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Electronic Product Recommendation System Using the Cosine Similarity Algorithm and VGG-16

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Abstract: The recommendation system is a mechanism for filtering a batch of data into numerous data sets based on what the user wants. Cosine similarity is one of the algorithms used in creating recommendation model. This algorithm employs a calculation approach between two things by measuring the cosine between the two objects to be compared. Image-based recommendation systems were recently introduced since word processing to generate recommendations had the issue of duplicating product descriptions for different types of items. Before processing with cosine similarity, image feature extraction requires the use of a deep learning algorithm, VGG16. The purpose of this research is to make it easier for customers to select the desired electronic goods by providing product recommendations based on product visual similarity. This model is able to recommend 10 products that are similar to the selected product. The presented product has a cosine value near one, and the discrepancy with the selected product's cosine value is modest. The mAP technique was used for model testing, and the smartwatch category received the greatest mAP value of 94.38%, while the headphone category had the lowest value of 70.84%. The average mAP attained is 81.50%. These findings show that mAP accuracy varies by category. This disparity is due to the unequal dataset in each category.

Keywords: Cosine Similarity; Deep Learning; mAP; Recommendation System; VGG16;

INTRODUCTION

Current technological developments have a favourable influence on a variety of business sectors (P. B. Halim et al., 2022). People who used to conduct their businesses in the traditional way can now do it online through e-commerce (Solihat & Sandika, 2022). Trading in e-commerce is highly convenient since the activities simply require electronic devices that are linked to the internet. Buyers no longer visit stores to purchase items since trading can be done anywhere (Syachrul Maulana Nizal & Dwiati Wismarini, 2022). Shopee, Tokopedia, Bukalapak, Lazada, and other e-commerce applications are popular in Indonesia (Muhiban & Putri, 2022).

E-commerce sells a wide range of things, including clothing, cooking equipment, electronics, and many more. The most popular products on the Bukalapak and Tokopedia platforms are electronic products (Farhan Hasrul et al., 2020). According to the research, Indonesians prefer to buy electronic products through e-commerce due to the simplicity of transactions. Because there are so many different electronic products to choose from, it can be difficult for buyers to decide which items to purchase. The consumer may lose interest in acquiring the item as a result of the time spent selecting it (Agarwal et

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al., 2018). As a result, we require a recommendation system to help customers purchase goods. The adoption of this approach can improve the buyer's time efficiency while picking things to purchase.

There are various approaches to developing a recommendation system. A local shoe recommendation system at a tarsius shoe store is one example of a recommendation system (Pradana et al., 2022). This recommendation system implements the Collaborative Filtering method. This method is often implemented in recommendation systems. Data processing based on consumer ratings. This system is based on a consumer rating of 0–5 and offers a list of the top ten desired outputs. There is also a recommendation system that uses another method, namely the recommendation system in the sales application (Sujasman & Syazili, 2020). This recommendation system uses the Cosine Similarity method. However, these two recommendation systems still process data based on text in product descriptions. There is an issue if the description is the same but the product presented is different. This will result in product suggestion mistakes in the recommendation system. Therefore, this research developed a recommendation system based on product images in order to reduce text similarities across items. To process digital image datasets, feature extraction must be performed first. For feature extraction, numerous deep learning architecture models may be applied. Brain tumor identification is one use of feature extraction models (Mandal, 2022). The VGG-16 feature extraction model is used for brain tumor identification. The accuracy rate in that research was 92.34%, and it was able to discriminate images of brains with tumors from brains without tumors.

Several merchants in e-commerce apps duplicate the description language of other distinct items and then use it to describe their own. It is intended that the items supplied by these merchants appear in product suggestions that match the descriptions that consumers are looking for. This makes the present text-based recommendation system less accurate. Therefore, in this research, a recommendation system based on product images will be developed in order to increase the accuracy of product suggestions.

