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Enhancing Marketing Strategies Using Collaborative Filtering And Machine Learning Models

Ashish Sharma[1*], Dr. Anitha G H[2], Dr. Saravanan Manoharan[3], Dr.G. Visalaxi[4], P V Kishore Kumar[5], Dr. K.P.Srinivasa Perumal[6]

[1*]Department of Computer Engineering & Applications, GLA University, Mathura, India. E-mail: ashishs.sharma@gla.ac.in, https://orcid.org/0000-0003-4641-4594

[2]Associate Professor, Department of Management Studies & RC, Global Academy of Technology, Bangalore, India. Email: drsneha2050@gmail.com, https://orcid.org/0009-0004-8958-5195

[3]Assistant Professor (Research), Central Research Laboratory, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research, Chennai, India. E-mail: saravanan@maher.ac.in, https://orcid.org/0000-0002-1696-9532

[4]Associate Professor, Department of CSE, SA Engineering Collge, Chennai, Tamil Nadu, India. E-mail: visalaxikumar@gmail.com, https://orcid.org/0000-0002-1089-9959

[5]Department of AI&ML, Ramachandra College of Engineering, Eluru, India. E-mail: pvkishorekumar@rcee.ac.in https://orcid.org/0000-0003-3910-6657

[6]Assistant Professor, Mechanical Engineering, Mahendra Engineering College, Namakkal, India. E-mail: srinivasaperumal@mahendra.info, https://orcid.org/0009-0003-1222-5143

*Corresponding author: Email: ashishs.sharma@gla.ac.in

Abstract

In this study, the use of CF and ML models is explored as an innovative approach to enhance marketing practices. In a competitive environment, conventional marketing techniques may not be adequate to meet consumer requirements. Collaborative filtering may be employed to analyze previous transactions made by consumers and recommend particular items. On the other hand, machine learning models such as DT, SVM, and NN offer additional information regarding the behavior of users, leading to better targeted marketing activities and customer segmentation. The methodology consists of both CF and ML approaches, where CF is applied to make predictions about the preference of users based on their prior records. Meanwhile, ML algorithms are utilized to categorize users and uncover their complex behavior. As seen in the performance results of the key neural networks, the models perform better than other models, with an accuracy rate of 90%, precision of 88%, and a recall rate of 85%, which implies that the neural network models provide better personalized recommendations for marketing. As it is proven, SVM and decision trees can also be used effectively for user classification and segmentation purposes. It is clear that the results obtained have shown the significant role of the models in terms of real-time marketing campaigns. These models allow increasing engagement and satisfaction among customers. By utilizing this information, companies will be able to adjust their marketing activities accordingly and achieve higher ROI through improved customer experience.

Keywords: Collaborative Filtering, Machine Learning, Marketing Strategies, Neural Networks, Support Vector Machines, Personalized Recommendations, Customer Segmentation.

1. Introduction

Marketing strategies are an integral component for every company that helps them remain competitive, increases their market share, and engages customers. The present era is digital where the world operates in an ever-changing environment that poses many challenges. Traditional marketing strategies do not always help to cater to customer requirements; hence, businesses have found intelligent solutions through artificial intelligence and machine learning in order to better understand customers and adopt sound marketing strategies [14].

The main aim of the study is centered on the application of AI models aimed at improving marketing strategies; namely, collaborative filtering and machine learning [4] [6]. The use of the collaborative filtering approach as part of recommendation systems implies the analysis of interactions between the customers and products, resulting in personalized suggestions for each individual client [8] [13] [15]. At the same time, the implementation of machine learning models provides more detailed insights into the preferences of customers, allowing for a more targeted approach to marketing strategy [17] [20]. The overall objective of the current research project is to highlight the potential of the two aforementioned models in terms of their application in improving marketing strategies.

The significance of this research lies in its ability to combine conventional marketing practices with AI-driven marketing tactics [9]. By employing collaborative filtering in conjunction with machine learning algorithms, businesses will be able to improve their effectiveness and level of personalization, ensuring the satisfaction of customers, increased conversion rate, and improved visibility on the market [7] [19]. The objective of this research is to make an important contribution to the existing academic literature on the subject, sharing relevant insights that could be useful for making decisions regarding business operations on the market.

