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Sales Forecasting Using Machine Learning Models: A Comparative Study

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Abstract
Sales forecasting is a critical activity for businesses, enabling them to make informed decisions about production, inventory, marketing, and other key areas. Traditional sales forecasting methods, such as time series analysis and statistical regression, are often unable to capture the complex relationships between factors influencing sales, leading to potential inaccuracies. This study aims to address these limitations by developing a sales forecasting model using deep learning and machine learning techniques. Deep learning methods, capable of modeling complex relationships and adapting to changing market conditions, are expected to improve the accuracy and cost-effectiveness of sales forecasting. This study involves data collection and preprocessing, model development and evaluation. LSTM model, performed quite well with an accuracy of approximately 80%. The Random Forest Regressor and XGB Regressor outperformed the LSTM model with accuracy scores of 94.79% and 98.7% respectively. On the other hand, the Linear Regressor model underperformed, delivering an accuracy of just 57.72%. This study reinforces the idea that a combination of traditional forecasting methods, machine learning, and deep learning models can be utilized effectively to gain more accurate sales forecasts. Based on the findings and conclusions of this study, it is recommended that the models should be continuously updated and improved with the influx of new data, to adapt to changing market conditions and trends.

Keywords: Sales Forecasting, Machine Learning, Data Collection, Training, Evaluation

Introduction

Sales forecasting is the process of estimating future sales, typically for a specific product or service. It is an essential tool for businesses of all sizes, as it helps them to make informed decisions about production, inventory, marketing, and other key areas. Traditional sales forecasting methods rely on statistical techniques to analyze historical sales data and other relevant factors to predict future sales (Cheriyan et al., 2018). Sales forecasting can be a challenging task, especially for businesses that operate in complex and dynamic environments. One of the key challenges is the identification of the factors that influence sales. These factors can be historical sales data, economic conditions, competitive landscape, and other factors. Traditional sales forecasting methods, such as statistical regression, time series analysis and judgmental forecasting often fall short in capturing the complex relationships between these factors (Wusu *et al*., 2022). Time series analysis approach to sales forecasting is a method that involves analyzing historical sales data over time to identify trends and patterns. Once these trends and patterns have been identified, they can be used to forecast future sales. Statistical regression is also a method that involves using statistical techniques to model the relationship between sales and other factors, such as economic conditions, marketing, and competitive landscape. Judgmental forecasting is a method that involves using the judgment and expertise of sales managers and other key stakeholders to forecast future sales. Judgmental forecasting methods are often used in conjunction with other forecasting methods, such as time series analysis and statistical regression.

Although, traditional sales forecasting methods have several advantages; they are relatively simple to implement and do not require a lot of specialized knowledge, however, traditional sales forecasting methods also have a number of disadvantages. One of the main disadvantages is their inability to capture the complex relationships between the factors

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that influence sales which can lead to inaccurate forecasts, especially in dynamic and complex environments (Green, 2022). Another disadvantage of traditional sales forecasting method is that they cannot learn from new data. This means that the forecasts must be updated manually whenever there are changes in the market environment. Hence, the introduction of machine learning techniques for sales forecasting. Deep learning is a type of machine learning that uses artificial neural networks to learn from data. Neural networks can model complex relationships between data points, which makes them well-suited for sales forecasting. Applying deep learning techniques to sales forecasting offers several advantages. Deep learning models can handle large and complex datasets, capturing intricate patterns and dependencies that may be missed by traditional methods. In addition, deep learning models can automatically extract relevant features from raw sales data, reducing the need for manual feature engineering. Also, deep learning models are flexible and can adapt to changing market conditions and trends (Fathallah *et al.,* 2017). Research shows that deep learning models have been shown to outperform traditional sales forecasting methods. A study by Salesforce found that deep learning models were able to improve the accuracy of sales forecasts by up to 20% while another study by IBM, found that deep learning models were able to reduce the cost of sales forecasting by up to 50% (Abdulrahman & Baykara, 2020) . Therefore, this study employed deep learning and machine learning techniques for sales forecasting.

