Advanced Furniture Sales Forecasting Using Machine Learning and Deep Learning Techniques

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Abstract: **Accurate sales forecasting in the furniture industry plays a vital role in maintaining optimal inventory levels and enhancing profitability. While underproduction limits revenue generation, overproduction leads to financial losses due to excess inventory. The objective of this study is to improve the accuracy of sales forecasting, align production with demand, and optimize inventory management in order to enhance profit margins within the furniture industry. To achieve this, historical sales data spanning from 2014 to 2023 was utilized, and various machine learning and deep learning models were evaluated. The results revealed that the linear regression model outperformed all other machine learning models, achieving the highest accuracy with an R-squared score of 1.0 and the lowest error metrics, including a mean squared error of 0.001331 and a mean absolute error of 0.000849. Among the deep learning models, the Long Short-Term Memory model delivered the best performance, achieving an R-squared value of 0.737649, significantly outperforming the standard Recurrent Neural Network, which achieved an R-squared value of only 0.131056. These findings demonstrate the effectiveness of linear regression for short-term predictions and the capability of long short-term memory models in capturing sequential patterns in sales data. Both models present valuable tools for improving inventory management and production planning in the furniture industry.**

Keywords: **Furniture, sales forecasting, Machine Learning Models, Linear Regression, Random Forest and Decision Tree, deep learning**

INTRODUCTION

To maintain a furniture sales production, a complete and accurate management of inventory flow is needed. By searching different articles, we concluded which approach is useful for the accuracy of the period to foreshadow in the furniture industry. The automation price highlights the significant increase in machine learning techniques in the industry of furniture as shown in numerous articles. Research shows that the data-driven approach, like Holt-Winters and linear regression, can upgrade the price strategies and improve retail sales foreshadowing accuracy in furniture and furnishing items [1][2].

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The combination of web mining techniques accepts the online data for effective utilization to confirm the pricing decisions, keeping the importance of competition in the furniture market [3]. The machine learning method, especially (ANN) artificial neural networks along with the Bayesian training, has been shown to enhance the demand in accuracy prediction, essential for managing inventory and sales approaches [5][6]. In a customized furniture manufacturing context, machine model learning has illustrated capacity in early estimated cost, improving production planning and decreasing uncertainties [4]. Future prediction techniques for supposing long short-term memory networks have been used to capture the chronological dependencies in data sales, refining the whole forecasting accuracy [8]. Consumer behavior and sales patterns require adaptation in demand forecasting methodologies after the pandemic of Covid-19 [10]. Numerous articles emphasized the effect of period analysis and XGBoost algorithm application in predicting sales trend and managing inventory [9] [30]. Artificial intelligence and augmented reality applications are transforming the furniture shopping experience by giving them immersive visualization tools that encourage customer involvement and support informed purchasing decisions [17] [23]. AR technologies have been improved through interaction in retail environments, taking it to better consumer satisfaction by recent studies [19] [22]. The AR collaboration in carpentry student's production line training indicates that it is a powerful tool for bridging academic instruction with practical skills [21]. AR implementation increases the sale process of furniture, as it attracts the customer towards a virtual view [26]. The furniture industry plays a pivotal role in sustaining and managing processes accurately. In research it is mentioned how resource management is improved by using lean tools and machine vision technologies having a high impact on production and quality control [35][38]. Sales forecasting accuracy is improved by utilizing and comparing the deep learning model LSTM with SARIMA and Prophet, which provides insight into how deep learning handles complex data more accurately [37]. To meet end users' needs and stay competitive in the industry, the use of advanced data analytics, machine learning, and sustainable practices is preferred [28]. [39]. In the furniture industry, production planning plays an important role in improving functional efficiency and optimized inventory management [40]. The objective of this study [42] is to develop accurate and reliable rainfall forecasting models using conventional machine learning algorithms, aimed at enhancing the precision of predictions in Australia. By analyzing historical meteorological data. The objective of this study [43] is to evaluate and compare the performance of various machine learning and deep learning models for customer churn prediction. This study [44] is to compare the performance of various statistical and machine learning models, including ARIMA, random forests, linear regression, gradient boosting, and support vector machines, for accurate rainfall prediction. This study [45] investigates the use of Twitter data for disaster prediction by classifying tweets as "Related to Catastrophe" or "Not Related to Catastrophe" using machine learning and natural language processing techniques. It also examines various data mining approaches applied to disaster management and crisis response. This study [46] aims to develop and evaluate the Enhanced QRS Morphological Feature Extraction (E-QRSM) algorithm for accurate classification of premature ventricular contraction (PVC) arrhythmias from ECG signals, improving detection efficiency and reducing manual analysis effort. The study [47] emphasizes how normalization and deep neural networks enhance the development of dependable forecasting models for decisions. The objective of [48] is to design a refined forecasting system that is capable of accurately predicting the furniture's sales based on the underlying features and market changes; SARIMA, Bi-LSTM, and Bi-GRU models are employed to increase the accuracy as well as the continuity of the prediction. This study [49] is primarily concerned with the accurate e-commerce sales forecast based on LSTM models using Taobao data to improve the inventory level, market trends, and decision-making. This study [50] seeks to analyze the performance comparison of the ARIMA, SARIMA, and LSTM models for an automobile company in India and establish that LSTM yields better results with further improvement by optimizing the said hyper-parameters. This study [51] seeks to understand the significance of big data in intelligent manufacturing with special reference to the furniture workshop, whereby the functions of scheduling of jobs, quality check, & prediction of equipment failure can be examined.

Problem Statements

This study aims to develop a predictive system that leverages historical furniture sales data to forecast future sales using artificial intelligence. By providing insights for informed decision-making, the system will help optimize inventory levels, preventing issues such as overstocking or stock shortages. This, in turn, will support the sustainability of profit margins within the industry.

Research Questions

I. Compare different machine learning algorithms and deep learning algorithms for furniture sales forecasting using historical data.
II. Impact of data preprocessing techniques on the performance of ML models for furniture sales?
III. Which specific model of ML provides the best accuracy based on evaluation metrics?

