automation (Coito et al., 2021). Smart warehouses are facilities with the purpose of organising work, minimising people's mistakes, and maximising productivity by employing different techniques and technologies, including for the organisation of goods flow and storage (Plakantara et al., 2024). Today, there is pressure for time, an increase in the volume of products transported, and a reduction in operational costs for modern logistics. Moreover, sustainability has emerged as a significant factor since organisations aim to minimise expenditure, rein in expenses, and reduce operating expenses such as wasting energy and increasing general impact on the environment (Khan et al., 2021). Another is scalability since as warehouses' operations scale up other systems, there must also be an increase in scale without compromising on effectiveness.

Technologies in automation, including robotics, IoT, AI, and machine learning, are making changes in conventional warehouses (Dhaliwal, 2020). Robots have specific uses in scaling up repetitive and manual tasks such as picking, packing, and moving goods. IoT facilitates monitoring and tracking of inventory and stock, machinery, and the conditions inside and outside the warehouse in real time (Khan et al., 2022). Machine learning (ML) and AI solutions are being applied to solve prediction of sales, equipment failure, and stock management problems (Khedr, 2024). These technologies combined make up the foundational need for smart warehouses as companies seek to increase efficiency and remain agile. Despite the advancements in automation, many warehouses still need help with three key issues: forecasting capability, stock management, and the effectiveness of reordering choices. Stock forecasting is the most sensitive aspect in order to avoid overstocking or lack of stock in future businesses (Kourentzes et al., 2020). Time management of stock facilitates the correct organisational placement of stocks so that they only take up a little space. Reorder decisions are so crucial in inventories that they can be achieved that they must stick out, but at the same time, they must not overstock (Upadhyay, 2024).

Most prior work has concerned itself with the universal application of automation technologies. Still, very little research has comparatively investigated the performance of various forecasting models to verify the effectiveness of some forecasting models for sales and inventory of warehouse products (Fildes et al., 2022). The majority of prior studies are more concerned with discussing and promoting the use of automation systems. To the authors' best knowledge, there is little research comparing multiple time series forecasting models (including LSTM and Prophet) or decision-making models (such as logistic regression) for reorder prediction (Ahmad et al., 2025). More studies are needed to compare and assess predictive models in regard to warehouse automation. Consequently, more research needs to be done that engages LSTM and Prophet in direct time-series forecasting of warehouse sales. In addition, as for the warehouse environment and prediction of guiding reorder points, logistic regression, usually used in classification tasks, needs to be given adequate attention in research (Liu, 2022). This has made it necessary to undertake a comprehensive comparative analysis of the forecasting and decision-making models in the warehouse environment.

The main focus of this paper is to fill this gap by comparing the LSTM and Prophet models for warehouse sales forecasting, as well as the logistic regression for the reorder point prediction. Warehouse data collected from Kaggle is used in this research to assess the efficiency and reliability of these models to automate primary warehouse functions. In other words, the paper's objectives are as follows: To establish which type of forecasting model, LSTM or Prophet, yields a more accurate sales forecast for warehouses and whether Logistic Regression is useful for anticipating reorder points. This study has important practical implications for companies managing smart warehouses. It becomes important for firms to know which of the models used in forecasting is more reliable in order to improve their decision-making in factors such as stock control, hence enhancing their operations while at the same time slicing costs (Tadayonrad & Ndiaye, 2023).

2. LITERATURE REVIEW

2.1. Automation in Warehousing

Technologies have infiltrated almost every aspect of warehousing and minimised human participation (Shozi, 2021). A key technology is ASRS, with robotics and IoT sensors also being significant (Jie et al., 2024). ASRS makes direct and random storage and access to stored items possible and more efficient, eliminating expatriate labour costs. It will be beneficial for managing extensive stock quantities across expansive warehouses where first accuracy and second speed are paramount. Robotics complement warehousing by automating some crucial tasks such as picking, sorting, and packaging (Merkert et al., 2023). Human employees can operate in partnership with robots like AGVs and robotic arms for different repetitive assignments (Grau et al., 2020), which are likely to be accomplished more efficiently by them.

