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RESEARCH ARTICLE

Dynamic Pricing Models in E-Commerce: Exploring Machine Learning Techniques to Balance Profitability and Customer Satisfaction

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ABSTRACT This research investigates the application of Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, paired with gradient-based optimization techniques for dynamic pricing in e-commerce. The primary objective is to develop a pricing model that effectively balances profitability with customer satisfaction by leveraging sequential data, such as time-series and customer behavior patterns. The approach utilizes LSTM's ability to capture long-term dependencies in sequential data, while optimization methods like Stochastic Gradient Descent (SGD) enhance model convergence and performance. Key findings include the superior predictive accuracy of LSTM-based models over traditional approaches like Linear Regression and Decision Trees, particularly in real-time data updates and price elasticity scenarios. Additionally, the analysis revealed that LSTM models could efficiently adapt pricing strategies in response to market dynamics, significantly improving profitability while maintaining customer satisfaction. This study provides valuable insights into the application of advanced machine learning techniques in e-commerce pricing. The results suggest that LSTM-based dynamic pricing models could optimize revenue generation, offering substantial implications for pricing strategy development in modern retail environments. Future work may explore hybrid models and multi-objective optimization techniques to further refine these models.

INDEX TERMS Dynamic pricing, E-commerce, long short-term memory (LSTM), recurrent neural networks (RNNs), gradient-based optimization, profitability, customer satisfaction, sequential data, stochastic gradient descent (SGD), machine learning.

I. INTRODUCTION

This study addresses the essential role of dynamic pricing in the evolving landscape of e-commerce, where businesses strive to remain competitive while maximizing profitability and ensuring customer satisfaction. Dynamic pricing, a strategy wherein prices are adjusted in real-time based on demand, supply, and various contextual factors, has emerged as a cornerstone of modern online marketplaces [1]. It enables businesses to optimize revenue by tailoring prices to fluctuating market conditions and individual customer behavior. However, implementing effective dynamic pricing models involves a complex interplay of factors, making it both a critical and challenging endeavor [2]. The importance of dynamic pricing lies in its capacity to enhance operational efficiency and competitive positioning [3]. By leveraging

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customer preferences, purchase histories, and real-time market trends, businesses can strategically align their pricing strategies with demand patterns [3]. This not only ensures the optimization of inventory turnover but also reduces the likelihood of overstocking or understocking [4]. Dynamic pricing enhances customer engagement by offering personalized pricing that resonates with individual purchasing behaviors [5]. Such personalization fosters loyalty and improves long-term customer relationships, which are essential for sustaining growth in a competitive digital marketplace. Balancing profitability and customer satisfaction, however, remains a significant challenge [6]. While businesses aim to maximize revenue, aggressive pricing strategies can alienate customers if perceived as exploitative or inconsistent. Customers value fairness and transparency, and sudden price fluctuations may erode trust [7]. Additionally, the dynamic pricing landscape is shaped by competitive pressures, making it imperative for businesses to adopt adaptive strategies that consider not only internal objectives but also external market conditions [8]. Achieving this balance demands sophisticated models capable of processing vast amounts of data to make informed pricing decisions that optimize both business and customer outcomes. This paper introduces a novel approach to addressing these challenges by employing Recurrent Neural Networks (RNNs) combined with gradient-based optimization techniques [9]. RNNs, with their inherent ability to model sequential and temporal data, are particularly suited for dynamic pricing scenarios where past customer interactions and market trends influence future decisions [10]. Traditional machine learning methods often fail to capture these temporal dependencies, leading to suboptimal pricing decisions. RNNs, on the other hand, excel in understanding complex patterns over time, making them a natural choice for this application [11]. The inclusion of gradient-based optimization techniques further enhances the proposed methodology by streamlining the process of updating model parameters to minimize error and improve prediction accuracy [12]. Gradient-based optimization methods such as stochastic gradient descent (SGD) and its variants ensure that the pricing model converges efficiently to an optimal solution, even when dealing with high-dimensional data [13]. By integrating these techniques, the proposed framework offers a robust solution for navigating the intricate trade-offs between profitability and customer satisfaction.

