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Assessing Fashion Retail Sales: A Comparative Study of Predictive Models with Focus on CNN-LSTM Hybrid Framework

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Abstract: Background: Accurate sales prediction in the retail sector, especially in the fast-paced fashion market, is crucial for optimizing inventory, reducing costs, and avoiding out-of-stock situations. Retailers and wholesalers face significant challenges in forecasting future sales and understanding market trends, both of which are essential for effective pricing strategies. Methods: This study compares several machine learning and deep learning techniques to forecast sales in the e-commerce fashion retail industry. The models evaluated include Linear Regression, Polynomial Regression, Decision Tree (DT), Support Vector Machine (SVM), XGBoost, Long Short-Term Memory (LSTM), and a hybrid CNN-LSTM framework. The hybrid CNN-LSTM approach leverages convolutional networks for identifying features and recurrent layers to model sequential patterns over time. The models' performances are assessed using metrics like R2 score, RMSE, MAE, and MAPE. Findings: The research reveals that the CNN-LSTM hybrid model significantly outperforms the others in terms of accuracy and robustness, making it the most effective for predicting sales in the fashion retail sector. Novelty and Applications: This study introduces a novel application of the CNN-LSTM hybrid model for sales prediction in the e-commerce fashion retail industry. The integration of convolutional and recurrent neural networks enables the model to effectively handle the intricacies of sales data, combining short-term feature extraction with long-term trend analysis. The superior performance of this model provides a valuable tool for retailers, helping them to predict sales more accurately and optimize product pricing based on anticipated sales. This approach offers a significant advancement over traditional sales prediction methods, contributing to more informed and strategic decision-making in the retail industry.

Keywords: Time Series forecasting, Sales forecasting, LSTM (Long Short-Term Memory), CNN – LSTM (Convolutional Neural Network- Long Short-Term Memory Network), Hybrid Machine Learning, DT (Decision Tree), XGBoost, SVM (Support Vector Machine) algorithm; supervised machine learning techniques.

1. INTRODUCTION

During the last two decades, the fashion business has changed and developed significantly. An inexpensive fashion trend has taken hold worldwide as a result of the rapidly evolving and fiercely competitive industrial environment, which has made fashion a crucial business strategy. Accurate sales forecasting and intelligent sales correction through price changes and promotions are common in many retail industries and also in fashion industries. The observed market response, sell-through rates, supply disruptions, uncertain product sales and extremely short product life cycles have greatly affected the sales prediction in fashion industries. Spreadsheets that use rule-based or manual price management can't handle big catalogues with thousands of items. These procedures are cumbersome, prone to mistakes, and frequently result in inventory accumulation or large revenue losses. Methods that use machine learning are both quicker and offer more reliable and accurate results.

The key factor in price optimization is to model the effect of sales on pricing decision. These sales models are usually derived using historical sales data. There are many machine learning algorithms which can be used for prediction using such time-series sales data. Long Short-Term Memory (LSTM) network model (Isaac et al., 2023) is one of the most frequently used models for such prediction in all different retail domain (Ensafi et al., 2022). Decision tree regression is a type of machine learning algorithm that uses a tree-like structure to predict continuous values. For training the decision the data is splitted recusively into smaller subsets. This decision of splitting is based on the features values in the dataset. At each split, the algorithm chooses the feature that best separates the data into two groups with different sales values. This trained decision tree is then used to predict sales for new data points by following the tree from the root node to the leaf node (Evangelatos et al., 2023). The predicted sales value will be found at the leaf node. XGBoost is a gradient boosting framework-based ensemble machine learning technique. The different decision tree used during the XGBoost training sequence is instructed to fix the mistakes of the one before it. This procedure is repeated until the required degree

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of precision is attained (Lindfors, 2021). Support vector regression (SVR) is a type of machine learning algorithm that is used to regress continuous values. SVR works by finding a hyperplane that separates the data into two groups with different sales values. The hyperplane is chosen such that it maximizes the margin between the two groups (Shuvo et al., 2024). CNN-LSTM is a hybrid model helps to capture both short-term fluctuations (like weekly patterns or promotional effects) through convolutional layers and long-term trends (like seasonal or yearly patterns) through LSTM layers.