There has been a growing interest in the application of deep learning for sales forecasting in recent years. Several studies have evaluated the performance of deep learning models on a variety of sales datasets, and the results have been promising. One of the earliest studies on deep learning for sales forecasting was conducted by (Shilong, 2021), who compared the performance of a deep neural network (DNN) model to traditional forecasting methods such as ARIMA and exponential smoothing on a retail sales dataset. They found that the DNN model outperformed the traditional methods in terms of accuracy. Adenusi et al., (2022) proposed a novel deep learning model for sales forecasting that incorporates both temporal and spatial information. The model was evaluated on a sales dataset from the manufacturing industry, and it was found to outperform traditional forecasting methods by a significant margin. Elalem et al. (2023) designed and tested a quantitative forecasting framework for new short-life-cycle products, denoted as the deep neural network (DNN), and compared the results to those of traditional statistical forecasting models. Their model takes the form of time-series clustering and data augmentation to provide an adequate amount of input data, even without an extensive history of sales for new commodities. Mediavilla et al. (2022) published a structured literature review of the 23 existing AI-based models adapted to demand forecasting in supply chain management (SCM), where the authors divided them into traditional machine learning, deep learning, and ensemble classifications. Huber and Stuckenschmidt (2020) proposed a machine learning-based framework for daily retail demand forecasting with a particular focus on calendric special days. Their model compares traditional time series models like exponential smoothing and seasonal naïve with modern machine learning methods, including feedforward neural networks (FNNs), long short-term memory (LSTM) networks, and gradient-boosted regression trees (GBRTs). Punia et al. (2020) suggested a hybridization of the deep learning structure with long short-term memory (LSTM) models and random forest (RF) algorithms to enhance the level of demand forecasting in the multi-channel retailing scenario. The input sequences are passed through the LSTM layer and then undergo the residual correction phase with the RF being utilized as feedback, hence making the model more adaptable and interpretable. A deep learning model based on the RNN/LSTM framework with a modified Adam optimizer was developed by Chandriah and Naraganahalli (2021) to enable automobile spare parts demand forecasting. They have a six-layered model with the weights in each layer optimized by a slight adaptation of the Adam algorithm, which adjusts learning rates on the level of weight vectors instead of weights; this improves convergence behavior and maintains the direction of the gradient. Kilimci et al. (2019) developed a hybrid deep-learning and support-vector-regression (SVR) forecasting model with nine traditional time series methods. Chung et al. (2023) came up with a hybrid machine learning model that uses multiple algorithms of K-means clustering, ElasticNet regression, and Gaussian Process Regression (GPR). The model overcomes the issues of nonlinear patterns of demands and high dimensions of the features because it is based on the K-means, which abnormally clusters similar data. Boukrouh et al. (2025) introduced a hybrid forecasting mechanism, which incorporated the Long Short-Term Memory (LSTM), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Holt-Winters frameworks so as to boost retail sales forecasting. An alternative that is proposed by Feizabadi (2022) is a hybrid machine learning-based forecasting model of demand that will be used to enhance the supply chain performance by combining the ARIMAX and neural network models. In order to improve the accuracy of the forecast, the model relies on both the time series data and the leading macroeconomic indicators. Xie et al. (2021) suggested an improved machine learning model to predict Chinese ports of call tourism based on big data. The

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model combines the least squares support vector regression with a gravitational search algorithm (LSSVR-GSA), thereby improving predictive performance and generalization.

Methodology

This research employed deep learning approach for sales forecasting. Dataset used in training the deep learning models was obtained from Kaggle. During preprocessing, the dataset was clean removing unwanted data. Three machine learning models, which include the Linear Regressor, the Random Forest Regressor, and the XGBoost Regressor, are developed and trained on the dataset. The developed model was tested and evaluated using evaluation measures that include R^2, Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Fig 1 shows the steps involved in developing the system.