LITERATURE REVIEW

The use of ML improves automated price prediction in furniture [1]. Sale prediction in furniture retail is improved using MLR and Holt-Winters [2]. The price of case furniture products in online data is enhanced using the web mining technique [3]. ML improves the efficiency in the production of customized furniture at early cost estimation [4]. Sales forecasting accuracy is improved in furniture companies using ANN with Bayesian training [5]. Prediction of accuracy in inventory and sales management is demonstrated using ML algorithms [6]. The use of the Multiple Forecast method produces better accuracy results in sales predictions [7]. LSTM enhances the forecasting accuracy by capturing the temporal dependencies [8]. Time series analysis gave better results in inventory management and furniture product sales planning [9]. COVID-19 impacts consumer behavior and demand forecasting methodologies in furniture companies [10]. Analytical methods are used to project future demand estimation for furniture up to 2025 [11]. Prediction accuracy and decision-making are gained for forecasts in the furniture market through ML [12]. Regional market dynamics and consumer preferences vary in retail sales of furniture across different cities [13]. Operational efficiency and decision-making are improved in the furniture supply chain through optimized planning [14]. Sustainable practice in furniture production improves operational and manufacturing performance [15]. Seasonal demand fluctuations are improved using comparative analysis of time-series forecasting [16]. Customer decision for buying online is improved using AR and AI-driven 3D models [17]. Pampanga and Philippine AR applications for made-to-order attract customer attention [18]. Sales success in the retail furniture industry is obtained using AR [19]. Customer satisfaction and a better furniture shopping experience are obtained using interactive mobile AR applications [20]. Students' understanding of production processes is improved by integrating AR and VR in carpentry training [21]. AR improves the experience for online furniture purchases [22]. Visualization of furniture before buying in the customer space is gained through the AR approach [23]. AR applications give a better shopping experience because of the interactive visualization of furniture [24]. AR technology is revolutionizing shopping habits by enhancing consumer satisfaction [25]. In Vietnam, furniture sales management is improved by using the AR system [26]. Digital marketing strategies are improved using an AI-based forecasting model [27]. The wooden furniture industry provides insights for market stakeholders using statistical techniques [28]. Supermarket sales trends, facilitating inventory management, are predicted with better results by using the FB-Profit algorithm [29]. In large retail companies, the XGBoost algorithm improves prediction accuracy for Walmart sales [30]. The analytical hierarchy method improves marketing tactics, and online furniture buying behavior is identified by identifying important variables [31]. Comparative analysis of traditional and ML algorithms shows strengths and weaknesses in home appliance demand forecasting [32]. Kansei engineering integrated with swarm optimization improves the design process of Ming-style furniture [33]. Sales forecasts and location analysis give a perspective of optimizing retail management using the regression model [34]. Efficiency and productivity at furniture companies are improving using tools and techniques for process simulation [35]. The LSTM model is used to improve the prediction of E-commerce sales data [37]. Machine vision technology helps quality assurance and production effectiveness in furniture manufacturing companies [38]. A system for managing sales information for desktop-based furniture enhances customer satisfaction by organizing data [39]. Production monitoring and control methods in a furniture company boosting operational efficiency [40].In order to anticipate future rainfall occurrences and spot trends in rainfall patterns, this study will use machine learning and deep learning approaches [41][44]. Using traditional machine learning algorithms, it aims to create a rainfall prediction model for Australia that is both accurate and dependable [42]. It also assesses how well four deep learning methods (LSTM, Bidirectional LSTM, CNN, and ANN) and six fundamental machine learning methods (Random Forest, Logistic Regression, and K-Nearest Neighbors) predict customer attrition [43]. Additionally, this study investigates the use of Twitter analysis to study disasters [45] and advances automated diagnostic methods for the identification and treatment of cardiac arrhythmias, which will ultimately enhance patient care and lessen the burden on healthcare systems [46].

This research [47] focuses on enhancing retail sales forecasting in the furniture industry through advanced deep learning techniques. It introduces a hybrid CNN-BiLSTM model with regularization to improve accuracy and generalization, surpassing traditional approaches. The study highlights the importance of normalization and deep neural networks in building reliable forecasting models for better decision-making. The goal of [48] is to create a sophisticated forecasting framework that can precisely predict furniture sales through the identification of fundamental patterns and market shifts, utilizing SARIMA, Bi-LSTM, and Bi-GRU models to enhance the precision and coherence of predictions. This study [49] aims to develop LSTM-based models for accurate e-commerce sales forecasting using Taobao data, focusing on temporal dynamics to enhance inventory management, marketing strategies, and decision-making. This study [50] aims to compare the forecasting accuracy of ARIMA, SARIMA, and LSTM models for an Indian automobile company, highlighting LSTM's superiority and exploring hyperparameters tuning to enhance performance further. This study [51] aims to investigate the role of big data in intelligent manufacturing, with a focus on its applications in furniture workshops, including job scheduling, quality control, predictive maintenance, energy management, and supply chain planning, and proposes a conceptual framework to tackle data challenges. This study [52] aims to assess the performance of various machine learning and deep learning models for accurate retail sales forecasting, supporting enhanced inventory management, improved customer satisfaction, and informed strategic decision-making in the retail industry. This paper [53] introduces an innovative e-commerce sales forecasting approach that dynamically constructs a Directed Acyclic Graph Neural Network (DAGNN) within a deep learning framework.

Comparative Analysis of Past Research Studies for Furniture Sales Forecasting

Table 1 summarizes some past research papers that are most relevant to our study. The following table represents the details of each paper according to the year in which it was published, the country name of which dataset is used, the algorithms or model used, the dataset used and the dataset time duration, the target feature, the accuracy achieved, the results, and the limitations and pros.

Table 1: Comparative Analysis

S. No	Country Year	Algorithms	Dataset & Target Feature	Result	Limitations
[2]	United States, 2024	Multiple Linear Regression Holt-Winters Method	U.S furniture retail sales data. 2019-2023 (five years) Target is Demand in the future for retail furniture sales in the U.	MLR (MAPE) : 3.47% Holt-Winters Method (MAPE) : 4.21%	Forecast demand is limited to 36 months to reduce extrapolation errors.
[3]	United States, 2023	Random Forest (RF), Deep learning	E-commerce dataset of three websites, 300 incidences of bookshelves and dressers. 21st January 2023 to 21st March 2023 Target feature is Price of furniture items	RF: $R^2$0.892 for bookcases, R^2 0.939 for dressers; DL: R^2 0.979 for bookcases and 0.874 for dresser	Prediction accuracy was not that much good due to a lot of variety in bookcase attributes
[4]	Lithuania, 2021	Decision Tree, Linear Regression, Random Forest, AdaBoost, Gradient Boosting, KNN, ANN	Lithuanian furniture manufacturing company’s five years historical data of 1026 products, Target feature is Cost of custom designed furniture	Highest R^2 values: RF (0.842) and Gradient boosting (0.84)	Complex models like ANN requires large amount of data for better training, when features are reduced after feature selection accuracy is dropped
[5]	Turkey,2017	ANN using Bayesian Training Rule	Monthly sales data of seven years from January 2009 to December 2015 of furniture manufacturing company in Turkey (Trabzon) Target features	Sitting groups MAPE (5.223%), MAPE of Bedrooms (5.951%), Teen Rooms MAPE (5.954%), Dining rooms MAPE (3.588%	Local demo graphic for (e.g population and region economic circumstances) are not taken on board by model

