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Optimising Sales Forecasts in ERP Systems Using Machine Learning and Predictive Analytics

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Abstract

Enterprise resource planning, or ERP, is stands for systems for central to today business environments, as they offer one-stop solution for defining business organisational sales, finance, and operations. Sophisticated sales forecasting for strategic planning and operations is significant herewith in these systems. In this paper, the authors investigate the use of ML with integrated predictive analytics for enhancing sales forecasts based on a sales data set that is readily available to the public. After preprocessing the data with Z-score normalisation and feature selection, high-quality, consistent data is obtained and ready for analysis. LSTM model SVM and XGBoost are tested and scored based on specific measures like the explained variance (R^2), average absolute error (MAE) and the root mean square error (RMSE). It is clear that the proposed LSTM model outperforms other models as indicated by its R^2 of 99.34% and a MAE of 11.64 with an RMSE of 13.57, which signifies its ability to analyse varied trends and patterns of the sales data set. However, it was observed that the SVM and XGBoost models have relatively lower predictive capability. As seen from the results, the overall trends and the seasonal behaviour are captured well by the LSTM model with high correlation during the long periods of the time series, but during the volatile period, the presence of high bias and noisy signals that the LSTM model cannot completely remove are noticeable leading to less accurate peak and bottom predictions. The next research steps will be directed toward improving the algorithm's performance of the LSTM model by adding more inputs into the program, like holidays, promotions, and economic signals.

***Keywords**: Sales forecasting, ERP system, Machine Learning, Predictive Analytics, E-commerce, Business Strategy.*

1. Introduction

In the contemporary information world, ERP systems are considered strategic organisational tools that provide value to a firm in efficiency, effectiveness, and competitiveness [1]. The features of ERP systems are numerous, but the highlight is the practice of sales forecasting that influences inventory control, budgeting, and organisational strategy[2][3]. With the constant evolution of various e-commerce platforms, their sensitivity to accurate sales forecasting has increased tremendously due to changing customer requirements and optimised cost when it comes to operations [4].

Whenever a company wants to predict sales in the future, historical data is used to estimate total quantities of goods to order, revenues to expect, and resources to apply.[5][6]. Benchmarks associated with traditional approaches, therefore, still remain increasingly unsuitable for the model's application, given that this kind of sales pattern cannot be easily interpreted by traditional methods due to its contemporary volatility[7]. This has created a path for other sophisticated approaches such as machine learning and predictive analysis that uses big data to demarcate complex patterns and make precise prognosis[8].

An exploratory analysis of the patterns and key elements in this data may be done using a machine learning algorithm that will yield considerable accuracy in sales forecast[9]. In consequence, a machine learning framework is trained to search for executions that mimic each other in order to be capable of predicting subsequent ones[10][11]. Over the last couple of years, machine learning models have proven to be crucial in the analysis of grocery sales[12]. Because it is easy to use and interpret it is suitable for modelling sales territory trends, erp sales forecast optimisation by using machine learning and analytically techniques. Applying another sophisticated tool of forecasting in organisations, one can obtain accurate demand estimates, gain improved inventory management, and satisfy consumers. Hence, the use of different sophisticated techniques in estimating demand can help organisations to forecast the demand with more accuracy, manage inventories more efficiently, and satisfy consumers[13].

A. Motivation and Contribution of Study

The increased relevance of sales forecasting in ERP systems has been the reason for this research since traditional techniques cannot effectively match the diverse nature of enterprises. The use of machine learning and predictive analyses can prove to have the potentiality for the improvement of the level of forecast precision, efficiency of the planning of the available resources, as well as effective decision-making in the advancement of the competitive business and economic environment.

- Analysed a sales dataset of 16 variables with 421,570 data points to uncover patterns influencing weekly sales.
- Designed a comprehensive preprocessing pipeline, including outlier handling and feature selection, to ensure data quality.
- Implemented Z-score normalisation for feature scaling, ensuring faster convergence and better model performance.
- Developed a robust machine learning framework integrating LSTM, SVM, and XGBoost for accurate sales forecasting.
- In order to identify the best forecasting strategy, different evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and coefficient of determination (R^2) were used for the model's assessment.