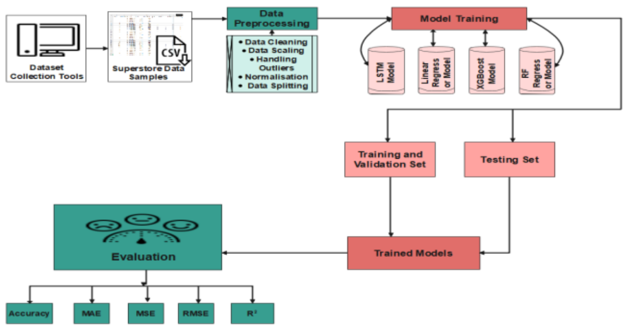

Fig 1: Block Diagram of the developed sales forecasting system

Data Collection

The dataset in this study is referred to as the Superstore Dataset (Vivek468, 2019). It is a time series of data in which the number of items bought per day is recorded between the years 1st January 2017 and the end of 2021. The five-year period translates to 1,826 records per day, which consist of five primary products, namely Book, Shoe, Ring, Necklace, and Pearls, with total sales of 1,296,992, 1,278,211, 983,555, and 1,083,180 units, respectively.

Data Preprocessing Techniques

In the study, the preprocessing stage involved examining the dataset for missing values. All the missing entries were either eliminated or substituted with relevant values so as to preserve the integrity of the data. It was also noted that duplicate records were removed to ensure that there is no bias or over-representation of some transactions. Then, the information was converted into a uniform format. Date columns were verified by checking that all dates were properly structured and all had the same format, and that is a prerequisite of time series analysis. These numerical characteristics, including the number of items sold, were normalized and brought to a similar range, and this way the models learn patterns easier. Categorical variables like product names and types were coded into numerical values in order to be utilized in machine learning algorithms. Lastly, the data was divided into training and evaluation sets; 80 percent were used to train the model, and 20 percent were utilized to evaluate the model. These preprocessing methods made the data accurate, consistent, and reliable forfuture analysis and prediction. The min-max scaling method was used to convert all the values into a normalized set between zero and one. Decomposition, Fourier transform, and wavelet transform were used for the methods of feature extraction to expose hidden cyclical patterns. Feature engineering was used in this research to extract meaningful variables using the historical sales data.

Deep Learning Time Series Prediction System.

The developed system was enhanced by the usage of deep learning techniques to become more precise in sales forecasting. The reason behind the adoption of Long Short-Term Memory (LSTM) networks was that they can learn temporal dependences as well as extract long-term sequential dependencies. The processed dataset was translated into input-output sequences, and then it was trained through the LSTM model. The regularization methodologies like dropout were used to prevent overfitting, whereas optimization algorithms like Adam were used to provide effective convergence. The model was then tested against unseen sales data to determine the accuracy of the trained model. The

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algorithm of the study is represented in Algorithm 1 while the sequence diagram and use case analysis is shown in Figures 2 and 3.

Algorithm 1: Sales Forecasting with LSTM and Machine Learning Models
Step 1: Import needed libraries: Pandas, NumPy, Sklearn, Matplotlib, TensorFlow/Keras, and XGBoost.
Step 2: Import the historical sales data by means of a CSV/Excel file.
Step 3: Data Preprocessing
- 3.1: Dealing with missing values (removing, quantifying, or modeling missing values).
- 3.2: Identify and deal with the outliers through the application of statistical detection and replacement.
- 3.3: Standardize the features by min-max scaling (range [0,1]).
- 3.4: Create time dependencies of lag features and moving averages.
- 3.5: Split training (80) and testing (20) chronologically.
- 3.6: Equilibrium dataset to avoid favoring where the majority of the sales are.

Step 4: Sequence Generating: Time Series.
- 4.1: Prepare the dataset in the form of supervised learning.
- 4.2: Sliding/expanding windows: Expanding windows Use sliding/expanding windows to get input-output pairs of LSTM.
- 4.3: Transform data [samples, time steps, features].

Step 5: Model Development
- 5.1: Featuring baseline machine learning models: linear regression, random forest regressor, and XGBoost regressor.
- 5.2: Construct an LSTM model of the following structure:
  - Input layer (sequence input).
  - Two covered LSTM layers of 64 and 32 units.
  - The dropout rates will be set to 0.2 to prevent overfitting.
  - Linear activation regression output layer (dense).

