2024 Second International Conference on Advanced Computing & Communication Technologies (ICACCTech) | 979-8-3315-1905-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICACCTECH65084.2024.00020

Implementation of models for Demand forecasting for e-commerce using time series forecasting

Narinder Yadav
Assistant Professor CSE
Chandigarh University,
Mohali(140413),India
narinder.e16474@cumail.in)

Abhishek Roushan
Department of CSE
Chandigarh University
Mohali(140413),India
22BCS10187@cuchd.in

Vatsala Singh
Department of CSE
Chandigarh University
Mohali(140413),India
22BCS10028@cuchd.in

Neha Kumari
Department of CSE
Chandigarh University
Mohali(140413),India
22BCS10009@cuchd.in

Diksha
Department of CSE
Chandigarh University
Mohali(140413),India
22BCS10493@cuchd.in

***Abstract*- The study delves into the significance of demand forecasting within the e-commerce realm, crucial for businesses to anticipate future customer needs and optimize inventory management and resource allocation strategies. Focusing on employing time series forecasting methodologies, specifically XGBOOST and SARIMAX (Seasonal AutoRegressive Integrated Moving Average with exogenous factors) models, the research aims to predict demand accurately in e-commerce scenarios. By analyzing historical sales data and integrating pertinent external variables like promotional events and seasonal trends, these models endeavor to forecast forthcoming demand trends for a variety of products or services offered by e-commerce platforms. The investigation scrutinizes the intricacies of the XGBOOST and SARIMAX models, highlighting their merits and limitations in the context of e-commerce demand forecasting. Moreover, the study assesses model performance using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to gauge accuracy and reliability in demand prediction. The SARIMA model deployed in this work has a MAPE value of 0.027 which is better than any previously formed SARIMA models on this particular dataset. The XGBOOST model implemented in this work has RMSE value of 2852.098 which is lesser than any of the work done on this dataset before. Also, the calculated accuracy comes out to be 98.348% for XGBOOST which is remarkable and is best on this data.**

Keywords-Demand Forecasting, Customers, Time Series Data, Customer behavior.

I. INTRODUCTION

In the realm of e-commerce, demand forecasting has become an indispensable aspect of business operations. It enables companies to anticipate forthcoming customer demands and optimize supply chain logistics accordingly. This introduction provides an overview of the historical evolution of demand forecasting in e-commerce. highlighting existing solutions employed by businesses to address this critical operational need. The trajectory of demand forecasting in e-commerce dates back to the nascent stages of online retailing when businesses primarily relied on basic methods and intuition to anticipate customer demands.

In a retail context, the demand forecasting problem involves accurately predicting the future demand for various products based on historical sales data and external factors. [3] In the automotive industry, a car manufacturer aims to forecast the demand for specific vehicle models and configurations. By analyzing sales of historical data, trends of market, economic indicators, and consumer preferences, the manufacturer can anticipate demand for vehicles such as sedans, SUVs, and electric cars. This helps the manufacturer optimize production planning, allocate resources efficiently across production lines, and adjust inventory levels at dealerships to meet customer demand while minimizing excess inventory and production bottlenecks.

For achieving the desired results we have taken "Walmart Sale Data" from Kaggle which consists of 4 datasets. These are **Features, Stores, Train** and **Test** The dataset comes from an American retail organization, Walmart Inc. The data includes information from 45 Walmart division stores, tracking their activities from 2010 to 2012, especially highlighting their weekly sales promotions.

The following figure shows the different attributes present in the **"features"** dataset,

979-8-3315-1905-6/24/$31.00 ©2024 IEEE
DOI 10.1109/ICACCTech65084.2024.00020

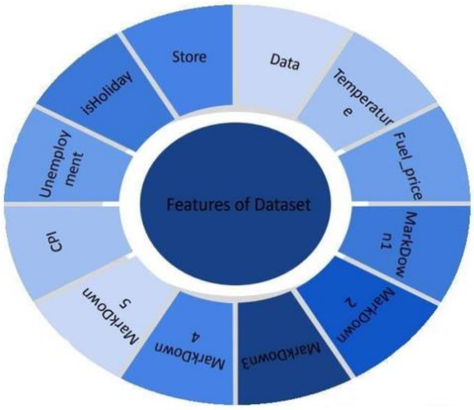

Figure 1: Features dataset [22]

The following figure shows the different attributes present in the **"stores"** dataset.