			Monthly sales of furniture items which includes bedrooms, dining room, teen rooms, sitting groups and armchairs.	), Arm chairs MAPE (3.057%)	
[8]	Poland (researchers) 2021	Long Short-Term Memory (LSTM) network	Furniture company's daily sales data from January 2017 to March 2019, Target is sales value Sales value	MSE (Mean Square Error): 3197.75	Possible dependency on historical sales data without the presence of external factors
[9]	Indonesia, 2024	SARIMA(Seasonal Autoregressive Integrated Moving Average)	PT XYZ (furniture) sales data from October 2020-April 2024, target is sales	MAPE: 16.02% SARIMA model accurately forecast sales from 2024 to 2026, fulfilling the business criteria	Restricted focus on the external factors that may affect the sales forecast
[12]	Bulgaria, 2023	CART Ensemble with racing (Arc70 model)	Traffic data of a large furniture supplier from January 2020 to October 2021,target is Store and Web Traffic	Store traffic R^2 = 0.957, MAPE: 7.15%	Difficult to decode because of ensemble methods as it requires a lot of computational capability
[15]	Slovakia, 2017	ANN with regression analysis	Data of a furniture manufacturing company, Target is Milling surface roughness, cost and duration	Regression analysis prediction for roughness R^2 = 0.49	ANN complexities leads to limited interpretability and an increased in computational cost
[16]	Canada, 2022	ARIMA, SARIMA, Prophet, LSTM, CNN	Sales data of a public superstore from 2014 to 2017,target is Furniture sales	Stacked LSTM RMSE: 128.51, MAPE of Stacked LSTM (17.34) For seasonal	Difficulty in tuning DL models, DL model requires large dataset for better performance
				sales trends Stacked LSTM provides the most accurate predictions, For holidays Prophet model performs well	
[27]	India ,2021	ANN, MLP(Multi layer Perceptron)	Customer reviews rating on Amazon.in and Snapdeal.in (February to July 2019 only six months), Target is Sales volume forecast (for coming 1 month)	Overall accuracy is reported to be outstanding and acceptable, but it goes down with increase in prediction horizon, ANN model forecasted sales volume in a better way,	Limited to Amazon and Snap deal for collection of data
[28]	China, 2019	ARIMA	Yearly sales, output, export, and import volumes of the wooden furniture company from 2001 to 2017, target is Sales, output, export, import of wooden furniture	Predictions for sales, output, and exports indicates ongoing growth; there are chances of oversupply by 2023	Limited dataset, short term time series
[29]	India, 2021	FB Prophet, ARIMA, Holt-Winters	Kaggle (supermarket sales data) from 2014 to 2017, Target is sale	FB Prophet MAPE: 8.3%, ARIMA MAPE: 14.3%, Holt-Winters MAPE: 11.8%	Scalability hurdles for large dataset; offered fusion approaches
[30]	United States (Walmart), 2020	XG Boost	Kaggle dataset of Walmart sales from 2014-2017, Target is	RMSSE: 0.141 and 0.113 lower than	Limited data, overfitting because of massive feature

			Walmart (Sales forecast)	Logistic Regression and Ridge algorithm	engineering
[36]	USA, 2024	LSTM, LGBM	American Multinational Company retail sales data (29 January 2011-19 June 2016), target is sales demand	LSTM WRMSSE: 0.8966, RMSE: 5124, MAE: 2459.05, WMAPE: 0.1445, LGBM WRMSSE: 0.7255, RMSE: 4233, MAE: 2325.28, WMAPE: 0.1158	LGBM tends to over fit, LSTM performance is low in retail sector
[37]	Turkey, 2023	LSTM, Prophet, SARIMA; ANN, ARIMA, Hybrid Models	E-commerce grocery sales data; Multiple dataset, Target is Sales forecast, total sales	LSTM $R^2 = 0.9113$, SARIMA $R^2 = 0.8791$, Prophet $R^2 = 0.8243$	Worst performance was given Prophet, ML models lacks to be easily understood

The comparison of related works on furniture sales forecasting reveals the following key points:

1) Traditional method Techniques like multiple linear regression, Holt-Winters, ARIMA, and SARIMA have been used but often show limitations in accuracy, particularly for long-term forecasts or complex datasets.
2) Machine learning Methods like random forests and gradient boosting have shown higher accuracy, but require significant data for effective performance.
3) DeepLSTM networks and hybrid models (e.g., LSTM + SARIMA) outperform traditional methods, capturing temporal patterns and achieving better accuracy, though they can suffer from overfitting and high computational costs.
4) Common issues across studies include the need for large datasets, the complexity of tuning models, and the risk of overfitting with deep learning models. Overall, while traditional methods remain common, deep learning techniques like LSTM are proving more effective for capturing complex, nonlinear sales patterns in furniture forecasting.

A. Source Table

The source table 2 summarizes the past research papers that have most useful content regarding furniture sales forecasting, providing the information about machine learning algorithms for a model with the best accuracy. These 13 sources provide extensive information about sales forecasting.

Table 2: Source Table

S. No	Ref. No	Source Name
S1	[2]	"Forecasting Retail Sales for Furniture and Furnishing Items through the Employment of Multiple Linear Regression and Holt–Winters Models"
S2	[3]	"Predicting Price of Case Furniture Products Using Web Mining Techniques"
S3	[4]	"Early cost estimation in customized furniture manufacturing using machine learning"
S4	[5]	"Application of Artificial Neural Networks Using Bayesian Training Rule in Sales Forecasting for Furniture Industry"
S5	[8]	"Forecasting Sales in the Supply Chain Based on the LSTM Network_ The Case of Furniture Industry"
S7	[12]	"Furniture market demand forecasting using machine learning approaches"
S8	[15]	"Sustainable Optimization of Manufacturing Process Effectiveness in Furniture Production"
S9	[16]	"Time-series forecasting of seasonal items sales using machine learning"
S10	[27]	"AI-Based Sales Forecasting Model for Digital Marketing"
S11	[28]	"Forecasting Supply and Demand of the Wooden Furniture Industry in China"
S12	[29]	"Time series forecasting model for supermarket sales using FB-Prophet"
S13	[30]	"Walmart sales forecasting using XG boost algorithm and feature engineering"

B. Feature Table

This table 3 summarizes some of the main features which are mostly used in past studies and are also important feature for this study. In furniture sales forecasting Order Date and Sales feature should always be used as it helps in predicting the forecast and maintains a proper inventory level

Table 3: Features Table

S NO	Ref. NO	Source Name
S1	[2]	"Forecasting Retail Sales for Furniture and Furnishing Items through the Employment of Multiple Linear Regression and Holt–Winters Models"
S2	[3]	"Predicting Price of Case Furniture Products Using Web Mining Techniques"
S3	[4]	"Early cost estimation in customized furniture manufacturing using machine learning"
S4	[5]	"Application of Artificial Neural Networks Using Bayesian Training Rule in Sales Forecasting for Furniture Industry"
S5	[8]	"Forecasting Sales in the Supply Chain Based on the LSTM Network_ The Case of Furniture Industry"
S6	[9]	"Time Series Implementation for Sales Forecasting of Furniture Products at PT XYZ"
S7	[12]	"Furniture market demand forecasting using machine learning approaches"
S8	[15]	"Sustainable Optimization of Manufacturing Process Effectiveness in Furniture Production"
S9	[16]	"Time-series forecasting of seasonal items sales using machine learning"
S10	[27]	"AI-Based Sales Forecasting Model for Digital Marketing"
S11	[28]	"Forecasting Supply and Demand of the Wooden Furniture Industry in China"
S12	[29]	"Time series forecasting model for supermarket sales using FB-Prophet"
S13	[30]	"Walmart sales forecasting using XG boost algorithm and feature engineering"

C. Mapping Table

Table 4 represents the features that are mentioned above and summarizes in which source the selected feature is utilized and whether our study is using that feature or not. The mapping table makes it easier to understand and represent which feature is used in which source.

