An Online Recommendation System Using Deep Learning for Textile Products

1st Ümit Turkut
Reisoğlu
İplik ve Mensucat San. Tic. A.Ş.
Bursa, Turkey
umitturkut@reisoglu.net

2nd Adem Tuncer
Dept. of Computer Engineering
Yalova University
Yalova, Turkey
adem.tuncer@yalova.edu.tr

3rd Hüseyin Savran
Dept. of Computer Engineering
Yalova University
Yalova, Turkey
hsavran@yalova.edu.tr

4th Sait Yılmaz
Reisoğlu
İplik ve Mensucat San. Tic. A.Ş.
Bursa, Turkey
sait@reisoglu.net

***Abstract*—Recommendation systems are frequently preferred in recent years ensuring customer satisfaction and accelerating sales. Thanks to these systems, it is aimed to accelerate the decision-making process of customers. Recommendation systems have become a necessary part, especially in online shopping. Most of the recommendation systems used in many different areas have been attracting attention, focusing on fashion, and clothing recently. In this paper, a deep learning-based online recommendation system has been proposed with a Convolutional Neural Network (CNN). Classes of different patterns in the CNN architecture have been determined according to users' and designers' pattern preferences. The deep learning model recommends patterns considering color compatibility for textile products. The proposed model has been trained and tested using our own pattern dataset including 12000 images. Experiments on pattern datasets show the effectiveness of our proposed approach.**

Keywords— recommendation system, convolutional neural network, color compatibility, deep learning

I. Introduction

Due to the recent developments in internet technologies, online shopping continues to grow rapidly. Customers prefer to purchase new products in color or pattern to be compatible with existing products. In online shopping, it takes a lot of time to search for all compatible products. Automated recommendation systems can speed up finding a wide variety of patterns that customers are interested in. The use of recommendation systems is increasing day by day, as it helps consumers effectively scan a huge number of products online and identify the right products that meet their needs [1]. Therefore, recommendation systems have attracted the attention of researchers, and different recommendation systems have been presented in the literature related to movie [2], video [3], music [4], fashion and clothing [5, 6, 7], etc.

The most widely used methods in recommendation systems are collaborative filtering [8], content-based methods [9], or systems where these two methods are used as a hybrid. The collaborative filtering technique uses the matrix factorization approach to model the interaction between users and products and captures collaboration between users' behavior and reviews on products. Content-based methods recommend products to users according to the product description and user profile. Traditional recommendation system methods, such as collaborative filtering and content-based methods, mainly rely on numerical and textual information, while deep learning methods try to extract features from images and videos such as clothing and fashion [10].

Recently, deep learning-based approaches have achieved good results in pattern recognition, image processing, clustering, and classification. It is seen that deep learning-based studies used also in recommendation systems give successful results. Guan et al. [5] proposed a personalized recommendation system with multi-view information (product images, descriptions, and review texts) integration, namely Deep-MINE, and designed a unified deep neural network model. They obtained women's dresses from Amazon.com to demonstrate the effectiveness of their model and an auto-encoder network was applied to these datasets. Liu et al. [6] adopted CNNs based approach to extract the visual characteristics of items such as shoes, dresses, trousers, bags, etc. The model takes into consideration the style features and visual category information to extract features from the images. Zhang et al. [7] proposed location-oriented clothing recommendations based on the hybrid CNN approach considering the correlation between clothing and locations. In their study, they combined a multilabel CNN with the support vector machine. Yu et al. [11] proposed a recommendation system by including the use of aesthetic features in addition to visual features. They indicated that the aesthetic features were extracted by a pre-trained neural network. An outfit recommendation system is proposed based on long-short term memory (LSTM) network in [12]. They aimed to learn the model of producing a global compatible outfit from existing outfit images and text descriptions. Lei et al. [13] proposed a comparative deep learning model that learns image and users' preferences jointly. The network consists of three sub-networks. One of the sub-networks was used to model users' preferences.

Most existing recommendation systems focus on fashion and clothing only. In this paper, we propose an online recommendation system based on color compatibility for textile products. The system recommends compatible pattern to consumers on a new product to be purchased with the existing products. Whether the patterns are compatible or not was evaluated according to the feedback received from the designers and participants. Unlike traditional recommendation system methods, CNNs were used in the study. To our best knowledge, there is no study that consider pattern recommendation considering color compatibility in textile products using deep learning algorithms. We think that our proposed study is the first in the literature.