Step 6: Model Training
- 6.1: Train machine learning on training data.
- 6.2: Fit LSTM Adam optimizer, Mean Squared Error (MSE) loss.
- 6.3: LSTM training of epochs of 32.
- 6.4: Monitor and keep track of training/validation loss and accuracy.

Step 7: Model Evaluation
- 7.1: Test on models on testing dataset.
- 7.2: Calculate measures of evaluation: R^2 Score, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).
- 7.3: Compare linear regression, random forest, XGBoost, and LSTM.
- 7.4: Graph actual and predicted values of sales and training and validation loss curves.

Step 8: Deployment
- 8.1: Store the trained models to be used in real-time prediction.
- 8.2: Create an easy Graphical User Interface (GUI) to interact with the forecasting system.

Step 9: Report Findings
- 9.1: Generalize model comparison and results.
- 9.2: Identify the most successful algorithm for successful sales prediction.

Implementation of the Sales Forecasting Model Implementation

The created sales forecasting system was developed with Python 3.9 on the Google Colab cloud-based Jupyter notebook environment, which is a popular and common research environment. The system combines the principles of deep learning and machine learning; the benchmark model is LSTM. Python libraries like Pandas, NumPy, Scikit-learn, Matplotlib, TensorFlow, Keras, and XGBoost were used in data preprocessing, training the model, and visualization. The sequence diagram and the use case analysis of the system is shown in figure 3 and 4. They were followed in the following steps:

i. Reading the sales dataset.
ii. Cleaning, scaling, balancing, feature engineering Preprocessing of the dataset.
iii. Division of dataset into training and testing.

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iv. Constructing machine learning (linear regression, random forest, XGBoost) models.
v. Developing and testing the LSTM deep learning solution.
vi. Carrying out a prediction of sales, using developed models.
vii. Assessment of the forecasting system.
viii. Comparison of LSTM and other machine learning algorithms.
3.5 Measures of Performance Evaluation.

The regression performance measures were used to evaluate the developed forecasting models as follows: R² Score (Coefficient of Determination), Mean Squared Error (MSE), Mean Absolute Error (MAE).

Results
Table 1 shows the result obtained from training the LSTM-based model. From the table, the results show a promising trend in the LSTM model's performance during the training phase. Throughout the training, the model's loss steadily decreased, both in terms of training and validation loss. This indicated that our model was learning from the data and improving its ability to forecast sales with each epoch. Similarly, the accuracy for both training and validation sets increased throughout the training. It is encouraging to see that the validation loss improved from 0.0087 in the first epoch to 0.00176 in the 15th epoch as shown in Figure 4 and 5. This suggests that the model generalizes well to unseen data and is not overfitting to the training set. The learning rate appears to be well managed, with the system reducing it from 0.0010 to 1.00E-04 after the initial epochs. The early stopping mechanism effectively halted training after 9 epochs, preventing unnecessary computation. This is a good strategy for saving resources when the model has ceased to improve significantly. From our results, the LSTM model performed very well.

