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Research Article

Leveraging CNN-LSTM Model for Adaptive Pricing in Fashion Retail Segment

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ABSTRACT

Introduction: Pricing optimization in the fashion retail sector can be very complex, thus necessitating correct forecasting by sales and adjustable pricing systems. Traditional pricing models usually do not consider the dynamic market conditions. Hence, advanced machine learning techniques must be employed to support effective decision-making. Herein, we directly propose a learning machine-based framework for sales prediction and price optimization to boost market competitiveness with higher profitability.

Objectives: The primary objectives of this study are:

1. To develop a robust machine learning-based sales prediction model for fashion retail.
2. To implement an optimized pricing strategy using deep learning techniques.
3. To maximize profit through a data-driven pricing approach.n.

Methods: A two-phase approach was employed in this research. The first phase involved sales prediction using various machine learning models, including Long Short-Term Memory (LSTM), Decision Trees, XGBoost, Support Vector Regression (SVR), Polynomial Regression, and Linear Regression. The most effective model, LSTM, was selected for further integration. In the second phase, a CNN+LSTM hybrid model was used for price optimization. CNN was utilized to extract features from historical sales data over a 28-day context window, and the LSTM model predicted demand for the next 14 days. A profit matrix was generated across 15 price levels per SKU, enabling optimal pricing selection.

Results: LSTM was much more accurate than other machine-learning methods in demand forecasting. The proposed hybrid CNN+LSTM model has been effectively used in detecting optimal price points that analyze historical sales patterns and maximize profitability. The model found price adjustments leading to better daily and total 15-day profits and thus enabling the retailers to make real-time data-based pricing decisions.

Conclusions: This study demonstrates the effectiveness of integrating deep learning and machine learning models for pricing optimization in fashion retail. The proposed framework provides a systematic approach to predicting sales and setting optimal price levels, ultimately enhancing profitability and competitive positioning in the market. The research highlights the potential of AI-driven pricing strategies in retail operations, paving the way for future advancements in automated pricing mechanisms.

Keywords: CNN, LSTM, Hybrid model, Price Optimization, Fashion-Retail.

INTRODUCTION

The world of omni-channel retailing has transformed the traditional fashion retail setup by bridging multiple sales channels: online, brick-and-mortar, and mobile applications. This allows consumer interaction with a brand with complete smoothness across all potential touchpoints, making the pricing strategies intricate and dynamic. Successful price optimization in the fashion retail environment fundamentally depends on the fact that consumers

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expect their prices to be consistent, competitive, and fair across all the sales channels. The traditional pricing models often fail to capture the equation of dynamic changes in demands, competitive positioning, and consumer behavioral patterns in real time.

It is by virtue of machine learning that further sophisticated pricing optimization techniques are being applied, importing various large-scale data analyses, predictive modeling, and automation. Contrasting with ordinary rule-based pricing schemes, ML-based models use historical sales trends, consumer tastes and preferences, and competitive pricing strategies to dynamically adjust pricing. This study explores how ML techniques should be used for pricing decisions optimization in fashion retail segment, enabling the retailers to earn maximum profits while staying competitive.

This study aims to propose a flexible framework using ML and deep learning through which respective pricing strategies of different channels can be compared. The primary objectives of this research are to assess the performance of different ML algorithms for sales prediction and to create a price optimization framework that dynamically changes prices responded to predicted sales data. Rest of the paper is structured as: Section 2 provides an overview of earlier studies of a similar kind that looked at different strategies used, and Section 3 explains the techniques, exploratory data analysis, and various statistical evaluations to determine which model works best, part 4 compares the outcomes of several experiments conducted with various machine learning methods, and section 5 provides a summary of the findings.

LITERATURE REVIEW

Pricing is one of the most critical levers available to a retailer. It affects revenue, market share, and improvements in profitability levels. Traditionally, several pricing strategies relied on by the merchant have included cost-plus pricing, value-based pricing, and inventory-sensitive pricing. Though these methods are simpler and uses static models that fail to capture sufficiently real-time fluctuations in demand, competition, or market conditions. Production costs plus a defined margin of importance form the basis of cost-plus pricing. Value-based pricing, on the other hand, is based on how much the buyer believes the product is worth. With inventory-sensitive pricing, the seller can adjust the sale price based on current stock levels, lowering the price to get rid of excess inventory or raising the price during a shortage.

