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Content Based VGG16 Image Extraction Recommendation

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Abstract

Data transfer across numerous platforms has increased dramatically due to the enormous number of visitors or users of the present e-commerce platform. With the rise of increasingly massive data, consumers are finding it challenging to obtain the right data. The recommendation engine may be used to make it simpler to find information that is relevant to the user's needs. Clothing, gadgets, autos, furniture, and other e-commerce items rely on product visualization to entice shoppers. There are millions of images in these items. Displaying the information sought by clients based on visual data is a difficult challenge to address. One strategy that is simple to use in a recommendation system is content-based filtering. This approach will eventually make suggestions to consumers based on previously accessible goods or product descriptions. Content-based filtering works by searching for similarities based on the properties of a product item. User interactions with a product will be recorded and analyzed in order to recommend certain similarities to users. Text-based datasets are used in the majority of content-based filtering studies. In this study, however, we attempt to leverage a dataset received from Kaggle in the form of images of futsal shoes. Then, VGG16 architecture is used to extract the image dataset. The top 5 most relevant item rankings are generated by this recommendation method using cosine similarity. In addition, the NDCG (Normalized Discounted Cumulative Gain) approach is used to assess the results of the suggestions. The NDCG was evaluated in ten test scenarios, with an average NDCG value of 0.855, indicating that the system delivers a reasonable performance suggestion.

Keywords: Image Based, Content Based Filtering, Recommendation System, VGG16

1. Introduction

Data transfer across numerous platforms has increased dramatically due to the enormous number of visitors or users of the present e-commerce platform. With the rise of increasingly massive data, consumers are finding it challenging to obtain the right data. This must be rectified as soon as possible and as successfully as possible. The recommendation engine may be used to make it simpler to find information that is relevant to the user's needs. A recommendation system is a system that predicts whether or not a product or thing will be purchased. The recommendation system employs different techniques, including collaborative filtering, content-based filtering, and hybrid recommendation, which combines the two preceding procedures.

Clothing, gadgets, autos, furniture, and other e-commerce items rely on product visualization to entice shoppers. There are millions of images in these items. Displaying the information sought by clients based on visual data is a difficult challenge to address [1]. Many researchers have undertaken studies to tackle this problem. However, they are still unable to satisfy users or buyers since this text-based solution requires a product description, which cannot properly explain the product[2][3]. Previous studies [4] have taken several techniques, including presenting a content-based comparable image retrieval system based on Particle Swarm Optimization (PSO) and K-means. The PSO algorithm is a population-based technique that uses color images such as histograms to leverage individual searches. Furthermore, other researchers [5] employed three steps in a content-based recommendation system. The first step is to remove the image's backdrop. Second, create a representation of the picture model and then proceed with feature extraction and normalization. The final step is to calculate the weight of each feature based on user browsing. The dataset utilized consists of around 600 photos of clothing and shoes from the Amazon and JD online stores. Color, texture, and form are the elements employed.

Some internet platforms, such as the Spotify music streaming platform, have employed content-based filtering approaches to raise interest in their offerings. They will recommend songs to consumers based on the information provided in the song, such as singers and

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song lyrics that employ similar descriptors. There are other e-commerce sites that employ this strategy, such as alibaba.com, which recommends things that consumers frequently buy based on the similarity of product descriptions or existing items with the product.

One strategy that is simple to use in a recommendation system is content-based filtering. This approach eventually make suggestions to consumers based on previously accessible goods or product descriptions. Content-based filtering works by searching for similarities based on the properties of a product item. User interactions with a product will be recorded and analyzed in order to recommend certain similarities to users [7].

Similarities in multimedia data, such as photos, music, or video, are examined in content-based filtering. Some researchers find it difficult to extract these numerous forms of data. The CNN (Convolutional Neural Network) technique is used in one of the picture extraction procedures. The CNN algorithm is a subset of the deep learning algorithm. This algorithm is used to read or detect data in the form of pictures or digital image data, which is then translated into a matrix array structure. One of the CNN architecture models is VGG16 which employs a convolutional layer using a small convolutional filter (3x3). According to [8], VGG16 has an accuracy of 92.7 percent, while according to [9], VGG16 has a reasonably decent accuracy of 70.63 percent.

This study use the VGG16 model to extract futsal images in e-commerce obtained from Kaggle which contains 1057 photos. Furthermore, cosine similarity may be used to calculate product similarity. Cosine similarity is a method for determining the similarity of two documents or texts. The cosine similarity method is utilized to seek similarities such as color characteristics, texture patterns, and product forms to eventually be used to make product recommendations to image-based users

2. Research Methods

Several steps were carried out in this work, beginning with the collecting of picture datasets from Kaggle website. The images are then extracted using VGG16 to generate an array matrix. The array matrix is computed for each item's similarity with cosine similarity. The most similar products are searched for as top-n recommendations based on the key items. Finally, the top-n recommendations' outcomes were analyzed using NDCG. Figure 1 illustrates these procedures.