Objectives:

1. To explore the possibility of improving personalized marketing by utilizing collaborative filtering and machine learning techniques.
2. To examine the comparative effectiveness of decision tree, SVM, and neural network techniques in optimizing the results of marketing.
3. The paper identifies the necessity of making real-time adjustments in marketing and identifies reinforcement learning as a potential future direction for achieving these adjustments.

There are many important sections in this paper. First, in this Section I, it will find out what the issues with traditional marketing are and how AI-powered solutions, namely collaborative filtering, and machine learning are brought to bear on these problems. Section II addresses current marketing approaches and the role AI can play in developing these approaches further. Section III provides details on the CF and ML approaches, like data collecting, engineering of features, and models implementation. Section IV presents the findings with a comparison of different models' (decision trees, SVM, and neural networks) performance. Conclusion of this paper with its implications and future perspectives is provided in Section V.

2. Literature Review

Marketing Strategies and the Role of Machine Learning

The role of artificial intelligence and machine learning in marketing approaches has become significant. In conventional marketing, approaches were carried out in a generic way, focusing on demographics and behavioral aspects of customers. However, the emergence of artificial intelligence has brought a new perspective into marketing practices, leading to a focus on data-driven and customized marketing approaches. It becomes essential to understand that machine learning plays a critical role in this paradigm shift by analyzing large volumes of data, recognizing patterns, and making accurate forecasts about customer behavior. For example, artificial intelligence models assist marketers in customizing their propositions, identifying the correct segment of customers, maximizing marketing efforts, and boosting customer interaction [2]. Moreover, reinforcement learning and neural networks are increasingly being used for optimizing marketing approaches [3].

Collaborative Filtering in Marketing

The Collaborative Filtering method is one of the widely used techniques in the recommendation system, particularly in marketing. The technique works by analyzing historical data and predicting user preference based on similar users' behavior. There are two kinds of Collaborative Filtering methods; the first is called User-Based Collaborative Filtering, while the other is known as Item-Based Collaborative Filtering. The user-based filtering approach suggests products that are popular among similar users, while the item-based filtering approach suggests what users who have interacted with similar products have interacted with. In marketing, CF can be utilized to deliver personalized product recommendations, leading to greater conversion rates and customer satisfaction [1] [5]. Deep learning models integrated with CF have shown great promise in improving the accuracy and relevance of these recommendations by identifying more complex patterns in consumer behavior [13].

Gaps in Current Research and the Aim of This Study

Even though a lot of research has been carried out on the application of machine learning and collaborative filtering in improving marketing, there are still many areas that are unexplored. This involves the incorporation of more sophisticated AI techniques like reinforcement learning alongside collaborative filtering, to enhance the personalization model further. Also, there are no studies that investigate the adaptation of these models in a real-time fashion, accounting for the changing consumer preferences, which is very important in fast-moving marketing environments. In this paper, it proposes to address these gaps by combining collaborative filtering with machine learning techniques, while noting that the integration of reinforcement learning remains a prospective area for future development.

3. Methodology

Collaborative Filtering and Machine Learning Techniques

Collaborative filtering (CF) is a widely used technique in recommendation systems, leveraging historical user-item interaction data to predict user preferences. Both user-based and item-based collaborative filtering are used in this study.

