E-commerce personalized recommendations: A deep neural collaborative filtering approach

Fayçal Messaoudi[1] and Manal Loukili[2]
[1]Artificial Intelligence, Data Science and Emerging Systems laboratory, National School of Business and Management,
Sidi Mohamed Ben Abdellah University, Fez, Morocco
[2]Artificial Intelligence, Data Science and Emerging Systems laboratory, National School of Applied Sciences,
Sidi Mohamed Ben Abdellah University, Fez, Morocco

ABSTRACT
In the ever-evolving landscape of e-commerce, personalized product recommendations have emerged as a critical tool for optimizing the shopping experience and driving sales growth. This study presents a comprehensive exploration and implementation of a Deep Neural Collaborative Filtering recommendation system, aimed at fine-tuning product recommendations to meet user preferences. Our results showcase the effectiveness of the model with a precision of 0.85, indicating its ability to provide relevant suggestions, a recall score of 0.78, demonstrating successful item retrieval, and a Click-Through Rate of 0.12, emphasizing user engagement with recommended products. While recognizing limitations related to data quality and scalability, this research highlights the potential for data-driven, machine learning-powered recommendation systems to revolutionize the e-commerce landscape. In an ever-competitive digital marketplace, advanced recommendation systems are poised to be pivotal in enhancing the shopping experience and sustaining sales growth.

Keywords:

Machine learning
E-commerce
Recommender System
Deep Learning
Collaborative Filtering

Corresponding Author:

Manal Loukili
Ecole Nationale des Sciences Appliquées, Université Sidi Mohamed Ben Abdellah,
Avenue My Abdallah Km 5, Route d'Immouzzer, Fès BP 72, Maroc.
Email: manal.loukili@usmba.ac.ma

1. INTRODUCTION

In the dynamic and fiercely competitive realm of e-commerce, data-driven insights and personalized customer experiences have emerged as the bedrock of success [1]. The ability to harness the power of data to optimize product recommendations and enhance the shopping journey is now paramount for businesses seeking to flourish in this ever-evolving landscape [2].

Machine learning, recognized for its transformative potential across various domains within e-commerce, has proven effective in addressing pivotal challenges such as personalized recommendations [3], customer churn prediction [4], demand forecasting [5], and sentiment analysis [6]. In light of this, our study embarks on a transformative journey aimed at elevating e-commerce sales through the development and implementation of a Deep Neural Collaborative Filtering (DNCF) recommendation system.

The e-commerce industry has witnessed remarkable growth, marked by its dynamism, diversity of products, and evolving consumer preferences [7]. To stay competitive in this environment, businesses must not only meet the demands of their customers but also anticipate them [8].

Personalized product recommendations serve as a key strategy in achieving this objective [9]. They enhance user engagement, increase sales conversion rates, and foster customer loyalty [10].

This research addresses the challenge of optimizing product recommendations, aiming to provide users with product suggestions that align with their preferences and needs. The DNCF model, a fusion of collaborative filtering and deep learning techniques, is introduced as a powerful tool for this purpose [11]. By analyzing user behavior, historical purchase data, and product attributes, the DNCF model generates recommendations that resonate with individual users.

The significance of this study lies in its potential to revolutionize the e-commerce shopping experience. As we delve into the exploration, implementation, and evaluation of the DNCF recommendation system, we uncover the capacity of data-driven, machine learning-powered systems to drive substantial improvements in e-commerce performance. Through precision, recall, and Click-Through Rate (CTR) metrics, we measure the model's success in providing relevant and engaging product recommendations.

The key motivations behind this study are:

- To leverage machine learning for enhancing personalized product recommendations in e-commerce.
- To address the challenge of aligning product suggestions with individual user preferences and needs.
- To evaluate the effectiveness of the DNCF model in improving user engagement and sales conversion rates.
- To contribute to the evolving landscape of e-commerce by introducing advanced, data-driven recommendation systems.

2. THEORETICAL BACKGROUND

The theoretical underpinnings of this study draw from two primary domains: recommendation systems and deep learning techniques. Understanding the foundational concepts within these domains is essential for comprehending the development and implementation of the DNCF recommendation system.

2.1. Recommendation Systems

Recommendation systems, often referred to as recommender systems, are instrumental in providing personalized suggestions to users [12], enhancing their online experiences [13], and facilitating decision-making [14]. These systems have gained prominence in various domains, including e-commerce [15], content streaming [16], social media [17], and more [18], [19], [20].
There are three primary types of recommendation systems:

- **Collaborative Filtering:**

Collaborative filtering (CF) relies on user-item interaction data to make recommendations [21]. It assumes that users who have interacted with similar items in the past will have similar preferences in the future [22]. CF techniques can be further categorized into user-based and item-based methods [23].

- **Content-Based Filtering:**

Content-based filtering leverages information about the content and attributes of items, as well as user profiles, to make recommendations [24]. It focuses on matching the characteristics of items with users' preferences [25].

- **Hybrid Methods:**

Hybrid recommendation systems combine collaborative filtering and content-based filtering approaches to harness the strengths of both methods and provide more accurate and diverse recommendations [26].

2.2. Deep Learning Techniques

Deep learning is a subfield of machine learning that has gained prominence for its ability to model complex patterns and representations in data [27]. It has been instrumental in enhancing the performance of recommendation systems through techniques such as neural collaborative filtering [28].

- **Neural Collaborative Filtering (NCF):**

NCF is a deep learning-based recommendation approach that combines the power of neural networks with collaborative filtering [29]. It introduces neural network layers to capture intricate user-item interactions, enabling the model to uncover hidden patterns and preferences.