Figure 1. Research method overview

2.1 Dataset

The dataset for this study consisted of 1057 photos of futsal shoes from the Kaggle website. Each image has a 225 x 225-pixel resolution and file size about of 8Kb. Figure 2 shows an example of a picture.

Figure 2. An example of futsal shoes image

2.2 Recommendation system

A recommendation system is a system that operates or works to filter relevant information from a huge amount of dynamically generated information, and then provides a suggestion to the user or the user on related topics[10]. The recommendation system has various benefits, one of which is that it has been shown to increase quality and decision making [11]. The recommendation system is divided into three parts: collaborative filtering, content-based filtering, and hybrid filtering [12]. Content-based is a popular strategy in recommendation systems since it is simple to implement and does not require a user rating of an item.

2.3. Content-based filtering

Content-based filtering is a technique for making recommendations based on the items on a platform. Item similarity is estimated based on the similarities of their characteristics, which are then compared [13]. This item has an independent nature, which means it is unaffected by whether the item is new (has never been picked by the user) or not. The disadvantage of this strategy is that comparable goods are restricted, thus you have no opportunity of receiving unexpected stuff [14]. Pazzani and Bilsus indicated in their study that it was possible that people who bought or viewed dolls had also seen pornographic videos. It is not advisable to recommend [15].

2.4 CNN Model (Convolutional Neural Network)

CNN is a deep learning technique that manages two-dimensional data and is frequently used with picture data [16]. CNN was created by Kunihiko Fukushima, a researcher at the NHK Broadcasting Science Research

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Laboratories in Kinuta, Setagaya, Tokyo, Japan [17]. Furthermore, Yan LeChun improved CNN using a CNN model called LetNet, which he effectively employed in his study on number and handwriting recognition[18]. The CNN idea is nearly identical to the Multilayer Perceptron Concept (MLP). Two-dimensional data was transmitted in CNN. Figure 3 depicts the CNN method's layers.

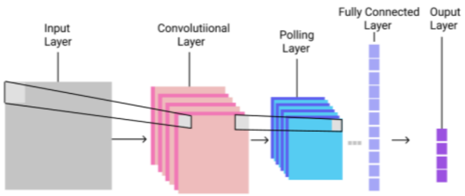

Figure 3. CNN layers [19]

2.4.1. Convolutional Layers

The convolutional layer apply a convolution operation on the preceding layer's output. The key mechanisms that underpin CNN are the layers that are utilized. In image processing, convolutional refers to the use of a kernel (yellow box).

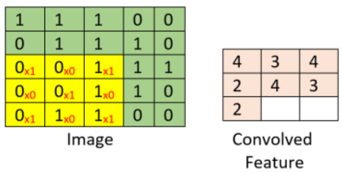

Figure 4. Convolutional computed [16]

The green box in Figure 4 depicts the complete picture to be convoluted. In addition, the kernel move from top to bottom. So that the findings are visible next to it. The goal of convolution is to extract the image's features[16].

2.4.2. Sumsampling Layers

Sumsampling Layers is a method for reducing the amount of picture data. Max pooling is the approach employed in sumsampling layers. Max pooling divides the convolutional layer's output into tiny grids and then takes the maximum value from each grid. The maximum selected group in Figure 5 is the grid with green, yellow, blue, and red hues. So that the process's outcomes may be observed on the following grid [16]

2.4.3. Fully Connected Layers

This layer is used in the MLP application to convert data so that it may be categorized linearly. There, it is mentioned that the convolutional layer with a kernel size of 1x1 perform the same function as the fully connected layer. As a result, its utilization on CNN is currently uncommon [16].

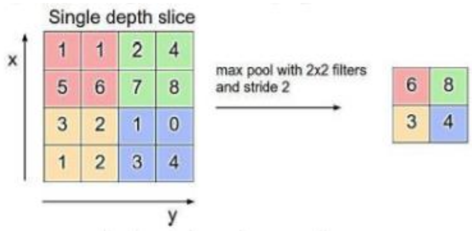

Figure 5. Max Pooling operation [16]

2.5. VGG16 Model

By loading the VGG16 model, this study employs a classification model with the Convolutional Neural Network (CNN) approach. K. Simonyan and A. Zisserman of the University of Oxford proposed the VGG16 architecture in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition." This model has a 92.7 percent success rate[8] VGG16 [20] has 16 layers, 13 of which are convolution layers and 3 of which are fully connected layers. Figure 6 depicts the VGG16 architecture.