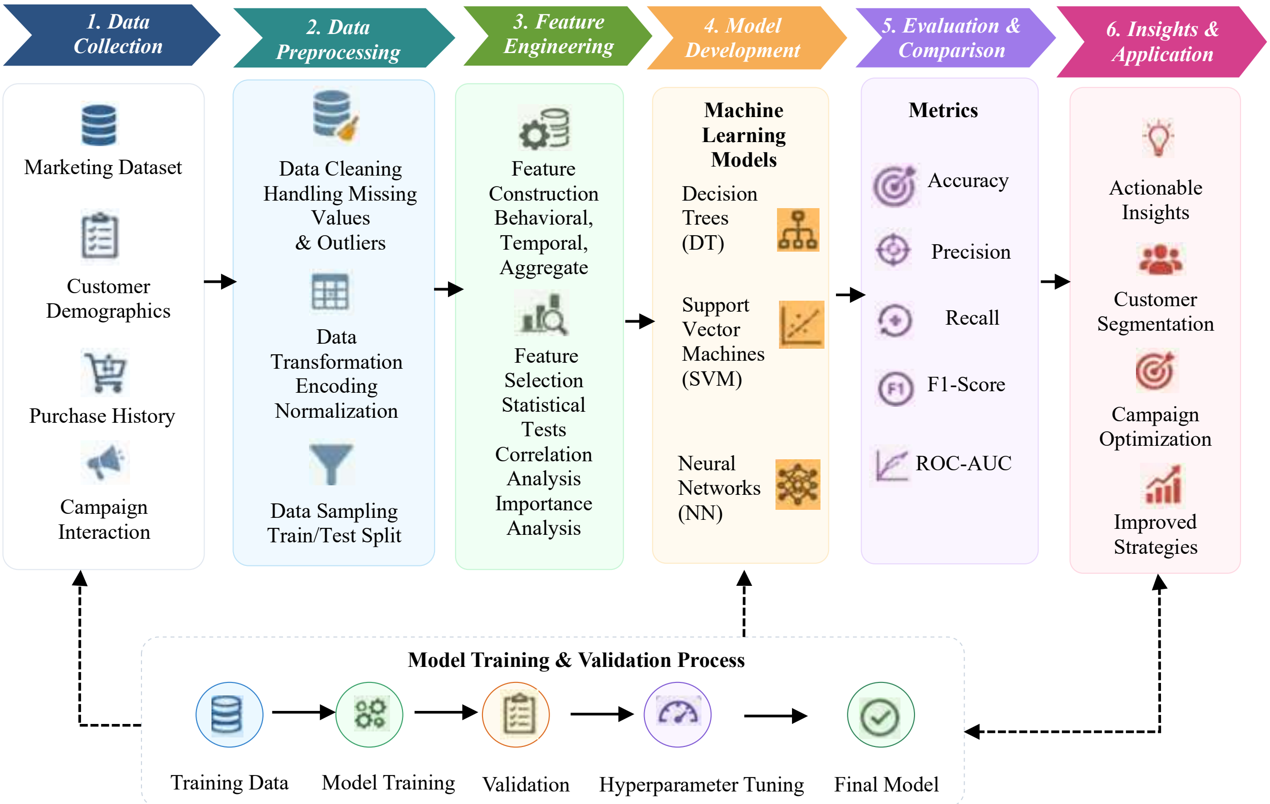

Figure 1: Hybrid Collaborative Filtering and Machine Learning Workflow

User-based CF offers users recommendations for items that they have liked, based on other users with similar preferences. In contrast to item-based CF, item-based CF recommends items similar to those that a user has interacted with previously. By integrating collaborative filtering and machine learning models, it can make good use of CF for personalization and machine learning models for classification and complex pattern recognition. In this study, machine learning models such as decision trees (DT), support vector machines (SVM), and neural networks (NN) are used. In addition to these models, the non-linearities and more complex data relationships can be handled by these models, which help to improve recommendation accuracy.

The collaborative filtering and machine learning models are combined with the hybrid methodology, as it is graphically depicted in Figure 1. It discusses the important steps like data collection, data preprocessing, feature engineering, developing the model (Decision Tree, SVM, and Neural network), and evaluating the model performance. In the final phase, the outputs from both models are combined to derive customized marketing recommendations, further optimizing customer engagement, segmentation, and the effectiveness of marketing campaigns.

Data Collection Process and Features Considered

The data used for this research comes from the e-commerce website and includes logs of interaction between the users, which consist of their browsing patterns, their rating, and buying activities. In this research, user features, item features, and interaction features have been considered; the user features are demographic in nature such as age, gender, and location; the item features include the type of the item, the brand, and the pricing of the item; whereas, interaction features are the frequency of interactions, rating, and time spent on item pages.