Smart sensors, through the IoT (Internet of Things), have a crucial function in measuring inventory and monitoring the delivery process, as well as controlling the environment, including the temperature and humidity of stored products (Ding et al., 2021). In its essence, IoT does more than enable continuous collection and analysis of data, which in turn thus assists warehouse managers in the deployment of resources and optimal utilisation of equipment and other aspects related to operations (Kumar et al., 2022). These technologies, along with machine learning algorithms, are basic ones for constructing smart warehouses where technology plays a vital role in getting automated control and data analysis (Van Geest et al., 2021).

2.2. Sustainability in Warehousing

Due to increased awareness of the effect of the natural environment on executive decisions, sustainability issues have now gained significance in warehousing (Hao et al., 2020). The four principles of green and sustainable warehouse management include conserving energy and avoiding wastage while embracing environmental conservation measures. Warehouse lighting and climate control systems, lighting control systems, and other such energy-efficient systems decrease the levels of carbon emission (Füchtenhans et al., 2023). Also, the layout of warehouses and automated operational systems can be optimised to decrease energy use since distances of transport within warehouses can be minimised, thereby decreasing fuel usage and, therefore, emissions. Several measures are observed in the sustainability of a warehousing business; one of them is waste management. AI-driven tools also minimise overstocking, and fewer perishable items are wasted since the goods are moved through the supply chain faster (Şimşek, 2024).

2.3. Time-Series Forecasting in Warehousing

Forecasting plays a crucial role in warehousing since it reflects the prediction of the demand for a specific item (Irhami & Farizal, 2021). On this object, time series forecasting models have a vital role in predicting the sales rates for further periods, controlling the inventory, and devising manufacturing schedules (Tadayonrad & Ndiaye, 2023). Earlier well-known methods, such as ARIMA (Autoregressive Integrated Moving Average), have been used for forecasting using only past data (Rafferty, 2021). This makes ARIMA suitable for short-range forecasting, in particular, because it needs help modelling trends in the data over very long periods. To overcome this limitation of the above models, new models have been developed in recent years, such as Prophet and LSTM models. Obviously, Prophet, furthering from Facebook, can work well with customised data that contain seasonality and missing data that can be desirable in warehouse sales forecasting with cyclical trends (Güler et al., 2023). Certainly, the Prophet works best in cases where the fluctuations are typical for certain seasons, such as in the case of holiday sales; for instance, the model can include external factors, such as holidays and promotions (Tang et al., 2022).

Long short-term memory (LSTM), which is one of the RNNs, is designed to handle temporal data well and, therefore, is the best model for forecasting over longer periods (Vennerød et al., 2021). LSTM is particularly advantageous in dealing with a sequence of data, which is helpful in warehousing since the sequential record of sales is useful in modelling the pattern of demand (Joseph et al., 2022). It excels at this because of its convolution property, which takes into account patterns that span many time steps as opposed to other models such as ARIMA or Prophet.

2.4. Inventory Reordering and Optimisation Models

The assessment of the right time to order more stock is a very vital factor in warehouse management (Sugiarto & Suprayitno, 2023). Some of the popular forecasting algorithms include Logistic Regression, decision trees, and random forests when determining reorder points to improve stock replenishment (Seyedan, 2023). Logistic regression can be used for binary classifiers, for example, if it is or is not time to reorder a product through the evaluation of previous sales and current stock (Ntakolia et al., 2021). Even though straightforward, Logistic Regression remains a benchmark for other complex models, and it is easy to use.

Decision trees and random forests, on the other hand, have more complex models for inventory management undertaking since they can capture nonlinear relations between the variables (Supsermpol et al., 2023). As a form of predictive model, the decision trees sort the data with the help of if-then rules, which can be helpful in determining reordering decisions (Dhebar & Deb, 2020). Random forests, as an extension of decision trees used in the ensemble method, prevent overfitting and help to take into account other factors influencing the likelihood of reorders, including suppliers' performance, time required for delivery, or climate fluctuations (Svoboda & Minner, 2022).