B. Structure of the paper

The study is set up as follows: In Section II, related sales forecasting research is discussed. In section III the author goes further and gives additional details over materials and techniques used. Section IV provides the experimental results of the developed research system. Section V The final section of the study gives a conclusion of the whole investigation.

2. Literature Review

This section discusses surveys and reviews articles on optimising sales forecasting using Machine Learning Algorithms. Table I presents an overview of studies focusing on optimising sales forecasting using machine learning approaches. It outlines diverse methodologies, datasets, and findings, showcasing the advancements and challenges in leveraging models.

This study analyses Jiang, Ruan and Sun (2021) the possibility of accurately predicting Walmart sales based on time series, time series with and without the incorporation of machine learning techniques, and solely machine learning models. Thus, to predict the Walmart grocery sales data from 2011-01-29 to 2016-06-19, they used the lightGBM machine learning model and the Prophet model that divides trends, seasons and holidays. For prediction and empirical analysis, data of dates between 2016-06-19 and 2016-08-14 are used. The findings indicate that it is possible to effectively predict the retail establishments' sales using the Machine learning model; Prophet model generates RMSE of 0.694 while that of LightLGB is 0.617[14].

In this study, Chen et al. (2021) Use the Neural Network sale prediction model to predict Walmart's sales. they also use datasets from the Kaggle platform to test our NN model. Our NN model outperforms other machine learning models, according to experiments. Our RMSE measurements are 2.92 and 2.58 lower, respectively, than those of the SVM and Linear Regression techniques. Furthermore, they interpret our NN model using SHAP to mine features of several dimensions and generate reliable predictions[15].

This study, Spuritha et al. (2021) suggests an XGBoost-based model that improves sales prediction performance overall by fitting learners to store-product subgroups with optimal parameters. With average RMSE, R2, and MAPE values of 6.63, 0.76, and 11.98%, respectively, the proposed model predicted sales for ten outlets carrying fifty items. Furthermore, dynamic pricing, which determines the ideal price of a product depending on demand, is applied to the predicted outcomes[16].

In this study, Wisesa, Adriansyah and Khalaf (2020) a short overview of ML methods in the reliability of B2B sales. The second part of the study describes various sales forecasting techniques and treatment. According to the performance review, the following recommendation of the most suitable model for the forecast of the B2B sales trend is provided. The reliability and repeatability of efficient analytical and prognostic tools are applied to reproduce the result of the analysis, estimation, and projection. The outcomes of the research should be accurate, precise, and feasible to use in making forecasts of sales, then it would be a handy asset. According to research, the Gradient Boost Algorithm predicts future B2B sales with a high degree of accuracy (MSE = 24,743,000,000.00, MAPE = 0.18)[17].

In this study, Ding et al. (2020) suggested a native sales forecasting system that mainly depends on the CatBoosting technique. To train the system, the dataset of Walmart sales is used as this is by far the largest dataset in this sector. They were able to use feature engineering to enhance the speed and accuracy of the prediction. In the trials our model has superior results when compared to more conventional techniques of machine learning such as SVM as well as linear regression, the average value of RMSE that has been computed is 0. 605. Our method has fewer hyperparameters to tune than current methods, which enlarges the application prospect and enhances the adaptive performance on different custom datasets[18].

This study's Niu (2020) method can effectively mine the features of several dimensions to generate precise estimates. This research evaluates the XGBoost sale forecast model using Walmart retail sales data from the Kaggle competition. Experimental results show that the strategy works better sharer higher accuracy than the other machine learning methods. In comparison, the Ridge and Logistic Regression methods are nearer to the actual coefficients of the seventeen states than the coefficients calculated by other methods; although the absolute difference is relatively small, the RMSSE measures for this study are 0.141 and 0.113 lower, respectively. This study also looks at the importance of ranking characteristics and comes up with some useful suggestions[19].