Dynamic pricing emerged to overcome the short comings in the traditional models. It is argued that dynamic pricing models could boost up revenue management incorporating real-time price adaptation around demand uncertainty, customer behavior, and competitive scenarios. Dynamic pricing is, thus, expected to boost revenue and improve inventory management to minimize stock-outs and overstock (M. Fisher et al., 2017; Riseth et al., 2019). Furthermore, dynamic pricing techniques enable retailers to instantaneously respond to market fluctuations and thus secure their competitive edge in a volatile marketplace. Traditional pricing even though being widely applied offers static limitations regarding dynamic systems. Most often they will require manual changes in price-the systems lack the ability to change tariffs rapidly in a harshly changing market condition. Besides, since most pricing methods rely on historical data without employing real-time external factors, this in turn makes these models quickly outdated. There is ongoing research geared toward somehow more dynamic, automated approaches capable of employing large datasets and real-time analyses.

More accurate sales forecasting gives the character for improved price optimization. The foundation of sales forecasting has been time-series analysis (ARIMA, Exponential smoothing), chosen in combination with regression analysis. Traditional models in most cases assume that historical sales patterns will not change; along with that, they do not factor in economic fluctuations, marketing initiatives, or competitor actions (Martins, 2023; Wang, 2023). ARIMA models work well in relatively stable environments but do poorly in non-linear relationships and in an environment where the market is suddenly influenced. Since pricing optimization is largely powered by sales forecasting, machine learning methods are becoming the preferred choice for dynamic pricing modelling. Advances in machine learning and artificial intelligence are revolutionizing the retail industry by enhancing pricing tactics and operational effectiveness. (Ajiga, 2024).

Linear regression models, although simple and interpretable, is accurate when the behavior of data is linear, which rarely occurs (Upadhyay, 2023; Wang, 2023; Dutta, 2022; Yi, 2023; Rajpoot, 2023; Ilyas, 2023; Kulkarni, 2023; S, 2024). Linear regression is extended by the addition of polynomial terms, which focus on non-linear relationships to get it solved. Choosing the wrong degree of polynomial is going to lead to overfitting (Wang, 2023). Various decision

Trees and Ensemble methods were also tested for sales predictions. These models exhibit simplicity in prediction however, tree-structured methods are prone to overfitting, especially in the presence of noise (Upadhyay, 2023; Mallik, 2022; Merdas, 2023; S, 2024; Vinod, 2022). Random Forests gives more accurate result by averaging multiple predictions. This method has proven effective in high-dimensional settings and is less susceptible to overfitting (Upadhyay, 2023; Mallik, 2022; Yi, 2023; Ilyas, 2023; Kulkarni, 2023; S, 2024; Vinod, 2022). In case of Gradient Boosting Machines (GBM), XGBoost builds models sequentially, with each new model correcting errors made by the previous ones. XGBoost, a popular implementation of GBM, has gained traction for its high accuracy and computational efficiency (Upadhyay, 2023; Yi, 2023; Rajpoot, 2023; S, 2024; Manna, 2023; Wisesa, 2020; Nana, 2022; Merdas, 2023). K-Nearest Neighbors (KNN) models perform predictions on the average sales of the k-nearest data points. This approach is simple but with larger datasets, it becomes computationally expensive (Mallik, 2022; Kulkarni, 2023; Mr. N.P. Saravanan, 2023). Another approach of Neural Networks i.e, Multilayer Perceptrons (MLP) with multiple hidden layers is capable of capturing non-linear relationships. The effectiveness of MLPs are heavily dependent on network architecture and hyperparameter tuning (Silva, 2021; Martins, 2023; Vinod, 2022; Wang, 2023). Another Neural Network model i.e, Convolutional Neural Networks (CNN) have its place in image processing and the CNNs also extract spatial features from data and have been used in sales forecasting work considering high-dimensional inputs (Upadhyay, 2023; Gandhi, 2023). Recurrent Neural Networks and LSTM are created for sequential data, RNNs and the improved type of LSTM will gain a master on capturing the temporal dependencies. Especially LSTM models have worked to solve some issues such as vanishing gradient problems and will make them perfectly fit for time-series forecasting in retail (Upadhyay, 2023).Other Techniques and Ensemble Techniques Computationally efficient baseline for machine learning by Naive Bayes which has a simple and independent assumption on feature (Mallik, 2022; Mr. N.P. Saravanan, 2023) as well as clustering algorithms like K-means, to segment customers, and reveal hidden patterns in purchases behavior (Mallik, 2022).Ensemble methods including bagging, boosting, and stacking improve the motivation of several models by making the whole more accurate and robust (Pavlyshenko, 2019; Merdas, 2023; Rajpoot, 2023).