The applied nature of these models in stock management is that they help to avoid overstock of products, situations when products are out of stock, and to determine the right time for restocking (Upadhyay, 2024). Compared to the conventional methods of decision-making, the ML tool helps in making better and more automated decisions by integrating real-time data and thereby improving the functionality of the warehouses against fluctuations in the demand load patterns (Hassan & Mhmood, 2021). When the new models are implemented into smart warehouses, they will help improve the efficiency as well as sustainability of the warehouses.

3. METHODOLOGY

3.1. Dataset

The data used in this work originates from Kaggle https://www.kaggle.com/datasets/kirbysasuke/retail-sales and consists of historical data of sales in a made, both at retail and in a warehouse. The data includes such attributes as item types, supplier details, and sales values by period. Retail sales refer to sales from the retail vendors, and warehouse sales depict the direct sales of the warehouse. Further, data on suppliers is included in the dataset, as well as the description of every item and its type, whether it is wine, beer, and so on – all this data is essential for analysing tendencies and forecasting further sales and subsequent reorders. The given set of data offers great opportunities for the creation of not only pure time series forecasting models but also for classification models to predict reorders.

3.2. Data Preprocessing

Before model development, the dataset was preprocessed to remove any unwanted data or data that was not fit for use. First, the observations with a lot of missing data were excluded, or if the data were records, the missing data were replaced with median values in continuous data. Subsequently, categorical features like the supplier names were converted into integers with Label Encoding to facilitate subsequent training of models. This step was crucial for the chosen Logistic Regression model as this model accepts numerical input only. Further, the normalisation of sales data was done to scale all features. This was vital in the LSTM and Prophet modelling since differences in scalas may significantly impact the results. In the end, again, the dataset was divided between training and testing data sets with a view to checking the performance of the models.

3.3. Model Development

Long Short-Term Memory (LSTM) neural network is a subcategory of Recurrent neural network tools (Muhuri et al., 2020). Recurrent neural networks specifically facilitate the processing of time series data by keeping track of the previous time step information (Wang et al., 2022). In this study, LSTM was used to forecast sales for the future warehouse using previous sales records. In the construction of the model, the input data were sequential, and the LSTM layers were tasked with processing the temporal data. In the process, each time step in the sequence gave a temporal dimension of sales data within the given period and enabled the model to learn from previous sales. Multiple layers were used to capture long-term dependencies in the LSTM architecture. Next, the model was developed, the results of future sales of the test set were determined, and patterns were searched to enhance the standards for future inventory and operation planning.

3.4. Prophet Model for Time-Series Forecasting

This work also used the Prophet model, a model developed by Facebook, to compare it with LSTM. Prophet is a tool developed for time series that includes seasonality, trends, and holidays (Stefenon et al., 2023). The premise of the method is that a given time-series data is decomposed into these components, and a separate model for each of them is applied. Prophet is most useful when data contains fluctuations accompanied by cycles, making it suitable for warehouse sales that may slightly differ with seasons or promotions. Credibly, two of Prophet's strengths include its capability to deal with missing observations and its capability to provide forecasts for models that possess uneven gaps within a time series (Rafferty, 2021). In this case, Prophet was trained on the same set of sales data, which was used to develop LSTM, and Prophet model performance was determined based on the forecast of future warehouse sales.

3.5. Logistic Regression for Reorder Predictions

Logistic regression was implemented as a binary classifier to determine when a reorder should be fier. The control variable was whether a reorder was required or not, depending on the level of sales and other comparable factors, such as the type of item and from which supplier. Logistic regression is a common technique used to predict binary data. In this case, logistic regression was used to determine if the stock levels had fallen below the required reorder point. These were the feeds used in the model: the warehouse sales feed, the retail sales feed, and the encoded supplier feed. Finally, the model predictions were tested on the test dataset to measure its efficiency in forecasting reorder points, which are valuable tools for determining the right inventory levels.