In this study, Li et al. (2020) suggested Using past sales data, forecasting the 28-day sales is performed using a deep learning technique with LSTM. In addition to other data, Walmart sales record consisting of daily sales for 30491 goods for 1913 days is used to train and test the model purposefully incorporating effective feature engineering techniques where RMSSE of 0.834 in trials was obtained and it was observed that the proposed model outperforms other approaches such as SVM and Linear Regression[20].

Table 1: Background Summary of Sales Forecasting Studies Using Machine Learning Techniques.

Author	Methodology	Source	Findings	Challenges/Future Work
Jiang, Ruan, and Sun (2021)	Prophet model and LightGBM; feature decomposition (trend, season, holiday)	Walmart sales dataset	Prophet's RMSE was 0.694, whereas LightGBM's was 0.617. For retail sales forecasting, the machine learning model LightGBM performs better.	Expanding to other datasets to test generalizability.
Chen et al. (2021)	Neural Network (NN); feature importance interpretation using SHAP	Kaggle Walmart dataset	The NN model performs better than SVM and linear regression. RMSE improvements of 2.92 and 2.58, respectively, in comparison to SVM and Linear Regression.	Investigating other NN architectures and additional features for improved accuracy.
Spuritha et al. (2021)	XGBoost model with optimised parameters	Sales data (10 stores)	MAPE: 11.98%, RMSE: 6.63, R^2: 0.76. Enhanced sales prediction accuracy and pricing optimisation.	Exploring other hyperparameter tuning strategies and pricing models.
Wisesa, Adriansyah, and Khalaf (2020)	Gradient Boost algorithm; reliability assessment for B2B sales forecasting	B2B sales dataset	MAPE: 0.18, MSE: 24,743,000,000.00. Reliable and dependable sales projections for business-to-business applications.	Adapting models for diverse B2B industries and datasets.
Ding et al. (2020)	CatBoost: feature engineering for boosting prediction accuracy	Walmart sales dataset	RMSE: 0.605. Outperforms Linear Regression and SVM. Requires less fine-tuning, improving generalisation across datasets.	Testing generalisation with other retail datasets and applications.
Niu (2020)	XGBoost; feature ranking and attribute mining	Kaggle Walmart dataset	Compared to Ridge Regression and Logistic Regression, RMSSE is 0.113 and 0.141 lower, respectively. The significance of rating attributes is demonstrated.	Further exploration of feature selection techniques and feature interaction effects.
Li et al. (2020)	LSTM-based deep learning model with feature engineering	Walmart sales dataset	RMSSE: 0.834. Outperforms SVM and Linear Regression for 28-day sales prediction.	Refining temporal feature extraction and exploring hybrid deep learning models.

3. Research Methodology

The methodology for optimising sales forecasts in ERP systems using machine learning and predictive analytics involves several critical steps. First, the publicly available "Sales Data" dataset is collected and processed to construct a clean and comprehensive data frame containing 16 variables and 421,570 data points. Data preprocessing, including handling missing values, outlier removal, and encoding categorical data, ensures the dataset's consistency and accuracy. Features are normalised using Z-score normalisation to enhance model convergence and performance. The most pertinent predictors are found using feature selection approaches, which reduce redundancy and maximise model accuracy. The dataset is then split into training and testing sets. They will be using a train set to test to create and another independent train set (80:20 ratio) to test it. It has deployed machine learning algorithms such as SVM, LSTM, and XGBoost in order to predict sales, and their effectiveness is evaluated using metrics like MAE, RMSE, and R^2. The analysis integrates insights from visualisations such as histograms, correlation plots, and holiday vs. non-holiday sales comparisons to refine model predictions and provide actionable insights for ERP-driven decision-making.