LITERATURE REVIEW

The recommendation system is a system in an application that aims to solve an issue that arises when a user picks things. This system has the ability to affect the user's purchasing decisions based on their preferences (Saleh et al., 2023; Sujasman & Syazili, 2020). The recommended system is helpful for people when they want to buy an item since it takes less time to pick it up. Furthermore, this system may present the goods that customers desire while also obtaining reduced pricing. As in previous research on recommendation systems utilizing the a priori algorithm, results are achieved that present product suggestions for every customer that accesses e-commerce (Badriyah et al., 2018).

The presented results are based on the user's previous shopping transactions. Another research looked at the implementation of the collaborative filtering approach in a sales recommendation system at a furniture store, and the findings showed that the system could generate recommendations for three goods (Februariyanti et al., 2021). This recommendation is based on the most recent product sales data and has a similarity value close to 1. This value indicates that the closer the product is to number 1, the more comparable it is. The recommendation system may be used for things other than sales product suggestions, such as earlier research on recommendation systems from Microsoft news data (Yunanda et al., 2022). From this research, it can provide recommendations for the 10 latest news according to user preferences with an accuracy value of 80.77%. This value indicates that the recommendation is correct based on the user's preferences. The method or algorithm utilized to create the recommendation system has a significant impact on the suitability of the recommendations supplied.

Previous research in his study of document plagiarism detection. The method utilized in this research is cosine similarity, which compares one item to another (Saeed & Taqa, 2022). This research computes the similarity value of a document to other documents based on the text in the document. This calculation can determine the point of similarity between the two identities (Singh et al., 2020). Sujasman M & Syazili A (2020) did another research on the implementation of cosine similarity for product suggestions, and the findings showed that the cosine similarity approach could be used in applications. The findings reveal a high percentage of product similarities, and these results may be used to find more items with comparable similarities (Sujasman & Syazili, 2020).

Furthermore, M. Dzikri Hisyam Ilyasa & Yuni Yamasari (2023) found a higher level of cosine similarity accuracy in their research on the comparison of cosine similarity and euclidean distance in the

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book recommendation model. Euclidean distance, hence it can be inferred that cosine similarity is more successful for the book recommendation model in this study (Dzikri et al., 2023). Moreover, further research on the implementation study of cosine similarity relevance calculations in both documents discovered that the application of cosine similarity in their research produced findings that could identify the contents of one document from another (Gunawan et al., 2018). This proves that using cosine similarity to compare two items is an appropriate method. Furthermore, the parameters that determine the level of accuracy of the recommendations offered are influenced by the feature extraction findings before they become input or feed into computing product similarity using the cosine similarity method.

As in the research on beetle species classification using the Convolutional Neural Network (CNN) algorithm conducted by Insidini Fawwaz, Tomy Candra, Delima Agustina Margareta Marpaung, Arun Dinis, and M Reza Fachrozi (2022). The use of the method is supported by the use of the VGG-16 model, which is one of the CNN architectures (Fawwaz et al., 2022). This model was already used in an earlier study by Ida Bagus, Pranowo, and Suyoto (2018). This study discovered that the VGG16 design has greater accuracy than the AlexNet architecture, which achieves 98% (Universitas Gadjah Mada et al., 2018). Furthermore, previous research by Halim J, Fajar A. (2023) stated that features retrieved using VGG16 are more efficient than ZFNet. Furthermore, the VGG-16 model provides high detection performance for the image used (J. Halim & Fajar, 2023). This architecture was created specifically for ImageNet, a big visual database project used in the development of visual object identification software (Mandal, 2022). This model supports the simplification of the preprocessing and pre-training of datasets that will be utilized in the creation of recommendation systems. Because the datasets utilized in this work are diverse, the VGG16 architecture was chosen as the model for extracting image features. Model testing is essential to guarantee that the model is capable of generating product recommendations.