The objectives of this study are to find out answer of the following questions: 1. Which machine learning model improves predicting accuracy when dealing with time series data? 2. The effectiveness of the neural network approach for seasonal goods like fashion apparels. 3. To evaluate the usefulness of hybrid models for predictive analysis in Fashion retail sector. The rest of the paper is outlined as follows, in section 2 a study of similar research conducted in past is done to understand the various approaches used so far. Section 3 discussed about the data used in the study, the methodology, Exploratory Data Analysis (EDA) and various evaluation statistical parameters used. Section 4 presented the results of the various experiment done using different ML algorithms and their comparison, finally section 5 summarized the conclusion.

2. RELATED WORKS

In order to perform research on demand forecasting the author (Khan et al., 2020) collected raw sales data from the market and made predictions about future product requests using this data. The machine learning engine computed weekly, monthly, and quarterly product and commodity demands from several modules, and the forecasts were based on data gathered from multiple sources. By comparing the expected and actual data and figuring out the error percentage, the forecasts; accuracy was assessed. According to simulation studies, the suggested method produced an intelligent demand forecasting accuracy of up to 92.38% in stores when applied to real-time organizational data (Isaac et al., 2023).
In order to estimate furniture sales, the researcher (Ensafi et al., 2022) looked into a number of forecasting models utilizing a publicly available dataset that contained a retail store sales history. At first, conventional time-series forecasting techniques were used, including Seasonal Autoregressive Integrated Moving Average (SARIMA) and Triple Exponential Smoothing. Later on, more sophisticated methods like as Prophet, Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) were employed. Several accuracy metrics, such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), were used to assess the performance of these approaches. The outcomes proved that the Stacked LSTM approach was better than the other approaches.
Long short-term memory (LSTM) technique was used (Li et al., 2020) to anticipate revenues for using historical sales data. The study uses Walmart sales dataset having about 1913 days data comprising of 30,491 sales records for training and testing algorithms (Upadhyay et al., 2023). The research found that the LSTM model performed better than SVM and linear regression by utilizing effective feature engineering techniques, with an RMSE of 0.834.
The superiority of LSTM over statistical techniques like Moving Average (MA), Autoregression (AR), (Isaac et al., 2023) Simple Exponential Smoothing (SES), and especially Autoregressive Integrated Moving Average (ARIMA) and its variants was highlighted by researcher (Nithin et al., 2022) in their investigation of recently developed deep learning algorithms for forecasting time series data. Their results showed that LSTM performed better than these traditional techniques (Li et al., 2020).
(Benhamidaet al., 2020) The author unveiled Stock Buy, an online platform that incorporates a forecasting algorithm. They created a program called Comb-TSB that chooses the most correct model from a group of models automatically. The author recommends a strategy based of clustering technique for goods having no historical data.
In order to estimate demand (Wanchoo et al., 2019) two machine learning models the Gradient Boosting Method (GBM) and the Deep Neural Network were compared. Noting that not all merchants have access to the supply chain variables required to develop a multivariate model; the research investigates the viability of these models for univariate time series.
The researcher (Gupta et al., 2014) created a flexible framework using machine learning algorithms to improve customer choice on e-commerce sites. In their study they use statistical and machine learning methods to estimate purchase decisions. The technique used increases accuracy by concentrating on client groupings rather than individual purchasers. The framework incorporates information from multiple sources. By combining web mining, big data technology, and machine learning algorithms, the research moves closer to personalized pricing and purchase forecasting, in the e-commerce arena (Khan et al., 2020).
The author (Lindfors et al., 2021) conducted a comparison of machine learning models that can incorporate extra data for retail sales forecasting and classical time series analysis. A comprehensive assessment of ARIMA, linear regression, artificial neural networks, decision trees, and Holt-Winter exponential smoothing forecasting techniques are done in the study. The empirical results show that ARIMA and Holt-Winter exponential smoothing are the best models for this specific dataset (Khan et al., 2020).
Researcher (Singha et al., 2022) looked into the application of sophisticated machine learning algorithms, such as the Long-Short Term Memory (LSTM) Network, Convolutional Neural Network (CNN), and Multi-layered Perceptron model (MLP), for time series forecasting. They used Kaggle Store Item Demand Forecasting dataset to evaluate various algorithms and perform a comparison study to determine which worked best.