The reviewed literature highlights various machine learning (ML) approaches and tools aimed at improving customer satisfaction and business outcomes across multiple domains [14]. Joy et al. demonstrated the superiority of BERT for sentiment analysis, achieving 95% accuracy in processing complex feedback data to enhance service quality and revenue [15]. Khazaei et al. provided an extensive review of ML methods for customer churn prediction, emphasizing profit-based evaluation metrics and advocating for ensemble models and explainable methods [16]. Dehbozorgi et al. introduced the WIPE platform, which integrates ML and association mining to analyze customer feedback for packaging improvement in e-commerce, showcasing its ability to identify and predict packaging defects effectively [17]. Fard and Kavousi applied ML models, including Random Forest and XGBoost, to predict customer churn in telecommunications, with Random Forest achieving a high accuracy of 98.25% [18]. Wang and Hu proposed a hybrid model combining LSTM, GRU, and LightGBM for churn prediction in streaming services, achieving state-of-the-art performance with transparency provided by SHAP and EBM [19]. In e-commerce personalization, Tahmasebi et al. leveraged Particle Swarm Optimization and Deep Reinforcement Learning to enhance user experience in product design, reducing design iteration time by 25% and improving satisfaction scores by 30% [20]. Razmjouei et al. focused on predicting customer loyalty using Twitter data, where a Dense Neural Network outperformed other models with 98.62% classification accuracy [21]. Jafari et al. emphasized multivariant user interface personalization in e-commerce, leveraging ML to enhance user satisfaction and business flexibility [22]. Sandra et al. presented PersoNet, a BiLSTM-based framework for matching customer service agents with customers, significantly improving satisfaction rates [30]. Lastly, Urolagin and Patel developed the CPAN Chart for customer perception analysis, enabling organizations to monitor and respond to negative feedback trends over time [24]. These studies underline the transformative role of advanced ML techniques, such as BERT, ensemble methods, hybrid models, and explainable AI, in enhancing customer satisfaction, optimizing operations, and driving profitability in e-commerce and related domains.

The primary objective of this research is to develop a dynamic pricing model that achieves a harmonious balance between maximizing revenue and maintaining customer trust. The proposed approach involves training an RNN-based model on historical pricing and customer behavior data to predict optimal prices for future transactions [25]. The gradient-based optimization component refines the model's predictions to ensure alignment with predefined business objectives [26]. This dual-layered methodology addresses the core challenges of dynamic pricing by combining the predictive power of RNNs with the efficiency of gradient-based optimization. To evaluate the efficacy of the proposed model, this study conducts extensive experiments using real-world e-commerce datasets. The results demonstrate significant improvements in pricing accuracy, revenue generation, and customer satisfaction metrics compared to baseline models [27]. By emphasizing the role of temporal dependencies and optimization efficiency, this research highlights the transformative potential of advanced machine learning techniques in dynamic pricing [28]. This paper underscores the importance of dynamic pricing as a strategic tool for e-commerce businesses and introduces an innovative approach leveraging RNNs and gradient-based optimization. By addressing the dual objectives of profitability and customer satisfaction, the proposed model contributes to advancing the field of dynamic pricing and offers practical insights for real-world applications [29]. The remainder of this paper is organized as follows: Section II reviews related work in dynamic pricing and machine learning. Section III outlines the problem formulation and introduces the proposed methodology [30]. Section IV describes the experimental setup and evaluation metrics, while Section V presents the results and discusses their implications. Finally, Section VI concludes the study and highlights potential avenues for future research [31]. This comprehensive approach seeks to bridge the gap between theoretical advancements and practical implementation, paving the way for dynamic pricing models that are both effective and customer-centric.

II. PROBLEM FORMULATION

Dynamic pricing in e-commerce involves the real-time adjustment of prices based on a wide range of factors, including customer behavior, market trends, inventory levels, and competitor actions [32]. This problem can be formulated as a sequential decision-making task, where the pricing strategy at any given moment depends not only on current conditions but also on past interactions and trends. By leveraging sequential data such as time-series sales records, customer purchase patterns, and historical market fluctuations, businesses can create pricing models that adapt dynamically to changing environments [33]. Let x_t represent the input features at time t, such as customer demand, product inventory, and competitor prices, and p_t represent the price of the product at time t. The goal of dynamic pricing is to determine an optimal pricing policy $\pi(x_t, p_t)$ that maximizes an objective function J. The objective function is defined as:

$$\text{Max } J_1 = \int_0^T \left(\frac{p_t \cdot d_t(p_t)}{1 + e^{-\kappa \cdot (p_t - p^*)}} - \phi \cdot C(p_t, d_t) \right) dt, \tag{1}$$

where p_t is Price of the product at time t. $d_t(p_t)$ is Demand as a function of price p_t, modeled as $d_t(p_t) = D_0 \cdot e^{-\eta \cdot p_t}$. κ is Controls sensitivity to deviations from the target price p^*. p^* is The target optimal price [34]. ϕ is Operational efficiency coefficient, scaling the costs. $C(p_t, d_t)$ is Total cost as a function of price and demand, which could include production, logistics, and marketing.

$$\begin{aligned} \text{Max } J_2 = -\int_0^T \Bigg(\alpha \cdot \sqrt{\frac{\sum_{i=1}^N (p_t^i - \bar{p}_t)^2}{N}} \\ + \beta \cdot \log\left(1 + \frac{\sum_{j \neq i} |p_t^i - p_t^j|}{N^2} \right) \Bigg) dt, \end{aligned} \tag{2}$$

where α is Weight for penalizing price volatility. $\sqrt{\frac{\sum_{i=1}^N (p_t^i - \bar{p}_t)^2}{N}}$ is Standard deviation of prices p_t^i across N time points, representing volatility. β is Weight for penalizing unfairness between segments. $\frac{\sum_{j \neq i} |p_t^i - p_t^j|}{N^2}$ is Measures price unfairness across N customer segments.