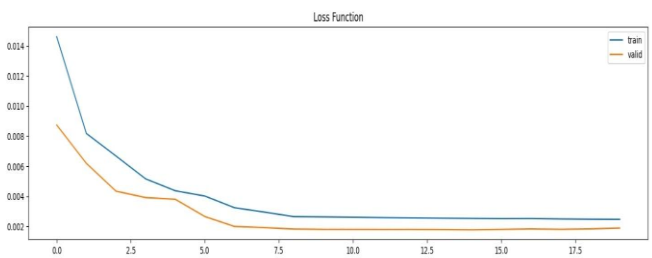

Figure 4: LSTM model loss function Chart

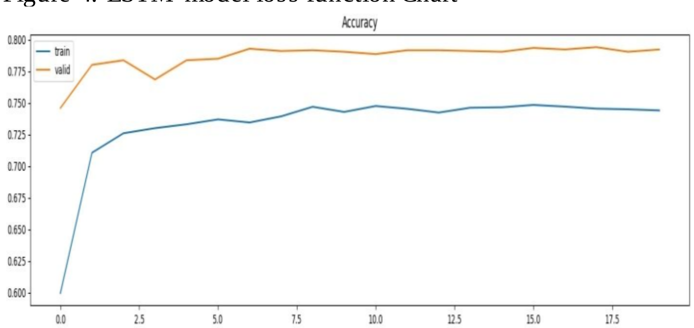

Figure 5: LSTM model Accuracy Chart

Table 2: LSTM Evaluation Results

Metrics	Scores
MSE	0.02364190028415306
RMSE	0.153759228289404
MAE	0.12152876368524165

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Performance Results of the Machine Learning Algorithm

This section evaluates the performance of three machine learning models: Linear Regression, XGBoost, and Random Forest Regressor. Their performance is then compared to the baseline LSTM model.

The Linear Regression (LR) model was trained on the dataset and evaluated. Results show an accuracy of 57.7% on the training set which is a low score that signals a low performance of the LR model on our dataset. the results for RMSE, MAE and MSE are 0.4211, 0.4022 and 0.1773 respectively which is significantly lower than LSTM as shown in Table 3, Figure 6.

Table 3: Linear Regression Evaluation Results

Metrics	scores
MSE	0.1773
RMSE	0.4211
MAE	0.4022

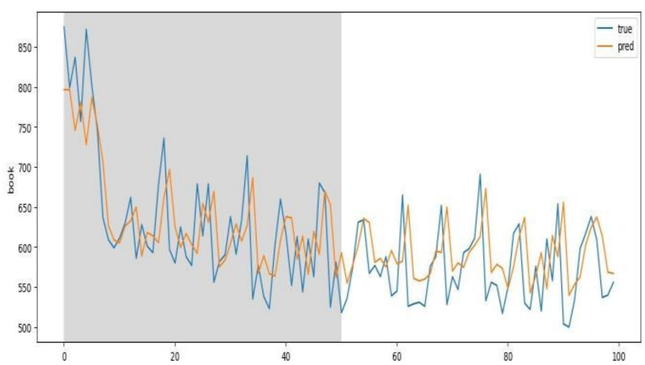

Figure 6 (a): Book

Results obtained after training and testing with XGBoost model shows an accuracy of 98.7% and 0.02364, 0.1538 and 0.1215 for MSE, RMSE and MAE respectively as shown in Table 4 and Figures 7. This shows that XGboost performed better than LSTM for sales forecasting on the dataset used.

Table 4: XGBoost Evaluation Results

Metrics	Score
MSE	0.02364190028415306
RMSE	0.153759228289404
MAE	0.12152876368524165

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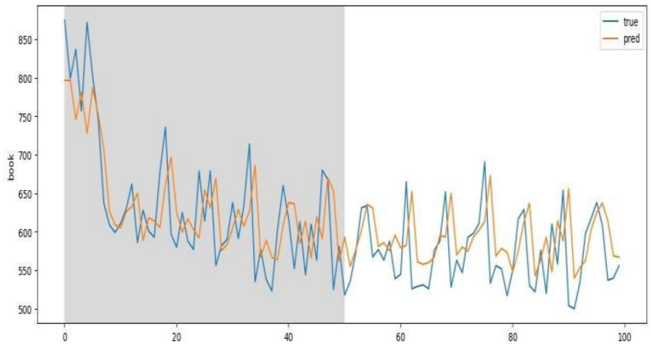

Figure 7(a): Book

Results obtained after training and testing with Random Forest model (RF) revealed an accuracy of 94.8% and MSE, RMSE and MAE scores of 0.192, 0.139 and 0.107 respectively as shown in Figure 8.