3.6. Evaluation Metrics

For LSTM and Prophet (Regression Models)

The performance of both forecasting models was evaluated using three key metrics:

Mean Squared Error (MSE) - Sums up the squared difference between the observed and the estimated values to realise the total amount of variance or error of the model used (Chicco et al., 2021).

Root Mean Squared Error (RMSE) - The square root of MSE provides an interpretation of the same scale as in the initial raw data measurement [40].

Mean Absolute Error (MAE) - Gives an idea of how well the model performed or how accurate the forecast was by averaging the absolute difference between a given model's estimate and the actual value (Chicco et al., 2021).

For Logistic Regression (Classification Model)

The classification model for reorder prediction was evaluated using the following metrics:

Accuracy - The proportion of all reorder decisions predicted out of all the total predictions.

Precision - The relative number of reorders that was given as positive, the ability of the model not to produce false positives.

Recall - The rate of actual reorders within the model, which is the capacity of the model to predict all needed reorder cases.

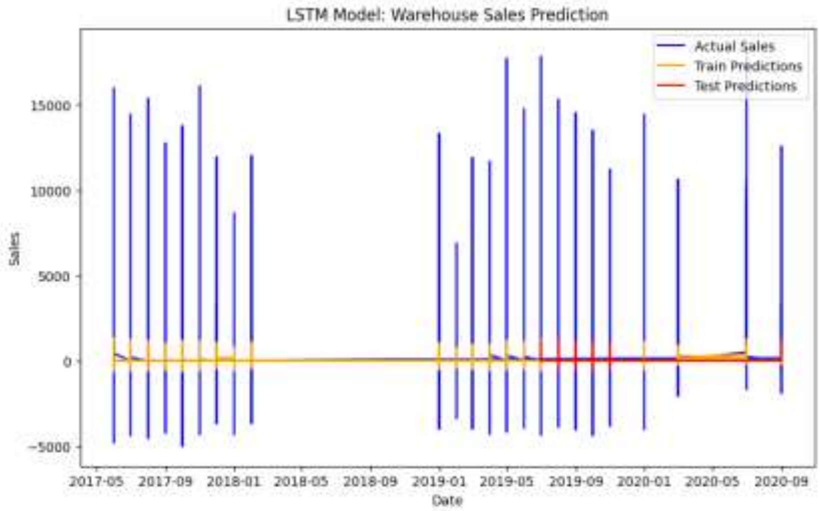
F1-Score - An average of the precision and recall measures, taking into consideration the importance of both false positives and false negatives, gives a high overall level of detail for the model.

4. RESULTS

4.1. LSTM

A line graph employed showing the actual sales and sales forecast from the LSTM model shows the extent of the forecast's accuracy. The plot also reveals that the model has been able to correctly estimate fundamental variations in the sales volumes, such as changes in rising trends or downward movements and fluctuations that are experienced seasonally.

Figure 1: LSTM Model: Warehouse Sales Prediction



The graph of the sales forecast from the LSTM model displays the model's competency in tracking the path of actual sales, which is extremely helpful in forecasting the demand for the warehouse's operation.

From the MSE, RMSE, and MAE, it is clear that the LSTM model achieves a fair level of predictability. Reducing the forecasting error of the LSTM makes it an efficient tool for sales forecasting, especially in warehouses, where the accurate prediction of sales is critical for strategy and inventory management, as shown in Table 1.

Table 1: LSTM Model

Model	MSE	RMSE	MAE
LSTM	71,107	266.66	36.02

Figure 2 shows a comparison of Prophet's customised forecast and the LSTM model, along with the sales that occurred from January 2017 to March 2020. Though Prophet performs well and is in line with the average trend, it sometimes falls short of LSTM in picking spikes or drops in sales. The analysis of the Prophet Sales Forecast Plot reveals that while Prophet serves to capture broad features, it fails to provide the same level of detail in short-term fluctuations in sales as provided by LSTM. Prophet's MSE, RMSE, and MAE indicate Prophet's lower accuracy than LSTM in this particular dataset. Prophet suits scenarios where large trends are more dominant. Still, when it comes to warehousing, where day-by-day or weekly fluctuations come into play since LSTM captures such short-term variations, it is the better model in this instance, as shown in Table 2.

