Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 2, April 2025, pp. 1223~1230
ISSN: 2302-9285, DOI: 10.11591/eei.v14i2.8572

Enhancing recommendation diversity in e-commerce using Siamese network and cluster-based technique

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Article Info

Article history:

Received Apr 8, 2024
Revised Oct 9, 2024
Accepted Oct 17, 2024

Keywords:

Clustering
Deep learning
Diversity
E-commerce
Recommender system

ABSTRACT

This study investigates the difficulty of improving product recommendations in e-commerce systems by tackling the common problem of poor diversity in suggestions. We present a novel approach that uses a Siamese network architecture and ResNet for feature extraction to recommend visually similar elements while incorporating diversity through a cluster-based mechanism. The Siamese network is used to compare product pairs, allowing it to recommend both comparable and dissimilar items from distinct clusters. The model was evaluated using a variety of evaluation metrics, resulting in an accuracy of 88.5%, a precision of 90.2%, a recall of 87.1%, and an F1 score of 88.6%. Our results demonstrate that our strategy maintains a high level of relevance in suggestions while efficiently incorporating variety, hence improving the overall user experience in e-commerce applications.

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1. INTRODUCTION

E-commerce is reliant on recommender systems, which customize user experiences by suggesting pertinent products based on past preferences and behavior [1]-[5]. These systems sometimes implement collaborative filtering, content-based filtering, or a hybrid approach to provide recommendations. However, despite their widespread use, the absence of variation in recommendations is a significant drawback of traditional recommender systems [6]. Researchers refer to this phenomenon as the "filter bubble," in which consumers are perpetually confronted with products that are similar to their own, thereby limiting their capacity to identify novel and diverse products that align with their preferences [7], [8]. Improving user happiness and increasing involvement depends on addressing the diversity in recommendations [9]-[11]. Using computer vision models such as ResNet, which extract rich visual characteristics from product photos [12], [13] to produce more diverse suggestions, one efficient strategy is to include visual variation into product recommendations [14].

Wang *et al.* [15] developed a deep ranking model to assess fine-grained image similarity in e-commerce, leveraging multiscale networks and an efficient triplet sampling algorithm to surpass traditional methods. He *et al.* [16] introduction of ResNet marked a significant breakthrough in image recognition by enabling residual learning to train deep networks for improved accuracy and depth while simplifying optimization. The research conducted by Simonyan and Zisserman [17] focused on the important role that network depth has in improving picture identification. This idea was then further developed in the building of VGGNet's incredibly deep convolutional networks. Lecun *et al.* [18] foundational work pioneered neural network learning, especially through the use of convolutional neural networks, which proved highly effective in document and image recognition by leveraging gradient-based algorithms to classify complex patterns. Huang *et al*. [19] enhanced network efficiency with the introduction of DenseNet, which improves accuracy and training efficiency by connecting each layer to all preceding layers, thereby strengthening feature propagation and reducing the number of parameters. Vaswani *et al*. [20] broadened the utilization of deep learning through the transformer model. Salimans *et al*. [21] and Zhuang *et al.* [22] investigated generative adversarial networks (GANs) [23]–[26], which advanced unsupervised learning and picture producing approaches. Although e-commerce has been extensively studied, there is still a lack of study on visual similarity-based [27]–[29] recommendation algorithms for renewable energy products. Our research addresses this crucial deficiency by highlighting the significance of diversity in recommendation systems, thereby making a substantial contribution to e-commerce and sustainability. By concentrating on varied recommendations, we not only tackle an insufficiently examined domain but also facilitate future inquiries in this developing topic.

This study presents an innovative method for e-commerce product recommendation utilizing Siamese networks and ResNet, emphasizing diversity. Our approach goes beyond simply recommending visually similar products. We incorporate elements from disparate visual groups, ensuring a harmonious blend of similarity and diversity. The proposed method improves the user experience by offering a more diverse and extensive array of recommendations.

The rest of the paper is organized as: section 2 describes our approach, giving an overview of the proposed recommendation strategy and the different techniques employed. Section 3 presents the experiment and the results obtained, detailing the chosen configuration and the testing methods used. Section 4 concludes the paper.