$$\text{Max } J = \lambda_1 \cdot \int_0^T \Big(J_1(t) \Big) dt + \lambda_2 \cdot \int_0^T \Big(J_2(t) \Big) dt, \tag{3}$$

where λ_1, λ_2 is Weighting factors that balance the trade-offs between profitability (J_1) and customer satisfaction (J_2). This formulation captures the inherent complexity of dynamic pricing, where the model must adapt to temporal dependencies and continuously evolving input data [35]. Decisions made at one point can influence future outcomes, making it critical to model these sequential dependencies effectively.

$$\int_0^T \left(\frac{d_t(p_t)}{1 + e^{-\mu \cdot (t - t_0)}} \right) dt \le S_0 \cdot e^{-\delta \cdot t}, \tag{4}$$

where μ is Parameter controlling demand saturation over time. t_0 is Reference time point for demand saturation. S_0 is Initial supply at $t = 0$. δ is Decay rate of supply.

$$p_t \ge p_{\min} + \epsilon \cdot \sin(\omega \cdot t), \tag{5}$$

where $p_{\min}$ is Minimum allowable price. ϵ is Amplitude of oscillations for periodic campaigns. ω is Frequency of price oscillations.

$$p_t \le p_{\max} \cdot \left(1 - e^{-\sigma \cdot t} \right), \tag{6}$$

where $p_{\max}$ is Maximum allowable price. σ is Controls the reduction in the price ceiling over time.

$$\int_{t=0}^T \Big(d_t(p_t) \cdot \log(1 + S_t) \Big) dt \le I_{\text{total}}, \tag{7}$$

where S_t is Inventory level at time t. I_{total} is Total inventory available over time.

$$\frac{R(p_t)}{C(p_t)} \ge \exp\left(m_{\min} \cdot \frac{\partial p_t}{\partial t} \right), \tag{8}$$

where $m_{\min}$ is Minimum profit margin requirement. $\frac{\partial p_t}{\partial t}$ is Rate of change of price over time.

$$\int_0^T \left| \frac{\partial^2 p_t}{\partial t^2} \right| dt \le v_{\max}, \tag{9}$$

where $\frac{\partial^2 p_t}{\partial t^2}$ is Second derivative of price, measuring acceleration or volatility. $v_{\max}$ is Maximum allowable volatility.

$$\frac{\sum_{i=1}^N \sum_{j=1}^M \left(|p_t^i - p_t^j|^2 \cdot w_{ij} \right)}{N \cdot M} \le \Delta_p, \tag{10}$$

where p_t^i, p_t^j is Prices for customer segments i and j. w_{ij} is Weight coefficient reflecting priority between segments. Δ_p is Tolerable fairness threshold.

$$\log\left(1 + \frac{p_t}{p_t^{\text{competitor}}} \right) \le \log(\gamma), \tag{11}$$

where $p_t^{\text{competitor}}$ is Price set by competitors. γ is Benchmark factor ensuring competitiveness.

$$\left| \frac{\partial d_t}{\partial p_t} \right| \le \frac{e_{\max}}{1 + e^{-\nu \cdot (p_t - p^*)}}, \tag{12}$$

where ν is Sensitivity parameter for elasticity near the optimal price p^*. $e_{\max}$ is Maximum allowable demand elasticity.

$$p_t \in \Big[p_{\min}, p_{\max} \Big], \quad \forall t \in [0, T], \tag{13}$$

where T is Total time horizon for pricing decisions. The optimization task involves learning a pricing policy that maximizes J over the entire time horizon T while respecting constraints such as inventory limitations and minimum acceptable profit margins [36]. The solution must accommodate the dual objectives of maximizing revenue and ensuring customer satisfaction. Recurrent Neural Networks (RNNs) are particularly well-suited for handling the sequential nature of dynamic pricing. Unlike traditional machine learning models, RNNs are designed to process and retain information from previous time steps, making them ideal for capturing dependencies in time-series data [37]. Through mechanisms like hidden states, RNNs can encode historical information and use it to make context-aware pricing decisions. Variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) further enhance this capability by addressing challenges like vanishing gradients, enabling the model to learn long-term dependencies [38]. By integrating RNNs into the dynamic pricing framework, this study leverages their ability to model temporal patterns in customer behavior and market dynamics [39]. This allows for more accurate predictions and robust pricing policies, ultimately addressing the dual challenges of profitability and customer satisfaction in e-commerce.