Table 4: Mapping Table (Features and Source)

feature	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S 10	S 11	S 12	S 13	Our Work
F1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F3	✗	✓	✗	✓	✓	✗	✓	✗	✓	✓	✗	✗	✗	✓
F4	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
F5	✓	✗	✗	✓	✓	✓	✓	✗	✓	✗	✓	✓	✗	✗
F6	✗	✗	✓	✗	✓	✗	✓	✗	✗	✓	✓	✗	✓	✗
F7	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓
F8	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✓
F9	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗
F10	✓	✓	✓	✓	✓	✗	✗	✓	✗	✓	✓	✓	✗	✗
F11	✗	✗	✓	✗	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓
F12	✗	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗

In our proposed approach, we enhance traditional sales forecasting models by incorporating additional factors, such as Customer Demographics and Product Category, along with Hyperparameters Tuning to improve accuracy. By integrating customer characteristics like age, income, and location, we gain deeper insights into purchasing behavior, allowing us to forecast demand more precisely. Understanding how different customer segments interact with various products helps refine predictions, enabling us to anticipate high-demand periods more effectively. Furthermore, we classify furniture items into specific categories (e.g., chairs, tables, sofas), which allows for a more detailed analysis of sales trends within each product type. This segmentation helps capture variations in demand, leading to more tailored and accurate forecasts for each category. To further enhance model performance, we apply hyper parameter tuning to optimize key parameters, such as learning rates, number of layers, and neurons. This ensures that our deep learning models are finely tuned, improving their accuracy and reducing the risk of overfitting. By combining these advanced techniques, our methodology offers a more comprehensive and reliable approach to furniture sales forecasting, leading to better inventory management and more informed business decisions

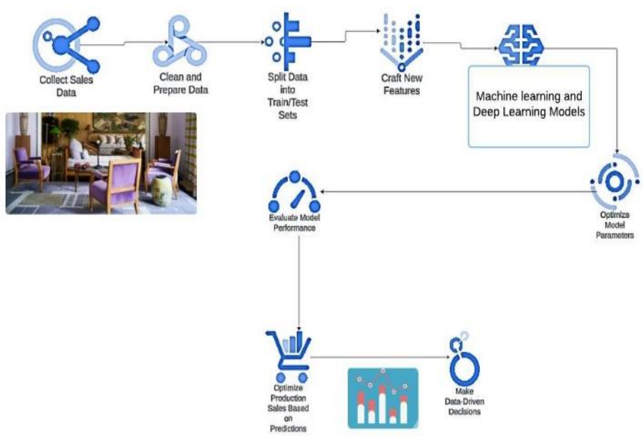

Figure 1: Overview of Methodology

Dataset Description

In this study data is gathered from a local market manually and a cash memo, that data is completely updated on an excel sheet, the dataset contains the data of 10 years starting from 2014 to 2023, 13 attribute and 9420 row entries shown in table 5.

Table 5: Dataset Table Description

Year	2014-2023
Size	9420 rows entries, 13 columns
Features	5 numerical features, 7 categorical features
Target	Sales

METHODOLOGY

The dataset utilized in this study, collected from a local market, was meticulously preprocessed to ensure high quality and usability. The overall methodology, as depicted in Figure 1, encompasses several critical steps. Initially, outliers were identified and systematically removed to enhance data consistency, and missing values were imputed using the median method. Subsequently, the dataset was divided into two subsets: 80% for training and 20% for testing. To analyze and predict sales trends, various machine learning and deep learning models were employed. The machine learning algorithms included linear regression, K-Nearest Neighbors (KNN), decision tree, support vector regression (SVR), gradient boosting, XGBoost, neural networks, and Random forest. For deep learning, Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) were implemented. To optimize model performance, hyperparameters tuning was conducted. This involved splitting the training data into subsets and experimenting with different parameter combinations. This approach not only prevents over fitting. The models were evaluated using key metrics such as R², MAE, RMSE, and MAPE to assess their accuracy and reliability in forecasting sales.

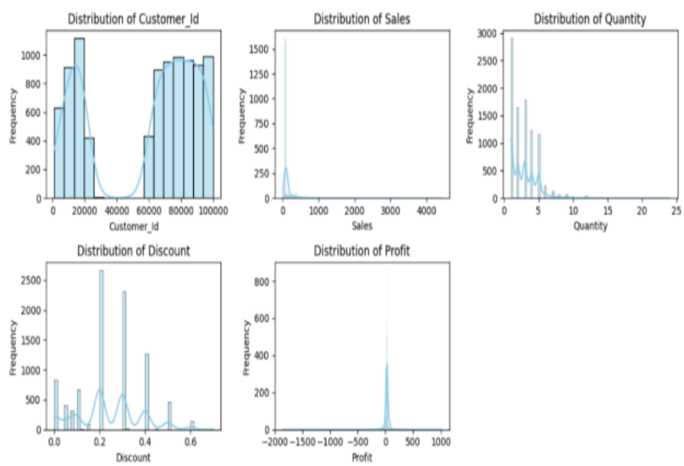

Figure 2: Numeric Features Distribution

The distribution of the dataset's primary numerical and category features is depicted in the figure 2 and 3. Numerical features are customer IDs are evenly distributed, while sales values are concentrated at the lower end, with few high-value outliers. Most orders involve small quantities, and discounts peak at certain levels, indicating promotional patterns. Profit values are mainly around zero, with occasional significant gains or losses, reflecting variability in profit margins. The majority of users access the platform using web devices, and there are more female clients than male ones. There are fewer guests and social sign-in users than regular members, who make up the greatest consumer base. Among the product categories, "Home &

Furniture" is the most popular. "Medium" orders are the most prevalent in terms of order priorities, followed by "High" and "Low." Finally, fewer transactions are performed with cash or wallets; most payments are made online.

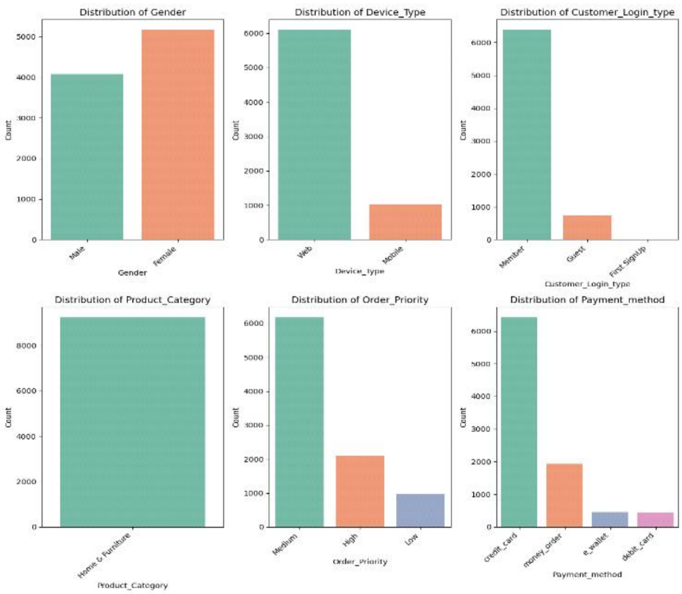

Figure 3: Categorical Features Distribution

The table 6 shows the names of 13 features which are used in a dataset and the feature description and its data type of furniture sales.

Table 6: Features Table

S. No	Feature Name	Description	Data Type
1.	Order_Date	The date on which order is placed	time
2.	Customer_Id	Every single customer's unique Id	Int64
3.	Gender	Customer's gender	object
4.	Device_Type	Type of device used for purchase (e.g. web or mobile)	object
5.	Customer_Lo gin_ type	Login type used by the customer (e.g. guest or member)	object
6.	Product_Cate gory	Category of product which is being purchased by a customer	object
7.	Product	Product name of a furniture (e.g.: sofa, dinning and beds etc.)	object
8.	Sales	Sales amount of a furniture item / Total sales of a furniture item	float64
9.	Quantity	Purchased item quantity	Int64
10.	Discount	Discount given on the sales	float64
11.	Profit	Profit gained on the sales	float64
12.	Order_ Priority	Order priority (high, medium, low)	object
13.	Payment _ method	Method through which payment is made (e.g.: credit card, e-wallet, money order)	object

The data formats of the different features in the dataset are displayed in Figure 4. While categorical characteristics like "Customer ID," "Gender," and "Product Category" are of type object, numerical features like "Sales," "Quantity," "Discount," and "Profit" are of type float64. Date and time values are represented by the "Order Date" feature, which is of type datetime. Determining how each feature should be handled during analysis is made easier by this classification.