As in the earlier study on rice purity detection systems conducted by Nova Eka Budiyanta, Melisa Mulyadi, and Harlianto Tanudjaja (2021), one evaluation matrix, namely the mean average precision (mAP), was utilized to quantify the accuracy of the detection system established (Eka Budiyanta et al., 2021). The accuracy attained in the research was 86.11%. Furthermore, this assessment measure was applied in another study of recommendation systems in health forums with identical rating questions done by Bryan Khufa Rahmada Aula, Chastine Fatichah, and Diana Purwitasari (Khufa Rahmada Aula et al., 2021). The mAP value in this research was 0.845, mAP was used as an assessment metric in this study to examine the viability of the recommendation system model.

METHOD

This research takes numerous steps towards developing an image-based recommendation system for electronic products. Figure 1 depicts various steps of the research.

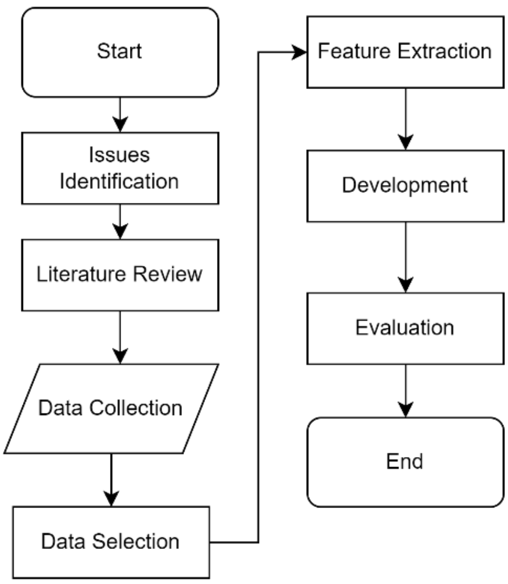

Fig. 1 Flowchart

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Issues Identification

The vast majority of product recommendation systems are still text-based. Meanwhile, some new sellers easily replicate popular product descriptions to include in other sorts of product descriptions. This makes recommendations for products less accurate. Therefore, the researchers developed a recommendation system based on images of products to reduce product recommendation mistakes.

Data Collection

The dataset utilised was 5082, which were separated into five categories, as indicated in Figure 2, namely headphones, smartwatch, SSD, power bank, and TWS. Due to the restricted dataset per category, this dataset is not fairly distributed in each category, and there are some duplicate product images. Because the complete dataset cannot be obtained, you must manually filter the data. This dataset, collected by Kiran Budati from Kaggle, has 174,000 images of electronic products (Budati, 2022).

Fig. 2 Dataset

Data Selection

Data selection in the dataset is performed initially before developing a model. This data was chosen by looking through the dataset. This check is used to examine whether there is any duplication in the dataset, which might cause problems while developing the system. If there is duplication in the dataset, it will be eliminated to avoid aberrant findings.

Feature Extraction

The chosen product image dataset is then subjected to feature extraction using the VGG-16 model. This procedure seeks to extract the key aspects of all product photos and then transform them into a matrix. This stage goes through numerous stages, including changing the image size to 224 by 224 pixels based on the VGG16 architecture's input. Table 1 shows this design, which consists of 12 convolution layers with 3 x 3 kernels. The convolution and pooling layers are organised into 5 blocks, each with numerous convolution layers and a single pooling layer. The pooling layer reduces the image size after the two convolution layers in block 1 employ 16 kernels each for feature extraction. The design of subsequent blocks is identical, except that blocks 1 and 2 use two convolution layers, but blocks 3-5 use three convolution layers with a varied number of kernels in each layer to deepen the network and enhance accuracy (Jiang et al., 2021).