Figure 2: Stores dataset [22]

II. LITERATURE REVIEW

This part pertains to the existing study conducted by many scholars. The purpose of this section is to highlight and reinforce this information via the use of the provided Literature Review.
In the study, A. Abbaspour et al. [1] used five machine learning models, i.e., ANFIS, MLPNN, RBFNN, DWTNN, and GMDH, and the parameters to identify the best model were RMSE, MAE, and correlation coefficient. This leads to the conclusion that the RBFNN model had performed well with a score of 0.99176 in the interaction between targets and outputs. The study conducted by Arnab Mitra et al. [2] has compared the performance of five regression techniques, i.e., random forest (RF), extreme gradient boosting (XGBoost), gradient boosting, adaptive boosting (AdaBoost), and artificial neural network (ANN), with a hybrid (RF-XGBoost-LR) model, and for prediction, the ARIMA model has been used. The parameters in this study were mean absolute error(MAE), mean squared error(MSE), and R^2.

The study conducted by Koussaila Hamiche et al. [3] has discussed time series analysis, which is robust, model-free, and does not require any prior patterns to predict demand. This leads to the conclusion that for no trend, no seasonality (NT and NS) reaches 25.1% and 26.57%, respectively, and for other trends, the range is between 1.5% and 15%. The study conducted by Zeynep Hilal Kimichi et al. [4] has discussed an improved demand forecasting approach. This approach has used a deep learning approach with time series models and support vector regression models. The parameter used to calculate the efficiency of this approach was MAPE (mean absolute percentage error). This leads to the result of an improvement of 2.69% success rate in the MAPE.

In their research. M. Nasseri et al.[5] conducted a comparison between the demand prediction accuracy of tree-based ensembles and deep learning models based on CHE long-short-term memory (LSTM). The parameters for this calculation were MAPE, MAE.RMSE.R^2. The work done by Aamer et al. [6] reviewed the use of machine learning applications in demand forecasting. This leads to the result that neural networks artificial neural networks, support vector regression, and support vector machines were the best.

The study conducted by Batuhan Cocaoglu et al. [7] discussed models that are up-to-date and also discussed the impact of models in business. This leads to the conclusion that a %5 impact leads to an improvement to 1 million and 15 impact leads to 2.65 million. In the study, Majid Rafice et al.[8] machine learning is one of the most important parts for predicting demands, understanding customers, and collecting their feedback. By knowing the customer needs and purchasing behavior retailers can improve their strategies to meet the customer needs and can increase sales,
In the study, Gerald Reiner et al.[9] focuses on evaluating improvements in supply chain processes. It discusses the impact of forecast errors on the bullwhip effect and other performance measures. It also describes the evaluation model used from the reference dataset. In conclusion, time series models show the best performance in comparison to regression model and optimal performance across most models is seen with 20 observations. The study conducted by Carla Freitas Silveira Netto et al.[10] examines demand forecasting in marketing, focusing on common models, challenges with big data, types of data used, and areas for future research. It suggests exploring forecasting for durable goods, integrating diverse data sources, and maximizing the utility of location data without hindering implementation.
In the study, Ing. Andrea Kolková et al.[11] found that both deep learning and statistical methods were effective in predicting demand from e-commerce data.
Research conducted by R. Rathipriyal et al.[12]confirms that both shallow and deep neural networks are effective for forecasting demand in pharmaceutical companies. According to Loobna Terrada et al.[13] This study aims to improve demand forecasting using advanced Deep Learning methods like ARIMA and LSTM.
In the study, Akash Singh et al.[14] discuss Demand forecasting as it plays the most important part in demand. planning with supply chain management and also predict the future product performance based on past data. There were two types of data, Historical and forecast proportions, which were examined to enhance the accuracy. The study conducted by Tugay et al. [15] implemented stacked generalization, also referred to as stacking

ensemble learning, to forecast demand. Subsequently, they assessed all methodologies using authentic data obtained from the e-commerce enterprise. The null hypothesis was rejected in the ANOVA test at a significance level of 5%, indicating that the predictions made by Random Forest (RF) and Linear Regression (LR) are notably superior to those of other methods in the first and second levels, respectively