- **Embeddings:**

Embeddings are a fundamental concept in deep learning, particularly in recommendation systems [30]. They involve mapping categorical variables (e.g., user IDs, item IDs) into continuous vector spaces. These embeddings facilitate the learning of latent representations, enhancing the model's ability to capture user and item interactions [31].

- **Deep Neural Networks (DNN):**

Deep neural networks are comprised of multiple layers of interconnected neurons [32]. They have been employed in recommendation systems to model complex relationships between users and items, leading to improved recommendation accuracy.

2.3. The Intersection of Collaborative Filtering and Deep Learning

The DNCF recommendation system presented in this study represents the synergy of collaborative filtering and deep learning. By incorporating neural networks, and embeddings, DNCF captures user-item interactions more effectively, resulting in highly personalized and engaging recommendations.

The theoretical foundation of this study rests on the principles of recommendation systems, with a focus on collaborative filtering, content-based filtering, and hybrid methods. Deep learning techniques, particularly neural collaborative filtering, and embeddings, play a pivotal role in enhancing the accuracy and effectiveness of recommendation systems.

3. METHODOLOGY

The methodology employed in this study revolves around the development and implementation of a Deep Neural Collaborative Filtering recommendation system, aimed at enhancing the e-commerce sales landscape. The step-by-step process encompasses data preparation, model development, training, evaluation, and fine-tuning.

3.1. Data Preparation

The first step involved the loading and exploration of the e-commerce sales data set. Essential libraries such as Pandas, NumPy, Matplotlib, and Seaborn were imported for data manipulation and visualization purposes. The dataset used in this study is “SalesDataAnalysis” [33], it comprised a comprehensive range of information, including Order Date, Order ID, Product, Product EAN, Category, Purchase Address, Quantity Ordered, Price Each, Cost Price, Turnover, and Margin, providing a detailed view of e-commerce transactions (Table 1).

Table 1. The e-commerce sales data set

	Order Date	Order ID	Product	Product_ean	catégorie	Purchase Address	Quantity Ordered	Price Each	Cost price	turnover	margin
0	2019-01-22 21:25:00	141234	iPhone	5.638009e+12	Vêtements	944 Walnut St, Boston, MA 02215	1	700.00	231.0000	700.00	469.0000
1	2019-01-28 14:15:00	141235	Lightning Charging Cable	5.563320e+12	Alimentation	185 Maple St, Portland, OR 97035	1	14.95	7.4750	14.95	7.4750
2	2019-01-17 13:33:00	141236	Wired Headphones	2.113973e+12	Vêtements	538 Adams St, San Francisco, CA 94016	2	11.99	5.9950	23.98	11.9900
3	2019-01-05 20:33:00	141237	27in FHD Monitor	3.069157e+12	Sports	738 10th St, Los Angeles, CA 90001	1	149.99	97.4935	149.99	52.4965
…	…	…	…	…	…	…	…	…	…	…	…
185949	2019-12-21 21:45:00	319670	Bose SoundSport Headphones	8.081038e+12	Électronique	747 Chestnut St, Los Angeles, CA 90001	1	99.99	49.9950	99.99	49.9950

185950 rows × 11 columns

Upon the data set being loaded, a preliminary analysis was conducted to understand its characteristics. The *info()* method was employed to obtain an overview of data types and non-null counts. Descriptive statistics were generated using *describe()* to gain insights into the central tendencies and spread of numerical columns. Additionally, missing values were checked using *isnull().sum()* to ensure data integrity (Figure 1).

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 185950 entries, 0 to 185949
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Order Date        185950 non-null  object
 1   Order ID          185950 non-null  int64
 2   Product           185950 non-null  object
 3   Product_ean       185950 non-null  float64
 4   catégorie         185950 non-null  object
 5   Purchase Address  185950 non-null  object
 6   Quantity Ordered  185950 non-null  int64
 7   Price Each        185950 non-null  float64
 8   Cost price        185950 non-null  float64
 9   turnover          185950 non-null  float64
 10  margin            185950 non-null  float64
dtypes: float64(5), int64(2), object(4)
memory usage: 15.6+ MB
```