2. METHOD

This section describes the approach used to create our diversified e-commerce product recommendation system. To determine the visual likeness of items, we use ResNet for feature extraction. After extracting the feature vectors with ResNet, we use clustering to classify comparable items. The clustered vectors are then sent into the Siamese network, which is trained on pairs of product vectors to detect similarities and differences between objects. The proposed model is designed to strike a delicate balance, ensuring that our system suggests similar products while also integrating diversity. Figure 1 displays the architectural diagram for our model.

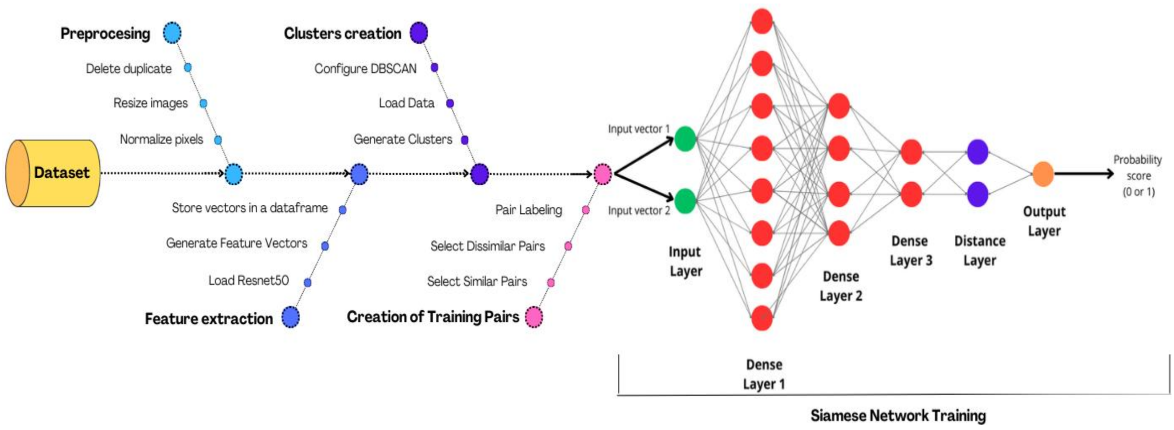


Figure 1. General framework of the proposed model

2.1. Data processing

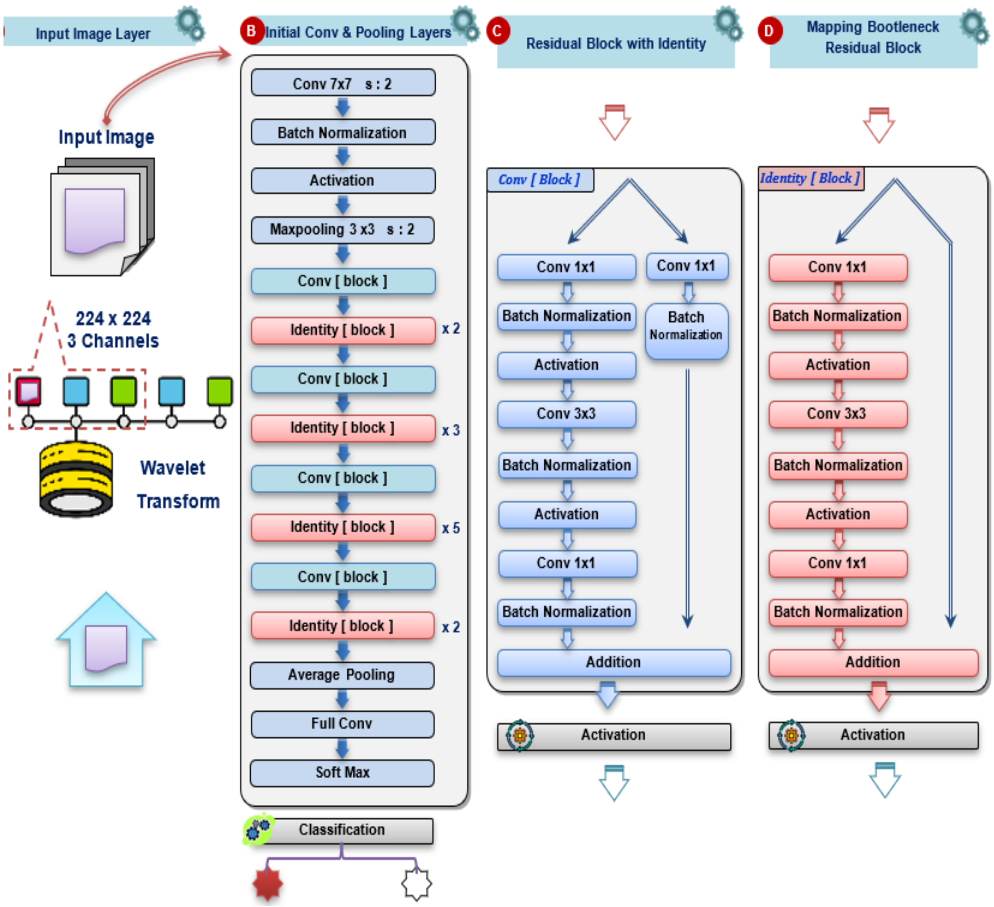
We use various data augmentation approaches [30] to increase the variety in our training set, such as rotating photos by degrees (e.g., -20° to +20°) to imitate diverse user perspectives and horizontal flipping to aid in product recognition from various angles. Random cropping and scaling [31] are used to push the model to focus on multiple image regions, resulting in a thorough comprehension of product attributes. Image normalization is also necessary, which involves scaling images to uniform dimensions (e.g., 224×224 pixels) and standardizing color formats (usually RGB). The pixel values are standardized to a standard range. Algorithm 1 represents the data preprocessing pseudo-code.