According to the research conducted by Smirnov et al. [16] they used information regarding the products demand from Ozon online marketplace. The algorithm's inputs consist of product attributes including price, name, category, and textual description. Regression challenges were addressed using different iterations of the gradient boosting algorithm, including XGBoost, LightGBM, and CatBoost. Currently, the forecasting accuracy stands at approximately 4.00. This system can operate autonomously or integrate seamlessly within a larger, more intricate framework. In their work. Alqatawna et al.[17] utilized time-series analyses techniques for forecasting the resource requirements of logistics delivery firms. This initiative facilitates the fulfillment of objectives and fosters growth. The SARIMAX model was identified as the top performer among the various methods evaluated. Across the UAE, KSA, and KWT regions, the SARIMAX model exhibited exceptional precision in forecasting order volumes and trends, with MAPE scores of 0.097, 0.158, and 0.137 respectively, along with corresponding RMSE values of 0.134, 0.199, and 0.215.

According to the work done by Moroff et al.[18] they implemented six distinct forecasting models from both statistics and machine learning and underwent evaluation concerning forecast accuracy and implementation complexity.

During this study, deep learning model Multi-Layer Perceptron (MLP) achieved the highest overall score of 81.9%. Following closely, the triple exponential smoothing model by Holt and Winters obtained the second-best value at 80.8%.

The research conducted by Feizabad et al. [19] introduces hybrid forecasting techniques, specifically Neural Network models and ARIMAX. The approach integrates both time series data and explanatory variables. According to the research conducted by Ho et al. [20] employs machine learning methods to forecast retail demand at IC Company across numerous products. The study conducted by Farzana et al. [21] examines a range of cutting-edge techniques for demand forecasting, with laying emphasis on machine learning.

III. METHODOLOGY

In this section of the study, the concentration is on the methodology employed for conducting Demand forecasting.

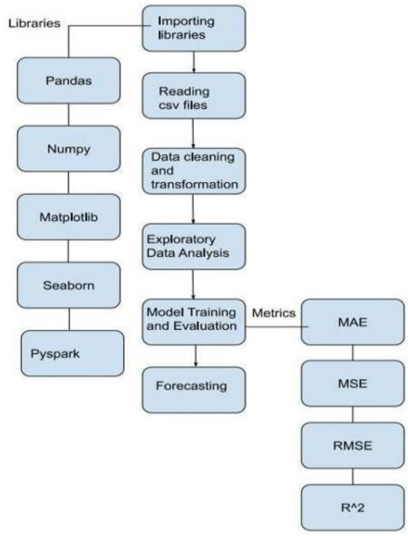

Figure 3 Methodology [22]

To target the problem specified related to segmentation of customer, 4 dataset has been taken from. Kaggle which were given by Walmart for sales forecasting and these were titled as **"Features", "Store", "Train", "Test".**

"Features.csv" consists of 421570 entries and contains the following information:

- **Store:** This column identifies each store uniquely within the dataset.
- **Date:** This column records the date of data collection.
- **Temperature:** This column shows the temperature recorded at the time of data collection, typically in Celsius or Fahrenheit.
- **Fuel Price:** This column indicates the fuel price at the time of data collection.
- **MarkDownl. MarkDown2, MarkDown3, MarkDown4, MarkDown5:** These columns represent different types of discounts or markdowns offered by the stores.
- **CPI:** CPI stands for Consumer Price Index, and this column contains the CPI value.
- **Unemployment:** This column shows the unemployment rate.
- **IsHoliday:** Column is a binary indicator (0 or 1) that indicates whether the date corresponds to a holiday.