```
Order Date          0
Order ID            0
Product             0
Product_ean         0
catégorie           0
Purchase Address    0
Quantity Ordered    0
Price Each          0
Cost price          0
turnover            0
margin              0
dtype: int64
```

Figure 1. Data set information

The distribution of key columns was visualized as a crucial step in understanding the spread and central tendencies of the data. This process enabled the uncovering of underlying patterns, potential correlations between variables, and anomalies that might have influenced e-commerce sales (Figure 2).

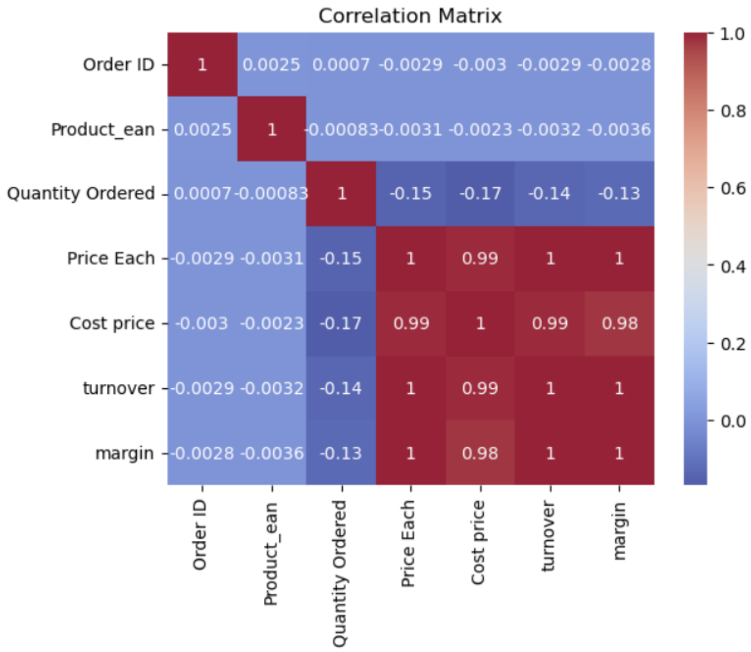

Figure 2. Correlation Matrix

The heatmap visualization of the correlation matrix, as depicted above, highlights the strength and direction of correlations between variables. Positive correlations are represented by warmer colors (red), indicating that as one variable increases, the other tends to increase as well. Conversely, negative correlations are represented by cooler colors (blue), indicating an inverse relationship. The relevance of this matrix to our study lies in its ability to uncover significant relationships that can impact the performance of our DNCF model.

3.2. Data Preprocessing

- **Outlier Detection and Handling in Data Preprocessing**

In the data preprocessing stage, we focused on identifying and managing outliers to ensure the accuracy of our model. We used a simple statistical method where outliers were defined as data points that lay beyond 1.5 times the interquartile range (IQR) above or below the first and third quartiles. These outliers were then handled effectively by applying a method known as robust scaling. This technique adjusts the data to lessen the impact of extreme values, ensuring that our Deep Neural Collaborative Filtering model trained on data that was representative of typical user behavior, without being unduly influenced by rare or extreme cases.

- **Date-Time Conversion**

The *'Date'* column was converted into a date-time format, representing a crucial step for time series analysis and chronological data manipulation. This conversion allowed for the effective aggregation of sales data based on time periods.

- **Monthly Aggregation**

To comprehend monthly sales trends and patterns, the month and year were extracted from the *'Date'* column. The resulting *'Month'* and *'Year'* columns facilitated the aggregation of sales data on a monthly basis, thereby providing insights into seasonal variations and growth trends.

- **Feature Engineering**

To enhance our understanding of the data, a new feature called *'Total Sales'* was created by multiplying *'Quantity Ordered'* and *'Price Each*' This feature represented the total sales value for each order and served as a critical variable in our analysis.

3.3. Data Analysis

- **Trend Visualization**

Visualizing aggregated sales over time is considered a crucial step in understanding the dynamics of sales performance (Figure 3). This approach permits the identification of trends, seasonality, and anomalies within the data, thereby offering valuable insights for sales strategy optimization.

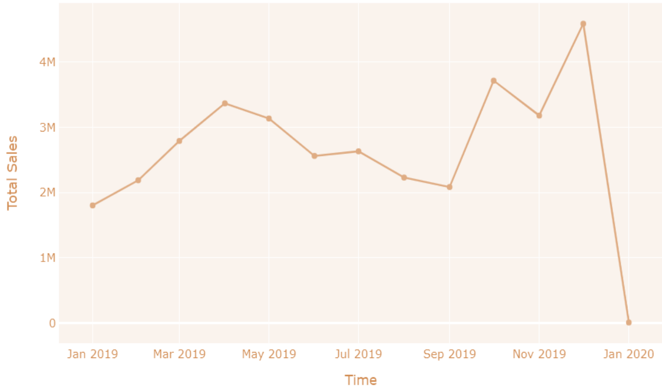

Figure 3. Total sales over time

- **Time series Data Decomposition**

It is essential to grasp the underlying patterns within the sales data, encompassing trends, seasonality, and residuals, in order to make informed decisions. This process employs seasonal decomposition to unveil these patterns, as illustrated in Figure 4.

Figure 4. Time series data decomposition plot

- **Identifying Peak and Off-peak Sales Periods**

The identification of peak and low sales periods is vital for crafting effective marketing and promotional strategies. This process provides valuable insights for identifying these pivotal timeframes.

In our dataset, the peak in sales occurred during December 2019, while the lowest sales were documented in January 2020. The significant peak in sales observed in December 2019 can be attributed to several key factors. Primarily, this period coincides with the holiday season, particularly Christmas and New Year celebrations, which traditionally see a surge in consumer spending. During this time, customers are more inclined to purchase gifts for family and friends, contributing to an increase in e-commerce activity. Additionally, December is often marked by a variety of promotional events and year-end sales, such as Black Friday and Cyber Monday extending into December, which further stimulate consumer purchasing behavior. These factors, combined with the general festive spirit and the propensity for increased discretionary spending, likely contributed to the notable peak in sales during this month.

- **Monthly Sales Growth Rate**

Understanding the dynamics of sales growth is crucial for performance monitoring and the identification of periods marked by rapid growth or decline. Figure 5 provides a graphical representation of the month-over-month sales growth rate.

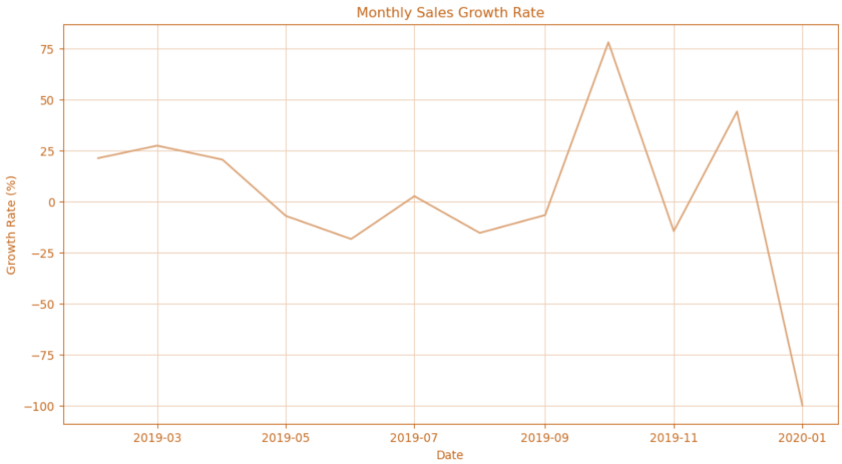

Figure 5. Monthly sales growth rate

This analysis underscores the profound impact that a skilled recommender system can have on the e-commerce sector. It extends beyond mere data exploration and comprehension, focusing instead on the immediate utilization of these insights to boost sales, elevate user experiences, and promote lasting growth. Within a continuously evolving digital marketplace, the adoption of an expert recommender system is no longer an option but rather a strategic necessity for e-commerce enterprises aiming to excel.