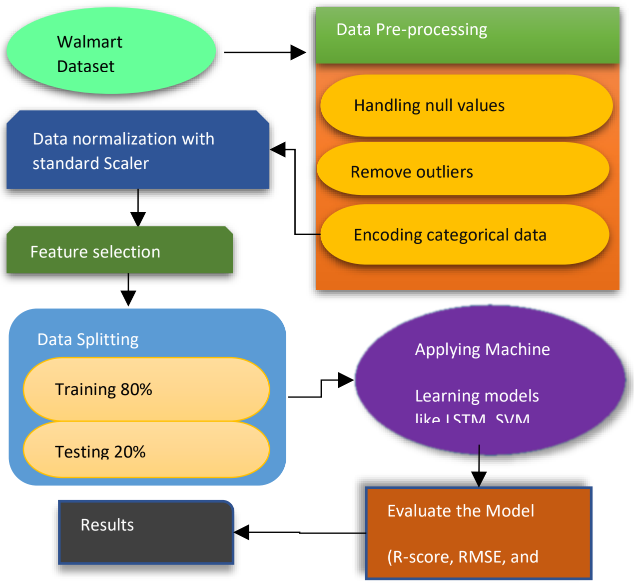

Figure 1: Flowchart for Sales Forecasting in ERP system.

The flowchart's subsequent phases are briefly described below:

A. Data collection and visualisation

The "Sales data" dataset, which is openly accessible on the Kaggle website, provided the data utilised in this investigation. A data frame with 16 variables was produced after the dataset was processed. There are 421570 data points for each variable. Weekly_Sales, the study's dependent variable, is a representation of each store's weekly sales. The following visualisation of data is provided in below:

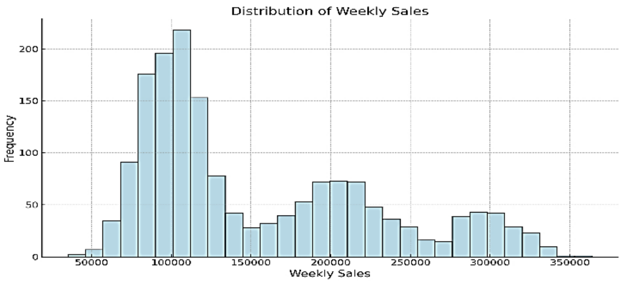

Figure 2: Histogram of Walmart's weekly sales.

Figure 2 shows the Distribution of weekly sales in the Walmart dataset. The histogram of the sales data shows a right-skewed distribution, with more weeks experiencing lower sales compared to those with higher sales. The central tendency is concentrated between the 100,000 to 150,000 range, suggesting that most weekly sales fall within this interval. The data is spread across a wide range, from around 50,000 to 350,000, with a few outliers on the right side indicating weeks with exceptionally high sales. These outliers highlight periods of significant sales spikes.

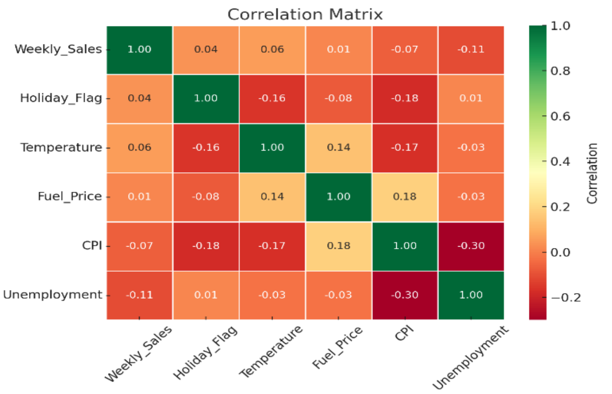

Figure 3: Correlation plot between variables.

The analysis shows weak to moderate correlations between weekly sales and various factors in Figure 3. Sales are slightly higher during holidays, with minimal impact from temperature. Sales decrease slightly as fuel prices and CPI rise, while unemployment has a moderate negative effect on sales. Additionally, holidays correlate with higher CPI and temperature slightly lowers fuel prices. Fuel prices and CPI are positively correlated, while CPI and unemployment show a moderate negative relationship.

