International Journal of Emerging Research in Engineering and Technology
Pearl Blue Research Group | Volume 7 Issue 2 PP 119-127, 2026
ISSN: 3050-922X | https://doi.org/10.63282/3050-922X.IJERET-V7I2P115

Original Article

Machine Learning-Based Retail Supply Chain Management Using ERP and Sales Data Analytics

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Received On: 12/03/2026 Revised On: 11/04/2026 Accepted On: 19/04/2026 Published On: 25/04/2026

Abstract *- Enterprise resource planning (ERP) solutions provide direct support for supply chain management and logistics operations, which are essential components of modern business operations that determine international market competitiveness. The research presents a machine learning (ML) approach to developing a retail supply chain management system that utilizes sales and ERP data for its operations. The team used Kaggle Superstore sales data to conduct exploratory data analysis and evaluate sales performance across regions and features. The model development process starts after completion of multiple preprocessing steps, which include handling missing values and outlier detection, categorical data encoding, data normalization and data partitioning. The proposed model performance evaluation uses Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 as performance metrics. The experimental results demonstrate that the DNN model can predict outcomes effectively, with an MAE of 2.277, an RMSE of 2.814, an MAPE of 13.72%, and an R^2 of 92.0%. The DNN approach demonstrates higher forecasting accuracy than traditional Decision Tree and Random Forest models, according to the comparative analysis. The research results demonstrate how deep learning methods can enhance demand-forecasting accuracy and support decision-making in ERP-based retail supply chain management systems.*

Keywords *- Enterprise Resource Planning (ERP), Retail Supply Chain Management, Machine Learning, Demand Forecasting, Sales Data Analytics.*

1. Introduction

The effectiveness of supply chain and logistics management systems determines how businesses compete in the global manufacturing industry. The fields have developed into essential business elements which business now use to build their professional relationships, according to research[1]. The term sales forecasting is an essential economic concept that modern industries need for their strategic planning. The research investigates the evolving methods, technologies and market developments that have transformed sales forecasting through customer behavior patterns. Retail strategies are often diverse because they include various elements such as market communications, price and product selection methods[2][3][4]. Contemporary enterprises produce apps utilizing diverse concepts and best practices to enhance operations and elevate performance [5]. Consequently, Enterprise resource planning (ERP) deployment frequently yields favorable results [6][7]. All functional area, such as project management, finance, sales, and supply chain management, and personnel, have their business operations and data integrated by ERP [8][9][10].

In the retail sector , accurate sales forecasting and effective inventory management are essential to achieving high profitability, minimizing stock levels [11][12][13], and optimizing resource utilization. ERP [6] systems collect vast amounts of data from finance, procurement, sales, and supply chain departments, creating significant analytical opportunities for predictive sales analysis. Supply chains are a significant area of theoretical and practical research. They have received more attention in recent years as a result of the pandemic, economic crises, conflicts, and other issues. Supply chains represent intricate systems including several interrelated and interdependent operations. Measuring the performance of all chain participants—suppliers, manufacturers, retailers, and end users—is essential to evaluating the effectiveness of supply chains. Globalization, technological advancements, customer demands, and sustainability regulations are all contributing to the increasing complexity of retail supply chain management[14].

In the rapidly evolving retail landscape, superstores are using data-driven methods to achieve three goals: better sales performance, improved customer satisfaction and more efficient business operations. The research uses the Recency Frequency and Monetary(RFM) framework to establish sustainable supply chain operations in superstores by analyzing the ability of AI-based customer segmentation to transform the retail sector[15]. Artificial intelligence(AI) refers to the creation of computer systems that can acquire knowledge and understanding and make decisions that typically require human intelligence. The combination [16] of Machine Learning(ML) with ERP-driven retail supply chain operations[17] creates a new solution that resolves existing challenges. ML enables systems to process extensive ERP and sales data through AI-based analysis which uncovers unknown patterns and delivers precise predictions without the need for programming. Retail organizations can achieve more precise demand forecasting and automated inventory optimization by using advanced ML[18] and DL[19] techniques which also improve supplier performance assessment and enhance overall supply chain resilience[20].

