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A DEEP LEARNING-BASED RECOMMENDATION SYSTEM FOR TEXTILE PRODUCTS

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Abstract

These days, it's more common to use recommendation algorithms to keep customers happy and boost revenue. It is hoped that consumers would be able to make more informed decisions thanks to these solutions. A recommendation system has become an essential aspect of internet buying. Recent emphasis has been focused on fashion and clothes as the subject of several recommendation algorithms. A Convolutional Neural Network (CNN)-based recommendation system has been proposed in this study (CNN). According to the preferences of the CNN's users and designers, distinct patterns have been assigned to different classes in the architecture. Color compatibility is taken into account by the deep learning model when recommending designs for textile items. Our own pattern dataset, which contains 12000 photos, was used to train and evaluate the suggested model. Using pattern datasets, we were able to demonstrate the efficacy of our technique.

Keywords— Convolutional neural networks, colour compatibility, and deep learning are all examples of recommendation systems.

INTRODUCTION

The growth of online shopping has been fueled by recent advancements in internet technology. It's more common for customers to buy new items in the same colour or design as their current ones. To find all of the appropriate items while buying online, it might take a long time. To uncover patterns that clients care about more quickly, automated recommendation systems are useful. Consumers are increasingly turning to recommendation systems to assist them sort through a large number of items on the internet and find the ones that best suit their requirements [1]. Research into recommendation systems has drawn the interest of scholars, and a number of distinct recommendation systems have been published [2–7] in the literature on various topics, such as movies, music, videos, fashion, and apparel, among others. Collaborative filtering [8], content-based approaches [9], or systems where these two methods are combined are the most often used recommendation systems. Collaborative filtering models interactions between people and goods using a matrix factorization method that incorporates cooperation between user behaviour and product evaluations. This kind of recommendation is based on the product description and user's preferences. Rather of relying on numerical and textual information, traditional recommendation system approaches such as collaborative filtering and content-based methods use deep learning to extract characteristics from photos and videos, such as clothes and fashion. In recent years, deep learning-based algorithms have been successful in pattern recognition, image processing, clustering, and classification. Deep learning-based research have been shown to be effective in recommendation systems, as well. An integrated multi-view recommendation system, called Deep-MINE, was suggested by Guan and colleagues [5] and a unified deep neural network model was constructed. Auto-encoder networks were used to Amazon.com's women's clothes to illustrate the model's efficacy. An strategy to extracting visual attributes such as shoes, dresses, pants and bags was used by Liu et al. [6]. The model uses style characteristics and visual category information to identify features in photos. Zhang et al. [7] used a hybrid CNN technique to select clothes based on the link between apparel and location. The support vector machine was used in conjunction with a multilabel CNN in this investigation. When it comes to making recommendations, it's important to take into account both visual and aural characteristics. They said that a neural network had been pre-trained to extract the aesthetic elements. In [12], a long-short-term memory (LSTM) network-based outfit suggestion system is suggested. Using existing photographs and descriptions of outfits, they set out to figure out how to create one that would be universally acceptable. A comparative deep learning model described by Lei et al. [13] learns picture and user preferences simultaneously. Three subnetworks make up the network. Using a

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sub-network, we were able to predict the preferences of our consumers. Fashion and apparel are the only areas where present recommendation algorithms have an emphasis. This research proposes an online recommendation system for textile items based on colour compatibility. Using the system's recommendations, customers may buy new goods that are compatible with their current purchases. According on the input from the designers and participants, it was determined whether or not the patterns are compatible. The research used CNNs instead of more typical recommendation systems. To the best of our knowledge, no research has examined the use of deep learning algorithms to propose patterns based on colour compatibility in textile items. In our opinion, our suggested research is the first of its kind.

Fig. 1. The proposed recommendation system architecture.