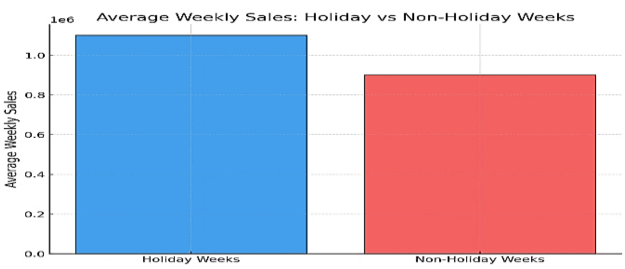

Figure 4: Average weekly sales vs non-holiday weeks.

Figure 4, comparing average weekly sales during holiday and non-holiday weeks, reveals that holiday weeks consistently show significantly higher sales. This increase can be attributed to factors such as heightened consumer spending during the holidays, retail promotions, and end-of-year spending. Retailers can leverage these insights for better inventory, staffing, and marketing planning while also refining demand forecasting and pricing strategies to optimise sales during holiday periods.

B. Data preprocessing

Data pre-processing really means the method of eliminating noise and outliers from the selected data. This entails getting rid of information that is largely unnecessary and redundant. Various pre-processing steps are given below in detail.

- **Handling null values:** To maintain data consistency, either use the imputation of the missing variable by mean or median or replace the missing variable with the average value of the variable.
- **Remove Outliers:** Using business logic, think about deleting or limiting numbers for severe outliers.[21]. Thus, the dataset is cleared of any outliers.

C. Encoding categorical data

To improve model performance, special characters and categorical data are converted to numerical values. Label encoding techniques are used to transform categorical data kinds into numerical data types[22]. Each attribute is assigned a distinct numerical value by label encoding, suggesting an innate ordering of the categories. Each class is assigned a distinct numerical value by label encoding, suggesting that the classes are naturally ordered[23]. But when it comes to output labels, there is no discernible hierarchy or connection between the various types.

D. Data Normalization

Data standardisation is a frequent preprocessing step in machine learning that makes sure features are of the same size, which helps the model converge more quickly and perform better[24]. Z-score normalisation is a popular technique for standardising data and is described as (1):

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

where the original value is represented by x, the standardised value by z, the feature mean by μ, and the feature standard deviation by σ.

E. Feature selection

Choosing the right features helps improve Sales Forecasting in ERP systems, as the machine learning models have shown[25]. However, the use of feature selection algorithms presents the best set of features to eliminate the duplication of information in the dataset[4].

F. Data splitting

Training test data and test test data are two different categories for the dataset. Models were trained using the training set, and assessments were made using the test set[26]. Only 20% of the data set was made up of testing data, whereas 80% of the data was made up of training data.

G. LSTM model for sales forecasting

The data parameters of distant nodes are difficult to learn, similar to the problems with disappearing and exploding gradients in conventional recurrent neural networks. Thus, its enhanced (LSTM) model is used in this investigation. The memory function of an LSTM may correlate time series data, identify characteristics, and perform long-term learning.

As previously said, all recurrent neural networks are made up of repeating the same modules. The LSTM's recurrent structure, which consists of four neural network layers and their unique interactions, is more sophisticated compared to the extremely basic recurrent structure of a standard recurrent neural network. The LSTM repeat module uses two components to calculate a single neurone: updating the neural network's state and calculating its output value [27]. The input gate, forgetting gate, and output gate are the three gate functions found in neurones. As input and output functions govern this gate function, the gate function accepts input, memory, and output values[28].

The forgetting gate determines how much information the neuronal state must forget at any one time[29]. Let's now examine the forgetting gate calculation procedure in more depth, as shown below (2):

$$f_t = \sigma(W_f.[h_{t-1}\, x_t] + b_f \qquad (2)$$

where ht-1 is the network's state that was hidden at the prior time step, f_t is the forgetting component to be available at output, and the values of the Wf, bf, and σ function define the proportion of information that is forgotten.