Retail supply chain management needs proper demand forecasting because it serves as the foundation for effective resource distribution, inventory management and operational decision-making. Nonetheless, conventional predictive paradigms and standardized ML frameworks often fail to capture the multidimensionality and nonlinearity of large-scale transactional data in the retail industry. Furthermore, the extent to which sales data generated by the ERP is analytically utilized is not maximized[21], contributing to the fact that many of the current methods of the process fail to achieve optimality in forecasting errors and ineffective supply chain planning. Thus, the presence of a superior predictive framework for efficiently processing ERP-generated sales data and enhancing demand-forecasting accuracy in a retail supply chain environment can be considered[22]. The key contributions of the research are discussed below:

- An ERP-based sales data combined with machine learning forecasting and decision support provides a data-driven framework of retail supply chain management.
- Deep Neural Network (DNN) model is trained to discover more complicated nonlinear trends in retail sales data and improve the predictive capabilities in demand.
- Created a processed pipeline of data, including missing values, outliers, encoding, and normalization to improve reliability of model.
- To give the most thorough assessment of predictive performance, proposed model is assessed using a number of performance measures, including R^2, MAE, RMSE, and MAPE.

1.1. Justification and Novelty of the Study

This research is justified by fact that in retail supply chain management, accurate demand prediction and effective decision-making are becoming increasingly important, yet standard statistical and ML algorithms are unable to recognize and forecast nonlinear correlations in large-scale sales data. As ERP systems continue to be used, large volumes of transactional data are generated, enabling sophisticated analytics to improve forecasting and operational cost-efficiency. The novelty consists of creating a combined predictive model that integrates ERP-based retail sales data with a DNN to better predict demand. The proposed framework, unlike traditional methods that rely heavily on individual forecasting techniques, employs a multidimensional process of data pre-processing and DL to learn more complex trends in retail data, leading to more credible and precise predictions for supply chain management in a retail hospitality organization.

1.2. Organization of the Paper

The rest of this paper is as follows: Section II is a literature review of related literature with regards to Retail Supply Chain Management. The dataset, data pre-processing, and model development are described in Section III, and experimental results and comparative analysis are discussed in Section IV. Lastly, Section V concludes paper by presenting the most important findings and proposing directions for future research.

2. Literature Review

A survey and critique of the notable research studies in Retail Supply Chain Management are reviewed to guide and support the basis and creation of the study.

V. Singh et al. (2025) proposed two DL-based models Artificial Neural Network (ANN) and a hybrid Long Short-Term Memory-Gated Recurrent Unit (LSTM-GRU) to predict product demand in Inventory. Based on experimental findings, the ANN model had R^2 of 90.31 and RMSE (Root Mean Squared Error) of 2.814, but it was highly surpassed by the LSTM-GRU model, having R^2 of 99.24 and RMSE of 0.0145 [23].

D. Santhakumar et al. (2025) also suggested a GAN-based forecasting model implemented with optimization strategies in the same year and achieved 96.4% demand prediction accuracy using advanced time-series modeling [24].

S. Birajdar et al. (2024) found that logistical costs for EC are higher than for other retail models due to a variety of problems with inventory management. This suggested approach comprises three stages: pre-processing, feature selection, and model training. A Fuzzy LIM-CNN was employed to train the model. The proposed approach outperforms CNN and Fuzzy LIM with an average accuracy of 91.67% [25].

K. Agnihotri et al. (2024) suggested a technique that includes feature selection, model training, and pre-processing. This step involved cleaning dataset with a text-processing method that assigned each document three numerical values: document length, token number, and token length. The best approach is to model feature selection using Latent Dirichlet Allocation (LDA). The suggested model has an average accuracy rate of 94.35%, which is greater than cutting-edge alternatives such as SVM and CNN [26].

W. Wang (2024). This technique is used at the second level to optimize the weights of each learning component after each ANFIS model's hyperparameters have been adjusted. This prediction model's ability to enhance the CBEC supply chain architecture is evaluated empirically. The proposed volume is predicted by the suggested predictive model with an average absolute error of 2.54, demonstrating a minimum decrease of 8.58% when compared to earlier studies [27].

S. Ghareeb et al. (2023) suggested that, to determine whether time-series data performs well with non-time-series algorithms, advanced ML techniques should also be utilized in conjunction with time-series approaches. This paper evaluates several time-series techniques, GB, and the Facebook Prophet model, which achieves 92.83% forecast accuracy. The Holt-Winters additive method yields a MAPE value of 12.84%, whereas the GB model attains a MAPE value of 22.25%[28].