“Stores.csv" contains this information:

- **Store:** This column serves as a unique identifier for cache store in the dataset, distinguishing one store from another.
- **Type:** In this column, the type or category of the cach store is specified. This categorization can include designations like "A." "B." or "C."
- **Size:** This column provides information about the physical size of each store.

In the first phase outliers, identified as weekly sales exceeding $200,000, were removed from the dataset to prevent skewing the model's predictions.

Handling Missing Values in Markdown Columns:

- In the code, missing values in markdown columns were handled by converting 'NA' strings to null values using PySpark's withColumn() and when() functions.
- After converting 'NA' strings to null, the null values were filled with 0
- Outliers in the data were identified based on the weekly sales exceeding $200,000.
- These outliers were removed from the dataset before model training using the query() method in Pandas, **Conversion of Categorical Columns to Numerical Values:**
- Categorical columns like store type ('A', 'B', 'C') were converted to numerical values ('0', '1', '2') for model training.

In the second phase, **exploratory data analysis** has been done on the data. This involves the following explorations:

- Stores are of three types: A, B, and C categorized on their sizes. Half of the stores, which are larger than 150,000, fall into the A category.

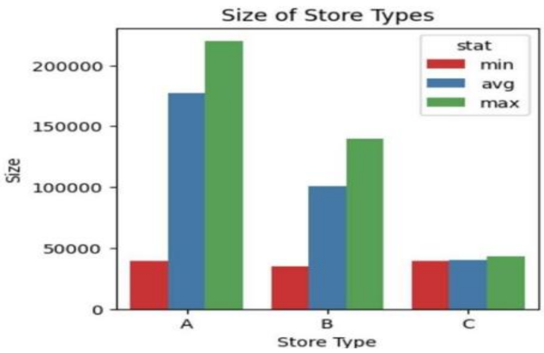

Figure 4: Size of Store Types [22]

- As anticipated, sales during holidays surpass those on regular days. The Christmas holiday marks the end of the year, yet shoppers typically flock to stores during the 51st week.
- January consistently records lower sales compared to other months, contributed to the increased sales during November and December.

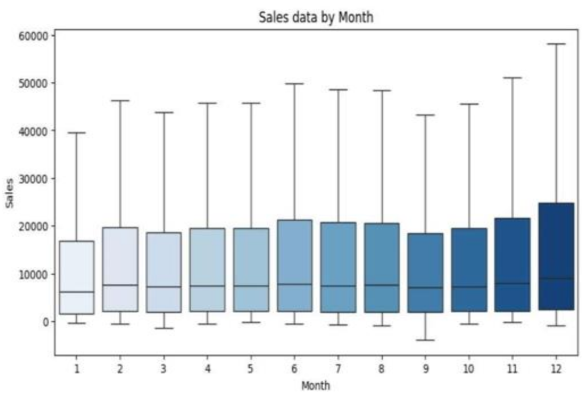

Figure 5: Sales data by Month [22]

- There is no discernible pattern between CPI, temperature, unemployment rate, and fuel price concerning weekly sales.
- Sales in 2010 surpassed those in 2011 and 2012. However, the absence of November and December sales data for 2012 does not significantly reduce its overall sales compared to 2010.

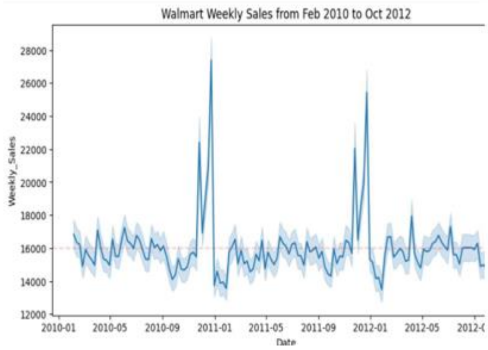

Figure 6: Weekly sales [22]

In the **third phase,** we implemented the **correlation matrix** for identifying the specific features which can be proved useful for our prediction. The correlation matrix provides correlation coefficients between pairs of numerical columns.