Figure 2: Prophet Forecast for Warehouse Sales

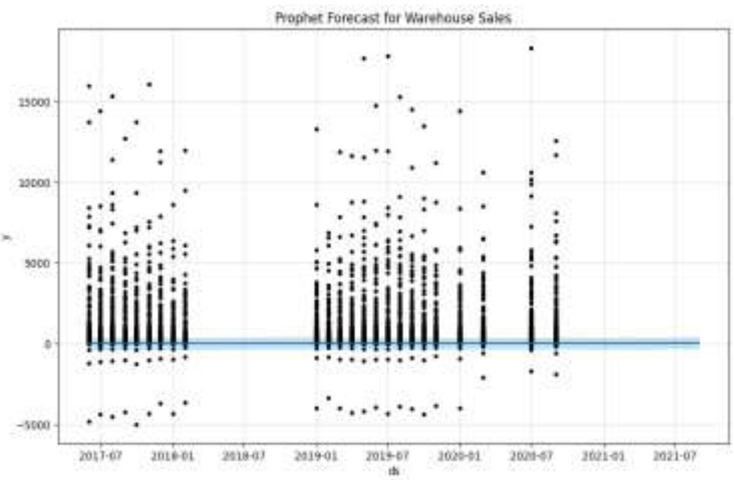


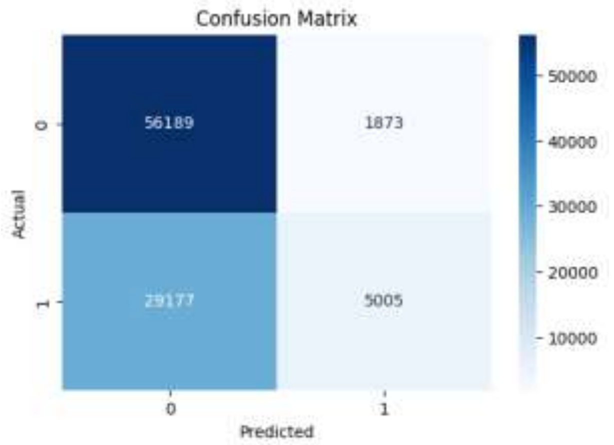
Table 2: Prophet Model

Model	MSE	RMSE	MAE
Prophet	73,687	271.45	46.45

4.2. Logistic Regression

Several binary Logistic Regression models were developed to determine if a reorder is needed with sales information and other variables like supplier details. Analysing the results of the work, the paper used the confusion matrix provided below to find out how many reorders were correctly and incorrectly predicted by the model. The matrix describes the true positive framework consisting of correct reorders while the false positive framework consists of over-reordering; the true negative framework is properly reordered, while the false negative framework is under-reordering.