T.K Thivakaran and M. Ramesh (2022) The suggested Big-Mart sales prediction system uses recurrent multi-level generative adversarial networks, deep reinforcement learning engines, and multivariate Poisson distribution schemes to provide more accurate results. The results and experiments demonstrate the efficacy of proposed DL-based sales forecasting model compared with alternative methods. The proposed deep learning technology surpasses existing sales prediction models by 5% to 10% [29].

Likewise, D. R. M. R. R. D. R. S. Eheliyagoda et al. (2021) suggested a decision support system that utilized ML technologies, including Autoregressive Integrated Moving Average (ARIMA) and LSTM models, along with Regression, Classification, and Association Rule Mining algorithms. Platforms such as Kaggle and other complementary resources for dataset analysis supplied the data. The analyzed data sets enabled the final platform to function with an accuracy above 90% across all four critical components [30].

The overview of the present studies in field of Retail Supply Chain Management is given in Table I, presenting the models proposed, the datasets used, the techniques implemented, performance outcomes and limitations of every study.

Table 1: Review of Existing Studies on Retail Supply Chain Management Using ERP and Sales

Author & Year	Method / Model	Key Techniques / Approach	Performance Results	Limitations / Future Work
V. Singh et al., 2025	ANN and Hybrid LSTM-GRU	DL models employed for inventory demand forecasting and time-series analysis	ANN: R^2 = 90.31, RMSE = 2.814; LSTM-GRU: R^2 = 99.24, RMSE = 0.0145	High computational complexity of hybrid models; future work could focus on improving scalability and testing on larger real-time datasets.
D. Santhakumar et al., 2025	GAN-based Forecasting Model	Generative Adversarial Network with optimization strategies for demand forecasting	Achieved 96.4% prediction accuracy	GAN training instability and high resource requirements; future work can explore lightweight GAN architectures and improved training stability.
S. Birajdar et al., 2024	Fuzzy LIM-CNN	Three-stage process: preprocessing, feature selection, and model training for inventory/logistics optimization	Average accuracy: 91.67%	Limited generalization across different e-commerce datasets; future work could evaluate performance across multiple supply chain environments.
K. Agnihotri et al., 2024	LDA-based Feature Selection with ML Models	Dataset preprocessing using text-processing features (document length, token number, token length) and feature selection using Latent Dirichlet Allocation	Average accuracy: 94.35%, outperforming SVM and CNN	Feature extraction limited to textual attributes; future research can integrate semantic embeddings and hybrid deep learning approaches.
W. Wang, 2024	ANFIS Optimization Model	Hyperparameter optimization of ANFIS and weight optimization using learning algorithms for CBEC supply chain prediction	Mean Absolute Error = 2.54; 8.58% improvement over previous methods	Future research may examine automated hyperparameter optimization and hybrid AI models due to model complexity and sensitivity to parameter tuning.
S. Ghareeb et al., 2023	Time-Series + ML Models	Evaluation of Gradient Boosting, Facebook Prophet, and Holt-Winters time-series forecasting models	Facebook Prophet accuracy: 92.83%; Holt-Winters MAPE: 12.84%; Gradient Boosting MAPE: 22.25%	Limited handling of sudden demand fluctuations; future work could integrate deep learning models for better temporal pattern learning.
T.K. Thivakaran & M. Ramesh, 2022	Deep Learning Sales Prediction System	Recurrent Multi-Level GAN, Deep RL Engines, and Multivariate Poisson Distribution Scheme for Sales Forecasting	5–10% improvement over existing sales prediction models	Model requires large datasets and computational resources; future work could explore model

				simplification and real-time deployment.
Eheliyagoda et al., 2021	Decision Support System using ML	LSTM, ARIMA, Regression, Classification, and Association Rule Mining for demand analysis	Achieved >90% accuracy across components	Limited integration of real-time data streams; future work may incorporate IoT-based data collection and adaptive learning models.

Although some studies have employed DL and ML techniques to forecast supply chain management and demand in retail, there are still gaps in the current literature. Most methods aim more at enhancing precision in prediction with individual models, including ANN, CNN or time-series systems, without paying much attention to ERP-based enterprise data combined with the robust deep learning systems. Moreover, some studies do not have a complete preprocessing pipeline and do not compare the forecasting systems with the traditional ones, which diminishes the reliability and practical implementation of the systems. Moreover, the available approaches are usually ineffective when dealing with complex nonlinear relationships found in high-volume retail transactional data. As such, an integrated predictive framework that integrates the ERP-driven sales analytics with the DL models is required to offer more accurate and trustworthy retail supply chain management demand forecasting.