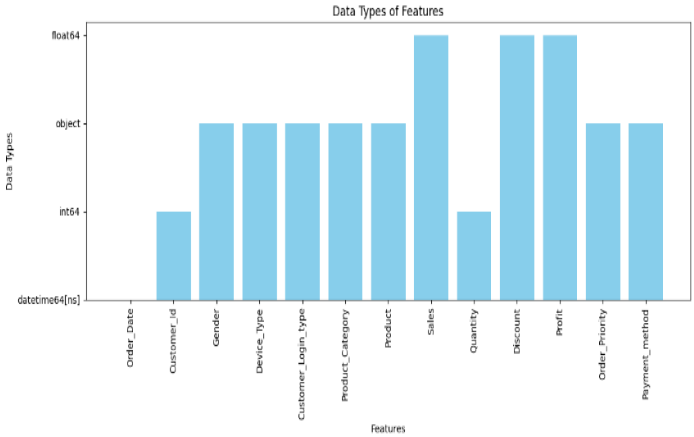

Figure 4: Features and their Data Types

Data Preprocessing

The data preprocessing is the main step in any prediction system. In this study, at the first step, libraries are imported in Python, such as pandas for handling the data and NumPy for numerical operations. After that dataset is loaded into a Data Frame, some basic questions are applied to know how many features (columns) there are, how many entries (rows) there are, the type of the features, whether there are any missing values in a dataset (which is being displayed using matplotlib), and whether there are any outliers. As figure 5 shows, there are only two columns named Device Type and Customer_Login_Type that have missing values. Device Type contains 2121 counts of missing values, and Customer_Login_Type contains 2121 counts of missing values. The missing values are imputed using the median, as the median is not affected by outliers.

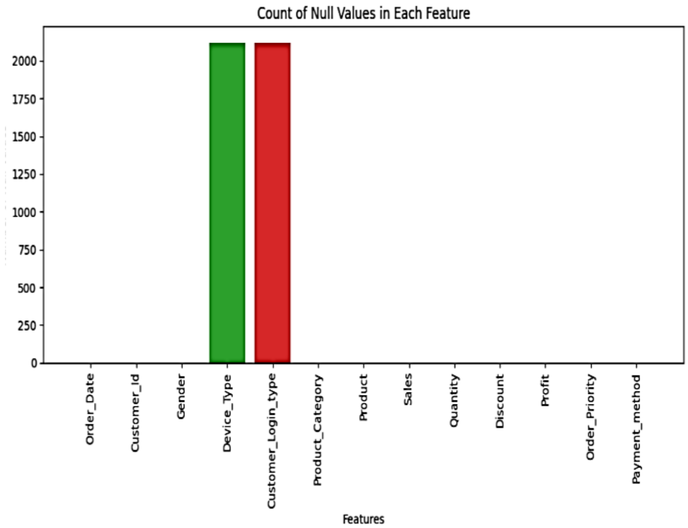

Figure 5: Missing Values Count

In figure 6 a box plot showing the distribution of the dataset's features, including Customer ID, Sales, Quantity, Discount, and Profit, is shown in Figure 7. Potential outliers are indicated by the plot, especially in aspects like Sales and Profit where extreme values greatly depart from the interquartile range. For accurate analysis, these outliers might need to be preprocessed or subjected to additional research.

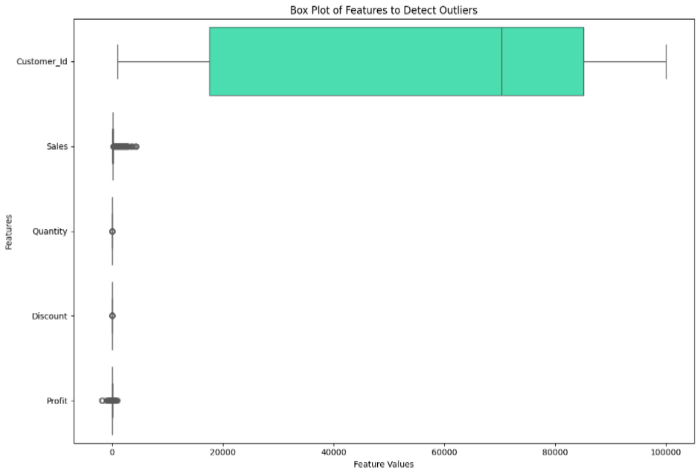

Figure 6: Outliers in Features

1) Holdout Validation Train and Test Split

In this study holdout validation technique is applied. In this technique, the dataset is divided into two subsets: one for training the model and the other for testing. The model learns the complex relationships between the various features, such as dates and their relationship to the target variable (sales). Typically, the dataset is split in an 80-20 ratio, with 80% of the data used for training and the remaining 20% reserved for testing. This method is shown in Figure 7. By training the model on the larger portion of the data and testing it on the remaining unseen portion, we assess its ability to generalize to new data.

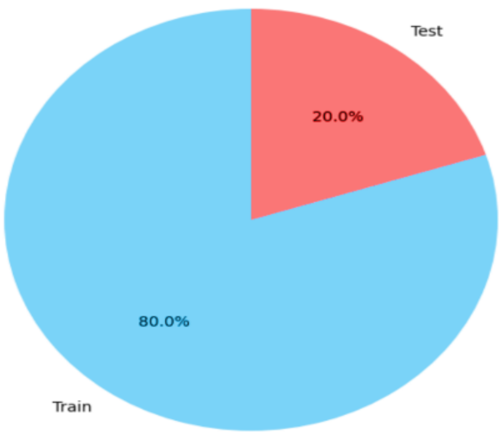

Figure 7: Train and Test Split

Machine Learning Models Utilized in Study

Building algorithms that can learn from and make predictions or judgments based on data is the focus of the artificial intelligence field of machine learning. To predict furniture sales, machine learning regression techniques were used in this study as shown in figure 8. Regression techniques are perfect for sales forecasting because they are very effective at predicting continuous data. These models forecast future sales trends by examining past sales data and finding trends. This helps companies to make data-driven decisions for better resource allocation, enhance demand planning, and optimize inventory management.

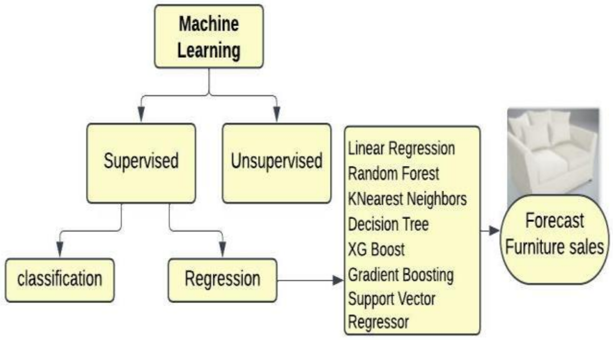

Figure 8: Machine Learning Classification

1) Linear Regression

Linear Regression is used to model the relationship allying a dependent variable (sales) and one or more independent variables (features) shown in figure 9. It is simplest and easiest algorithm to use for prediction in machine learning. The equation of the line in simple linear regression (with one independent variable) is given by eq. (1).

$$y = \beta_0 + \beta_1 x + \epsilon \tag{1}$$

Where:

- y is the predicted value (e.g., predicted sales).
- x is the independent variable (e.g., actual sales).
- β0 is the intercept of the line (where the y-axis is crossed by a line).
- β1 is the coefficient (slope) that represents the relationship of the independent variable xxx and the dependent variable y.
- ϵ is the error term, accounting for the discrepancy between actual and predicted values.