Recommendation System

Fig. 1 depicts the architecture of the proposed recommendation system. Figure shows how a customer submits a picture of their couch to the system in order to find a pillow that is suitable with it. Using a random pattern from the database, a snapshot of the pillow that will be bought is mixed with a pattern from the database, and the resulting image is then given to a deep learning algorithm for analysis. Among the photographs that have been blended with various patterns, the deep learning system returns the images that are most compatible to the user. Consumer preferences must be taken into account in recommendation systems since different people think in various ways. The research [5] used a survey to gather information on participants' cognitive styles, which they then included into their models. An online poll was utilised to classify the patterns employed in the CNN model's training phase, and participants were asked to choose their favourites from a list of options. It was established that two sequential patterns that differed in the most in terms of their scores were classified into separate classes as a consequence of this survey. According to the number of rates, the designs were ranked from 1 to 5. the patterns

(a)

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(b)

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

Class 5 has the highest rates. In Fig. 2, you can see two pillow designs for the couch. The CNN classification result shows that Fig. 2 (a) is in class 5 and (b) is in class 1, which is the class with the lowest rates. Only the Class 5 pattern is available to the customer, according to these findings. It's common for recommendation systems to rely on data from items that have been bought or reviewed by customers [14]. Specifically, purchases are seen as a kind of positive feedback. Customers' comments and evaluations are regularly gathered, and the CNN model is trained repeatedly in addition to the survey research for pattern categorization.

CNN Architecture

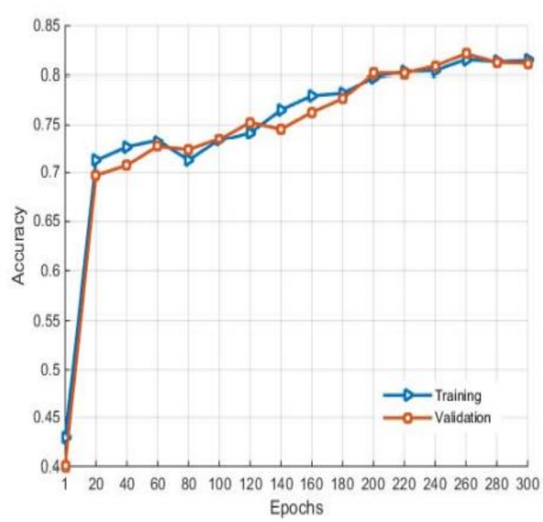
Researchers' interest in deep learning methodologies has grown recently because to the proliferation of high-speed processors resulting from technological advancements, particularly in studies using massive amounts of data. More layers and automated input preparation and feature extraction are part of deep learning, the advanced level of conventional artificial neural networks [15]. CNN is the most often used deep learning algorithm, and it has shown to be superior than classical methods. Large-scale picture classification challenges have recently been solved using CNNs [16]. Convolution, pooling, and fully linked layers make up a CNN. The convolution layer uses a variety of filters to extract certain information from a picture. A nonlinear activation function is used once each layer of convolutional resampling is completed. Rectified Linear Units (ReLU) are the most common activation function in CNNs, despite the fact that there are numerous others. The pooling layer is then used to reduce the feature maps' spatial size. The most popular pooling method is max pooling, which sums together the most frequently utilised features. It is necessary to flatten the feature map that is generated after the convolution and pooling layers before feeding it into the fully connected layer as input. As you can see in Table I, we used a CNN-based technique to build our system. The CNN design contains four convolutions, four pooling, and two fully linked layers, as shown in the table. After each convolution, batch normalisation [17] and the ReLU activation function were used. For avoiding overfitting, dropout [18] is used to remove units from the training layer.

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

The CNN model was trained and tested using a dataset of 12000 photos that we created ourselves. There were no exceptions. We used an Adam optimizer with a batch size of 32 to train the network for 300 epochs. There was a dropout rate of 0.5 percent. A total of five classes were created based on the preferences of consumers and designers. Figure 3 shows the accuracy of the CNN model. Classification results may be expressed in a graph like



this, but so can users and designers' desires.

Fig. 3. Accuracy graphic of the proposed approach.

Data from several performance measures are shown in Table II. 82.08 percent of the results are correct. Using the above equations, we get the following metrics:

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B. CNN Architecture

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

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

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

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

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

A CNN recommendation system for textile items that takes colour compatibility into account was given in this study. The CNN model was trained and tested using a dataset of 12000 photos that we created ourselves. Overall accuracy, precision, recall and f1 score measures were used to assess the suggested model's performance. 82.08 percent accuracy, 82.00 percent precision, 83.50 percent recall, and a f1-score of 82.30 percent were all achieved. suggestions seem to give comparable patterns, even if the photos are grouped explicitly according to preference, both for users and designers. Customers' purchases and evaluations may also be used as input to the recommendation system since they reflect their preferences. The training of the recommendation system is

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performed at regular intervals based on the input it receives from the user community. The recommendation system's performance will improve as a result of the input.

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