3. Research Methodology

The suggested strategy starts with gathering Superstore Sales data, as seen in Figure 1, followed by data pre-processing, including management of missing values, identification and elimination of outliers, Label encoding and normalization. Subsets for training and testing are developed from the dataset. The DNN model uses pattern recognition and prediction. Lastly, error metrics (MAE, MAPE, RMSE, and R^2) are used to assess model performance, and results are analyzed to assess the efficacy of the suggested approach

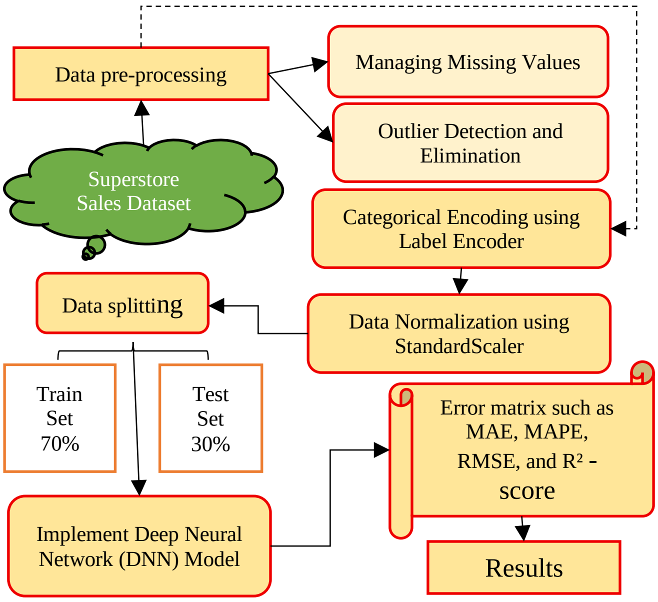

Fig 1: Proposed flowchart for Retail Supply Chain Management using Machine Learning

The subsequent part provides a breakdown of every step in the proposed methodology:

3.1. Data Gathering and Analysis

The Superstore retail dataset from Kaggle serves as the Sales Forecasting dataset which this research study uses for its predictive analysis work. The dataset includes order and ship dates customer product details and sales information which enables both time-series analysis and unknown future predictions. The data is contained in a file called train.csv and has about 9,800 rows and 18 columns. The EDA is shown below:

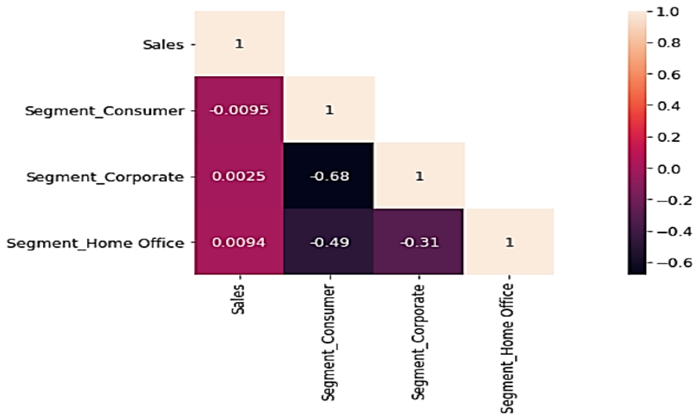

Fig 2: Correlated Features of Category vs. Sales

Figure 2 is a heatmap of the correlation of sales with the distinct customer categories, which encompass Consumer, Corporate, and Home Office[31]. The heatmap suggests the relationships between these variables visually on a color gradient scale. By contrast, the moderate negative correlations are found between the segment categories, including Consumer and Corporate (-0.68) and Consumer and Home Office (-0.49) meaning that the increase in one segment can be accompanied by the reduction in another.