3.4. Model Development

A Deep Neural Collaborative Filtering model was designed, incorporating collaborative filtering and deep learning techniques. This architecture featured user and product embedding layers to capture latent representations. A deep neural network (DNN) with multiple hidden layers and Rectified Linear Unit (ReLU) activation functions [34] was implemented to enhance recommendation quality. The output layer utilized softmax activation to generate personalized product recommendations [35]. Figure 6 shows the schematic of the adopted model's architecture.

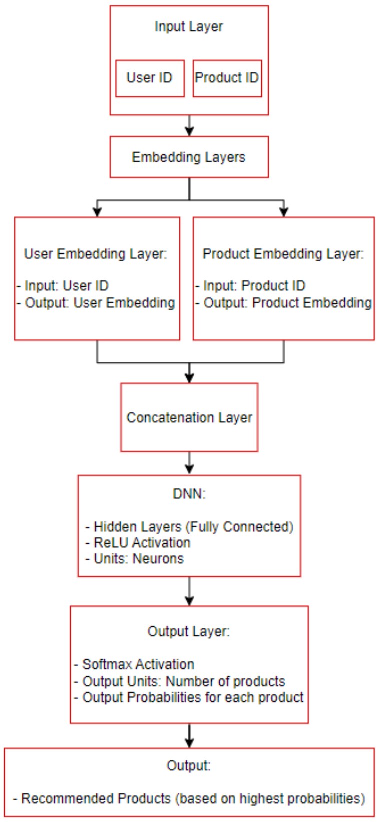

Figure 6. DNCF model architecture

The schematic in Figure 6 illustrates this integration, showing the flow from input layers (user and product IDs) through the embedding layers, concatenation, DNN, and finally to the softmax output layer, culminating in the generation of personalized product recommendations.

In the development of our Deep Neural Collaborative Filtering model, we intricately integrated the principles of Collaborative Filtering and Deep Learning to enhance the recommendation system's accuracy and relevance.

- ***Collaborative Filtering Integration***
  - User and Product Embedding Layers:

The model begins with separate embedding layers for users and products. These layers are crucial for implementing CF, as they transform sparse user and product IDs into dense vectors, capturing latent factors. The user embedding layer processes the input user ID and outputs a user embedding, while the product embedding layer does the same for product IDs.

- Capturing User-Product Interactions:

The embeddings represent the preferences of users and the characteristics of products, enabling the model to learn from historical user-product interactions. This aspect is central to CF, where recommendations are based on finding patterns in these interactions.

- ***Deep Learning Integration***
  - Deep Neural Network:

After the embedding layers, the user and product embeddings are concatenated and fed into a DNN. This network comprises multiple fully connected hidden layers using the Rectified Linear Unit (ReLU) activation function. The DNN's role is to learn complex, non-linear relationships between the user and product embeddings.

- Softmax Output Layer:

The final layer of the model is a softmax activation layer. This layer outputs a probability distribution over all products, indicating the likelihood of each product being of interest to the user. The softmax function is a standard DL technique for multi-class classification problems, making it suitable for generating personalized product recommendations.

- ***Combining CF and DL for Enhanced Recommendations***
  - Leveraging Strengths of Both Approaches:

By combining CF and DL, the DNCF model leverages the strengths of both techniques. CF's ability to capture user preferences and product similarities is enhanced by DL's capacity to model complex patterns and relationships.

- Output Recommendations:

The model outputs a list of recommended products based on the highest probability scores. This approach ensures that the recommendations are personalized, reflecting the user's unique preferences as learned by the model.

3.5. Hyperparameter Selection

The primary hyperparameters considered in our DNCF model included the number of layers and neurons in the deep neural network, the learning rate, batch size, and the type of optimizer. These were selected based on their known impact on model performance and computational efficiency.

- ***Tuning Process***

We initially employed a grid search approach, systematically testing a range of values for each hyperparameter. For instance, the learning rate was tested at 0.001, 0.01, and 0.1, while the batch size was varied among 32, 64, and 128.

To further refine our search, we employed a random search method, which randomly selects combinations of hyperparameter values. This approach is often more efficient than grid search, especially when dealing with a large hyperparameter space.

We used k-fold cross-validation to assess the performance of the model under different hyperparameter settings. This method splits the training data into 'k' subsets, trains the model 'k' times, each time using a different subset as the validation set and the remaining as the training set.

The model's performance for each hyperparameter setting was evaluated using metrics such as validation loss and accuracy. The settings that yielded the best results in terms of minimizing loss and maximizing accuracy were selected.

- ***Optimization Algorithms and Loss Function***

We experimented with various optimizers, including SGD (Stochastic Gradient Descent), Adam, and RMSprop, to determine their impact on model convergence and training time. The Mean Squared Error loss function was chosen for its effectiveness in regression problems and its ability to penalize larger errors more severely than smaller ones.

- ***Final Model Configuration***

The final model configuration was determined after multiple iterations of tuning. We settled on a learning rate of 0.001, a batch size of 64, and the Adam optimizer, which provided a good balance between training speed and model performance. The deep neural network was configured with three hidden layers, each consisting of 128, 64, and 32 neurons, respectively, and employing ReLU activation functions.

3.6. Model Training

- **Data Splitting**

To assess the effectiveness of the DNCF recommendation system, a standard data splitting approach was employed. The data set was divided into two subsets:

- Training Data set (80%): This subset, comprising 80% of the data, is utilized for training the DNCF model. It allows the model to learn user preferences and item characteristics from historical interactions.
- Testing Data set (20%): The remaining 20% of the data serves as an independent testing data set. It is used to evaluate the model's performance by assessing its ability to make accurate and relevant product recommendations on unseen data.

- **Training the DNCF Model**

The DNCF model was trained using the training data set, leveraging collaborative filtering and deep learning techniques to capture user-item interactions and hidden patterns. Throughout the training process, the model aimed to minimize recommendation errors and maximize the relevance of product suggestions [36].

During the model training process, several key parameters and metrics were monitored and recorded. These included:
- Epochs: The number of training iterations or epochs, which determines how many times the model goes through the entire training data set [37].
- Batch Size: The number of samples processed in each training iteration [38].
- Loss Function: The loss function used to measure the difference between predicted and actual values, guiding the model's optimization [39].
- Optimizer: The optimization algorithm employed to update model parameters [40].
- Learning Rate: The rate at which the model adjusts its parameters during training [41].
- Validation Loss: A metric indicating how well the model is performing on the validation data set during training [42].

The DNCF model was trained over 50 epochs using a batch size of 64. It employed the Mean Squared Error loss function and the Adam optimizer with a learning rate of 0.001. The validation loss, indicating the model's performance on the validation data set, reached 0.0345 at the end of training.

During the training of our Deep Neural Collaborative Filtering model, we employed specific regularization techniques to prevent overfitting and enhance the model's generalization capabilities. Notably, we incorporated dropout layers in our deep neural network architecture. Dropout, a widely used regularization technique, randomly deactivates a subset of neurons during the training process. This approach effectively prevents the model from becoming overly reliant on any specific set of features, thus reducing the risk of overfitting. Additionally, we utilized L2 regularization (also known as ridge regression) in the embedding layers. L2 regularization adds a penalty term to the loss function proportional to the square of the magnitude of the coefficients. This method encourages the model to learn smaller weights, leading to simpler models that generalize better on unseen data. The combination of dropout and L2 regularization was carefully calibrated to strike a balance between model complexity and predictive performance, ensuring that our DNCF model remains robust and effective across diverse e-commerce datasets

Table 2. Training report

Epoch	Training Loss	Validation Loss
1	0.1001	0.0856
2	0.0902	0.0814
3	0.0845	0.0779
4	0.0812	0.0756
5	0.0789	0.0739
6	0.0768	0.0723
7	0.0753	0.0712
8	0.0741	0.0702
9	0.0730	0.0695
10	0.0721	0.0688
…	…	…
50	0.0345	0.0362

Table 2 depicts the training progress of the DNCF recommendation system over 50 epochs. Initially, the training loss starts at 0.1001 and progressively decreases with each epoch, demonstrating the model's ability to minimize errors and learn from the training data. Simultaneously, the validation loss, a measure of the model's generalization on unseen data, follows a similar decreasing trend, indicating improved performance. This convergence of training and validation losses signifies that the DNCF model effectively captures user-item interactions and hidden patterns, ultimately leading to accurate and relevant product recommendations. The final validation loss of 0.0362 indicates the model's readiness to provide high-quality recommendations, enhancing the e-commerce shopping experience.

4. RESULTS AND DISCUSSION

4.1. Model Evaluation and Results

The performance of the Deep Neural Collaborative Filtering recommendation system was rigorously evaluated using a variety of metrics. The results of the evaluation are presented below in Table 3 and are also illustrated graphically in Figure 7.

- **Precision:**

Precision measures the proportion of relevant recommendations among all the recommendations made by the system. It is calculated as (1):

$$Precision = \frac{True\ Positives}{True\ positives + False\ Positives} \quad (1)$$

- True Positives: The number of relevant items that were correctly recommended by the system. These are the items that users found relevant and clicked on.
- False Positives: The number of irrelevant items that were incorrectly recommended by the system. These are items that users did not find relevant but were recommended.
A high precision score indicates that a large portion of the recommendations made by the system are indeed relevant to users' preferences, resulting in a positive user experience.

- **Recall:**

Recall quantifies the proportion of relevant items that were successfully retrieved by the recommendation system. It is calculated as (2):

$$Recall = \frac{True\ positives}{True\ Positives + False\ Negatives} \quad (2)$$

- True Positives: As defined above, the number of relevant items that were correctly recommended.