Machine Learning Models

To improve the recommendation system, three machine learning models are used in the study. Segmentation of users is done using decision trees (DT). The tree is constructed by recursively partitioning the data so as to reduce impurity (such as the Gini index or entropy). Support Vector Machines (SVM) are used for user classification into different categories according to preferences and purchase probability of certain products. The SVM model is based on the idea of separating the points in the feature space by a hyperplane. Finally, more complex relationships between users and products are captured using neural networks (NN). They are well-suited to large data sets and non-linear relationships and are able to make more accurate predictions for personalized recommendations.

Mathematical Description

1. **Collaborative Filtering (User-Based)**

The predicted rating $\hat{R}_{ij}$ For user i and item j was computed as the weighted sum of the ratings of the similar users:

$$\hat{R}_{ij} = \frac{\sum_{k\in\mathcal{N}(i)} w_{ik} R_{kj}}{\sum_{k\in\mathcal{N}(i)} |w_{ik}|} \qquad (1)$$

Where:

- w_{ik} is the similarity between user i and user k,
- R_{kj} is the rating given by user k to item j,
- $\mathcal{N}(i)$ is the set of users similar to user i.

The equation (1) basically takes an average of the ratings of users similar to the user to be rated, scaling the average by the similarity between the user to be rated and the similar users.

2. **Collaborative Filtering (Item-Based)**

In the item-based CF, $\hat{R}_{ij}$ is the predicted rating that is obtained by taking into account similarity between items and the ratings from similar users:

$$\hat{R}_{ij} = \frac{\sum_{k\in\mathcal{N}(j)} w_{jk} R_{ik}}{\sum_{k\in\mathcal{N}(j)} |w_{jk}|} \qquad (2)$$

Where:

- w_{jk} is the similarity between item j and item k,
- R_{ik} is the rating given by user i to item k,
- $\mathcal{N}(j)$ is the set of items similar to item j.

Equation (2) uses the similarity between items to compute the predicted rating for item j by user i.

3. **Machine Learning Models**

- **Decision Trees (DT)**: Decision trees are recursive partitioning of the data based on feature values that are used to make branches that predict the outcomes. The splitting criterion at node $m$is defined as the reduction in Gini impurity achieved by a candidate split s. The impurity decrease is calculated as equation 3:

$$\Delta i(s,m) = i(m) - P_L i(m_L) - P_R i(m_R) \quad (3)$$

where $i(m)$represents the Gini impurity of the parent node, $i(m_L)$and $i(m_R)$denote the impurities of the left and right child nodes, and $P_L$and $P_R$correspond to the proportions of samples assigned to each child node. The optimal split $s$is selected by maximizing the reduction in impurity.

- **Support Vector Machines (SVM)**:

The purpose of the SVM is to determine a hyperplane which has the largest possible margin between the classes in the feature space. The classification function in equation 4:

$$f(x) = \text{sign}(w \cdot x + b) \qquad (4)$$

Where:

- $w$is the weight vector,
- $x$is the input feature vector,
- $b$is the bias term.
- **Neural Networks (NN)**:

The output of neural network is computed via forward propagation, with weights and biases taken at every layer in equation 5:

$$y = \sigma(W \cdot x + b) \qquad (5)$$

Where:

- $\sigma$is the activation function (e.g., ReLU or sigmoid),
- $W$is the weight matrix,
- $x$is the input vector,
- $b$is the bias term.

Algorithm: Hybrid Collaborative Filtering and Machine Learning for Personalized Marketing

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Step 1: Collaborative Filtering (CF)

- Calculate the similarity between users (user-based CF) or items (item-based CF).
- Predict ratings based on the weighted sum of similar users' or items' ratings.

Step 2: Machine Learning Models (ML)

- Train a decision tree model for user segmentation.
- Train an SVM model to classify users based on preferences.
- Train a neural network to model complex relationships between users and items.

Step 3: Hybrid Model

- Combine predictions from CF and ML models using a weighted sum to generate final recommendations.