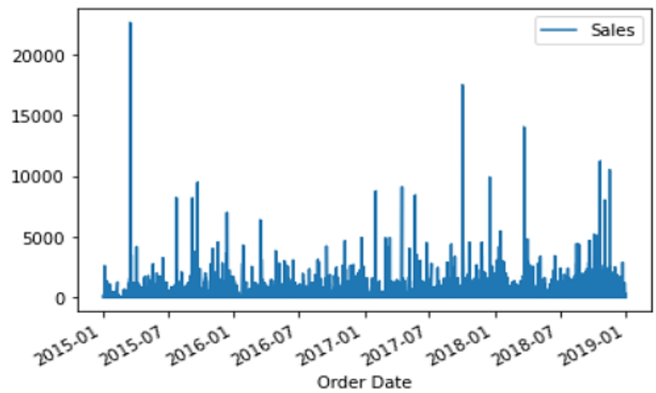

Fig 3: Time-Series Representation of Sales

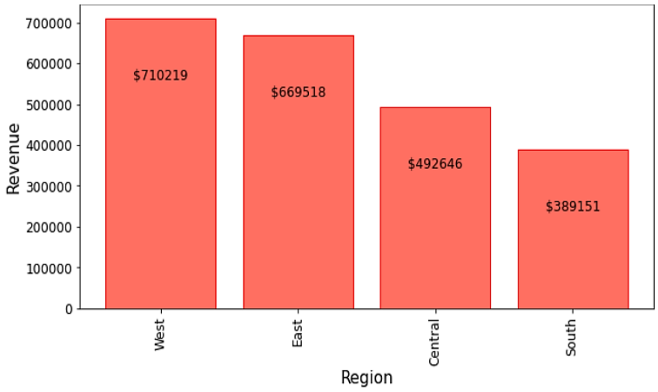

Fig 4: Region-wise Revenue Generation

Figure 3 shows the time-series sales trend between 2015 and 2019, and it is very variable with many fluctuations and demand peaks. Most of the sales values are moderate, but there are a few sharp peaks, which represent the demand during periods of high demand, resulting in dynamic behavior in retail sales over a period of time. Figure 4 depicts region's revenue allocation, with West region commanding the highest, and the East coming second. The Central and South regions are bringing in relatively lower revenue, with the South performing the lowest in totality.

3.2. Data Pre-processing

Data preparation, which involved data concatenation, cleansing, and missing data by applying appropriate imputation methods and data types to maintain consistency and accuracy. To increase reliability, outliers are statistically determined and removed. Moreover, categorical variables are coded into numbers, then they are labeled and normalized to bring uniformity in the data to develop the model.

This data pre-processing method in Machine Learning employed to encode categorical values. Categorical features have to be encoded prior to the training of the model because most ML algorithms accept only numeric values. In Label Encoding different categories (which are unique) are coded using integers in the range 0-Classes.

3.3. Normalization with Standard scaler

The feature of scaling in ML is the standard scaler also known as standardization. The approach transforms each feature to a unit variance and mean at zero. Even though most of the data shall be within a fairly similar range of 0, this method not confine the data within a unified range or alter its binning, which means that despite scaling, it is still possible to find outliers in the data. Normal scaling is characterized by Equation (1):

$$x_{scaled} = \frac{x-\bar{x}}{\sigma} \qquad (1)$$

Where x is an example point, x_{scaled} is a scaled sample point, $\bar{x}$ is average of practice examples, and σ is standard deviation of training samples.

3.4. Data Splitting

The dataset is separated into training and testing subsets, with around 70% designated for model training and the remaining 30% allocated for testing and performance evaluation.

3.5.Proposed Deep Neural Network (DNN) Model

In this study, a multi-layered ANN called a DNN is used to extract intricate patterns and nonlinear correlations from data [32]. One of the most promising AI technologies available today is DNN, which has been studied for its potential in intermittent sales forecasting. Artificial neural network (ANN) complicated architectures are defined using this ML and DL approach [33]. NNs use numerical data as inputs, and by assigning weights to these inputs, they model the relationship between inputs and outputs. In the input layer, output layer, and several hidden layers, each neuron performs a weighted summation before an activation function. The basic mathematical representation in Equation (2):

$$z = \sum_{i=1}^{n} w_i x_i + b \qquad (2)$$

Where x_i represents input features, w_i denotes the corresponding weights, and $b$is the bias term.

The model is then made nonlinear by passing the weighted sum through an activation function, allowing it to learn intricate decision boundaries. ReLU, sigmoid, and tanh are examples of common activation functions. It is derived in Equation (3):

$$a = f(z) \qquad (3)$$

Where a is output of neuron and $f(z)$is the activation function.