Most Correlated Columns:
MarkDown4 and MarkDown1: These columns have a high positive correlation, suggesting that they are strongly related.
MarkDownl and MarkDowns: These columns also show a positive correlation, though slightly lower than MarkDown and Mark Town). They may share some commonality in their influence on the dataset.
MarkDown2 and Temperature: These column exhibit a negative correlation, implying an inverse connection. This indicates that as one variable (MarkDown2) increases, the other variable (Temperatures decreases, and conversed.

Least Correlated Columns:
Fuel Price and Unemployment: These columns show a low correlation cline so 0, indicating there is no linear relationship between them.
CPI and Weekly Sales: The Consumer Price Indes (CPT) and Weekly Sales columns also exhibit a low correlation. implying that fluctuations in CPI do not have a strong linear impact on weekly sales in this dataset.
MarkDown and Mark Dewal: These columns show a relatively low correlation compared to other markdean columns, suggesting that they may have different patterns of influences on the dataset.
In the **fourth phase**, the two-time series **XGBoost** and **SARIMA** models are implemented

XGBOOST is an ensemble learning technique rooted in decision trees, celebrated for its super nice performance ass diverse machine learning tasks. In the data, capturing nonlinear patterns, and is robust to overfitting due to regularization techniques. In the given work, XGBoost was used to predict weekly sales Based on futures like store details, department, de

Holiday manus, and additional factors like temperance, fuel price, much towns, CPt, and unemployment..

SARIMA Model:
SARIMA is a time series forecasting model that integrates autoregressive (AR), differencing, and moving average along with seasonal patterns (S). This combination enables it to capture both trends and seasonal fluctuations present in the data. In the given work, SARIMA was used for overall sales forecasting, aggregating sales data across all stores and departments to predict future sales trends.
The results obtained from the SARIMA model were evaluated based on metrics like mean absolute percentage error ,mean absolute error and root mean squared error. The model's performance was assessed in terms of its ability to accurately forecast overall sales trends over time.

Neural Networks:
A neural network is a computational model inspired by the structure and functioning of the human's brain. It consists of interconnected nodes called neurons. The most common type of neural network is the feedforward neural network, which includes input layer, hidden layers and output layer.
Each neuron in a neural network processes data by performing a sum of the inputs, applying function to the result, and then it passes the output to the neurons in the next layer. The weights and biases associated with the connections between neurons are learned from data through a process called training, often using optimization algorithms like gradient descent.
Key challenges in training neural networks is to find the appropriate architecture and hyperparameters for a given task, as well as avoiding issues like overfitting or disappearing gradients.

Gaussian Processes for Regression (GPR):
Gaussian Processes for Regression (GPR) is a non-parametric, approach to regression analysis. It is used when we want to design complex, non-linear relationships between input variables and output variables.
GPR assumes output variable is Gaussian random variable with mean based on input variables, with covariance capturing uncertainty in prediction, crucial for underlying data patterns.
GPR provides flexibility estimating uncertainty and managing small data sets but it can be computationally expensive for large data sets. And performance depends on kernel functions and hyperparameters.

Comparison between SARIMA and XGboost:
SARIMA is computationally efficient for small to medium data sets. But there are problems with large datasets or multivariate time series. XGBoost is more computationally intensive. It requires more memory and CPU resources for large data sets.
SARIMA models struggle with missing data, impeding AR, MA or seasonal components. This results in inaccurate predictions. On the other hand, XGBoost is robust to lost dice. By learning the best way to deal with those dice.
SARIMA is a model that requires manual adjustment of parameters. This requires careful selection of parameters through inspection and diagnostic testing. There are fewer hyperparameters to modify, machine or work with more easily. XGBoost, on the other hand, has a more complex and flexible hyperparameter space.
SARIMA is suitable for linear and seasonal data. short term forecast and well-understood historical models. XGBoost is best suited for non-linear, high-dimensional data and multivariate forecasts. It is highly flexible and can handle complex interactions between variables. Rolling or is suitable for dice sets that do not follow a clear seasonal or linear pattern.