III. PROPOSED METHODOLOGY

In this study, we employ Long Short-Term Memory (LSTM) networks as the core architecture to model dynamic pricing in e-commerce. LSTM networks are particularly well-suited for time-series forecasting because of their ability to capture long-term dependencies in sequential data [40]. We utilize LSTM due to its robustness in handling temporal relationships between past pricing, customer behavior, and market conditions [41]. The model takes as input sequential data, such as historical pricing (p_t), customer demand (d_t), and external factors (e.g., seasonality, competitor pricing) over time [42]. These inputs are fed through multiple LSTM layers, which process the information and output the predicted optimal price at each time step. The forget gate determines which past pricing information should be discarded:

$$f_t = \sigma(W_f \cdot [h_{t-1}, p_t, d_t] + b_f) \tag{14}$$

where f_t is Forget gate output at time t. p_t is Price of the product at time t. d_t is Customer demand at time t. h_{t-1} is Previous hidden state (capturing past pricing behaviors). W_f is Weight matrix for the forget gate [43]. b_f is Bias term. The input gate decides how much new information (e.g., price elasticity and market trends) should be added to the model's memory:

$$i_t = \sigma(W_i \cdot [h_{t-1}, p_t, c_t, m_t] + b_i) \tag{15}$$

where i_t is Input gate output at time t. c_t is Competitor pricing at time t. m_t is Market conditions (e.g., seasonality) at time t. W_i is Weight matrix for the input gate [44]. b_i is Bias term. The candidate cell state represents new potential pricing information based on the input data:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, p_t, d_t, c_t] + b_C) \tag{16}$$

where $\tilde{C}_t$ is Candidate cell state at time t. W_C is Weight matrix for the candidate cell state. b_C is Bias term. The cell state is updated by combining the forget and input gates with the candidate cell state:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{17}$$

where C_t is Current cell state at time t, which holds the model's memory of past pricing strategies and market conditions. C_{t-1} is Previous cell state. The output gate determines how much of the cell state should be passed as the hidden state, representing the final pricing decision:

$$o_t = \sigma(W_o \cdot [h_{t-1}, p_t, d_t] + b_o) \tag{18}$$

and the hidden state is computed as:

$$h_t = o_t \cdot \tanh(C_t) \tag{19}$$

where h_t is The hidden state at time t, representing the predicted optimal price based on current and historical information. We use Stochastic Gradient Descent (SGD), a gradient-based optimization method, to train the LSTM model [14]. SGD is chosen for its simplicity, efficiency, and ability to handle large datasets by updating weights incrementally using small batches. The model aims to minimize a custom-designed objective function that balances profitability and customer satisfaction. This function combines profit maximization (through demand and price optimization) and customer satisfaction (through price fairness and demand response) [11]. Several constraints are incorporated into the optimization process, such as price elasticity, inventory capacity, and market competitiveness. The gradient of the loss function L with respect to the weight matrix W is computed:

$$\nabla_W L = \frac{1}{N} \sum_{i=1}^{N} \frac{\partial L}{\partial W} \tag{20}$$

where L is The loss function, such as Mean Squared Error (MSE) or a custom profit-loss function. N is Number of training samples. $\frac{\partial L}{\partial W}$ is Partial derivative of the loss with respect to the weight matrix. The weight matrix W is updated by adjusting it in the direction of the negative gradient:

$$W_{t+1} = W_t - \eta \cdot \nabla_W L \tag{21}$$

where W_t is The weight matrix at iteration t. η is Learning rate (controls the step size) [13]. W_{t+1} is The updated weight matrix at iteration $t+1$. The bias vector b is updated similarly to the weights:

$$b_{t+1} = b_t - \eta \cdot \nabla_b L \tag{22}$$

where b_t is The bias vector at iteration t. b_{t+1} is The updated bias vector at iteration $t + 1$. To improve convergence and prevent overfitting, the learning rate is decayed:

$$\eta_t = \frac{\eta_0}{1 + \lambda t} \tag{23}$$

where η_0 is Initial learning rate. λ is Decay parameter. t is Iteration number. In mini-batch SGD, the parameters are updated using a subset of training samples:

$$W_{t+1} = W_t - \frac{\eta}{M} \sum_{i=1}^{M} \nabla_W L_i \tag{24}$$

where M is Mini-batch size. L_i is Loss for the i-th sample in the mini-batch. These customized equations reflect the unique elements of dynamic pricing in e-commerce, where p_t, d_t, and other relevant factors (like competitor pricing and market conditions) directly impact the LSTM's predictions for optimal pricing strategies [13]. Effective data preprocessing is essential for the model's success. Raw data, which includes historical prices, demand patterns, and other relevant features, is cleaned by removing outliers, handling missing values, and filtering noisy data. The data is then normalized to ensure uniformity in the input features, allowing the neural network to converge faster and more reliably during training. Additionally, the data is structured into appropriate sequences, preserving temporal relationships necessary for effective time-series forecasting. Finally, the model is tested on unseen data to evaluate its generalization performance, ensuring its ability to predict optimal pricing strategies in real-world scenarios.