Table 5: Random Forest Regressor Evaluation Results

Metrics	Scores
MSE	0.019198498818168135
RMSE	0.13855864757628134
MAE	0.10701125252863597

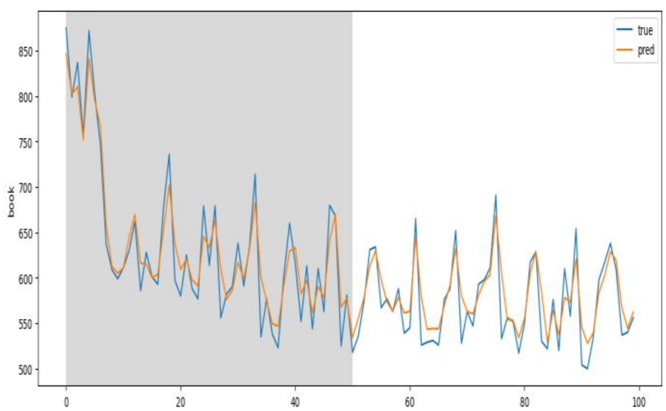

Figure 8(a): Book

Discussion

The contrast in performance among the LSTM model, the Linear Regressor, the Random Forest Regressor, and the XGBoost Regressor demonstrates the importance of choosing the right model for a given task. Our base model - LSTM model, performed quite well with an accuracy of approximately 80%. The strength of LSTM models in handling sequential data, such as time series, is evident in our case. These models are capable of learning from the temporal dependencies in the data, which is crucial in forecasting tasks. The model's loss decreased steadily throughout the training, indicating successful learning, and the model was able to generalize well to unseen data. However, the computational cost and time associated with training LSTM models can be high, which is a potential drawback. Machine learning models delivered varied results. The Random Forest Regressor and XGB Regressor outperformed the LSTM model with accuracy scores of 94.79% and 98.7% respectively. This suggests that for this particular task, ensemble methods such as Random Forest and boosting methods like XGBoost can provide superior results. These models can capture complex relationships in the data and are less prone to overfitting, making them a good choice for

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many prediction tasks. On the other hand, the Linear Regressor model underperformed, delivering an accuracy of just 57.72%. It is important to note that linear regression models assume a linear relationship between the input variables and the output variable. In many real-world scenarios, including ours, this assumption may not be held. The data may exhibit non-linear relationships, and in such cases, linear regression models may not deliver optimal results. Table 6 shows the comparison of all the models used. These results highlight the fact that there is no one-size-fits-all solution in machine learning. Different models have different strengths and weaknesses, and their performance can greatly vary depending on the nature and complexity of the task at hand. The choice of model should be guided by an understanding of the data and the specific requirements of the task. While LSTM, Random Forest, and XGB models have shown promising results, it's important to continue exploring other models and techniques for further improvements.

Table 6: Summary of Results

Machine Learning Model	Accuracy
LSTM	79%
Linear Regressor	57.72%
Random Forest Regressor	94.79%
XGB regressor	98.7%

Conclusion

The purpose of this study was to develop a sales forecasting model by using deep learning techniques and compare its performance with traditional forecasting methods. The findings from this study highlight the potential of deep learning models, particularly LSTM (Long Short-Term Memory), in improving the accuracy of sales forecasting. The LSTM model demonstrated a high degree of accuracy approximately 80% and showed a promising trend in its ability to learn and improve over the training process. Additionally, it was successful in generalizing to unseen data, which is a key indicator of a robust model. In comparison to machine learning models, LSTM displayed commendable performance. However, certain machine learning models such as Random Forest Regressor and XGB Regressor showcased higher accuracy scores, 94.79% and 98.7% respectively, indicating their strong predictive power. On the other hand, the Linear Regressor model achieved a comparatively lower accuracy score, highlighting that not all machine learning models are equally effective in all contexts. This study reinforces the idea that a combination of traditional forecasting methods, machine learning, and deep learning models can be utilized effectively to gain more accurate sales forecasts. It also emphasizes the need for businesses to explore and adopt advanced AI technologies to improve the accuracy of their sales forecasts, which can subsequently enhance decision-making processes related to production, inventory management, marketing, and more. Based on the findings and conclusions of this study, it is recommended that the models should be continuously updated and improved with the influx of new data, to adapt to changing market conditions and trends.

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