978-1-7281-9352-6/20/$31.00 ©2020 IEEE

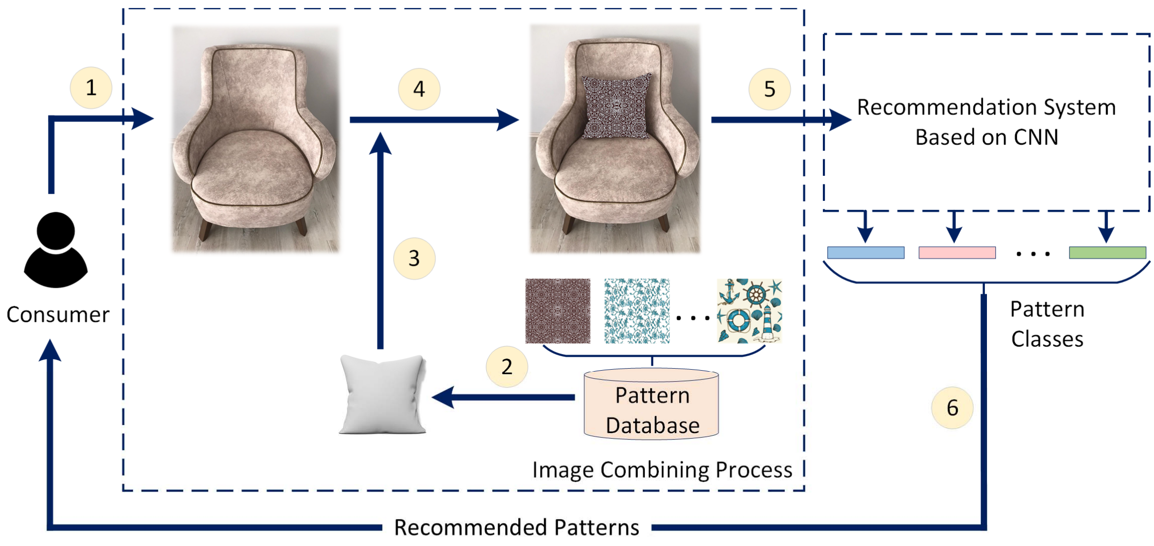

Fig. 1. The proposed recommendation system architecture.

II. The Proposed Approach

A. Recommendation System

The proposed recommendation system architecture is shown in Fig. 1. As seen in the figure, a consumer who wants to buy a pillow compatible with the sofa takes the photo of the sofa and uploads it to the system. Then, patterns in the database randomly are put on the pillow that is intended to be purchased and is combined with the photo uploaded to the system, and finally, the combined image is sent to the deep learning algorithm. The deep learning algorithm sends the most compatibles back to the consumer among the images combined with different patterns.

Since consumers have different cognitive styles, it is necessary and meaningful to consider consumer preferences in recommendation systems. The study [5] obtained the cognitive styles of participants by applying a survey and integrated them into their models. In the classification of the patterns used in the training process of the CNN model in this study, an online survey was conducted to the participants and asked to choose between the patterns according to their preferences. As a result of the survey, each pattern was sorted ascending order according to the scores they have, and two sequential patterns with the highest score differences were determined and divided into different classes from these points. The patterns were classified from 1 to 5 according to the number of rates they have. The patterns with

(a) (b)

Fig. 2. (a) Compatible pattern (b) Incompatible pattern.

the most rates are in class 5. Fig. 2 shows sample patterns for two pillows for the sofa. Fig. 2 (a) is in class 5 according to the CNN classification result, while Fig. 2 (b) is in class 1, that is, the class with the lowest rates. According to these results, only pattern in class 5 is offered to the consumer.

Recommendation systems generally tend to use the information of products previously purchased or rated by consumers to make appropriate recommendations [14]. Particularly, products purchased are treated as positive feedback. In addition to the survey study in the classification of patterns, consumer feedback and ratings are constantly collected, and the training of the CNN model is repeated periodically.

B. CNN Architecture

Deep learning approaches have attracted the attention of researchers in recent years with the spread of high-speed processors depending on technological developments, especially in studies related to large-scale data. Deep learning, the advanced level of standard artificial neural networks, has an approach that has more layers and also provides automatic data preprocessing and feature extraction from the data [15]. The most widely used deep learning method is CNN and has achieved superior performance compared to traditional algorithms. CNNs have recently been used in large-scale image classification problems [16].