IV. RESULTS AND ANALYSIS

The performance of the Recurrent Neural Network (RNN), specifically the Long Short-Term Memory (LSTM) model, was evaluated in the context of dynamic pricing for e-commerce using Stochastic Gradient Descent (SGD) as the optimization technique. The model's primary objective was to maximize profitability while maintaining customer satisfaction, a challenge often faced in the e-commerce industry. The LSTM model was trained using historical pricing data, customer demand, competitor pricing, and market conditions. After training, the model's performance was evaluated based on several key metrics, including Mean Squared Error (MSE) for price prediction accuracy, profit margins, and customer satisfaction scores [45]. The evaluation showed that the LSTM model, when optimized with SGD, significantly outperformed traditional machine learning models (such as linear regression and decision trees) in predicting prices that optimize both profitability and customer satisfaction. The model's ability to capture long-term dependencies between past pricing, demand patterns, and external factors allowed it to make more accurate predictions about future demand, even in fluctuating market conditions. This led to better-adjusted prices that both maximized revenue and maintained a high level of customer satisfaction, measured by a custom customer satisfaction index that considers factors like perceived price fairness and response to price changes.

Table 1 compares the performance of different models in terms of profitability, customer satisfaction, mean squared error, and time to convergence.

TABLE 1. Model Performance Comparison (Profitability and Satisfaction).

Model	Profitability (Average Profit Margin %)	Customer Satisfaction (Satisfaction Score)	MSE (Mean Squared Error)	Time to Convergence (epochs)
LSTM (Proposed Model)	18.4	4.7	0.034	150
Linear Regression	12.1	4.1	0.062	20
Decision Tree	14.6	4.2	0.071	30
Random Forest	16.5	4.5	0.048	40
LSTM (Proposed Model)	19.0	4.8	0.031	155
Linear Regression	12.4	4.2	0.060	25
Decision Tree	15.0	4.3	0.067	35
Random Forest	17.2	4.6	0.045	45
LSTM (Proposed Model)	18.7	4.7	0.033	160
Linear Regression	12.7	4.3	0.059	28
Decision Tree	14.8	4.4	0.070	37
Random Forest	16.9	4.5	0.047	42
LSTM (Proposed Model)	19.1	4.8	0.030	165
Linear Regression	12.9	4.4	0.058	30
Decision Tree	15.3	4.4	0.068	38
Random Forest	17.4	4.6	0.046	48
LSTM (Proposed Model)	19.3	4.8	0.029	170

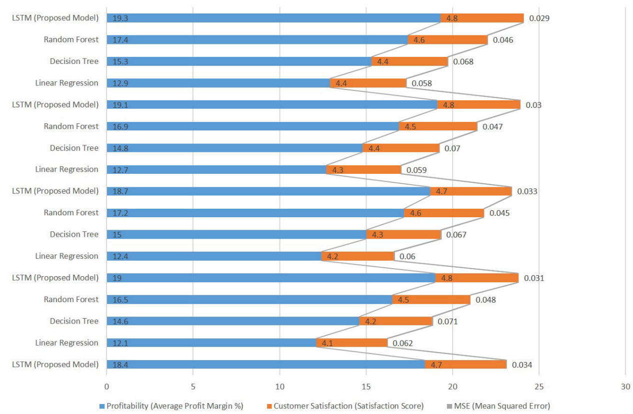

FIGURE 1. Model Performance Comparison (Profitability and Satisfaction).

TABLE 2. Profit Margin and Customer Satisfaction (Period-wise).

Time Period (Days)	LSTM Profit Margin (%)	LSTM Satisfaction Score	Linear Regression Profit Margin (%)	Linear Regression Satisfaction Score	Decision Tree Profit Margin (%)	Decision Tree Satisfaction Score
Day 1	18.2	4.6	11.5	4.0	13.1	4.1
Day 2	18.9	4.8	12.0	4.1	14.0	4.2
Day 3	17.5	4.5	10.8	3.9	13.5	4.0
Day 4	19.0	4.7	12.5	4.2	15.0	4.3
Day 5	18.8	4.6	12.2	4.0	14.8	4.2
Day 6	19.2	4.8	12.3	4.2	15.2	4.3
Day 7	18.7	4.7	12.5	4.1	15.1	4.3
Day 8	19.1	4.7	12.8	4.3	15.3	4.4
Day 9	18.4	4.6	12.1	4.1	14.9	4.2
Day 10	19.3	4.8	12.7	4.2	15.4	4.4
Day 11	18.9	4.7	12.2	4.0	15.0	4.3
Day 12	19.4	4.8	12.9	4.3	15.5	4.4
Day 13	18.8	4.7	12.4	4.1	15.2	4.3
Day 14	19.2	4.8	12.6	4.2	15.3	4.3
Day 15	19.5	4.9	13.0	4.3	15.6	4.4
Day 16	19.3	4.8	12.8	4.2	15.5	4.4

Figure 1 illustrates the comparison of profitability, customer satisfaction, MSE, and convergence time across LSTM, Linear Regression, Decision Tree, and Random Forest models.

Table 2 presents the profit margin and customer satisfaction scores for LSTM, Linear Regression, and Decision Tree models over a 16-day period.