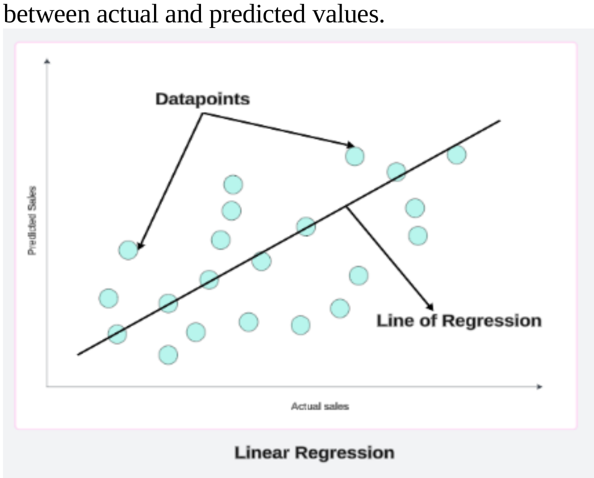

Figure 9: Linear Regression

2) Random Forest

Random Forest is used for regression tasks and it performs well on small amount of data by obtaining good prediction accuracy. It is an ensemble technique, it creates multiple decision trees while in training period and combining their results to make final prediction about sales graphically shown in figure 10 and mathematically shown in eq. (2). It reduces risk of over fitting.

$$\hat{y} = \frac{1}{n} \sum_{i=1}^{n} h_i(x) \tag{2}$$

$h_i(x)$Represents the output of the ith tree, and the average of all predictions gives the final output.

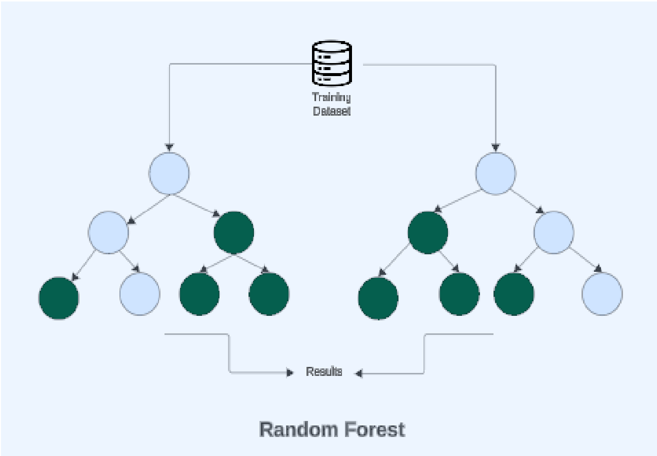

Figure 10: Random Forest Tree Structure

3) K-Nearest Neighbor

KNN is a simple, congenital and non-parametric algorithm in machine learning which is used for regression tasks. It works on the idea to classify a data point based on how its neighbors are classified shown in figure 11. It makes prediction by identifying the 'k' data points that are most similar and closest to the new data point and then assign them the common class. The most commonly used equation for calculating the distance of two points shown in eq. (3)

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (3)$$

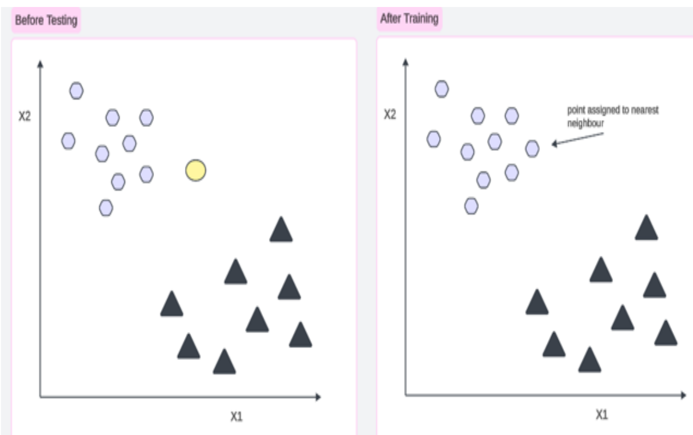

Figure 11: K-Nearest Neighbor

4) Decision Tree

A decision tree is a machine learning algorithm which falls under the category of supervised learning and it is used for regression. Based on features values it splits the data into subsets, it makes decision at each node until it reaches a final outcome shown in figure 12. Its goal is to build a prediction model that predicts the target variable (sales) by simply making decision rules from the data features graphically shown in fig. To determine the best feature for splitting, decision trees often use information gain based on entropy shown in eq.(4):

Information Gain = Entropy (Parent) - $\frac{N_i}{N} \times \text{Entropy(Child)}$ (4)

Where:

- Information Gain = Entropy (Parent) - $\frac{N_i}{N} \times$ Entropy(Child)
- - $\frac{N_i}{N}$ is the child node samples number, and NNN is the parent node total number samples.
-

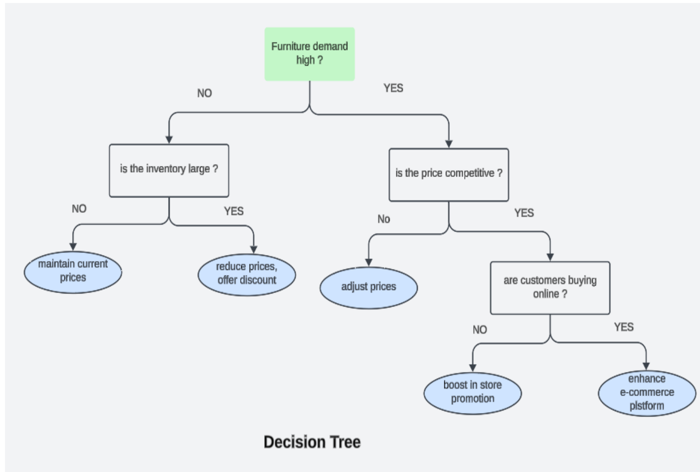

Figure 12: Decision Tree

5) Xg Boost

XG Boost (Extreme Gradient Boosting) is an advanced application of the gradient boosting. It is an effective machine learning algorithm which is suitable for regression. It works by combining many weak learners (decision trees) in order to create a strong model by consecutively learning from the errors of previous trees graphically shown in figure 13 and mathematically shown in eq. (5).

$$\text{L} = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{k} \Omega(f_k) \quad (5)$$

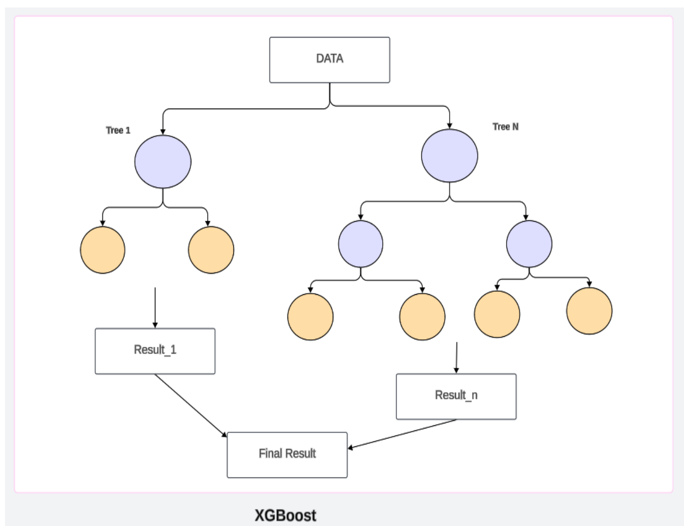

Figure 13: Extreme Gradient Boosting

6). Gradient Boosting

Gradient Boosting is an algorithm that builds an ensemble of decision trees to predict continuous future sales. It creates a strong predictive model by combining many weak learners tree each correcting the errors of the previous tree. Sum of all trees is a final model shown in figure 14 and mathematically shown in eq. (6)

$$\hat{y} = \sum_{m=1}^{M} a_m h_m(x) \qquad (6)$$

Here, $h_m(x)$ indicates the prediction of the m-th tree, and a_m is the learning rate.