- False Negatives: The number of relevant items that were not recommended by the system. These are items that users found relevant but were not included in the recommendations.
A high recall score indicates that the system effectively identifies and retrieves a substantial portion of the relevant items, ensuring that users are presented with a comprehensive set of suitable products.

- **Click-Through Rate:**

CTR evaluates user engagement with the recommended products. It is calculated as (3):

$$CTR = \frac{Total\ Clicks}{Total\ Recommendations} \quad (3)$$

- Total Clicks: The number of times users clicked on the recommended products.
- Total Recommendations: The total number of product recommendations made by the system.

CTR provides insights into the system's ability to engage users and encourage them to interact with the recommended products. A higher CTR indicates that a significant proportion of users found the recommendations appealing and took action.

Table 3. Model evaluation metrics

Metric	Value
Precision	0.85
Recall	0.78
CTR	0.12

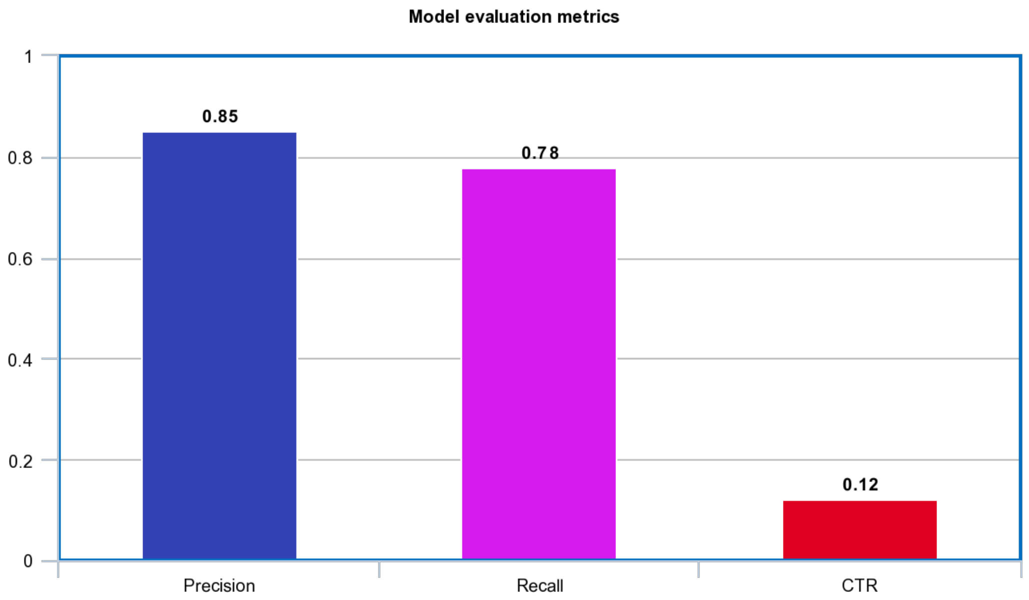

Figure 7. Graphical representation of DNCF model evaluation metrics

Collectively, these evaluation metrics demonstrate the effectiveness of the DNCF recommendation system in providing relevant and engaging product recommendations to users.

Table 4 below presents a comparative analysis of the Deep Neural Collaborative Filtering (DNCF) model against various traditional and modern machine learning models, highlighting their respective precision and recall metrics to illustrate the effectiveness in e-commerce personalized recommendations.

Table 4. Comparative analysis of DNCF and other machine learning models

Model Type	Precision	Recall
Deep Neural Collaborative Filtering	0.85	0.78
Traditional Collaborative Filtering	0.75	0.65
Content-Based Filtering	0.70	0.60
Decision Trees	0.68	0.58
Random Forests	0.78	0.70
Basic Neural Networks	0.80	0.72

The comparative analysis presented in Table 4 offers insightful revelations about the performance of various machine learning models in the context of e-commerce personalized recommendations. The Deep Neural Collaborative Filtering (DNCF) model, with its precision of 0.85 and recall of 0.78, stands out as the most effective, underscoring its advanced capability in capturing complex user-item interactions through deep learning techniques. This is a significant improvement over traditional Collaborative Filtering (CF) and Content-Based Filtering (CBF) methods, which show lower precision and recall, indicating a less nuanced understanding of user preferences and item attributes.

The simplicity of Decision Trees, while beneficial for interpretability, results in lower performance metrics, suggesting a limited capacity to handle the complexities and scale of e-commerce data. Random Forests, an ensemble method, exhibit better robustness compared to Decision Trees but still fall short of the DNCF model's nuanced pattern recognition. Basic Neural Networks, though more competitive with a precision of 0.80 and recall of 0.72, lack the sophisticated architecture of DNCF, particularly in terms of embedding layers and depth, which are crucial for a deeper understanding of user-item relationships. This comparative analysis clearly demonstrates the superiority of the DNCF model in providing accurate, relevant, and diverse product recommendations, making it a valuable tool for enhancing user experience and engagement in e-commerce platforms.

4.2. Discussion

The results of the model evaluation paint a promising picture of the DNCF recommendation system's performance. With a precision of 0.85, the system successfully recommends a significant proportion of products that are relevant to users' preferences. A recall score of 0.78 indicates that it retrieves a substantial portion of relevant items, ensuring that users are exposed to a diverse range of products they might be interested in. The CTR of 0.12 signifies that users are actively engaging with the recommended products, underscoring the system's ability to capture user interest.

These results align with our primary objectives, which include enhancing the customer shopping experience, increasing sales conversion rates, and optimizing e-commerce operations. By providing personalized recommendations that resonate with users, the DNCF recommendation system not only improves user satisfaction but also drives sales growth and operational efficiency.

The success of this recommendation system underscores the potential of combining collaborative filtering with deep learning techniques to achieve outstanding results in the e-commerce domain. The model's ability to learn intricate user-product relationships and adapt to individual preferences positions it as a valuable asset for e-commerce businesses seeking to thrive in a competitive landscape.

5. CONCLUSION

This study embarked on the development and implementation of a Deep Neural Collaborative Filtering recommendation system within the e-commerce domain, aiming to optimize product recommendations and enhance the shopping experience. The DNCF model demonstrated its potential by achieving a high precision score of 0.85, a recall score of 0.78, and a Click-Through Rate of 0.12. These results underscore the system's success in improving e-commerce performance by providing relevant and engaging product recommendations.