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Table 1. VGG-16 Architecure Model

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (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, 56, 56, 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

Development

The extracted image features are then computed using the cosine similarity algorithm, yielding results in the form of image-based suggestions for electronic products that people seek. During this procedure, the similarity value (degree of similarity) of each image in the existing dataset will be determined (Resta et al., 2021), which will subsequently be used to calculate the cosine using equation (1) (Rifai & Anugrah, 2021).

$$\cos a = \frac{A,B}{|A||B|} = \frac{\sum_{i=1}^{n} A_i \; x \; B}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \; x \; \sqrt{\sum_{i=1}^{n}(B_i)^2}} \quad (1)$$

A = vector of A, which will be compared later.
B = vector of B, which will be compared later..
$A.B$ = multiplication result of A and B
| A | = length of vector A
| B | = length vector B
| A || B |= The result of the cross product between vector A and vector B

Evaluation

The resulting recommendation model is then assessed using the mAP method. To acquire the mAP value, the AP value must first be calculated using equation (2).

$$AP = \frac{1}{11}\sum_{r\in\{0,0.1,\ldots.1\}} Pinterp(r) \qquad (2)$$

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After calculating the AP value using equation (2), the mAP value may be calculated using equation (3).

$$mAP = \frac{\sum_{i \in classes} AP_i}{Total\ no.of\ classes} \qquad (3)$$

RESULT

The first stage is to extract features using the VGG16 architecture. During the feature extraction process, the image from the dataset is passed through 12 convolution layers. From block 1 through block 5, the process of convolution and layer pooling, as shown in Figure 3, resulted in the picture feature extraction procedure for electrical devices with the VGG16 architecture being 4096 one-dimensional arrays.

: 0	0	1	2	3	4	5	6	7	8	...	4086	4087	4088	4089	4090	4091	4092	4093	4094	4095
0	0.0	1.452874	0.0	0.0	0.0	2.776242	6.045958	0.33643	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0891	3.003376

Fig. 3 Results of fiture extraction on one data

These findings are used as input in the calculation step of the product similarity value with the cosine similarity method, which is then compared with the comparison matrix for each product, as shown in Table 2.

Table 2. Value of Cosine on each data

	002U4F5Q.jpg	006ILD0A.jpg	008JX6ME.jpg	00CN92VG.jpg	00HJPHCE.jpg
02U4F5Q.jpg	1.0	0.213686	0.370435	0.158802	0.281478
006ILD0A.jpg	0.213686	1.0	0.227623	0.397296	0.226670
008JX6ME.jpg	0.370435	0.227623	1.0	0.39821	0.475088
00CN92VG.jpg	0.158802	0.397296	0.39821	1.0	0.39108
00HJPHCE.jpg	0.281478	0.226670	0.475088	0.39108	1.0

Table 2 shows the cosine value of each product. When the same two products are compared in the matrix, the cosine value is 1. For example, in the comparison of "02U4F5Q.jpg" with "02U4F5Q.jpg," the outcome is a cosine value of "1.0," which is reached since the images are the same. Table 2 also demonstrates how the cosine similarity method works, specifically by comparing image 1 with as many more images as there are in the dataset. When "006ILD0A.jpg" and "02U4F5Q.jpg" are compared, the cosine value of "0.213686" is obtained. The computed value is low, indicating that images 1 and 2 are not comparable to each other. This is also true for other image products.

Following the calculation of the cosine value in each image Furthermore, existing datasets are used in testing. This test will use one image and display ten goods that are comparable to the tested image. For the first time, headphone products were tested, as shown in Figure 4.

Fig. 4 Testing Product

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Fig. 5 Results of Recommendation Product

Figure 5 shows the test findings. This model recommends ten products that are comparable to the one being examined. The product examined is green and black in colour, with a microphone on the headset. The findings of products 1 and 3 show the same thing, but in a different colour. Each of these products also has a cosine value. The value is "0.797828" for the first product, "0.76327145" for the second product, and "0.7333251" for the third product. This cosine value has relevance; that is, if the cosine value approaches one, the product is more similar to the specified product.

Following the testing of the headphone product, product testing in each category is performed to check whether the findings are valid or not. The results of the model's ten product suggestions have the largest cosine value, as shown in Table 3.