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3. METHODOLOGY AND EXPERIMENT

Predicting sales using a variety of supervised machine learning algorithms is the main goal here. This section describes the methodology to achieve the said goal. The complete methodology is divided in three stages: Data collection and data pre-processing, feature selection and feature engineering, and Model selection and evaluation. Fig. 1 shows the structure of the proposed methodology

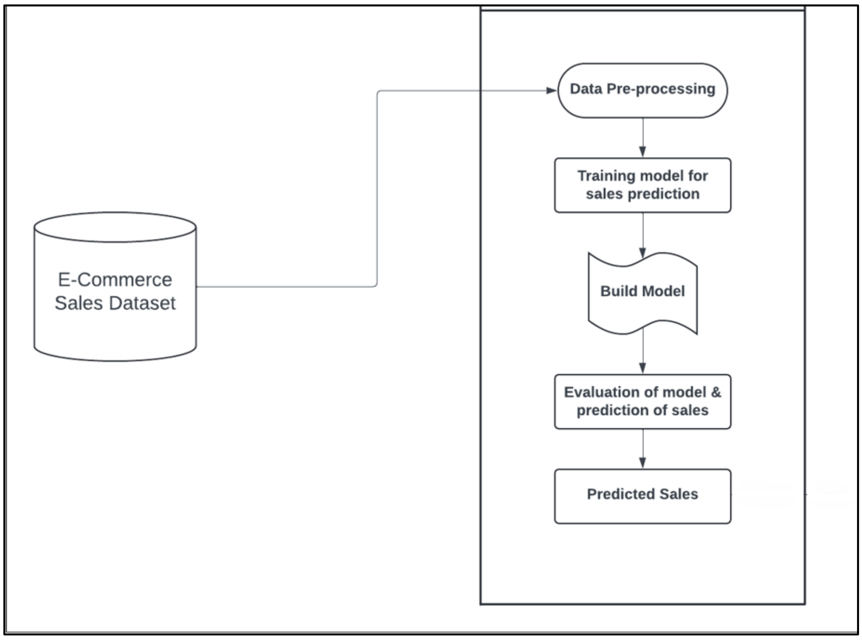

Figure 1. PROPOSED METHODOLOGY

3.1 Data Collection and Pre-Processing

The dataset used in the study is a sales data collected for a period of 3 years from June 24, 2018 to June 20, 2020. Table 1 lists all the attributes of the data set which is considered for the study.

TABLE 1. ATTRIBUTES OF THE DATASET

Variable Name	Feature	Range of permissible values
Date	Date of Sales	June 2018 to June 2020
Month	Month of Sales	Values between 1 to 12
Season	Season of Sales	Winter, Summer, Autumn, Spring
Price	Price of Item	1.2 to 2.5
Sku_name	SKU name of item	400 different values
Gender	Gender of purchaser	Male, Female
Category	Category of item	Boots, Jeans, Jackets, shoes, top, t-shirt
Collection	Collection of items	AW, P, SS
Price_tier	Price Tier of item	High, Low, Middle
Style	Style of item	Casual, Sports
sales	Sales in Quantity	2.0 to 3925

Data pre-processing is first and an important step while creating machine learning model. Missing values in the dataset creates problem for the model. Here, we imputed missing values and also used one-hot encoding to convert our categorical data into numerical data so that machine learning model can use it. Min-Max normalization is used to shift and rescale all values between 0 and 1.

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3.2 Feature Selection and Feature Re-engineering

At this stage of research selecting important features and creating new features using the existing features is done. A key component of enhancing machine learning performance is feature selection. This is done by reducing the dimensionality of the data and removing unnecessary or redundant features. In contrast, feature engineering aims to capture more intricate or non-linear interactions between the predictors and the target variable by generating new features from the existing ones (Wanchoo et al., 2019; Upadhyay et al., 2023). Here, we create more features like Month, Quarter, Weekday, Quarter using the Date of sales to train the model more effectively. To develop the final dataset for the forecast, we calculated the correlations between the attributes in order to better understand the data. This is done to make sure that they are appropriate for machine learning methods, and to prevent either overfitting or underfitting the models. The heatmap of the dataset's features is displayed in Figure 2.