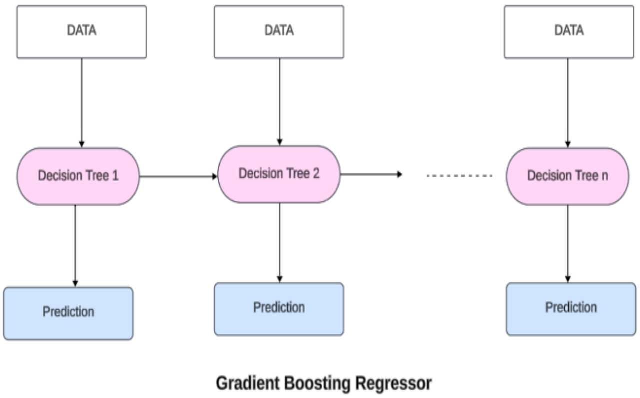

Figure 14: Gradient Boosting

7) SVR (Support Vector Regression)

SVR is a type of Support Vector Machine (SVM), it is used for regression tasks. SVR's goal is to find hyper plane that fits the data, it makes sure that most of the data points fall within a certain margin around this hyper plane shown in figure 15. SVR focuses on fitting the hyper plane within a tolerance level (epsilon). The SVR algorithm searches for function f(x) that deviates from the actual target values by a margin ϵ but remains as flat as possible mathematically shown in eq (7) , (8) and (9)

$$f(x) = \omega^T x + b \qquad (7)$$

Where:

- w = weight vector.
- x = feature vector.
- b = bias term.

The goal is to minimize:

$$\frac{1}{2}\|\omega\|^2 \qquad (8)$$

Subject to:

$$|y_i - (\omega^T xi + b)| \leq \epsilon \qquad (9)$$

Large epsilon ϵ allows for more tolerance or errors but it reduces model's prediction ability.

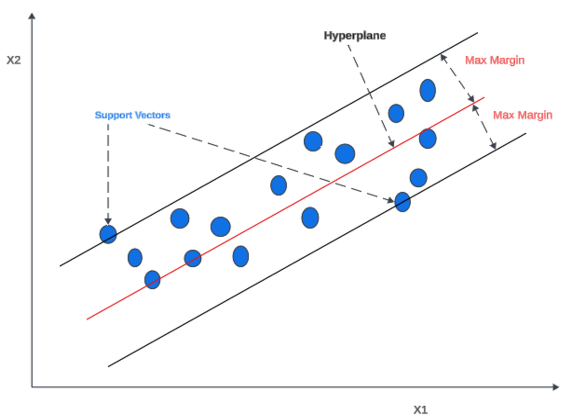

Figure 15: Support Vector Regression

Deep Learning Models Utilized In Study

Deep learning is a subset of machine learning inspired by the structure and function of the human brain, known as artificial neural networks. In order to automatically identify patterns in vast amounts of data, it entails training models with numerous layers of neurons. It can be separated into supervised and unsupervised learning, as the figure 16 illustrates. Tasks like classification and regression (such as predicting furniture sales) are carried out in supervised learning. Applications like time-series analysis and sales forecasting are made possible by sophisticated models like Long Short-Term Memory (LSTM), a kind of Recurrent Neural Network (RNN), which is designed especially for sequential data.

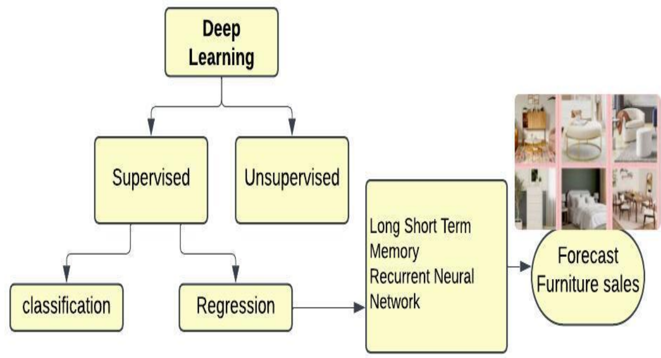

Figure 16: Deep Learning Overview

1) Long Short-Term Memory (LSTM)

LSTM is an advanced version of RNN, it is good for capturing and processing sequential data such as time series. It uses memory cell gates for controlling the flow of information shown in figure 17, allowing them to utilize or discard information as needed and it avoids gradient problems that plagues traditional RNN's. LSTM is highly suitable for time series furniture sales forecasting.

LSTM has three gates forget gate, input gate, and output gate.

Forget Gate:

It decides how much information should be discarded from the cell state.

$$f_t = \sigma(W_f . [h_{i-1}, x_i] + b_f) \qquad (10)$$

Input Gate:

It decides which new information should be added to the cell state.

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \qquad (11)$$

$$\tilde{C}_t = \tanh(W_c . [h_{t-1}, x_t] + b_C) \qquad (12)$$

$$C_t = f_t . C_{t-1} + i_t . \tilde{C}_t$$

Output Gate:

It decides the output of current time step.

$$O_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \qquad (13)$$

$$h_t = o_t . \tanh(C_t)$$

Where,

$x_i = at\ time\ t\ (input)$

$h_t = at\ time\ t\ (hidden\ state)$

$C_t = at\ time\ t\ (cell\ state)$

$\sigma = activation\ function\ (sigmoid)$

$W_f, W_i, W_o, W_c = weight\ metrices$

$b_f, b_i, b_o, b_c = terms\ of\ Bias$

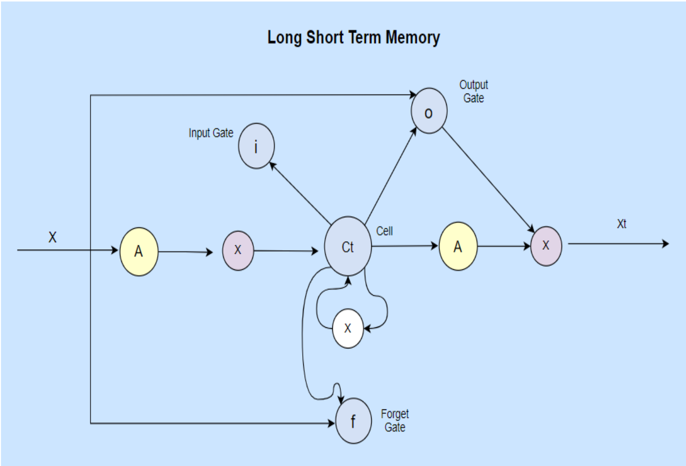

Figure 17: Long Short-Term Memory

2) Recurrent Neural Network

RNN is a model of deep learning which is used to for evaluating sequential data, which includes patterns of historical sales over an extended time frame contain hidden layers shown in figure 18. RNN is good for forecasting furniture future sales demand based on furniture past sales as it preserves information in the long run. For every step t, RNN processes the current input state x_t, updates its hidden state h_t, and optionally produces an output o_t.