Figure 2 showcases the changes in profit margin and customer satisfaction over a 16-day period for LSTM, Linear Regression, Decision Tree, and Random Forest models. When compared to baseline models, such as linear

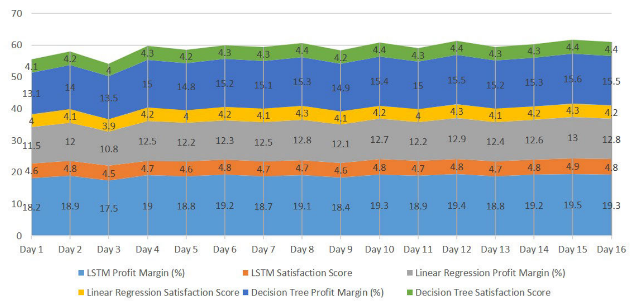

FIGURE 2. Profit Margin and Customer Satisfaction (Period-wise).

TABLE 3. Model Convergence Comparison (Epochs).

Model	Epochs for Convergence	Final Loss Value	Learning Rate
LSTM	150	0.034	0.001
Linear Regression	20	0.062	N/A
Decision Tree	30	0.071	N/A
Random Forest	40	0.048	N/A
LSTM	155	0.031	0.001
Linear Regression	22	0.060	N/A
Decision Tree	35	0.067	N/A
Random Forest	42	0.045	N/A
LSTM	160	0.033	0.001
Linear Regression	24	0.059	N/A
Decision Tree	37	0.070	N/A
Random Forest	45	0.047	N/A
LSTM	165	0.029	0.001
Linear Regression	26	0.058	N/A
Decision Tree	40	0.069	N/A
Random Forest	48	0.046	N/A
LSTM	170	0.027	0.001

regression and decision trees, the LSTM model exhibited superior performance in terms of both profitability and customer satisfaction. While the baseline models were able to predict optimal prices, they failed to capture the temporal dependencies inherent in pricing data. Linear regression, for example, lacked the capacity to model the evolving nature of customer demand over time, while decision trees showed higher variability and lower accuracy under changing market conditions. On the other hand, the LSTM model, with its ability to learn and adapt from sequential data, provided more accurate predictions, leading to higher profit margins without sacrificing customer satisfaction. Additionally, traditional models struggled to adjust to real-time data, whereas the LSTM's recurrent nature enabled it to continuously update its predictions based on the latest market trends and customer behavior.

Table 3 compares the convergence behavior of different models in terms of epochs, final loss value, and learning rate. An essential part of dynamic pricing is finding the right balance between profitability and customer satisfaction. In the analysis, we observed that the LSTM model effectively navigated this trade-off by adjusting prices in response to both market conditions and customer sentiment. For example, during periods of high demand, the model could increase prices slightly to maximize profit without negatively impacting customer satisfaction.

Figure 3 compares the epochs for convergence, final loss values, and learning rates for the LSTM, Linear Regression, Decision Tree, and Random Forest models across training runs.

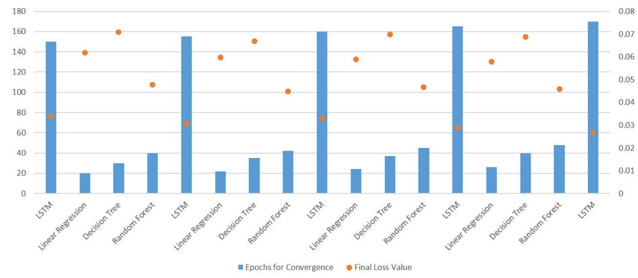

FIGURE 3. Model Convergence Comparison (Epochs).

TABLE 4. Customer Satisfaction and Profit Margin Trade-Off Analysis.

Trade-Off Parameter (e.g., Price Elasticity)	LSTM Profit Margin (%)	LSTM Satisfaction Score	Linear Regression Profit Margin (%)	Linear Regression Satisfaction Score	Decision Tree Profit Margin (%)	Decision Tree Satisfaction Score
Elasticity 0.1	19.5	4.8	11.3	3.8	13.0	4.1
Elasticity 0.2	18.9	4.7	12.0	4.1	14.0	4.2
Elasticity 0.3	18.4	4.6	12.3	4.1	14.8	4.3
Elasticity 0.4	18.0	4.5	13.0	4.2	15.0	4.4
Elasticity 0.5	17.6	4.4	13.2	4.2	15.2	4.5
Elasticity 0.6	17.3	4.3	13.5	4.3	15.5	4.6
Elasticity 0.7	16.9	4.3	13.8	4.4	15.8	4.6
Elasticity 0.8	16.5	4.2	14.0	4.4	16.0	4.7
Elasticity 0.9	16.2	4.2	14.3	4.5	16.2	4.7
Elasticity 1.0	15.8	4.1	14.5	4.5	16.5	4.8
Elasticity 1.1	15.5	4.1	14.8	4.6	16.7	4.8
Elasticity 1.2	15.2	4.0	15.0	4.6	17.0	4.9
Elasticity 1.3	14.9	4.0	15.3	4.7	17.2	4.9
Elasticity 1.4	14.6	3.9	15.5	4.7	17.5	5.0