Figure 2. HEAT MAP OF FEATURES

3.3 Model Selection and Evaluation

In this study, we have compared various machine learning models like Linear Regression, Polynomial Regression, Decision Tree, Support Vector Machine, XGBoost and some deep leaning models like LSTM and a hybrid model of Convolutional Neural Network + LSTM for sales prediction. There are many methods for evaluating performance of forecasting models. But here we are using four commonly used measures. Coefficient of Determination (R^2), Root Mean Squared Error (RMSE) is the standard deviation of the prediction errors. Mean Absolute Error (MAE) is obtained as the arithmetic average of the absolute difference between estimated value and actual value. Mean Absolute Percentage Error (MAPE) is used to measure error in forecasting expressed in percentage If Y_t is the actual value and F_t is the forecasted value for t time period, and n is the total number of observations, then RMSE, MAE and MAPE is calculated as:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2 \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t| \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Yt - Ft}{Yt}\right| \tag{4}$$

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For training and testing of model we split our data in a ratio of 70:30 to create training dataset and testing dataset respectively.

4. RESULT AND EVALUATION

Python 3.0 and the Scikit-learn (sklearn) module were used to conduct these experiments using various machine learning algorithms. The primary goal of these studies was to determine which of the two algorithms—deep learning and machine learning—is more effective at predicting sales by taking into account different aspects of the sales time-series data. The research comprised an exhaustive comparison of results of all algorithms discussed in previous section. The evaluation methods like R^2, RMSE, MAPE, MAE were selected in order to do a comprehensive comparison.
Following are the steps which are followed for experimentation:

1. The first step is importing the relevant libraries, such as NumPy, pandas, matplotlib, and seaborn, which will be needed to build the model.
2. Next, open the IDE and load the dataset.
3. After the data has been loaded, prepare the data for the experiment by changing the date's format to datetime.
4. Checked if there are any missing or null values.
5. Next, the date column is used to create three more columns, namely months, years, and seasons.
6. The outliers were then removed as the next step.
7. Imported the sklearn library for the model's construction, then chose the characteristics and targets for the X and Y axes to forecast sales.
8. Dividing the data into a training and testing set in ratio of 70:30.
9. To estimate the sales, Linear Regression, Polynomial Regression, Decision Tree, XGBoost, LSTM, SVR and CNN-LSTM models were created.
10. Determined R^2, RMSE, MAPE, MAE in order to calculate the error in the prediction model.

The results obtained after following the above steps are summarized in table 2.

TABLE 2. FORECAST EVALUATION

Algorithm	R^2	Mean Absolute Percentage Error (MAPE)	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)
Linear Regression	0.846	19.53	55.92	37.24
Polynomial Regression	0.859	20.76	60.22	39.74
Decision Tree	0.44	84.57	352.69	232.77
XGBoost	0.54	77.24	318.61	210.28
SVR	0.38	97.36	387.12	255.49
LSTM	0.875	18.91	54.84	36.19
CNN + LSTM	0.89	18.54	53.77	35.48

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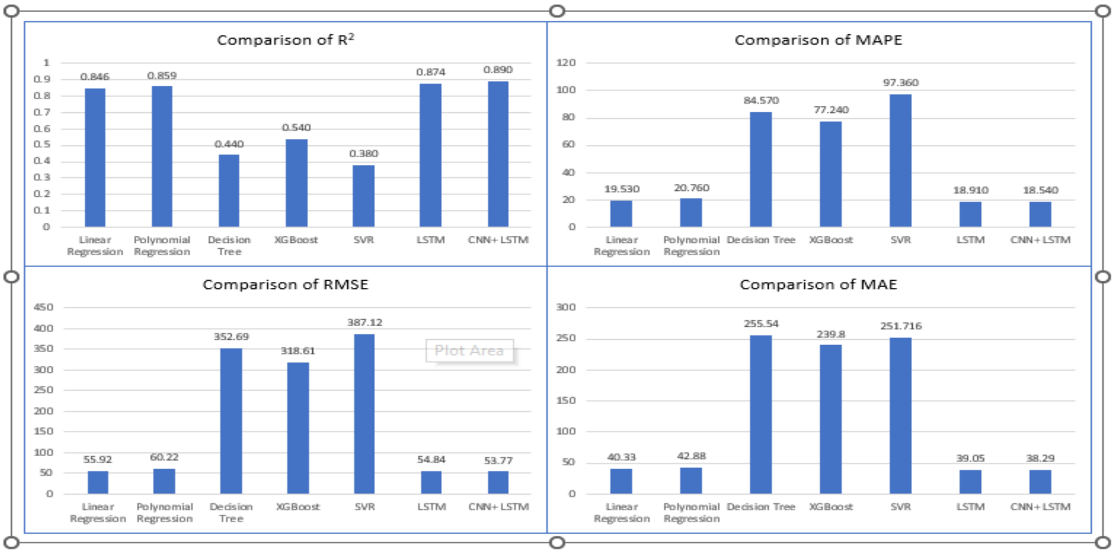