$$h_t = \tanh(W_h \,.\, h_{t-1} + W_x \,.\, x_t + b_h) \tag{14}$$

Where,

$h_t = hidden\ state\ (current)$

$h_{t-1} = hidden\ state\ (previous)$

$x_t = input\ (current)$

$W_h, W_x = for\ hidden\ state\ and\ input\ (weight\ metrices)$

$b_h = Bias\ term$

Tanh = activation function

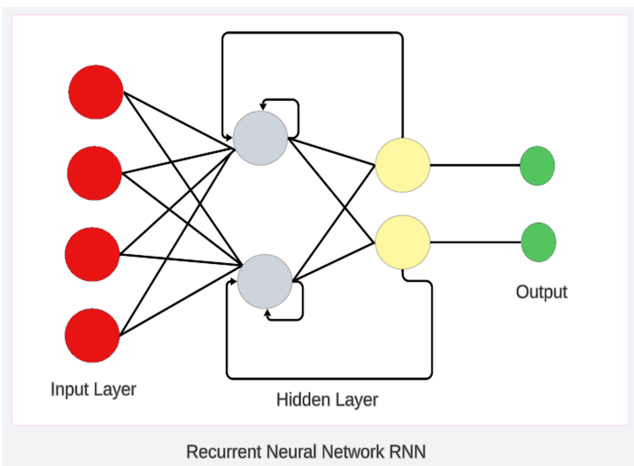

Figure 18: Recurrent Neural Network

RESULTS AND DISCUSSION

The results of this study provide a comprehensive analysis of model performance for furniture sales forecasting using both machine learning and deep learning algorithms. The comparison focuses on evaluating predictive accuracy, error metrics, and overall suitability of each model. The findings not only highlight the strengths and limitations of different approaches but also emphasize the importance of choosing the right model for the given dataset. Below, we provide detailed insights into the performance of the tested machine learning and deep learning models.

A. Deep Model Performance with Machine Learning Algorithms

Metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 coefficient are used to examine the performance of different machine learning models for furniture sales forecasting in Table 7. With a remarkably low MSE (0.001331), MAE (0.000849), and RMSE (0.036485), as well as an R2 value of 1.000000, which indicates a perfect fit to the data, linear regression performs the best overall among the models. This implies that in this situation, linear regression is a very accurate and dependable method of forecasting furniture sales. While they also perform well, other models like Random Forest (R2 = 0.999509) and KNN (R2 = 0.999350) have larger error metrics than linear regression. For example, KNN records an MSE of 41.853727, whereas Random Forest reaches an MSE of 31.581066. These models are less accurate than linear regression, yet they are still useful. Models with greater error values, such as XGBoost (R^2 = 0.864576) and Decision Tree (R^2 = 0.998281), are less suitable for this task. With the lowest R2 value (0.408526) and the greatest MSE (38060.244532), SVR notably performs the poorest, showing that it has a difficult time identifying the underlying patterns in the data. Overall, because of its high accuracy and low error, linear regression is the best model for predicting furniture sales.

Table 7: Machine Learning Model Results

Model	MSE	MAE	RMSE	R^2
Linear Regression	0.001331	0.000849	0.036485	1.000000
Random Forest	31.581066	3.237491	5.619703	0.999509
KNN	41.853727	2.503054	6.469446	0.999350
Decision Tree	110.593790	4.971839	10.516358	0.998281
XG Boost	8714.268883	44.898177	93.350248	0.864576
Gradient Boosting	9451.635102	45.926250	97.219520	0.853117
SVR	38060.244532	31.222301	195.090349	0.408526

B. Model Performance with Deep Learning Algorithms

Deep learning models perform well with large and complex datasets; our study uses deep learning LSTM and RNN models for time series data. The R^2 coefficient, which gauges how well a model predicts the variance in the output variable, is used to compare the performance of two deep learning models, LSTM (Long Short-Term Memory) and RNN (Recurrent Neural Network), in Table 8. With an R^2 value of 0.737649, the LSTM model is able to explain roughly 73.76% of the data's variance. This demonstrates how well it can handle sequential data by efficiently capturing long-term dependencies [8, 37]. On the other hand, the RNN model only explains 13.11% of the variance, achieving a far lower R^2 value of 0.131056. The RNN's shortcomings, including its inability to handle long-term dependencies and problems like disappearing gradients, are to blame for this subpar performance [53]. In general, the LSTM performs better than the RNN, proving that it is appropriate for sequential data issues such as time-series forecasting.

Table 8: Deep Learning Model Results

Deep Learning Model	R^2 coefficient
LSTM	0.737649
RNN	0.131056

Evaluation Criteria

The evaluation of the machine learning models was conducted using the following criterion:

A. Mean Square Error

It is used to calculate the average square of errors between predicted values and actual values shown in eq (15). It is sensitive to outliers as it places a higher weight on outliers. It is used for regression.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (15)$$

Where,
y_i = actual value
$\hat{y}_i$ = predicted value
n = number of data points

B. Root Mean Squared Error

The square root of the average of the squared error between predicted values and actual values shown in eq (16). It calculates how well model is able to predict the accuracy of target value (accuracy). It is used for regression model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(predicted_i - actual_i)^2}{N}} \qquad (16)$$

C. Mean Absolute Error:

It is the median (absolute error) difference between the actual values and predicted values shown in eq (17). It focuses on central tendency and is less sensitive to outliers. It is useful when the distribution of the dataset is skewed. It is used for regression model.

$$MedAE = median(|y_i - \hat{y}_i|) \qquad (17)$$

Where,
y_i = actual values
$\hat{y}_i$ = predicted values

D. Mean Absolute Percentage Error

It measures the accuracy of prediction in forecasting or in regression. It is the average percentage difference of predicted and actual values. Lower MAPE value indicates that model predict almost the same values as actual values. MAPE become distorted if actual values are very small or zero.

$$MAPE = \frac{\sum\frac{|A-F|}{A}\times 100}{N} \qquad (18)$$

Where,
A = actual value
F = Forecasted value
N = Number of fitted points

E. R Squared (R^2):

It measures how well a model fits data. It ranges from 0 to 1. The closer the value to 1 the better the model performance. It shows variance of percentage of target value. It is used for regression.

$$R^2 = 1 - (\text{SSE/SST}) \qquad (19)$$

Where,
SSE = $\sum(y_i - \hat{y}_i)^2$ squared errors sum.
SST = $\sum(y_i - \tilde{y}_i)^2$ total sum of squares.

CONCLUSION

This study illustrates how well deep learning and machine learning models predict furniture sales. With an R2 of 1.0, linear regression was the most accurate model among those assessed, making it perfect for short-term forecasting. With an R2 of 0.737649., LSTM outperformed RNNs for sequential data by a significant margin. These findings demonstrate how integrating these strategies can improve inventory control and match production to demand, which will ultimately increase furniture sector profitability. To further increase predicting accuracy, future studies should investigate the incorporation of further elements, including marketing trends, consumer behavior data, and economic factors. Furthermore, experimenting with hybrid models that combine the advantages of deep learning and machine learning approaches might provide more reliable results. Adding real-time data to the study and investigating alternative deep learning architectures, such as GRU (Gated Recurrent Unit), may also yield insightful information for more flexible and dynamic sales forecasting.

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