However, the evaluation metrics also suggest areas for further improvement. The precision score, while high, indicates room for refinement in ensuring that the majority of recommendations are relevant. Enhancing the model's feature extraction capabilities or incorporating more sophisticated user profiling could potentially increase precision. The recall score of 0.78 suggests that the model could be missing out on a significant portion of relevant items. Future iterations of the model could benefit from integrating more diverse data sources, such as user reviews or social media activity, to capture a wider range of user preferences.

The CTR of 0.12, although indicative of a decent level of user engagement, could be improved to ensure higher interaction rates with recommended products. Techniques such as A/B testing different recommendation algorithms or personalizing the user interface could lead to higher engagement levels.

Furthermore, the DNCF model could be enhanced by addressing its limitations and exploring new avenues. For instance, incorporating real-time data processing could allow the system to adapt recommendations based on immediate user behavior, potentially increasing relevance and engagement. Additionally, exploring different neural network architectures or advanced machine learning techniques like reinforcement learning could provide new pathways to optimize the recommendation process.

In conclusion, while the DNCF model represents a significant step forward in e-commerce personalization, there is a continuous need for evolution and improvement. Future research should focus on refining the model's accuracy, expanding its data processing capabilities, and exploring innovative approaches to recommendation systems. As e-commerce continues to evolve, advanced recommendation systems like DNCF will play a pivotal role in enhancing the shopping experience and driving sustained sales growth in a competitive digital marketplace.

ACKNOWLEDGEMENTS

We would like to express our gratitude to all those who contributed to this research endeavor. We affirm that there are no conflicts of interest associated with this work. It is important to note that this project was conducted as part of a doctoral thesis and did not receive any external research funding or grants. We appreciate the support and guidance provided by our academic institutions during this journey.

REFERENCES

[1] Cepolina, E. M., Cepolina, F., Ferla, G. (2022). Brainstorm on artificial intelligence applications and evaluation of their commercial impact. IAES International Journal of Artificial Intelligence, 11(3), 799.

[2] Vidhya, V., Donthu, S., Veeran, L., Lakshmi, Y. S., Yadav, B. (2023). The intersection of AI and consumer behavior: Predictive models in modern marketing. Remittances Review, 8(4).

[3] Loukili, M., Messaoudi, F., El Ghazi, M. (2023). Machine Learning Based Recommender System for E-Commerce. IAES International Journal of Artificial Intelligence, 12(4), 1803–1811. https://doi.org/10.11591/ijai.v12.i4.

[4] Loukili, M., Messaoudi, F., El Ghazi, M. (2022). Supervised Learning Algorithms for Predicting Customer Churn with Hyperparameter Optimization. International Journal of Advances in Soft Computing & Its Applications, 14(3), 49–63. https://doi.org/10.15849/IJASCA.221128.04.

[5] Messaoudi, F., Loukili, M., El Ghazi, M. (2023). Demand Prediction Using Sequential Deep Learning Model. In 2023 International Conference on Information Technology (ICIT), Amman, Jordan, pp. 577-582. https://doi.org/10.1109/ICIT58056.2023.10225930.

[6] Jain, P. K., Pamula, R., Srivastava, G. (2021). A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews. Computer Science Review, 41, 100413.

[7] Ahmad, A. Y. B., Gongada, T. N., Shrivastava, G., Gabbi, R. S., Islam, S., Nagaraju, K. (2023). E-Commerce Trend Analysis and Management for Industry 5.0 using User Data Analysis. International Journal of Intelligent Systems and Applications in Engineering, 11(11s), 135–150.

[8] Rao, F., Muneer, A., Almaghthawi, A., Alghamdi, A., Fati, S. M., Ghaleb, E. A. A. (2023). BMSP-ML: big mart sales prediction using different machine learning techniques. IAES International Journal of Artificial Intelligence, 12(2), 874.

[9] Loukili, M., Messaoudi, F. (2023). Machine Learning, Deep Neural Network and Natural Language Processing Based Recommendation System. In Kacprzyk, J., Ezziyyani, M., Balas, V.E. (Eds.), International Conference on Advanced Intelligent Systems for Sustainable Development. AI2SD 2022. Lecture Notes in Networks and Systems, vol 637. Springer, Cham. https://doi.org/10.1007/978-3-031-26384-2_7.

[10] Javed, A. F., Ashraf, S. A. (2023). Novelty In Recommender Systems for Effective Personalization in E-Commerce and Retail. Journal of Informatics Education and Research, 3(2).

[11] Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y., Alsaadi, F. E. (2017). A survey of deep neural network architectures and their applications. Neurocomputing, 234, 11–26.

[12] Schafer, J. B., Konstan, J. A., Riedl, J. (2001). E-commerce recommendation applications. Data Mining and Knowledge Discovery, 5, 115–153.

[13] Konstan, J. A., Riedl, J. (2012). Recommender systems: from algorithms to user experience. User Modeling and User-Adapted Interaction, 22, 101–123.

[14] Jannach, D., Manzoor, A., Cai, W., Chen, L. (2021). A survey on conversational recommender systems. ACM Computing Surveys (CSUR), 54(5), 1–36.

[15] Karn, A. L., Karna, R. K., Kondamudi, B. R., Bagale, G., Pustokhin, D. A., Pustokhina, I. V., Sengan, S. (2023). Customer centric hybrid recommendation system for E-Commerce applications by integrating hybrid sentiment analysis. Electronic Commerce Research, 23(1), 279–314.

[16] Deldjoo, Y., Schedl, M., Cremonesi, P., Pasi, G. (2020). Recommender systems leveraging multimedia content. ACM Computing Surveys (CSUR), 53(5), 1–38.