Algorithm 1. Data preprocessing

```
Input: Raw_Image_Data
    Step1:
          Handle missing or corrupt entries by removing unopenable images and filling gaps
with placeholders.
          Remove duplicate images using hash values or pixel comparisons.
    Step2:
          Apply transformations such as rotation (-20° to +20°), horizontal flipping, and
random cropping to enhance dataset diversity.
    Step3:
          Resize all images to a uniform dimension (224x224 pixels) and normalize pixel
values to a common scale (0 to 1).
          Convert all images to the same color format (RGB).
 Output: Preprocessed_Image_Data
```

2.2. Features extraction

We employ a pre-trained ResNet-50 model as our primary feature extractor. This network transforms product photos into comprehensive feature vectors. Figure 2 shows the ResNet-50 architecture: Figure 2(a) the input image, which is 224×224 with three RGB channels, is first improved with a wavelet transform before being fed into the ResNet model. Figure 2(b) the image is then subjected to an initial 7×7 convolution with a stride of 2, followed by batch normalization, activation, and 3×3 max pooling with a stride of 2. These steps lower spatial dimensions and extract the basic attributes. Figure 2(c) residual blocks with identity mapping contain many convolutional layers, allowing the network to skip specific layers. This aids in training deeper networks by facilitating the flow of information and gradients. Figure 2(d) the bottleneck residual block, a version of the residual block, compresses input dimensions using 1×1 convolutions before performing major convolutional operations, lowering computational costs while maintaining model depth and capacity.



(a) (b) (c) (d)

Figure 2. ResNet-50 architecture: (a) input image layer, (b) initial convolutional and pooling layers, (c) residual block with identity, and (d) mapping bottleneck residual block

This results in a weighted feature vector emphasizing elements most relevant to visual similarity. The pseudo code is represented in Algorithm 2:

Algorithm 2. Feature extraction

```
Input: Raw_Image_Data
    Step1:
          Handle missing or corrupt entries by removing unopenable images and filling gaps
with placeholders.
          Remove duplicate images using hash values or pixel comparisons.
    Step2:
          Apply transformations such as rotation (-20° to +20°), horizontal flipping, and
random cropping to enhance dataset diversity.
    Step3:
          Resize all images to a uniform dimension (224x224 pixels) and normalize pixel
values to a common scale (0 to 1).
          Convert all images to the same color format (RGB).
 Output: Preprocessed_Image_Data
```

2.3. Clustering

Subsequent to ResNet's extraction of feature vectors from the product images, the following phase is clustering them according to visual similarity. Clustering is employed to deliver recommendations that are pertinent and varied. We utilized the density-based spatial clustering of applications with noise (DBSCAN) algorithm [32], which is adept at clustering high-dimensional feature spaces and can autonomously identify the number of clusters according to data distribution. DBSCAN characterizes clusters as areas of high point density, while points in low-density regions are designated as outliers. This technique is beneficial since it does not necessitate a predefined number of clusters and may accommodate clusters of diverse forms and sizes, rendering it suitable for our objective. The main steps for clustering are as follows:

a. Feature vector collection: we start with the feature vectors obtained from the Resnet model; each one represents a product's visual characteristics.
b. Parameter selection: we carefully select the maximum distance between two samples to be considered in the same neighborhood (eps) and the minimum number of points to form a dense region (min_samples) parameter for DBSCAN. These parameters are fine-tuned based on a subset of the data to ensure that the clusters formed are meaningful and align with human-perceived visual similarities.
c. Clustering execution: the feature vectors are subjected to DBSCAN, which generates a collection of clusters that comprise visually comparable products. Noise is the term used to describe anomalies that do not conform to any cluster.
d. Cluster validation: after clustering, we manually evaluate a sample of the clusters to verify that the items within each cluster share common visual traits. This phase ensures that the clusters are consistent with our goal of grouping visually similar products.

The Siamese network is trained by learning from pairings of vectors, each of which is labeled as "similar" or "dissimilar" based on visual characteristics. We generate two kinds of pairs:

– Similar pairs: these pairs consist of two vectors from the same cluster, representing products with high visual similarity.
– Dissimilar pairs: these pairs consist of vectors from different clusters, representing products with low visual similarity.

Each pair is fed into the Siamese network, which then learns to minimize the distance between the feature vectors of similar pairs and maximize the distance for dissimilar pairs.

3. RESULTS AND DISCUSSION

3.1. Dataset

The dataset used in this study consists of 217 product images from a renewable energy e-commerce platform. These products include various items related to renewable energy technologies, such as solar panels, wind turbines, and energy storage systems.

3.2. Model configuration

To justify the choice of our Siamese network architecture, we state that these values were selected after obtaining the best results through an iterative trial-and-error process. Ultimately, the optimal configuration is demonstrated in Table 1.

Table 1. Siamese network architecture

Layer	Type	Dimension	Activation function
Input	Embedding vectors	2048×2	-
1	Dense layer	512	ReLU
2	Dense layer	256	ReLU
3	Dense layer	128	ReLU
4	Distance layer	128	-
Output	Fully connected layer	1	Sigmoid

3.3. Evaluation metrics

To evaluate the proposed model, we use several metrics:
Accuracy: we employ accuracy as a general measure of performance. It is calculated by determining the proportion of correct predictions (both true positives and true negatives) relative to the total number of predictions made. In (1) illustrates the mathematical expression for this metric.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Recall: recall is critical for evaluating our model's capability to identify all relevant instances. In (2) provides the mathematical formulation of this metric.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

F1 score: The F1 score is the harmonic mean of precision and recall. In (3) represents the mathematical formulation of this metric.

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

Intra-cluster similarity: intra-cluster similarity assesses how similar items within the same cluster are to each other. It is calculated by averaging the similarity of each item to the centroid of its cluster. In (4) presents the mathematical expression for this metric.

$$Intra - Cluster\ Similarity = \frac{1}{|C|} \sum_{i \epsilon C} Similarity(i, \mu c) \tag{4}$$

Inter-cluster similarity: inter-cluster similarity evaluates the similarity between items belonging to different clusters. Lower inter-cluster similarity indicates that the clusters are well-separated. In (5) provides the mathematical formulation of this metric.

$$Inter - Cluster\ Similarity = \frac{1}{|C1||C2|} \sum_{i \epsilon C1} \sum_{j \epsilon C2} Similarity(i, j) \tag{5}$$

Diversity score: the diversity score measures the variety among items in a set, with higher scores indicating greater diversity. It is calculated by subtracting the average similarity between different items from 1. In (6) represents the mathematical expression for this metric.

$$Diversity\ Score = 1 - \frac{1}{n(n-1)} \sum_{i \neq j} Similarity(i, j) \tag{6}$$

where: TP represents the correctly predicted positive instances, TN are the correctly predicted negative instances, FP refers to incorrect positive predictions, and FN indicates incorrect negative predictions. Similarity (i, c) measures the similarity between an item ii and the centroid cc of its cluster, while Similarity (i, j) denotes the similarity between two items ii and jj across or within clusters. C1 and C2 are the clusters involved, and n is the number of items.

3.4. Discussion

The Siamese network performed well in identifying and recommending visually similar products, with high accuracy (88.5%), precision (90.2%), recall (87.1%), and F1 score (88.6%), demonstrating its ability to classify product pairs for high-quality recommendations in e-commerce. In fact, the integration of a diversity mechanism improved the recommendation process by combining comparable items from different clusters. The intra-cluster similarity score of 92% demonstrated the model's ability to deliver visually consistent products, while the inter-cluster similarity measure of 45% showed a successful integration of many possibilities. Table 2 has a thorough summary of these findings.