Hyperparameters for both the models
SARIMA and XGBoost are two machine learning models that use hyperparameter tuning to improve the accuracy and performance of the model. Sarima is defined by seven parameters: p (AR term), d (differential term), q (MA term), m (seasonal AR term), d (seasonal difference).), q (seasonal MA term) and m (seasonal quantity). These parameters play an important role in fitting time series data.

SARIMA tuning involves selecting the best combination of these parameters using various methods such as grid search, AIC/BIC parameters, ACF and PACF plots, cross-validation, etc. Grid search is A brute-force method for finding various combinations of hyperparameters, while AIC, the /BIC parameters penalize overfitting and help select simpler models with better performance. ACF and PACF plots analyze whether the point How are the data related at different delays? It provides insight into which late orders to include… Cross-validation evaluates the performance of different Sarima configurations on the training and validation sets.

However, tuning SARIMA can be time-consuming due to trial-and-error requirements with different hyperparameters. It has to contend with irregular, complex, and non-stationary data that cannot be easily differentiated from stationary series. On the other hand, XGBoost uses decision trees in its optimization framework to improve its performance. Model Both models require careful tuning to ensure accurate predictions and optimum performance.

IV. RESULTS AND DISCUSSIONS

The following are the results obtained by performing the study:

Accuracy	98.348
MAE	1570.744
MSE	8.13E+06
RMSE	2852.098
R2	0.98348

Table 1: XGB Regressor Evaluation Metrics [22]

MAPE	0.027
MAE	1.28E+06
RMSE	1584689.36
MSE	8.43E+06

Table 2: SARIMA Evaluation Metrics [22]

1. The XGBoost model showed high accuracy in predicting weekly sales, with a low MAE, MSE, and RMSE, indicating minimal error in predictions.

2. SARIMA demonstrated good performance in overall sales forecasting, as evidenced by low MAPE, MAE, and RMSE values, signifying accurate predictions of sales trends.

3. It's important to note that while XGBoost excelled in identifying complex relationships and nonlinear patterns in weekly data, SARIMA proved effective in modeling and forecasting seasonal variations and trends in overall sales. The following figure shows the actual vs predicted values of sales by implementing the XGBOOST model.

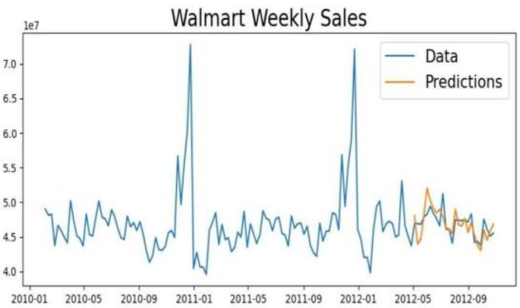

Figure 9: Actual vs Predicted data [22]

The following figure shows the RMSE values produced by using the **XGBOOST** model on the train and test data respectively.

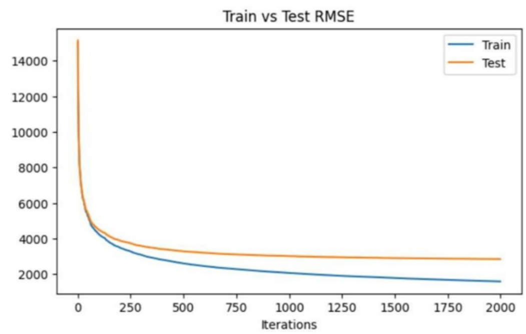

Figure 10: RMSE of train vs test [22]

Below table shows the different evaluation metrics of the model in comparison to the already existing ones.