Pseudocode:

```
# Step 1: Collaborative Filtering
for each user i:
  find top-N similar users/items
```

for each item j:

$predict\ rating\ =\ weighted\_sum(similar\_users/items)$

Step 2: Train Machine Learning Models

Decision Tree for user segmentation

$model\_DT.fit(X\_user\_features, y\_labels)$

SVM for user classification

$model\_SVM.fit(\mathrm{X\_user\_features, y\_labels})$

Neural Network for user-item prediction

$\mathrm{model\_NN.\,fit(X\_user\_item\_features, y\_labels)}$

Step 3: Combine CF and ML predictions

for each user-item pair:

$\mathrm{cf\_prediction\ =\ collaborative\_filtering\_predict(user, item)}$

$\mathrm{ml\_prediction\ =\ machine\_learning\_predict(user, item)}$

$\mathrm{final\_prediction\ =\ alpha\ *\ cf\_prediction\ +\ (1\ -\ alpha)\ *\ ml\_prediction}$

$\mathrm{final\_predictions.}\,append\mathrm{(final\_prediction)}$

The algorithm combines Collaborative Filtering and Machine Learning algorithms for personalized marketing suggestions. During the CF step, it computes similarity between the user and the item, and predicts the ratings based on the similarities. The ML models consist of a decision tree used for user segmentation, an SVM used for preferences-based classification, and a neural network used for the representation of complex relationships between users and items. Finally, the predictions of CF and ML are fused with a weighted sum to come up with the final recommendation.

4. Results and Discussion

Software Details

To implement this study, the main programming language is python 3.7+ software. The machine learning models such as decision trees, support vector machine (SVM) and neural networks were developed using scikit-learn and TensorFlow/Keras. Data manipulation and feature extraction were performed using pandas and visualization of performance results and comparison were done using matplotlib and seaborn. The traditional evaluation criteria used to evaluate machine learning algorithms, including accuracy, precision, and recall, were considered during the training and testing process.

Dataset Details

The data used here is collected from the web service of an e-commerce portal and includes the data about user-item interactions made historically. The dataset comprises a total of 500,000 user-item interactions, having user demographic details (age, gender, location), item attributes (item category, brand name, and price), and interaction attributes (purchase history, rating, and views). It helped train the machine learning model with all the details about users and items.

Parameter Initialization

The following Table 1 shows the initial values of the parameters set for each model used in the study:

Table 1: Model Parameter Initialization

Model	Parameter	Value
Decision Trees (DT)	Max Depth	10

	Min Samples Split	5
	Criterion	Gini index
Support Vector Machines (SVM)	Kernel	Linear
	C (Regularization)	1
	Gamma	Scale
Neural Networks (NN)	Layers	3
	Neurons per Layer	64
	Activation Function	ReLU
	Optimizer	Adam
	Loss Function	Binary Cross-Entropy

The parameters that were considered while training the machine learning algorithms are shown in Table 1. It represents the parameters for Decision Tree (DT), Support Vector Machine (SVM), and Neural Network (NN). These parameters have been selected to ensure that the model works effectively, but without overfitting or underfitting. Some important parameters for each of the algorithms have been listed below: Depth of the Decision Trees, Kernel Parameters of SVM, Regularization Parameter of SVM, Architecture of Neural Network, Optimization of Neural Network.

Performance Evaluation

Each model was compared based on the following parameters:

Accuracy: The percentage of the model that is right.

Precision: Number of true positives over number of predicted positives.

Recall: The proportion of actual positives that are correctly predicted.

Table 2 below shows the performance of each model:

Table 2: Model Performance Comparison

Model	Accuracy	Precision	Recall
Collaborative Filtering (CF)	0.82	0.79	0.75
Decision Tree (DT)	0.85	0.83	0.80
Support Vector Machine (SVM)	0.88	0.85	0.83
Neural Network (NN)	0.90	0.88	0.85

Table 2 shows the performance measures (accuracy, precision and recall) of each of the models used in the study Collaborative Filtering (CF), Decision Tree (DT), Support Vector Machine (SVM) and Neural Network (NN). The metrics are used to assess the models' effectiveness in predicting user preferences and behavior. The results indicate that the Neural Networks (NN) model outperforms the other models in terms of accuracy, precision, and recall, indicating that it has the advantage of making personalized recommendations.