3.6. Evaluation Metrics

In this step, evaluated the predicted outcomes from the test dataset in order to compare the training models [34]. Use the following four metrics to assess and compare each model in order to have a thorough comparison:

3.6.1. R-Squared

R^2 serves as a metric for assessing the regression model's alignment with the data. Elevated R^2 values signify a superior alignment between the model and the data. R^2 has a range of 0 to 1. An R^2 score of 1 indicates that the model properly predicts the response data, whereas an R^2 score of 0 indicates that the model does not explain any variance in response data with respect to its mean. The formula derived in Equation (4):

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad (4)$$

3.6.2. Mean Absolute Error (MAE)

MAE is a frequently used statistic to assess a prediction model's accuracy. Without considering the direction of the mistakes, it computes the mean magnitude of the error across a set of forecasts. A lower MAE number indicates improved performance. The MAE formula in Equation (5).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |(y_i - y_i^P)| \qquad (5)$$

Where y_i is actual value,y_i^P is projected value, and n is number of observations.

3.6.3. Root Mean Squared Error (RMSE)

This statistic, level of discrepancy between the real data and the model's predictions is measured by the square root of MSE. Superior model performance is shown by reduced RMSE values. It is expressed in Equation (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{\dot{P}})^2} \quad (6)$$

3.6.4. Mean Absolute Percentage Error (MAPE)

MAPE calculates error as a proportion, more precisely, it is the dataset's average percentage difference between forecasts and their intended goals. It can be measured by using Equation (7).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} / \left(\frac{(y_i - y_i^{\dot{P}})^2}{y_i}\right) /* 100 \quad (7)$$

These metrics collectively indicate how well and accurately model predicts the target variable.

4. Results and Discussion

The experimental environment and the results of the recommended DNN model in terms of computational efficiency and prediction performance. The model is run on a 32- or 64-bit Windows platform using Python, Jupyter Notebook and visualization libraries. It was operated on a machine with a multi-core CPU, an advanced graphics card, and sufficient RAM to efficiently handle massive amounts of data.

4.1. Predicted Results

The proposed DNNs are carried out based on evaluation metrics such as R^2, MAE, RMSE, and MAPE. The DNN model's success in retail supply chain management is summed up in Table II. The model achieved low prediction errors (MAE = 2.277, RMSE = 2.814) and a MAPE of 13.72, indicating good forecasting accuracy. The model explains the majority of variation in data, as indicated by a high R^2 value of 92.0%, demonstrating strong predictive performance.