Table 3. Value of Cosine on Result Recommendation

No	Product	Value of Recommendation Cosine Similariy									
		No-1	No-2	No-3	No-4	No-5	No-6	No-7	No-8	No-9	No-10
1	Headphone	0.797828	0.76327145	0.7333251	0.72628266	0.706049	0.70422804	0.6927774	0.6880969	0.68657947	0.68105453
2	Smartwatch	0.9052833	0.8417543	0.8330722	0.821254	0.821254	0.81465906	0.81055313	0.81055313	0.8101722	0.8101722
3	SSD	0.7778003	0.724385	0.71581966	0.7047858	0.6945938	0.68867415	0.6830584	0.6822856	0.68169874	0.6810568
4	Power Bank	0.789832	0.77746916	0.74848384	0.7290355	0.72297436	0.71719265	0.71447647	0.7078901	0.68418497	0.6821223
5	TWS	0.738146	0.72734714	0.72263485	0.7160028	0.71573305	0.7136579	0.70861447	0.7025379	0.6979226	0.6969074

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Following the testing of the headphone product, product testing in each category is performed to check whether the findings are valid or not. The results of the model's ten product suggestions have the largest cosine value, as shown in Table 3.

Table 3 shows the cosine value for each category, and each recommendation is a 10. Headphones, smartwatches, SSDs, power banks, and TWS were all evaluated. A smartwatch with a cosine value of "0.9052833" achieves the greatest cosine value.

Table 4. Product Recommendation Suitability

No	Product	Product Recommendation Suitability									
		No-1	No-2	No-3	No-4	No-5	No-6	No-7	No-8	No-9	No-10
1	Headphone	1	1	1	1	0	0	1	1	0	1
2	Smartwatch	1	1	0	1	1	0	0	0	0	0
3	SSD	1	1	0	1	1	1	0	1	1	1
4	Power Bank	0	1	1	0	1	1	1	0	0	1
5	TWS	0	1	1	0	1	0	1	1	1	0

In Table 4, each product is represented by a number between 1 and 0. The number 1 indicates that the suggestion produced is consistent with the product input, or that it is true, while the number 0 indicates that the recommendation results are inconsistent with the product submitted, or that it is false.

Table 5. Value of mAP on each Categories

No	Product	mAP
1	Headphone	79.44%
2	Smartwatch	94.38%
3	SSD	81.46%
4	Power Bank	72.78%
5	TWS	79.44%
	Average	81.50%

Following an analysis of the suggestions' compliance, the mAP test was performed on the models in each category. Table 5 shows the outcomes of the testing. The average mAP attained in this final result is 81.50%.

DISCUSSIONS

According to the results of this research, the recommendation model based on cosine similarity with the VGG-16 model architecture was successful in delivering suggestions that matched the input product. It was effective in generating suggestions for each category in this survey, which included headphones, smartwatches, SSDs, power banks, and TWS. Smartwatches have the greatest accuracy score of 94.38%, while power banks have the lowest accuracy score of 72.78%.

The accuracy of the test results differs. One of the most causal aspects is that the dataset used is imbalanced. This has a significant impact on object detection accuracy. The smartwatch product recommendation has the highest mAP value because it provides the most comprehensive collection of data compared to other products. Data variations can be noticed due to image angle and position, lighting conditions, and data quality. In contrast, the small amount of data and minimal variety in power bank products cause recommendations for similar products to be inaccurate. Therefore, dataset balance is a crucial aspect in developing an ideal and optimal system recommendation model to generate superior electronic product recommendations. For further development, this model can improve the quality of the data and the amount of data in the dataset to increase the accuracy of recommendations for each product category.

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CONCLUSION

Based on the findings of the study, it is possible to infer that employing cosine similarity to compare two images yields good results. The smartwatch category had the most accuracy with a value of 94.38%, while the power bank category had the lowest accuracy with a score of 72.78%. The average accuracy obtained is fairly high, at 81.50%. By displaying the results of testing on each category of electronic products, it is possible to deduce that the unequal distribution of product data from each category has an influence on the accuracy gained. However, the calculation results on the cosine value produce good results, so this model may still be used to search for comparable results in electronic items, allowing it to serve as the foundation for an electronic product recommendation system.

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