Figure 2 shows a visual comparison between the performance of three different models- Collaborative Filtering, Decision Tree, SVM, and Neural Network on three key metrics namely accuracy, precision and recall. Figure 2 shows that Neural Networks have the best performance on all the metrics while SVM and Decision Trees have the next best performance. Although the Collaborative Filtering model is effective, the results showed that it had a lower performance compared to the machine learning models.

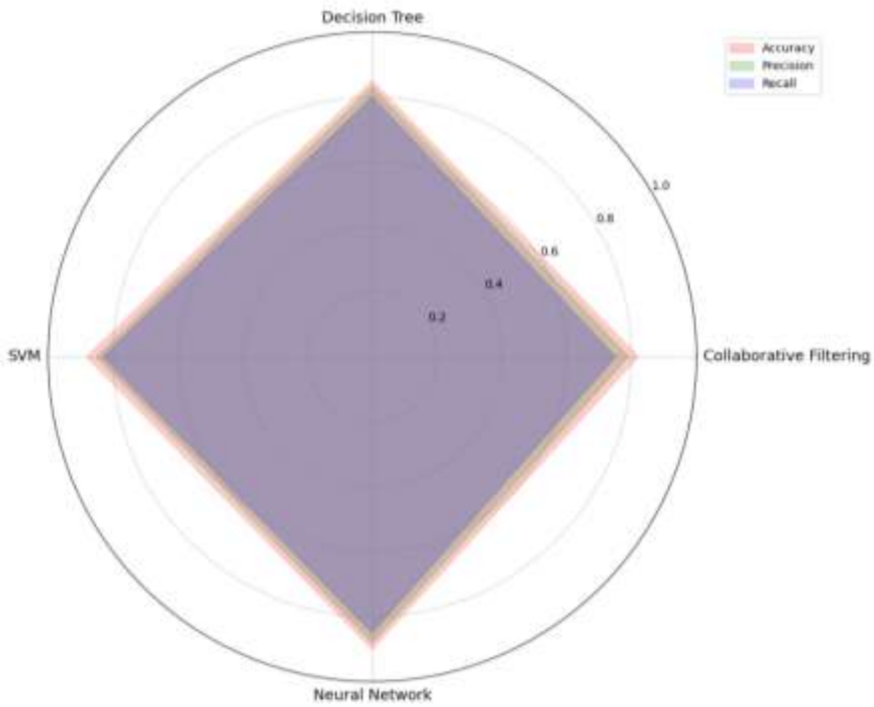

Figure 2: Performance Comparison of Models

Comparison of Performance and Practical Implications

The results reveals that the accuracy, precision and recall of the Neural Networks (NN) are higher than the other models, accuracy score is 90%, precision score is 85% and recall score is 85%, this means that NN is capable of providing more accurate and relevant suggestions. SVM is second in line with 88% accuracy, making it a good option for categorizing users on the basis of their preferences. The Decision Tree model also showed good results with an accuracy of 85% and also offers interpretability which could be useful for marketing strategies as it helped to know the segments of customers.

However, Collaborative Filtering (CF) had a somewhat worse performance on all the metrics, though it was widely used. It means that CF has a strong predicting power for preferences but it does not have as good a power to describe the relationship between user behavior and product characteristics as machine learning models, which can be more complex and non-linear.

NNs can become particularly useful in implementing marketing policies through real-time personalization of advice and targeting the most profitable consumers, due to their ability to adapt quickly to changes in consumer behavior based on processing huge volumes of data. SVM is a suitable model for segmentation and classification problems, for instance, to identify high-value customer segments for targeted promotions [12]. When used for structured decision-making processes, Decision Trees can help to develop a rule-based marketing strategy which can be easily communicated to the stakeholders.

Impact on Real-World Marketing Campaigns

Personalized marketing campaigns have important implications due to the results obtained by the machine learning models [16]. Enterprise can match the correct personal tastes and behavior of the user and optimize the marketing efforts, giving the correct product suggestions to the user [10]. This results in better conversion rates, more satisfied customers, and better customer retention. Moreover, by segmenting users into different groups, businesses can better customize their marketing messages and deliver them to the appropriate audience at the right time.