The input value and the new input are the two components that make up the input gate (3,4):

$$i_t = \sigma(W_i.[h_t, x_t] + b_i) \qquad (3)$$

$$\tilde{c}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c)(4)$$

The input gate filters input layer information when the tanh function's output value falls between -1 and 1, and the input gate computation formula is as follows (5):

$$C_t = f_t.C_{t-1} + i_t.C_t \qquad (5)$$

where Ct Is the state of the neural network updated right now [30]. Here is how the output gate and hidden state are calculated (6,7):

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \qquad (6)$$

$$h_t = o_t.\tanh(C_{t)} \qquad (7)$$

H. Performance metrics

Model evaluation is an important phase of the machine learning system[31]. It gives a chance to estimate the effectiveness of ML models and obtain the insights into their assets and liabilities. For an evaluation of the forecasting models, the mean absolute error (MAE), mean square root error (RMSE), and R^2value are employed as will be explained next.

Mean Absolute Error (MAE)- The strategy applied uses the average of absolute error [5]. The average absolute difference between point I, coordinates, yi and xi, is determined by MAE. Here is the formula of MAE which is shown below in Eq. (8):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (8)$$

where y_i stands for an actual value, n for the number of observation and $\hat{y}_i$for an estimated value.

R-Square Error (R^2) – The measure of the variability of the errors between the actual and projected observations is given as the root mean squared error which is the square root of mean of the squared differences.[32]. It is always determined between 0 to 1. The statistical formula of the R-Square is shown below in the Eq. (9):

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (9)$$

In this case, 'n' stands for the number of samples, 'y_i' for actual values, and '$\hat{y}_i$ ' for anticipated or forecasted values.

R² Score: Another name for it is the coefficient of determination, which indicates the extent to which a model can explain the in terms of the dependent variable, the extent of variance. The R² score is used to evaluate the scattered data surrounding a fitted regression line[3]. Greater R² values for similar datasets show less difference between the anticipated and actual data. It determines the correlation between the projected and actual data on a scale of 0 to 1. It is provided by Equation (10).

$$R^2 = 1 - \frac{SS_{res}}{SS_{total}} = \frac{\sum(y_i - \hat{y}_i)^2}{\sum(\hat{y}_i - \mu)} \qquad (10)$$

where, SSres is the sum of square of residuals, SStotal is the total sum of square, µ is the mean value, $\hat{y}_i$ is the true value and $\hat{y}_i$ is the forecasted value.

4. Result Analysis and Discussion

The experiment was performed on the supercomputer with 4 GB RAM, GPU, Windows 10, and the Python simulation tool. This section provides the results of models in terms of R-Sqaure, RMSE and MAE performance measures for the sales prediction on the sales dataset. The LSTM model's performance is shown in Table II below.

Table 2: LSTM Model performance for sales prediction on the Sales dataset

Matrix	LSTM
MAE	12.37
R2	99.05
RMSE	16.37

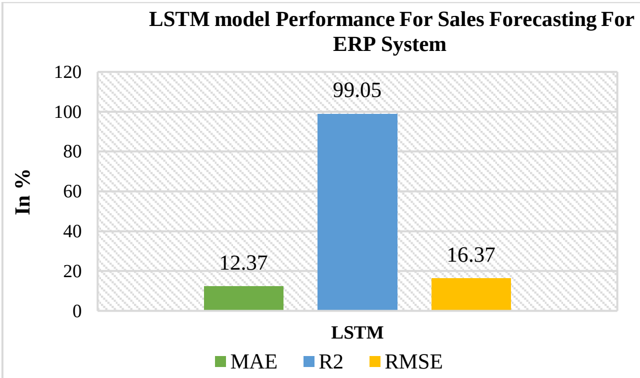

Figure 5: Results of the LSTM model.