Contemporary studies use regression algorithms to define the optimal price point. Rahman et al. (2024) show Random Forest Regressors to be successively better than Decision Trees and Logistic Regression when predicting retail prices. Overall, accuracy attained by this model was 94% which was specific to the data used and may vary based on the datasets. Aggressive time-series analysis has captured the imagination of retail pricing and includes a plethora of models like LSTMs and Temporal Fusion Transformers (TFTs). These models look into the future to anticipate sales, thereby customizing their pricing plans. Phyu and Khine (2023) proposed a Seq2Seq LSTM architecture meant to capture long-range temporal dependencies more explicitly than standard LSTM and Vanilla RNN. Additionally, hyperparameters have had great performance increased with Bayesian Optimization for improving prediction accuracy (Phyu, 2023). Reinforcement learning methods have been studied in adaptive pricing strategies, where Q-learning and deep Q networks (DQN) are the most pre-eminent. The methods work to learn the optimal pricing policies working with the environment to derive the reward based on its profitability. Such methods look promising, though the very essence of difficulty lies in the exhaustive computation involved and how to incorporate them into the existing systems. Unsupervised learning techniques such as K-means clustering help find customer segments according to the purchasing behavior and price sensitivity. Such segmentation allows retailers to adopt the proper pricing strategy for each segment to thus stack up profits while assuring satisfactory service to customers.

Additionally, integrating advanced machine learning models with legacy retail systems demands substantial infrastructure and expertise investments. A key challenge is model interpretability, as pricing recommendations require clear explanations for effective decision-making. This has driven interest in hybrid models that balance machine learning accuracy with the transparency of traditional methods (Karmakar, 2023). Future research may focus on dynamic ensemble techniques that adapt to market conditions while incorporating external factors like macroeconomic indicators and competitor pricing data.

METHODS

This research adopts the method of pricing optimization for the fashion retail segment, which is divided into several phases. The process initiates with elaborative data preparation; this is followed by sales prediction and, finally, dynamic price optimization. This methodology is further illustrated in Figures 1 and 2, showcasing the various stages of the research problem and the overall technology at play, respectively.

Phase 1: Data Preparation

1.1. Overview and Data Collection

The dataset spans from June 2018 to June 2020 and comprises diverse features such as date, month, season, price, SKU name, gender, category, collection, price tier, style, and sales.