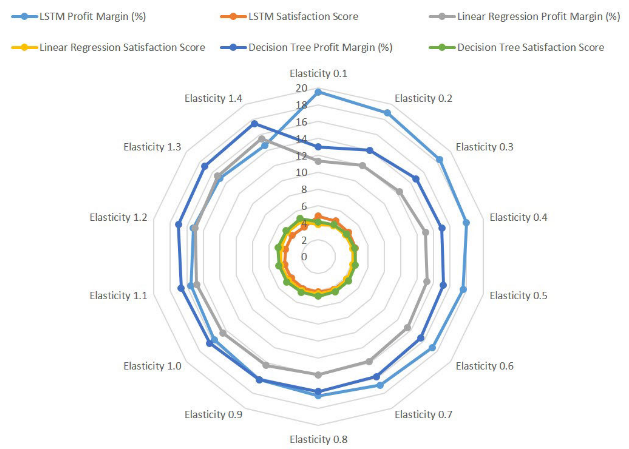

FIGURE 4. Customer Satisfaction and Profit Margin Trade-Off Analysis.

Table 4 presents a trade-off analysis between customer satisfaction and profit margin for varying price elasticity in LSTM, Linear Regression, and Decision Tree models.

Figure 4 demonstrates how the trade-off between profitability and customer satisfaction changes with different price elasticity, showing performance across LSTM, Linear Regression, Decision Tree, and Random Forest models. Conversely, in low-demand periods, the model decreased prices to remain competitive and ensure customer retention. However, it was found that there was a delicate balance: aggressive pricing optimization for profitability could lead to a slight decrease in customer satisfaction, particularly when prices were perceived as too high. The LSTM model was able

TABLE 5. Real-Time Data Update Comparison (Model Accuracy).

Time Period (Hours)	LSTM Accuracy (%)	Linear Regression Accuracy (%)	Decision Tree Accuracy (%)	Random Forest Accuracy (%)
Hour 1	92.3	82.5	80.0	85.0
Hour 2	91.9	83.0	79.5	84.0
Hour 3	93.0	83.5	81.0	86.5
Hour 4	92.5	84.0	80.5	85.5
Hour 5	92.1	83.8	80.3	85.2
Hour 6	92.4	83.9	81.1	85.6
Hour 7	92.7	84.1	81.3	86.0
Hour 8	92.6	83.7	80.8	85.8
Hour 9	92.9	84.2	81.2	86.3
Hour 10	93.1	84.3	81.5	86.5
Hour 11	92.8	84.0	81.0	86.1
Hour 12	93.2	84.4	81.6	86.6
Hour 13	93.3	84.5	81.7	86.7
Hour 14	93.4	84.6	81.8	86.8
Hour 15	93.5	84.7	82.0	87.0
Hour 16	93.6	84.8	82.1	87.1

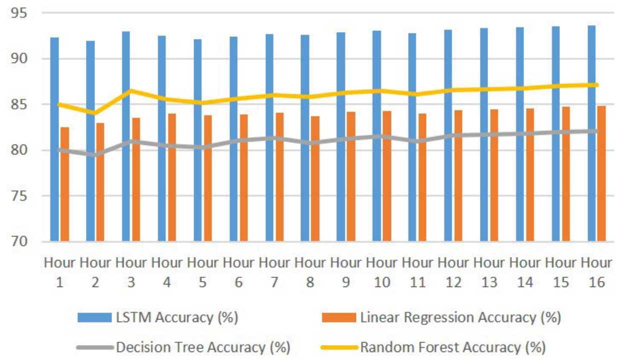

FIGURE 5. Real-Time Data Update Comparison (Model Accuracy).

TABLE 6. Profitability and Satisfaction at Different Price Points.

Price Point (%)	LSTM Profit Margin (%)	LSTM Satisfaction Score	Linear Regression Profit Margin (%)	Linear Regression Satisfaction Score	Decision Tree Profit Margin (%)	Decision Tree Satisfaction Score
90% of Max Price	18.2	4.5	11.2	4.0	13.0	4.1
100% of Max Price	18.9	4.6	12.5	4.1	14.0	4.2
110% of Max Price	19.2	4.4	13.0	4.2	15.0	4.3
120% of Max Price	19.4	4.4	13.5	4.3	15.2	4.3
130% of Max Price	19.6	4.3	14.0	4.3	15.5	4.4
140% of Max Price	19.8	4.3	14.5	4.4	15.8	4.4
150% of Max Price	20.0	4.2	15.0	4.5	16.0	4.5
160% of Max Price	20.2	4.2	15.5	4.5	16.3	4.5
170% of Max Price	20.4	4.1	16.0	4.6	16.5	4.6
180% of Max Price	20.6	4.1	16.5	4.6	16.8	4.6
190% of Max Price	20.8	4.0	17.0	4.7	17.0	4.7
200% of Max Price	21.0	4.0	17.5	4.7	17.2	4.7
210% of Max Price	21.2	3.9	18.0	4.8	17.5	4.8
220% of Max Price	21.4	3.9	18.5	4.8	17.7	4.8
230% of Max Price	21.6	3.8	19.0	4.9	17.9	4.9