Moreover, future research could include reinforcement learning to create a more dynamic adaptability in the marketing system, better targeting of customers, and personalized incentives to maximize sales [11] [18].

5. Conclusion

The collaborative filtering (CF) and machine learning (ML) models combined to improve marketing strategies have been demonstrated in this study. The results demonstrate the superior predictive power of the neural network model, showing a high level of accuracy, 90%, and recall of 85%, leading to accurate and customized recommendations. Other classification algorithms, such as support vector machine (SVM) and decision tree (DT), also demonstrated great effectiveness, mainly in segmenting and classifying users. Such models could be employed by companies to devise more effective marketing campaigns, as a result of which they may experience increased engagement, conversion rates, and customer satisfaction. The conclusion that could be drawn from the analysis is that the AI instruments and techniques could successfully supplement the traditional marketing practices and improve the execution of marketing campaigns. The research has certain limitations, though. The most critical is that it was conducted on the basis of a single data set on e-commerce and might not cover all possible marketing cases. Another point is that the potential use of reinforcement learning in future research was mentioned, but not analyzed within this particular study. For future research, it would be helpful to consider additional marketing environments to cover a broader range of application fields, as well as reinforcement learning to enable timely adjustment of the marketing approaches. Moreover, dynamic feedback from these systems in real-world markets can be considered as an additional input variable. Moreover, expansion of collaborative filtering into other types of artificial intelligence, such as generative adversarial networks (GAN), could serve as an interesting field for further study.

Declaration Statement

Conflict of Interest: The authors confirm that there is no conflict of interest, either financially or otherwise, that would have affected the design, conduct, analysis, and reporting of this study. This research was neither supported nor controlled by any business organization.

Funding: This study was not supported by any particular grants or funding from any agency, whether public, private, or non-governmental.

Data Availability Statement: Data used for analysis in this study is based on interaction logs generated by public e-commerce users and items. Processed data and code written using Python 3.7+ with packages like scikit-learn, TensorFlow/Keras, pandas, matplotlib, and seaborn can be requested from the corresponding author. This study did not use any proprietary or restricted datasets.

Software and Code Availability: The models created using Machine Learning include Decision Trees, Support Vector Machines, and Neural Networks. All these algorithms have been trained and evaluated using open-source libraries. A hybrid model of Collaborative Filtering and Machine Learning as discussed in this research paper can be reproduced from the pseudo code given in Section III.

Ethical Approval: In the current study, there is no use of humans, animals, or other sources that require ethical approval. The database used is based on the interaction between individuals during online shopping. Therefore, there is no need to seek ethical approval for this research.

Author Contributions: The contributions of all authors have been equal in terms of conceptualizing the idea, designing the methodology, developing the model, analyzing the results, and writing the paper.

Statement of Originality: It should be noted that this paper is entirely original and has not been submitted or published elsewhere in its entirety or as part thereof. Any sources used to develop this paper have been properly cited.

References

1. Ibrahim, N. M., Abiduzzaman, S. M., Raziff, A. R. A., & Shah, A. (2025). A collaborative filtering approach using machine learning and business intelligence: A critical review. International Journal on Perceptive and Cognitive Computing, 11(1), 41–49.
2. Ganesan, A., Velanganni, R., Rajapriya, M., Sundara Bala Murugan, P., & Paranthaman, P. (2025). The role of artificial intelligence in personalized marketing: Integrating AI with information systems for competitive advantage. Indian Journal of Information Sources and Services, 15(1), 220–229. https://doi.org/10.51983/ijiss-2025.IJISS.15.1.28