Figure 3: Confusion Matrix



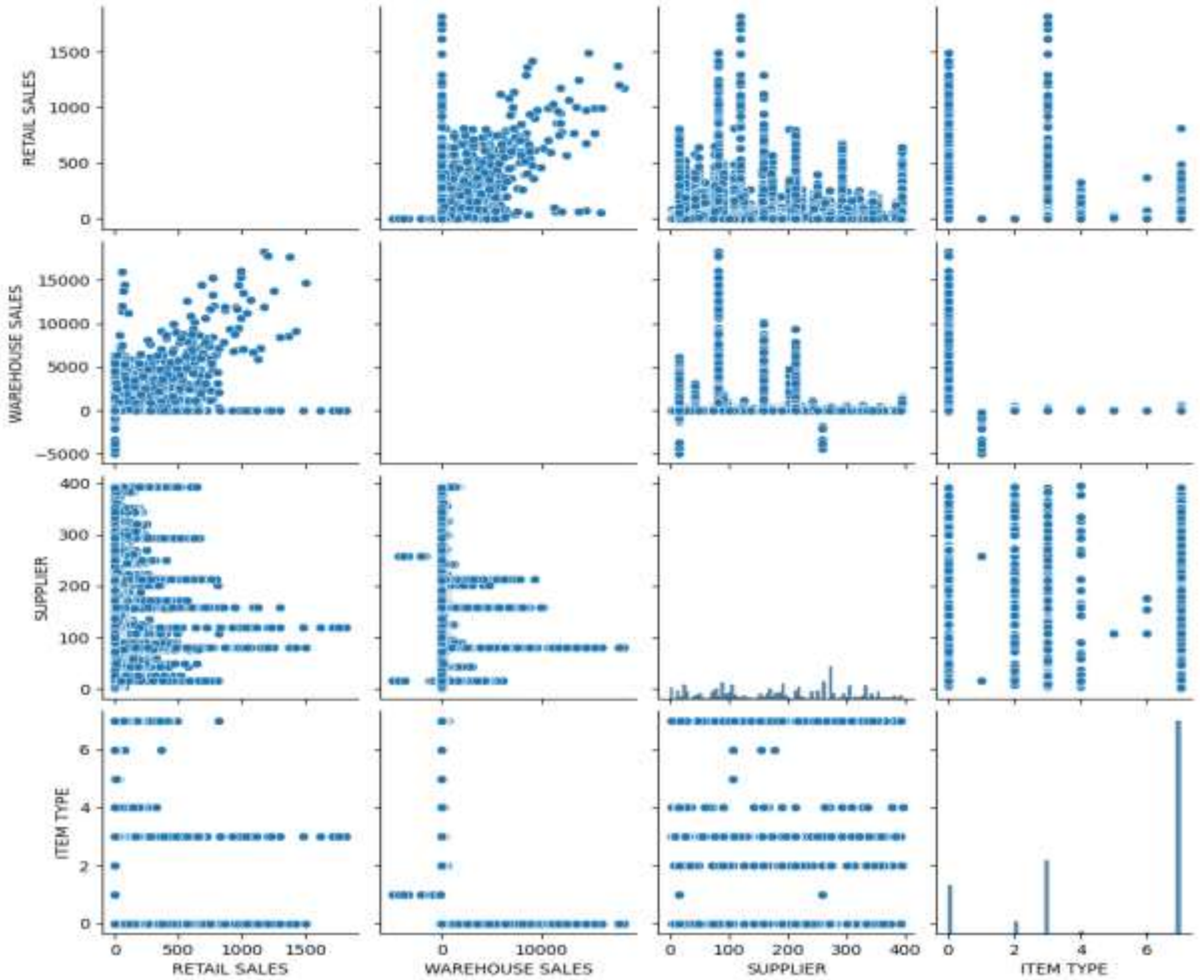
The Confusion Matrix for the Logistic Regression model shows high degrees of accuracy in cases where a reorder is not needed. Still, there are low values in cases where the reorder is needed, meaning the model has several false negatives. Relatively more error is seen in terms of low recall, 14.64%, which suggests here that many times, necessary reorders are being missed, hence acting as a false negative. This is a significant area for improvement in the model, especially in predicting reorders due to labour restrictions of the existing model. Precision indicates that if the model gives a reorder point, which in its case is often accurate, then it is helpful in providing the right time to reorder. However, this is hampered by the fact that the model needs to identify all reorders necessary to maintain optimal stocks, as shown in Table 3.

Table 3: Logistic Regression

Metric	Value
Accuracy	66.34%
Precision	72.77%
Recall	14.64%
F1-Score	24.38%

The logistic Regression model's low recall highlights a significant limitation: the shortcoming of the model is that it fails to identify that a reorder is needed in some cases, leading to stockouts. These results imply that there are other models that better estimate the shorthand to the curr logistic regressions model. In future work, decision trees or ensemble models are more suitable for this classification task. The overall pair plots is depict in Figure 4.

Figure 4: Pairplots



5. DISCUSSION

The LSTM model was more accurate in warehouse sales forecasting because it possessed architectural benefits over the Prophet model. LSTM stands for Long Short-Term Memory, and it is intended to work well with complex and nonlinear data by preserving the memory over length. This enables LSTM to capture both long and short-term patterns of sales, which are especially important when determining demand in a warehouse setting that is frequently influenced by short-term specials and seasonality, amongst other factors. LSTM is able to model the underlying patterns in the data over multiple steps of sales behaviour to learn from and store for the next forecast period, making LSTM a model that is superior to some of the simpler time-series models.