The LSTM model demonstrates exceptional performance in sales prediction; Figure 5 shows its evaluation metrics. The model shows high accuracy when it comes to sales forecasting with an MAE of 12.37; it also exhibits a robust fit with an R-squared value of 99.05. Moreover, it was identified that in the proposed model the RMSE of 16.37 stresses on the low error rate when compared to other models. These results suggest that LSTM has the capability to identify and model the sales data patterns and forecasts accurately.

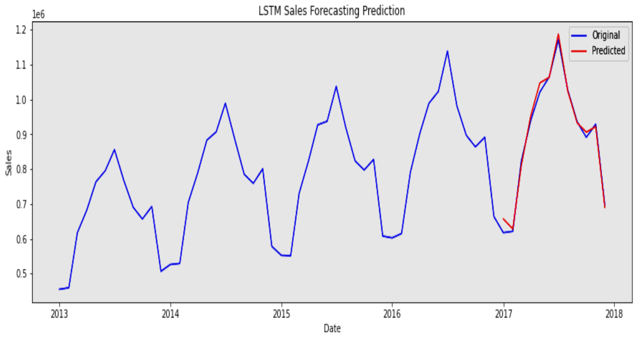

Figure 6: Sales forecasting based on the LSTM model.

The last panel in Figure 6 illustrates that the LSTM model is able to follow the long-term increasing trend and seasonality of the sales data well in general, though it fails to identify many of the specific local maxima and minima, especially towards the end of the forecast horizon. Despite the ability to estimate the oscillations, the model underestimates some of the peaks and overestimates a number of peaks, which should be improved. To increase the model performance, improve should increase the training data, tweak different parameters, adding features like holidays, and promotions, and using the Method of the ensemble to get better patterns and accuracy.

Table 3: Comparative Analysis for Sales Forecasting on the sales dataset.

Models	**MAE**	**R2**	**RMSE**
LSTM	11.64	99.34	13.57
SVM[32]	32.02	56.58	-
XGB[16]	-	76	6.63

A comparison of several models is shown in Table III. for sales prediction on the sales dataset. The LSTM model emerges as the best model with the least MAE of 0.01164, a highly desirable R-Square of 99.34 percent and the highest RMSE of 13.57 percent. On the other hand, the result of the SVM model reveals an even higher MAE of 32.02 and a lower R-Square figure of 56.58 signifying lower accuracy of fit and a poorer fit on the actual data. The XGBoost (XGB) model does not offer an MAE values but a relatively high R-Square of 76 and a lower, yet not significantly low RMSE of 6.63 emphasises the credibility of the model but reduces it to second best performance unlike LSTM. This has highlighted LSTM model as the one that perfectly fits the best Regarding sales forecasting forecasting.

5. Conclusion and Future Work

In today's competitive environment and world economy, the place of sales forecast in management decision making for business strategies development, inventory and resources management is invaluable. However, it's probably the biggest limitation bottled in most of the traditional approaches to forecasting, that only most of them merely exploit historical values for their forecasts. The necessity of applying machine learning and prediction analytics for sales forecast within ERPs discussed with regards to this paper. By using intricate machine learning algorithms including but not limited to, Support Vector Machines (SVM) , Long Short-Term Memory (LSTM), and XGBoost, the study comparatively offers a better accuracy rate to forecasts among them, LSTM did it excellently well. The LSTM model had a value of R² 99.34%, MAE of 11, 64 and RMSE of 13, 57 which better imitates complicate curvatures of sales and offers insightful data on the sales pattern that could form the basis for efficient inventory control and strategic planning in this case. Nevertheless, there are some limitations to the current work. However, the dataset generated in the analysis may not incorporate full details of the factors that affect sales, ranging from macroeconomic factors to competitors and customers' current or next action plans. However, the LSTM model had difficulties in capturing deep volatile emotional features which causes drastic changes in the sales volume. These challenges suggest that the model should be refined to some extent and the dataset should be made more extensive.

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