Evaluation Metrics	ARIMA	SARIMA	SARIMA (Our model)	XGBOOST (Existing model)	XGBOOST(Our model)
MAE	317530.9	3.64	1.28E+06	2.49E+03	1.57E+03
MAPE	0.143	0.087	0.027	0.056	0.268
MSE	1.17E+07	2.42E+07	8.43E+06	9.82E+06	8.13E+06
RMSE	0.287	2213147	1584689	4001.29	2852.098

Table 3: Comparison of Evaluation metrics [22]

V. CONCLUSION AND FUTURE SCOPE

The SARIMA (Seasonal Autoregressive Integrated Moving Average) is meant for forecasting time series based data, and analyzing historical sales data to detect trends, seasonal variations, and anomalies. In contrast, the strength of XGBoost lies in capturing intricate data relationships and nonlinearities, making it adept at predicting time-dependent variables like sales demand over time. XGBoost learns influential patterns and trends in sales behavior, empowering it to forecast future sales accurately.

The XGBoost model and SARIMA model exhibited strong performance in predicting weekly sales and overall sales forecasting, respectively. XGBoost achieved high accuracy with minimal prediction errors, effectively capturing complex relationships and nonlinear patterns in the weekly sales data. Conversely, SARIMA accurately modeled seasonal variations and trends in overall sales, delivering precise forecasts.

Moving forward, there are several avenues for enhancing predictive capabilities in retail operations. One avenue involves exploring insertable methods such as stacking or blending XGBoost with complementary models to improve predictive performance and capture a wider array of patterns and trends.Hyperparameter tuning can optimize model performance for both XGBoost and SARIMA models. Exploring advanced time series techniques such as Prophet, LSTM, or attention-based models can further improve forecasting accuracy, particularly for long-term sales predictions. Integrating these models with real-time data streams and business processes enables dynamic decision-making based on the latest sales insights. Lastly, implementing market basket analysis techniques can uncover product associations and customer purchase patterns, leading to targeted marketing efforts and personalized recommendations.

REFERENCES

[1] A. Abbaspour Ghadim Bonab. "A comparative study of demand forecasting based on machine learning methods with time series approach."J. Appl. Res. Ind. Eng. no. Online First, Mar. 2021. doi: 10.22105/jaric.2021.246283.1192.

[2] A. Mitra, A. Jain, A. Kishore, and P. Kumar, "A Comparative Study of Demand Forecasting Models for a Multi-Channel Retail Company: A Novel Hybrid Machine Learning Approach." Oper. Res. Forum, vol. 3, no.4. p. 58. Scp. 2022, doi: 10.1007/s43069-022-00166-4.

[3] K. Hamiche, H. Abouaïssa, G. Goncalves, and T. Hsu, "A Robust and Easy Approach for Demand Forecasting in Supply Chains," IFAC-Papers Online, vol. 51, no. 11, pp. 1732-1737, Jan. 2018, doi:10.1016/j.ifacol.2018.08.206.

[4] Z. H. Kilimci et al., "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain." Complexity, vol. 2019, pp. 1-15, Mar. 2019, doi 10.1155/2019/9067367.

[5] M. Nasseri. T. Falatouri. P. Brandtner, and F. Darbanian, "Applying Machine Learning in Retail Demand Prediction-A Comparison of Tree-Based Ensembles and Long Short-Term Memory-Based Deep Learning." Applied Sciences, vol. 13. no. 19, Art. no. 19, Jan. 2023, doi: 10.3390/app13|9|1|12.

[6] A. Auner, L. P. E. Vani, and L. M. Priyatna, "Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting, Operations and Supply Chain Management An International Journal, vol. 14, pp. 1-13, Jan. 2021, doc 10.31387/oscm0440281.

[7] AZ Acar, B. Kocaochu, and H. Ymar, "Demand Forecast, Up-to-date Models, and Suggestions for Improvement an Example of a Business," Journal of Global Strategic Management, vol. 5, pp. 26-37, Jun 2014, doi: 10.20460/JGSM.2014815650.