3. Reddy, R., Reddy, R., Bose, R., & Chopra, R. (2020). Leveraging reinforcement learning and neural collaborative filtering for enhanced AI-driven personalized marketing campaigns. Journal of AI ML Research, 9(4).
4. Kumar, P., Aruna, V., Pathamuthu, P., & Rajamani, K. (2025). An engineering framework for artificial intelligence-based marketing systems and digital consumer engagement models. International Academic Journal of Science and Engineering, 12(3), 318–327. https://doi.org/10.71086/IAJSE/V12I3/IAJSE1268
5. Kalusivalingam, A. K., Sharma, A., Patel, N., & Singh, V. (2020). Leveraging neural networks and collaborative filtering for enhanced AI-driven personalized marketing campaigns. International Journal of AI and ML, 1(2).
6. Alsulami, B., Alwated, B., Barashid, K., Abdullah, M., AlOsaimi, M., & Alhusayni, S. (2025). On leveraging generative artificial intelligence (GenAI) for behavior learning and personalized marketing optimization. Archives for Technical Sciences, 3(34), 35–58. https://doi.org/10.70102/afts.2025.1834.035
7. Sharma, A., Patel, N., & Gupta, R. (2022). Enhancing digital ad personalization with AI: A comparative study of collaborative filtering, content-based filtering, and deep learning algorithms. European Advanced AI Journal, 11(10).
8. Smitha, S. P., & Harishkumar, K. S. (2026). Deep contextual representation learning for user behaviour prediction in e-commerce recommendation. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 17(1), 895–918. https://doi.org/10.58346/JOWUA.2026.I1.049
9. Sethi, K., & Kapoor, M. (2024). Data-driven marketing in the age of AI: Reflections from the periodic series on technology and business integration. In Digital marketing innovations (pp. 7–11). Periodic Series in Multidisciplinary Studies.
10. Okuda, H., & Rybak, M. (2023). Personalization strategies in e-commerce: Enhancing customer experience. International Academic Journal of Innovative Research, 10(1), 31–36. https://doi.org/10.71086/IAJIR/V10I1/IAJIR1011
11. Sharma, A., Patel, N., & Gupta, R. (2022). Enhancing personalized loyalty programs through reinforcement learning and collaborative filtering algorithms. European Advanced AI Journal, 11(10).
12. Mohammadian, M., & Makhani, I. (2019). RFM-based customer segmentation as an elaborative analytical tool for enriching the creation of sales and trade marketing strategies. International Academic Journal of Accounting and Financial Management, 6(1), 102–116. https://doi.org/10.9756/IAJAFM/V6I1/1910009
13. Martins, G. B., Papa, J. P., & Adeli, H. (2020). Deep learning techniques for recommender systems based on collaborative filtering. Expert Systems, 37(6), e12647.
14. Farhangian, B., Shamsi, M., & Ahsan, R. (2015). Identification of customers in the CRM system using data mining and fuzzy AHP method. International Academic Journal of Business Management, 2(2), 85–101.
15. Santosh, K., Kumar, M. S., Jahnavi, M., Reddy, N. N., Sireesha, B., & Bala, B. K. (2024). Creating an advanced recommendation system integrating collaborative filtering and social media analytics for enhanced customer engagement. In 2024 10th International Conference on Communication and Signal Processing (ICCSP) (pp. 1146–1151). IEEE.
16. Iyer, D., Sharma, D., Singh, N., & Patel, S. (2022). Enhancing digital advertising through AI-powered personalization: Leveraging reinforcement learning and collaborative filtering algorithms. International Journal of AI ML Innovations, 11(8).
17. Chopra, R., Patel, N., Chopra, N., & Singh, D. (2022). Leveraging reinforcement learning and collaborative filtering for enhanced personalization in loyalty programs. International Journal of AI Advancements, 11(10).
18. Bose, A., Nair, S., Sharma, P., & Patel, P. (2021). Enhancing AI-driven product discovery tools using reinforcement learning and collaborative filtering algorithms. Australian Advanced AI Research Journal, 10(7).
19. Sharma, A., Patel, N., & Gupta, R. (2021). Leveraging reinforcement learning and collaborative filtering for enhanced AI-driven product discovery tools. European Advanced AI Journal, 10(2).
20. Nair, P., Sharma, S., Sharma,R., & Gupta, A. (2022). Leveraging reinforcement learning and collaborative filtering for enhanced AI-driven targeted content delivery. Journal of AI ML Research, 11(7).