Figure 3. GRAPHS OF VARIOUS EVALUATION MEASURES

The measurement of error, known as the root mean square error (RMSE), should ideally be minimized for all machine learning models. When comparing different models, the one with the lower RMSE is chosen for deployment, as a smaller error indicates a higher level of model efficacy. Another factor taken into consideration when evaluating model performance is the R^2 Score, which represents the correlation between variables within the model. The value of R^2 Score lies between 0 to 1, where the value of 1 or close to 1 signifies a higher degree of correlation between the various attributes used in the model's design. Therefore, a value close to 1 is desirable for an effective machine learning model. Figure 4 shows the accuracy of various models

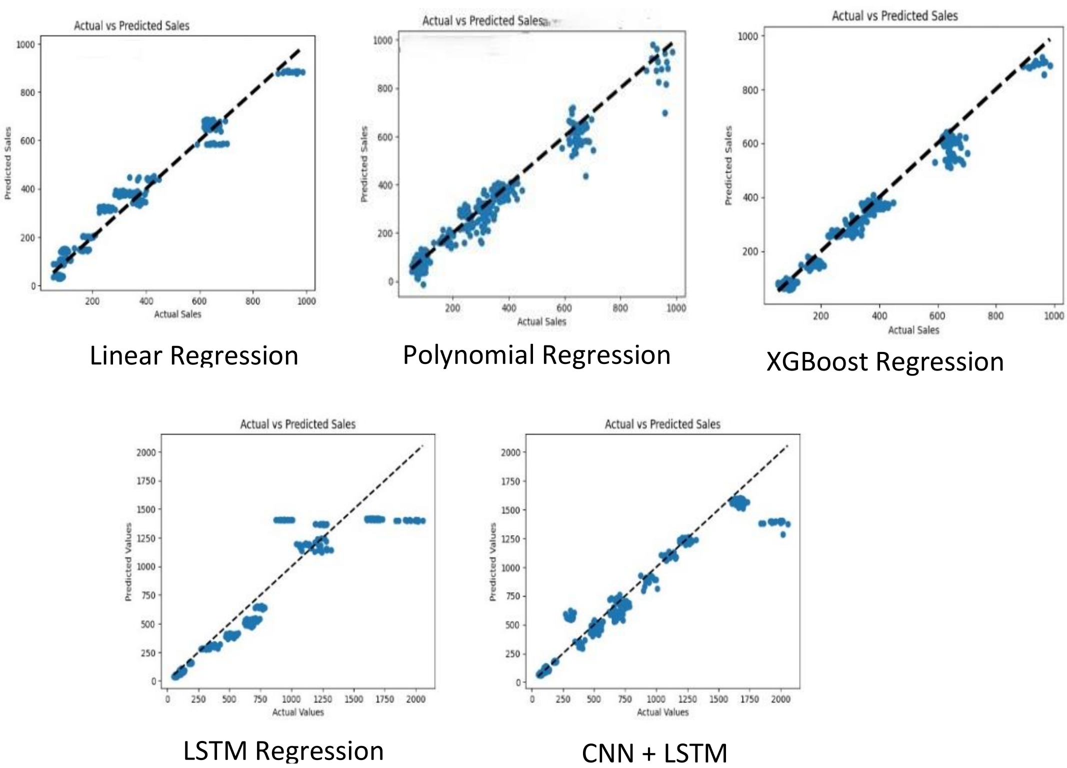

Figure 4. COMPARISON OF ACTUAL AND PREDICTED SALES OF VARIOS MODELS

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5. CONCLUSION AND FUTURE WORK

It is difficult to predict sales of product in fashion retail market since so many factors influence it and it is difficult to get the correct real time data. In spite of this challenge this research has tried finding out the best-fit model which can help retailers predict the future sales value. After examining the performance of various machine learning algorithms based on metrics such as RMSE and R2, it's evident that hybrid model like CNN + LSTM is most suitable for the dataset utilized in this study. This study contributes to retailers for sales prediction by demonstrating the efficacy of deep learning algorithms. In the future, more ensemble models can be tried to explore the combine effects of various machine learning algorithm. Also, deep learning models that take into account more features and implementing hyperparameter tuning can be implemented for further improvements in model performance.

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