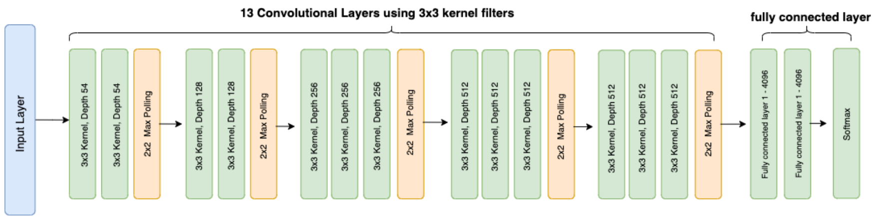

Figure 6. VGG16 Architecture model [21]

The convolution layer in the layer above has a layer size of 3x3. The number of filters in each layer is what distinguishes each convolution. There are 64 filters in the first two convolution layers. Then there are 128 kernels in layers 3 and 4. Then there are 256 filters on levels 4, 5, 6, and 512 filters on layers 7, 8, 9, 10, 11, and 12[21].

2.6. Cosine Similarity

Cosine similarity is a method that is used to calculate two items in the form of two vectors and then to discover an equation size by using the keyword of an item. According to the formula 1.

$$Cos_s a = \frac{A \cdot B}{|A||B|} = \frac{\sum n_{i=A_i \times B_i}}{\sqrt{\sum_{i=1}^{n}(A_i)^2 x \sqrt{\sum_{i=1}^{n}(B_i)^2}}} \qquad (1)$$

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Where A is the vector being compared for similarities. While B is a vector B, its similarity will be compared. Then A.B is the Dot product of vectors A and B. |A| denotes the length of vector A, while |B| denotes the length of vector B. |A||B| is the cross product between |A||B|.

2.7. NDCG (Normalized Discounted Cumulative Gain)

The recommendation system is evaluated using the NDCG model in the final step of this project. The first stage is to assess the relevance value of the suggestion document to the item chosen by the user; in this study, the relevance value was assigned by M. Danil Al Fikrah, a futsal player from the "Kembara FC" squad, one of the teams in the Nusa Tenggara Barat province of Indonesia. The relevance rating supplied is between 0 and 3. The researcher employs[22] the relevance value range 0-3 since several studies have been done utilizing the relevance value range 0-3.

As in research[23], which use a grading system for the value of relevance, specifically 0-3. Furthermore, in the evaluation of NDCG, study [24] employed a score range of 0-3. The researcher utilizes a relevance value in the range of 0-3, which suggests that a number closer to 3 is more relevant. In this case, the user is given the option of assigning a relevance value depending on the form and color of the shoe. Then, for the recommendation sequence, identify the optimal value for the divisor of the Discounted Cumulative Gain (DCG).

The NDCG measure is used by the researcher to evaluate the approach in this case. The NDCG is one of the criteria used to rank search engine results. Meanwhile, in formula 2, the DCG average is defined as follows:

$$\mathrm{DCG}_l = \sum_{i=1}^{l} \frac{r_{el_i}}{log_2(i+1)} \quad (2)$$

While NDCG is the standard form of DCG, it can be defined using formula 3.

$$\mathrm{NDCG}_l = \frac{DCG_1}{lDCG_1} \quad (3)$$

Where DCG is the recommendation sequence's DCG value and iDCG is the ideal sequence's DCG value.

3. Results and Discussions

The author present the research findings in this part, beginning with data collection, picture extraction, similarity calculations, and evaluation using NDCG.

3.1. Dataset and Parameter Setup

Researchers utilized a futsal shoe image dataset of 1057 photos from the Kaggle website, https://www.kaggle.com/ms1437/futsal-shoes. At this point, the researchers prepare the picture data for recommendations and define the image model width and height. In this study, 5 photos were used to get the top-n recommendations.

3.2. Machine Learning Model

VGG16 from the Keras library is used in the machine learning model. Several pre-trained models are included in the Keras module and may be readily loaded. In this study, a recommendation system was created based on content similarity. As a result, researchers first load a Convolutional Neural Network (CNN) capable of interpreting picture content. The VGG16 model was trained using ImageNet by the researchers. Following that, the researcher eliminated the latest CNN model that was used to predict each class from the picture model. The layer architecture of the VGG16 model employed in this work is depicted in this code:

```
Layer (type)                 Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten (Flatten)           (None, 25088)             0

 fc1 (Dense)                 (None, 4096)              102764544

 fc2 (Dense)                 (None, 4096)              16781312

=================================================================
Total params: 134,260,544
Trainable params: 134,260,544
Non-trainable params: 0
```

3.3. Image feature extraction

The following stage is to feed all image data from the futsal shoes picture into the CNN model. Following that, the researcher extracted photos for all of them. This technique produces an array matrix as its result. The time necessary to extract the futsal shoes image, which amounted to 1057 photos, was 9 minutes and 23 seconds. This experiment uses Google Colaboratory with a standard GPU.