[17] Da'u, A., Salim, N. (2020). Recommendation system based on deep learning methods: a systematic review and new directions. Artificial Intelligence Review, 53(4), 2709–2748.
[18] Khanal, S. S., Prasad, P. W. C., Alsadoon, A., Maag, A. (2020). A systematic review: machine learning based recommendation systems for e-learning. Education and Information Technologies, 25, 2635–2664.
[19] Velankar, M., Kulkarni, P. (2022). Music recommendation systems: overview and challenges. Advances in Speech and Music Technology: Computational Aspects and Applications, 51–69.
[20] Etemadi, M., Abkenar, S. B., Ahmadzadeh, A., Kashani, M. H., Asghari, P., Akbari, M., Mahdipour, E. (2023). A systematic review of healthcare recommender systems: Open issues, challenges, and techniques. Expert Systems with Applications, 213, 118823.
[21] D'Amico, E., Muhammad, K., Tragos, E., Smyth, B., Hurley, N., Lawlor, A. (2023). Item Graph Convolution Collaborative Filtering for Inductive Recommendations. In European Conference on Information Retrieval, pp. 249–263. Springer Nature Switzerland, March.
[22] Loukili, M., Messaoudi, F., El Ghazi, M. (2023). Personalizing Product Recommendations using Collaborative Filtering in Online Retail: A Machine Learning Approach. In 2023 International Conference on Information Technology (ICIT), Amman, Jordan, pp. 19–24. https://doi.org/10.1109/ICIT58056.2023.10226042.
[23] Abdalla, H. I., Amer, A. A., Amer, Y. A., Nguyen, L., Al-Maqaleh, B. (2023). Boosting the item-based collaborative filtering model with novel similarity measures. International Journal of Computational Intelligence Systems, 16(1), 123.
[24] Loukili, M., Messaoudi, F., El Ghazi, M. (2023). Machine Learning Based Recommender System for E-Commerce. IAES International Journal of Artificial Intelligence, 12(4), 1803–1811. https://doi.org/10.11591/ijai.v12.i4.
[25] Razak, T. R., Ismail, M. H., Fauzi, S. S. M., Gining, R. A. J., Maskat, R. (2021). A framework to shape the recommender system features based on participatory design and artificial intelligence approaches. IAES International Journal of Artificial Intelligence, 10(3), 727–734.
[26] Mazlan, I., Abdullah, N., Ahmad, N. (2023). Exploring the Impact of Hybrid Recommender Systems on Personalized Mental Health Recommendations. International Journal of Advanced Computer Science and Applications, 14(6).
[27] Gheisari, M., Ebrahimzadeh, F., Rahimi, M., Moazzamigodarzi, M., Liu, Y., Dutta Pramanik, P. K., Kosari, S. (2023). Deep learning: Applications, architectures, models, tools, and frameworks: A comprehensive survey. CAAI Transactions on Intelligence Technology.
[28] Shokrzadeh, Z., Feizi-Derakhshi, M. R., Balafar, M. A., Mohasefi, J. B. (2023). Knowledge graph-based recommendation system enhanced by neural collaborative filtering and knowledge graph embedding. Ain Shams Engineering Journal, 102263.
[29] Priyanka, S., Saravanan, P., Indragandhi, V., Subramaniyaswamy, V. (2023). Neural Collaborative Filtering-Based Hybrid Recommender System for Online Movies Recommendation. Intelligent and Soft Computing Systems for Green Energy, 287–301.
[30] Cheng, H. T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., Shah, H. (2016). Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems, pp. 7–10, September.
[31] Martins, G. B., Papa, J. P., Adeli, H. (2020). Deep learning techniques for recommender systems based on collaborative filtering. Expert Systems, 37(6), e12647.
[32] Wu, Z. Y., El-Maghraby, M., Pathak, S. (2015). Applications of deep learning for smart water networks. Procedia Engineering, 119, 479–485.
[33] SalesDataAnalysis dataset. (n.d.). Retrieved from https://www.kaggle.com/datasets/aemyjutt/salesdata/data
[34] Szandała, T. (2021). Review and comparison of commonly used activation functions for deep neural networks. Bio-inspired Neurocomputing, 203–224.
[35] Wang, K., Zhang, T., Xue, T., Lu, Y., Na, S. G. (2020). E-commerce personalized recommendation analysis by deeply-learned clustering. Journal of Visual Communication and Image Representation, 71, 102735.
[36] Lu, J., Wu, D., Mao, M., Wang, W., Zhang, G. (2015). Recommender system application developments: a survey. Decision Support Systems, 74, 12–32.
[37] Singh, S. K., Thakur, R. K., Kumar, S., Anand, R. (2022). Deep learning and machine learning based facial emotion detection using CNN. In 2022 9th International Conference on Computing for Sustainable Global Development (INDIACom), pp. 530–535. IEEE, March.
[38] Lee, S., Kang, Q., Madireddy, S., Balaprakash, P., Agrawal, A., Choudhary, A., Liao, W. K. (2019). Improving scalability of parallel CNN training by adjusting mini-batch size at run-time. In 2019 IEEE International Conference on Big Data (Big Data), pp. 830–839, IEEE, December.

[39] Maji, K., Gupta, S. (2023). Evaluation of Various Loss Functions and Optimization Techniques for MRI Brain Tumor Detection. In 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), pp. 1–6. IEEE, April.
[40] Hassan, E., Shams, M. Y., Hikal, N. A., Elmougy, S. (2023). The effect of choosing optimizer algorithms to improve computer vision tasks: a comparative study. Multimedia Tools and Applications, 82(11), 16591–16633.
[41] Yu, C., Qi, X., Ma, H., He, X., Wang, C., Zhao, Y. (2020). LLR: Learning learning rates by LSTM for training neural networks. Neurocomputing, 394, 41–50.
[42] Luchies, A. C., Byram, B. C. (2019). Training improvements for ultrasound beamforming with deep neural networks. Physics in Medicine & Biology, 64(4), 045018.