A CNN consists of convolution, pooling, and fully connected layers. The convolution layer extracts certain features from an input image by applying different types of filters. After each convolution layers, a nonlinear activation function is applied. Although there are many activation functions, Rectified Linear Units (ReLU) is the most used in CNNs. Then, the pooling layer is generally applied for reducing the spatial size of the feature maps. The most common approach used in pooling is max pooling that summarizes the most activated presence of a feature. The feature map obtained at the end of the convolution and pooling layers is flattened into a one-dimensional vector and fed into the fully connected layer as input.

The overall CNN architecture of our approach is shown in Table I. As seen in the table, the CNN architecture has four convolutions, four pooling, and two fully connected layers. Batch normalization [17] and ReLU activation function were applied after each convolution. Dropout [18] is used for preventing the model from overfitting by dropping some of the units in layers during the training.

TABLE I. THE ARCHITECTURE OF THE CNN

Layer	Filter size	Stride	Output
Input Image	-	-	256×256×3
Conv, Batch Norm, ReLU	5×5	2	126×126×32
Max-Pooling	3×3	2	62×62×32
Conv, Batch Norm, ReLU	5×5	1	58×58×32
Max-Pooling	3×3	2	28×28×32
Conv, Batch Norm, ReLU	3×3	1	26×26×64
Max-Pooling	3×3	2	12×12×64
Conv, Batch Norm, ReLU	3×3	1	10×10×64
Max-Pooling	3×3	2	4×4×64
Flatten	-	-	1×1×1024
Dropout	0.5	-	1×1×1024
Fully Connected 1	-	-	1×1×128
Fully Connected 2	-	-	1×1×64
Softmax	-	-	1×1×5

III. EXPERIMENTS

We used our own pattern dataset consisting of 12000 images for training and testing of the CNN model. All images were resized to 256×256. We trained the network for 300 epochs using an Adam optimizer with a batch size of 32. Dropout rate was 0.5. The dataset was divided into 5 classes consist of users' and designers' preference for patterns. The accuracy graphic of the CNN model is given in Fig. 3. Although the accuracy graphic expresses the classification result, it also expresses the success of the users' and designers' preferences.

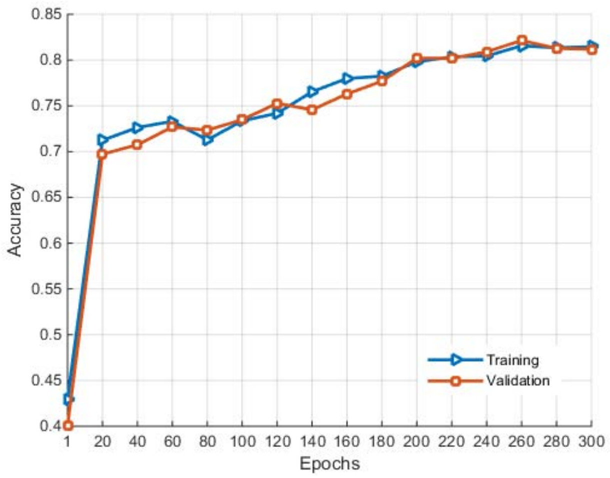

Fig. 3. Accuracy graphic of the proposed approach.

Table II shows results of performance metrics for all classes. The overall accuracy obtained is 82.08%. Accuracy, precision, recall and f1-score metrics are computed with following equations:

$$Accuracy = (TP+TN) / (TP+TN+FP+FN) \quad (1)$$

$$Precision = TP / (TP+FP) \quad (2)$$

$$Recall = TP / (TP+FN) \quad (3)$$

$$F1\text{-}score = 2\times Precision\times Recall / (Precision+Recall) \quad (4)$$

where *TP* is true positive, *TN* is true negative, *FP* is false positive, *FP* is false positive, and *FN* is false negative.

TABLE II. RESULTS OF PERFORMANCE METRICS

Classes	Precision	Recall	F1-score
1	0.963	0.895	0.927
2	0.763	0.708	0.734
3	0.788	0.817	0.802
4	0.765	0.962	0.852
5	0.817	0.793	0.804

IV. CONCLUSION

In this paper, we presented a recommendation system based on CNN considering color compatibility for textile products. We used our own pattern dataset consisting of 12000 images for training and testing of the CNN model. We evaluated the performance of the proposed model in terms of overall accuracy, precision, recall, and f1 score metrics. The overall accuracy obtained is 82.08%, precision is 82.00%, recall is 83.50%, and f1-score is 82.30%. Even though the images are classified directly according to the users' and designers' preferences rather than the characteristic similarities of the images, recommendations appear to offer compatible patterns.