Table 2. Model performance results

Metric	Accuracy	Recall	F1 score	Intra-cluster similarity	Inter-cluster similarity	Diversity score
Value (%)	88.5	87.1	88.6	92	45.3	52.7

Figure 3 illustrates the efficacy of the Siamese network in producing top K product recommendations, with K denoting the quantity of recommendations offered for each user. The plot demonstrates a unique pattern, with precision fluctuating as K rises. This pattern occurs because the model is engineered to suggest one thing that closely resembles the query product, succeeded by another item that is deliberately less similar, sourced from a different cluster. This method guarantees that the suggestions encompass a combination of closely related and varied items. Consequently, with every second recommendation, there is a discernible decline in precision, indicating the inclusion of a less analogous item. The alternating high-low pattern in the accuracy curve underscores the model's approach to balancing similarity and variety, guaranteeing that the user receives both pertinent and diverse product recommendations.

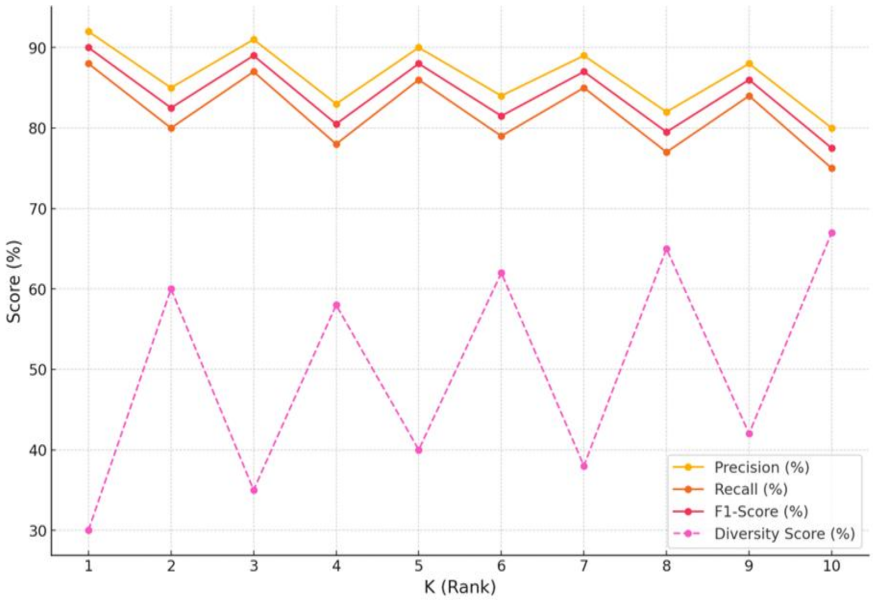


Figure 3. Top K recommendations results

4. CONCLUSION

This study has effectively illustrated the utilization of a Siamese network for product recommendations, employing ResNet-based feature extraction, to develop a visually-oriented product recommendation system that harmonizes relevance and diversity. The model attained elevated performance metrics, with an accuracy of 88.5%, underscoring its efficacy in precisely recognizing and recommending analogous products. The implementation of a diversity mechanism, which integrates extremely similar recommendations with those from disparate clusters, mitigates the prevalent shortcoming of traditional recommendation systems that frequently lack a diverse array of options. This combination of similarity and diversity, shown in the alternating accuracy of the Top K suggestions, enhances the user experience by providing a wider array of product choices, hence increasing the probability of user engagement and pleasure. The proposed approach satisfies the requirements for accurate recommendations while also creatively broadening user options, establishing it as a strong solution for contemporary e-commerce settings.

ACKNOWLEDGMENTS

The authors express their gratitude to the Algerian Ministry of Higher Education and Scientific Research (MESRS) for financially supporting the PRFU Research Project (Ph.D. Thesis), coded: C00L07UN360120230002, conducted at Chadli Bendjedid El Tarf University, Algeria.

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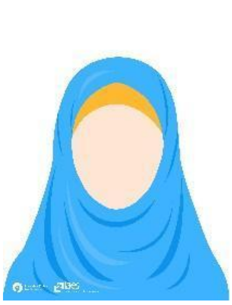

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