[8] M. Zobdi. M. Rafice, V. Kayvanfar, and A. Salamiraad, "Demand. forecasting has machine learning algorithms on customer information: an applied approach. International Journal of Information Technology, vol. 14, Feb. 2022, doi: 10.100741870-022-00875-3.

[9] G. Reiner and 1. Fichtinger, "Demand forecasting for supply processes in consideration of pricing and market information, International Journal of Production Economics, vol. 118, no. 1, pp. 55-62. Mar. 2009, daic 10.1016/j.jpe.2008.08.000.

[10] A. Kolková and M. Navrátil, "Deonard Forecasting in Python: Deep Leaming Model Hased on LSTM Architecture versus Statistical Models," Acta Polytechnica Hungarica, vol. 18, pp. 123-141. Jan 2021, doi: 10.12700/APH. 18.8.2021.8.7.

[11] R. Rathipriya, A. A. Abdul Rahman, S.. Dhamodharavadhani, A. Meero, and G. Yoganandan, "Demand forecasting model for time-series pharmaceutical data using shallow and deep neural network model." Neural Computer & Application, vol. 35, no. 2, pp. 1945-1957, Jan. 2023, d 10.1007600521-4122-417889-0.

[12] 1. Tetrada, M. El Khain, and O. Hassan, "Demand Forecasting Model using Deep Learning Methods for Supply Chain Management 4.0," International Journal of Advanced Computer Science and Applications, vol. 13. May 2022, dai: 10,14569-11ACSA. 2022.0130581.

[13] PS Sumov and V. A. Sudakos, "Forecasting new product demand using machine learning, J. Phys. Conf. Ser, vol, 1935, no. 1, p. 012033,May 2021, doi: 10.1088/1742-6596/1925/1012033

[14] N. Akatawa, 11. Abu-Salih, N. Obeul, anal M. Almiare, "Incorporating Time-Series Forecasting Techniques to Predict Logistics Companies Staffing Needs and Under Volume, Compotation, vol. 11. no 7. Art. no. 7, Jul. 2023, doi, 10.3390/computation11070141

[15] N. U. Moroil, E. Karn, and J. Kamphues, "Machine Learning and Statistics A Shaly for avsessing innovative Demand Forecasting Models, Procedia Computer Science, vol. 180, pp. 40-49, Jan. 2021. doi: 10.1016/j. рмось 2021.01.127

[16] J. Feizabadi, "Machine learning demand forecasting and and supply chain performance." International Joumal of Logistics Research and Applications, vol. 25, no. 2, pp. 119-142, Feb. 2022, doc 10.1080/13675567.2020.1803246.

[17] S. F. G and P. N. "Maclame Learning in Demand Forecasting - Review," Rochester, NV, Nov. 19. 2020, dec: 10.2139.3733548

[18] 1. Ho, L. Tran, H. Tiran, and 5. Bao "Machine Learning in Demand Forecasting, Jan. 2022.

[19] E. Tarallo, G. K. Aubare. CI. Shirzabukuro, J. Melle, and D. Anuncio, "Machine Learning in Prodenang Demand for Fast-Mowing Consumer Goods: An Exploratory Research, IFAE-PapersOnLine, vol. 52. но. 13, pp. 737 747, Jan 2019, doi: 10.1016/facol 2009.11.303.

[20] R. Carbonica, R. Validov, and K. Lafiambsrise, Machine Leaming-Based Demand Forecasting in Supply Chains." IJIT. vol. 3. pp. 40-57, Okt. 2007, doi: 10.10181007100

[21] D. T. Wiyanti, I. Kharisudin, A. B. Setiawan, and A. K. Nugroho, "Machine-learning algerilen for demand forecasting problem. J. Phys. Conf. Ser, vol 1918, no. 4, p. 042012. Jan, 2021. doi: 10.1088/1742-596-1918-4.04.2012.

[22] Yadav, N. (2024). Implementation of models for Demand forecasting for e-commerce using time series forecasting. Unpublished Paper. Adapted from the current study.