Table 2: Performance Results of the Model in Retail Supply Chain Management

Matrix	DNN
MAE	2.277
RMSE	2.814
MAPE	13.72
R^2	92.0

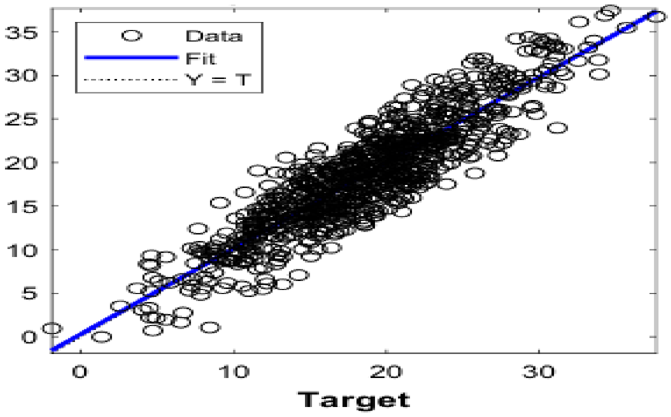

Fig 5: Scatter plot for DNN Model

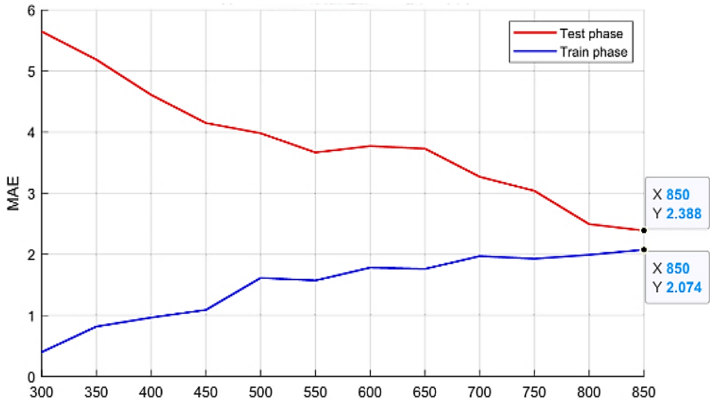

Fig 6: Learning Curve for the Proposed DNN

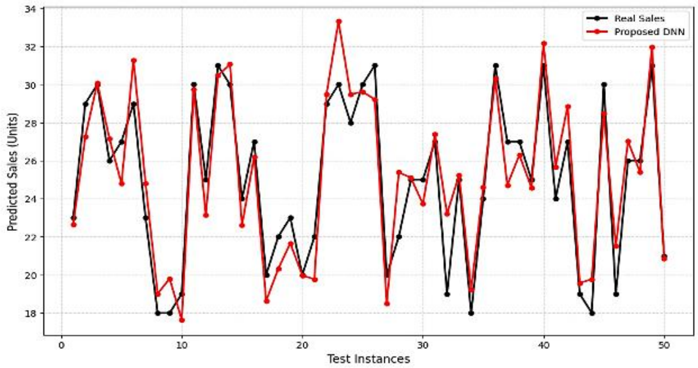

Fig 7: Predicted vs. Actual Sales Using Proposed DNN Model

Figure 5 shows that there is a strong connection between the actual and anticipated values, as the data follows a close regression line and is close to the Y = T reference line and therefore shows that the prediction has a high degree of accuracy.

Figure 6 indicates that the trend of the MAE of the proposed DNN model is that as the sample size gets bigger, the test error reduces, and the train error minimally increases. When the samples are 850, the model reaches a test MAE of 2.8 and a train MAE of 2.07, which means that the learning performance is stable and better. Figure 7 compares sales with actual and DNN predictions of 50 test cases. The forecasted values are close to the actual sales pattern, which demonstrates the model's excellent performance and high accuracy in terms of forecasting.

4.2. Comparative Analysis

The accuracy of the suggested model is contrasted with that of other models currently in use, as indicated in Table III. The findings show that Decision Tree (DT) model has better performance with an R^2 of 54.7. Random Forest (RF) model also boosts accuracy in prediction to a higher level of 87 with the R^2 of 87 and a relatively high MAE of 55,133.85. Comparatively, the DNN model proposed has the most optimal performance, as indicated by an R^2 of 92.0 and a very low MAE of 2.277, which indicates its capability to predict more effectively and capture more complex patterns in supply chain management of retailing business.

Table 3: Comparison of Different Models for Retail Supply Chain Management

Model	Study	R^2	MAE
DT	[35]	54.7	-
RF	[36]	87	55,133.85
DNN	Proposed	92.0	2.277

The research fulfills the requirement of precise, empirically-supported demand forecasting in ERP-based retail supply chain, where more sophisticated sales trends are not always reflected in conventional models. The research demonstrates greater forecasting accuracy and improved operational planning by applying a DNN. The results facilitate improved inventory management, cost efficiency, and prompt decision-making in ERP systems. The main strengths are high predictive performance and a strong ability to estimate nonlinear relationships.

4.3. Limitations and Future Work

In spite of a high forecasting performance of the proposed DNN model, this research has various limitations. Train-test split on datasets containing various periods across types of superstores, means this model may not be as generalizable to different types/mixes of retail contexts and data characteristics. In addition, this model primarily depends on historical sales data and does not consider any external variables that can have a substantial impact on demand (seasonality, economic fluctuations, promotions/promotion-related behavior of customers). Additionally, DL models may require more time and need resources due to the high computational complexity. Future research direction would focus on integrating real-time data stream for ERP, accounting for external market and seasonal variables, integrated with hybrid deep learning models -LSTM-DNN or transporter (Tn5) based model to improve forecast accuracy and scalability in a dynamic retail supply chain environment.

5. Conclusion

Enterprise resource planning (ERP) is an important driver of supply chain growth and sustainability across organizations. ERP implementations have key success factors (CSFs). This research shows the conceptualization and practical implications of deploying a Deep Neural Network (DNN) model empowered ERP and sales data-based analytics for demand forecasting on the retail supply chain. It is a robust predictive model, with an R2 of 92.0, a low MAE of 2.277, and an RMSE of 2.814, while the MAPE is within 13.72, ensuring accuracy and generalization for our testing set and acceptable performance across sample testing in these analyses. The model has proved its ability to approximate complex, non-linear relationships contained in retail data, with actual sales trajectories closely matching the projections. DNN is the primary indicator for a prediction task, which, in turn, makes it comparably better than traditional ML models. The findings confirm that the proposed method is both effective and practical to improve supply chain performance in terms of operational efficiency as well as data-driven decision-making processes within the context of retail supply chain management.+

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