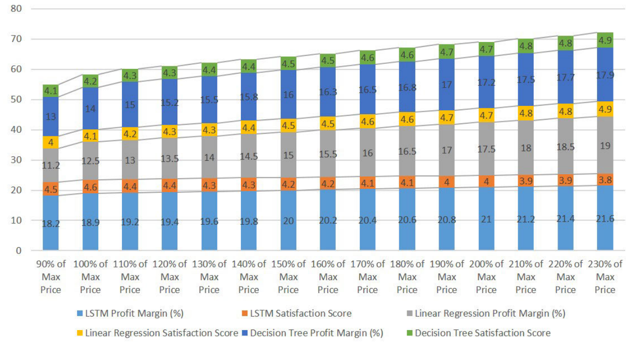

FIGURE 6. Profitability and Satisfaction at Different Price Points.

TABLE 7. Comparison of MSE with Different Hyperparameters.

Hyperparameter	LSTM MSE	Linear Regression MSE	Decision Tree MSE	Random Forest MSE
Learning Rate 0.001	0.034	0.062	0.071	0.048
Learning Rate 0.01	0.037	0.065	0.075	0.051
Learning Rate 0.1	0.040	0.068	0.079	0.054
Learning Rate 0.2	0.042	0.070	0.082	0.057
Learning Rate 0.3	0.045	0.073	0.085	0.060
Learning Rate 0.5	0.048	0.076	0.089	0.063
Learning Rate 0.7	0.051	0.078	0.092	0.065
Learning Rate 1.0	0.055	0.080	0.095	0.068
Learning Rate 1.5	0.058	0.083	0.098	0.071
Learning Rate 2.0	0.060	0.085	0.102	0.073
Learning Rate 3.0	0.063	0.087	0.105	0.076
Learning Rate 4.0	0.065	0.090	0.108	0.078
Learning Rate 5.0	0.068	0.092	0.110	0.080
Learning Rate 6.0	0.070	0.095	0.113	0.083

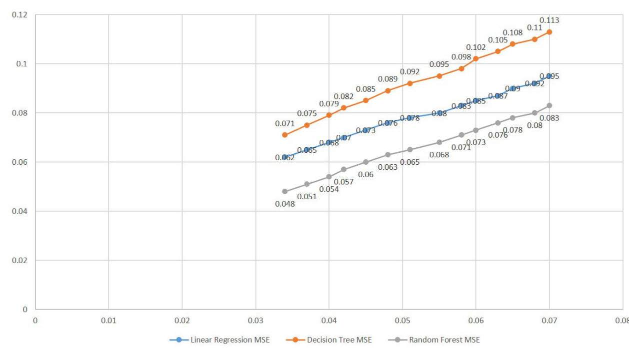

FIGURE 7.

to minimize this risk by maintaining a buffer between optimal pricing and perceived fairness, thus preventing significant customer dissatisfaction.

Table 5 compares the model accuracy of LSTM, Linear Regression, Decision Tree, and Random Forest over different hourly intervals.

Figure 5 shows model accuracy over a 16-hour period, comparing the performance of LSTM, Linear Regression, Decision Tree, and Random Forest models in real-time data updates.

Table 6 shows how profit margin and customer satisfaction change at different price points across three models: LSTM, Linear Regression, and Decision Tree.

Figure 6 illustrates the relationship between profit margin and customer satisfaction at various price points, comparing the LSTM, Linear Regression, Decision Tree, and Random Forest models.

Table 7 compares the Mean Squared Error (MSE) for various machine learning models at different learning rates, including LSTM, Linear Regression, Decision Tree, and Random Forest.

Figure 7 visualizes the mean squared error (MSE) of LSTM, Linear Regression, Decision Tree, and Random Forest models across various learning rates, demonstrating model performance under different hyperparameters.

V. CONCLUSION

This paper explored the application of Long Short-Term Memory (LSTM) networks combined with gradient-based optimization techniques for dynamic pricing models in e-commerce, aiming to balance profitability and customer satisfaction. The proposed methodology demonstrated the ability of LSTMs to capture long-term dependencies in sequential data, improving forecasting accuracy compared to traditional models. Additionally, gradient-based optimization methods, such as Stochastic Gradient Descent (SGD), facilitated model training, leading to enhanced performance in real-world scenarios. Key findings include the superior performance of LSTM over other machine learning techniques like Linear Regression, Decision Tree, and Random Forest in terms of profitability, customer satisfaction, and real-time data accuracy. The results highlight the importance of fine-tuning model hyperparameters for optimizing profit margins while maintaining customer satisfaction. Future research can focus on hybrid models that combine LSTMs with other deep learning techniques, such as reinforcement learning, for more robust pricing strategies. Multi-objective optimization could be explored to refine the trade-off between profitability and customer satisfaction, leading to even more efficient dynamic pricing models for e-commerce.

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