On the other hand, Prophet, while being good at capturing seasonality and trends, needs to capture short-term variations. Prophet works well to break time-series data down into trend, seasonality, and holiday features, which is most helpful when making long-term forecasts in situations with less volatility. However, its use of linear trends and additive components undermines its effectiveness at estimating disparities, especially where there is rapid non-linearity, which is a common factor in the sales of a warehouse. While Prophet is more appropriate when it comes to forecasting stable and rhythmic uplifts like seasonal variations, the fluctuation in the sales pattern is more complex than what Prophet can provide with LSTM.

It took a lot of work to implement the logistic regression used in the prediction of reordering points, too. While the first metric gave decent precision, the second value needed to be higher, meaning a lot of cases where a reorder should have occurred were missed. However, Logistic Regression, which falls under the class of linear classifiers, fails to model intermediate-level interactions between the multiple factors that come into play when reordering decisions are made, such as supplier delays, changes in sales, and lead times. Consequently, it had a lower accuracy in predicting all required reorders, which is crucial for efficient stock management to be performed in the warehouse.

Implications for Smart Warehousing

The findings emerging from the study have significant implications for the development of effective and efficient smart warehouses. As shown by the LSTM model above, the right sales forecasting can improve several management decision-making activities. In other words, warehouses are able to set and order stock in a manner that caters to demand without the pitfall of overstocking the warehouse. This not only dramatically cuts down on unnecessary inventory but also prevents a potential scenario of stockouts, a scenario which can severely inconvenience business operations and cost potential sales. In addition, it helps in efficiency through improved resource positioning or employment, such as labour and space for storage, thereby contributing to a successful and growing warehouse business.

The drawback in the reorder prediction made by Logistic Regression implies the prospects of other elaborate classifiers in smart warehouses. This paper also showed that the reordering point is essential for the continuous flow of resources and that wrong forecasting is likely to lead to stockouts or delayed and excessive inventory holding costs. Random forests or gradient boosting are two more complex models able to spot curvilinear relations between features, enhance the reorder point's accuracy, and enhance the procedures controlling inventory.

6. CONCLUSION

In this paper, LSTM, Prophet, and Logistic Regression models were used to analyse the warehouse sales prediction and reorder points. The study showed that LSTM gave better sales forecasting than Prophet, giving smaller errors and a better ability to track short-term oscillations. The fact that the LSTM model can perceive both long-term tendencies and much-sophisticated nonlinear dependencies gave it the upper hand and put it in the position of the best-perfecting model of sales forecasting in the context of dynamic warehouse conditions. Prophet is a good model for measuring cyclical patterns and trends, but it has low short-term forecasting errors. Regarding reorders, specifically Logistic Regression provided adequate accuracy; however, it had very low recall. That is, it omitted numerous critical reorder situations, which is detrimental to managing stock.

The study also has broad practical relevance to the design of smart warehouses. LSTM, as an operational AI tool, more specifically, can improve existing alternatives by raising the accuracy of sales predictions, which, in turn, makes the process of demand forecasting and stock control more effective. It also means less waste, appropriate stock management, and regular restocking, and it is helpful in sustaining and growing warehouse departments. Warehouses can enhance their service quality without creating negative environmental effects such as stockouts and excessive stock.

However, this study has some limitations. It only provide an idea about one that operates a single warehouse, which restricts the scope of the dataset heavily. Secondly, the recall of the Logistic Regression model is low, and this means that there is merit in the use of superior techniques in the classification of products that have to be reordered. Further studies aiming at extending outcomes using deep reinforcement learning to adapt inventory stock correspondingly and investigating additional accurate neural network models or population modes for enhancing the predictive performance in forecasting and classification are also suggested. These advanced models could give much better real-time approaches to handling stock within intelligent warehouses.

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