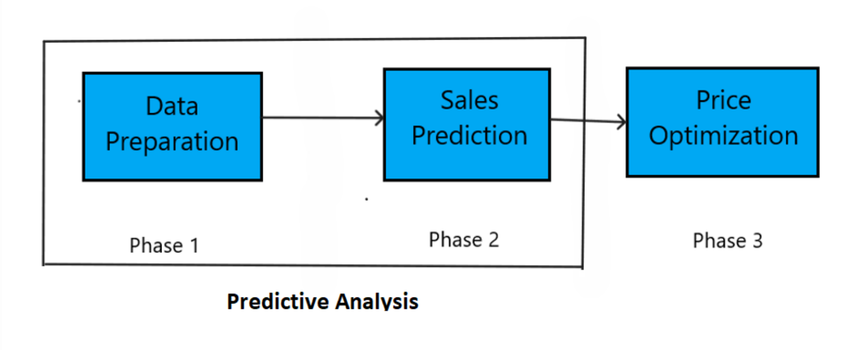

Figure 1: Phases of Research Problem

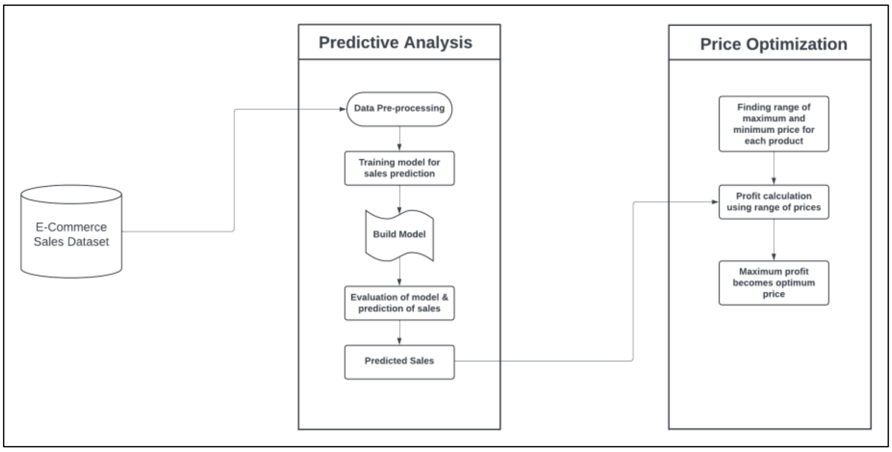

Figure 2: Framework of Research Solution

1.2. Preprocessing Steps

To make the data ready for model training various preprocessing steps were performed during the data preparation phase:

- **Encoding: One–hot** encoding was used to transform all categorical variables into a numerical format so that the various machine learning models can utilize it.
- **Linearity Test:** A Spearman Rank correlation test was performed on the categorical features. The test revealed that these features exhibit a non-linear relationship with the sales data.
- **Stationarity Test:** The KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test was applied to the Sales and Price features. Both features were confirmed to be stationary, which is crucial for reliable time-series analysis.
- **Feature Engineering: Additional features were generated from the Date variable. These include Day of the week (7 weekdays), Quarter (4 quarters), Month (12 months), Season (4 seasons), Weekend indicator (weekday/weekend)**
- **Feature Selection:** Based on the correlation analysis, the top five features most correlated with Sales were selected. Additionally, sales data from the previous 7 days was incorporated as features. Using more than 7 days of historical data was found to reduce model accuracy.

Phase 2: Sales Prediction

Many machine learning models were developed during this phase and the results were compared to know the best predicted sales.

Table 1: Model Comparison for Sales Prediction

Algorithm	R^2	MAPE	RMSE	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

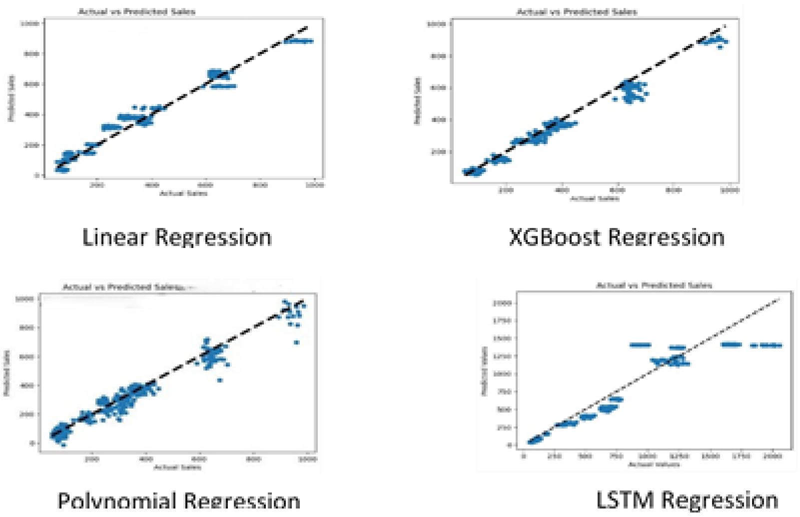

Figure 3: Actual and Predicted Sales of Various Models

Among the tested models, the LSTM model demonstrated superior performance, achieving the highest R^2 and the lowest error metrics.

Phase 3: Sales Prediction and Price Optimization

After establishing a robust sales prediction model, the focus shifts to optimizing pricing strategies using the predicted sales data.

Step 1: Prediction File Generation: After model training, a prediction file was created that includes:

- Historical sales and price data for a 28-day context window.
- New dates for a 14-day forecast horizon with the "Sales" field left blank.
- The "Price" column is varied to represent 15 different price levels. This creates 15 separate time-series predictions for each SKU.

Step 2: The CNN component was used to automatically extract features from the short-term, high-frequency patterns in the 28-day context window. The extracted features were fed into an LSTM network to predict sales over the next 15 days.