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3.4. Cosine Similarity

After all of the pictures have features, the similarity matrix in each image pair is calculated. The cosine similarity matrix is used by the researcher to calculate the similarity using formula (1). For example, if one of the shoes is selected as a key item, the recommendation function is used to create items with similarity values arranged from highest to lowest. Several applications in e-commerce used top 5 or top 10 item recommendations to the user. Based on several experiments that have been carried out in [25] and [26], namely by looking at the similarity with the top 5 recommendations. The researcher decided the five most similar photos to utilize. Figure 7 illustrates the main image on the left, followed by 5 recommended items ordered by similarity score.

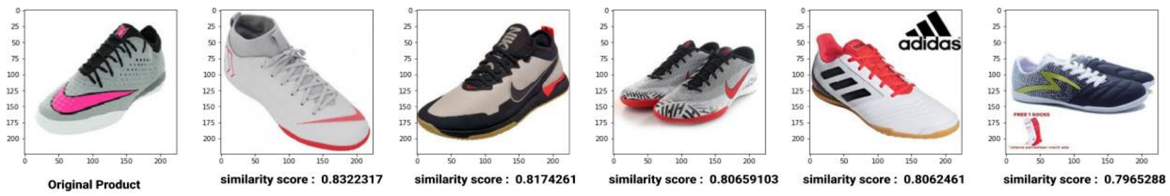

Figure 7. The result of 5 recommendation futsal shoes

3.5. NDCG Evaluation

Experts conduct the evaluation of recommendations. The supplied relevance value ranges from 0 to 3. This suggests that the closer the value is near 3, the better or more relevant it is. Following that, the optimal DCG value is sought, which is employed as a DCG divisor in the recommendation sequence. Table 1 shows the NDCG computation.

Table 1. Scenario 1 Relevance score

i	Recommendation order		Ideal order	
	Document Order	Relevance *i*	Document Order	Relevance *i*
1	D	2	D4	3
2	D2	2	D1	2
3	D3	1	D2	2
4	D4	3	D3	1
5	D5	1	D5	1

The NDCG score is derived as follows using formulae (2) and (3) based on Table 1:

$$DCG_5 = \frac{2}{log_2(1+1)} + \frac{2}{log_2(2+1)} + \frac{1}{log_2(3+1)} + \frac{3}{log_2(4+1)} + \frac{1}{log_2(5+1)}$$

$DCG_5 = 2+1.261+0.5+1.291+0.386= 5.438$

$$IDCG_5 = \frac{3}{log_2(1+1)} + \frac{2}{log_2(2+1)} + \frac{2}{log_2(3+1)} + \frac{1}{log_2(4+1)} + \frac{1}{log_2(5+1)}$$

iDCG = $3 + 1.261 +1 + 0.430 + 0.386 = 6.077$

NDCG = 5.438/6.077 = **0.895**

The NDCG score in scenario 1 is 0.895, as can be observed. In this experiment, ten scenarios were employed, and key items were found at random. It is utilized with the same calculation formula as in the previous scenario, scenarios 2 to 10, in the following scenarios. Table 2 displays the results of the NDCG score computation in scenarios 2-10.

Table 2. NDCG score scenario 2-10

Scenario	**DCG score**	**iDCG score**	**NDCG score**
Scenario 2	3.946	3.946	1.000
Scenario 3	7.008	7.139	0.981
Scenario 4	7.456	7.639	0.976
Scenario 5	4.253	5.892	0.721
Scenario 6	4.008	5.208	0.769
Scenario 7	2.560	2.560	1.000
Scenario 8	3.665	5.261	0.696
Scenario 9	3.446	4.577	0.752
Scenario 10	1.496	2.560	0.760

The average value is calculated when all scenarios have gotten the outcomes of the NDCG values. The computation result is shown in table 3.

Table 3. Average NDCG score

No	**Scenario**	**NDCG score**
1	Scenario 1	0.895
2	Scenario 2	1.000
3	Scenario 3	0.981
4	Scenario 4	0.976
5	Scenario 5	0.721
6	Scenario 6	0.769
7	Scenario 7	1.000
8	Scenario 8	0.696
9	Scenario 9	0.752
10	Scenario 10	0.760
Average score		**0.855**

4. Conclusion

The recommendation system's purpose is to provide recommendations to users by utilizing specific objects or domains. The top 5 recommendations based on this research are in the form of shoe products utilizing the VGG16 algorithm and cosine similarity. From the top 5 recommendations, the average value of the similarity score is 0.812. Moreover, an evaluation using NDCG is performed, and it is known from the calculations in table 3 that the average value of NDCG is 0.855,

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indicating that the degree of relevance created is near to 1, showing that the recommendation system given is extremely relevant. Other datasets and models, in addition to VGG19 and ResNet50, can be employed in future study.

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