Products purchased or ratings by consumers can also be considered as feedback to the recommendation system, as they reveal the consumers' preferences. Training of the recommendation system is repeated with the feedback obtained in certain periods. The performance of the recommendation system fed by the feedback will increase.

ACKNOWLEDGMENT

This study is supported by The Scientific and Technological Research Council of Turkey (TUBITAK) TEYDEB 1507 program under project number 7180506. The authors would like to thank Ece Çelikkıran, Yunus Emre Yıldız, and other employees of Reisoğlu İplik for their help.

REFERENCES

[1] W. Zhou, P. Y. Mok, Y. Zhou, Y. Zhou, J. Shen, Q. Qu, and K. P. Chau, "Fashion recommendations through cross-media information retrieval," J. Visual Commun. Image Represent., vol. 61, pp. 112–120, 2019.

[2] L. Zhao, Z. Lu, S. J. Pan, and Q. Yang, "Matrix factorization+ for movie recommendation," In IJCAI, pp. 3945–3951, July 2016.

[3] P. Covington, J. Adams, and E. Sargin, "Deep neural networks for youtube recommendations," In Proceedings of the 10th ACM conference on recommender systems, pp. 191–198, September 2016.

[4] X. Wang, and Y. Wang, "Improving content-based and hybrid music recommendation using deep learning," In Proceedings of the 22nd

ACM international conference on Multimedia, pp. 627–636, November 2014.

[5] Y. Guan, Q. Wei, and G. Chen, "Deep learning based personalized recommendation with multi-view information integration," Decision Support Systems, vol. 118, pp. 58–69, 2019.

[6] Q. Liu, S. Wu, and L. Wang, "DeepStyle: Learning user preferences for visual recommendation," In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 841–844, August 2017.

[7] X. Zhang, J. Jia, K. Gao, Y. Zhang, D. Zhang, J. Li, and Q. Tian, "Trip outfits advisor: Location-oriented clothing recommendation," IEEE Trans. Multimedia, vol. 19(11), pp. 2533–2544, 2017.

[8] J. B. Schafer, D. Frankowski, J. Herlocker, and S. Sen, "Collaborative filtering recommender systems," In The adaptive web, Springer, Berlin, Heidelberg, pp. 291–324, 2007.

[9] M. J. Pazzani, and D. Billsus, "Content-based recommendation systems," In The adaptive web Springer, Berlin, Heidelberg, pp. 325–341, 2007.

[10] W. Xu, and Y. Zhou, "Course video recommendation with multimodal information in online learning platforms: A deep learning framework," British Journal of Educational Technology, 2020.

[11] W. Yu, H. Zhang, X. He, X. Chen, L. Xiong, and Z. Qin, "Aesthetic-based clothing recommendation," In Proceedings of the 2018 World Wide Web Conference, pp. 649–658, April 2018.

[12] Y. Jiang, X. U. Qianqian, and X. Cao, "Outfit Recommendation with Deep Sequence Learning," In 2018 IEEE Fourth International Conference on Multimedia Big Data (BigMM) IEEE, pp. 1–5, September 2018.

[13] C. Lei, D. Liu, W. Li, Z. J. Zha, and H. Li, "Comparative deep learning of hybrid representations for image recommendations," In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognitionpp. 2545-2553, 2016.

[14] D. Anil, A. Vembar, S. Hiriyannaiah, G. M. Siddesh, and K. G. Srinivasa, "Performance Analysis of Deep Learning Architectures for Recommendation Systems," In 2018 IEEE 25th International Conference on High Performance Computing Workshops (HiPCW) IEEE, pp. 129–136, December 2018.

[15] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521(7553), 436–444, 2015.

[16] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," In Advances in neural information processing systems,(pp. 1097–1105, 2012.

[17] S. Ioffe, and C. Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.," In International Conference on Machine Learning, pp. 448–456, June 2015.

[18] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," J. Mach. Learn. Res., vol. 15(1), pp. 1929–1958, 2014.