Step 3: Pricing Evaluation

For each SKU, the following steps were performed:

- **Profit Calculation:**
  Profit = Sales × (Unit_Price – Cost_Price)
- **Profit Matrix Generation:** A matrix was created, with each column denoting one of the 15 price levels and each row denoting a day. The profit for that particular price level on that day is shown in each cell.
- **Optimal Price Determination:**
  - **Daily Optimization:** The optimal price for each day is determined by selecting the price level that yields the maximum profit.
  - **15-Day Optimization:** The optimal price over the 15-day forecast horizon is determined by aggregating the daily profits.

Step 4: Model Architecture for Price Optimization: The dynamic pricing model leverages a combined CNN + LSTM architecture for both feature extraction and sales forecasting. The combination of CNN is used for short-term feature extraction and bidirectional LSTM for capturing long-term dependencies. This hybrid model enables to effectively forecast sales and, in turn, optimize pricing dynamically.

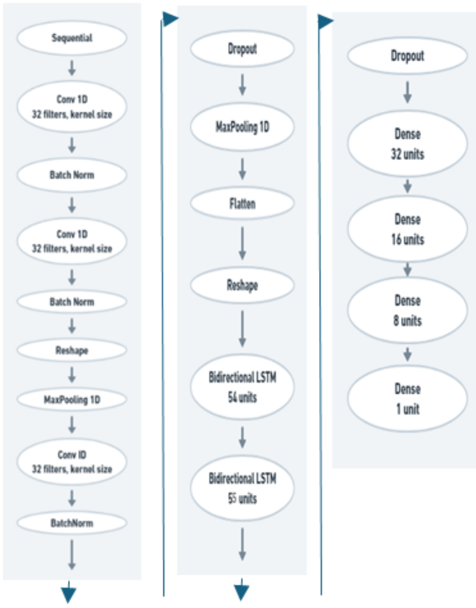

Figure 4: CNN+LSTM Architecture

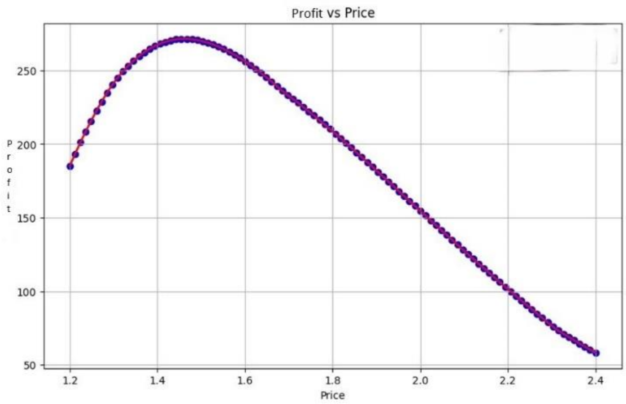

Figure 5: Product-wise Profit Based on Price

RESULTS

The CNN+LSTM model achieved the highest accuracy:

- **Training Accuracy**: 0.97

- **Testing Accuracy**: 0.96
- **Profit Optimization**: The model successfully identified optimal price points, leading to increased profitability.

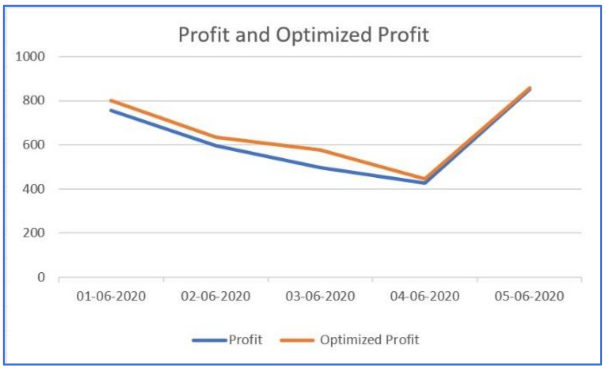

Figure 6: Comparing Profit and Optimized Profit Date-wise

CONCLUSION AND FUTURE WORK

This research introduces a robust ML-driven framework for sales prediction and pricing optimization in fashion retail segment. The CNN+LSTM model outperforms traditional approaches, demonstrating superior predictive accuracy and profit optimization capabilities. The dynamic pricing model enhances retailers' ability to respond to market fluctuations efficiently. Future research will explore the integration of reinforcement learning techniques for adaptive pricing strategies and the incorporation of real-time competitive pricing data to further improve the framework's effectiveness.

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