Image Based Similar Product Recommendation System For E-commerce Platform

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Abstract

Research on online product recommendations is crucial, as text-based search functionality has limitations. Image-based similarity search offers enhanced visual search experiences, benefiting e-commerce platforms. A machine-learning-based image-based recommender system was designed using Singular Value Decomposition (SVD) and Principal Component Analysis (PCA) to reduce dimensionality and enhance computational efficiency. The K-Means++ clustering method identified similar product groups, refining the recommendation process.

The study compared four unsupervised clustering algorithms on a dataset of 44,446 product images from the Kaggle platform. The PCA-SVD transformed K-means++ methodology showed higher performance, delivering higher recommendations compared to other strategies, indicating its potential for revolutionizing e-commerce product recommendations.

Keywords: K means-++;Principal component Analysis;Principal Component Analysis through singular value decomposition; Similar image recommendation

1. Introduction

Modern web services and the internet have been growing in the past few decades, making access to a wealth of information easier than ever[1]. In order to filter out the essentials, users may have a difficult time taking away information from this mass of information. Our inability to browse through all of the content on a website makes recommendation systems essential to our user experience, while also exposing us to more inventory we would otherwise never find. Recommender systems provide recommendations to users about the best option among a set of choices. The use of recommender systems is very useful in order to provide the user with the products or services he or she needs. The recommendation system is part of machine learning that helps users find products and content based on data on the website[2]. Recommendation systems have always been in demand in every industry and domain as matching a user's preference is always the most important thing in modern-day business[3].

In a product selling company, it is quite convenient to recommend products based on the user's needs in order to achieve a user-friendly environment. For this reason, e-commerce websites using recommendation systems to create a better internet shopping experience. Visual appearance plays a crucial role in marketing and selling clothing and electronic products. It has the ability to captivate consumers, enabling them to easily recognize and differentiate between different products, ultimately influencing their purchasing decisions. An image recommendation is concerned with finding related objects to a given object that is represented by an image. Image recommendation relies on extracting most descriptive and distinctive features and utilizing them to get matching recommendations [3]. In addition to suggesting relevant images based on the ones the user has already seen or liked, image recommendations can also suggest similar pictures. Using this feature can help users discover new images they might like.

It is highly crucial for an e-commerce platform to incorporate a sophisticated recommendation system that leverages image-based matching to not only drive sales but also provide users with a seamless experience. But most of E-commerce based search engines services employ text-based searching [4]. A textual or key-word-based recommendation system may misdirect users to inferior quality or related products that they do not need. In addition, this kind of approach had some limitations and missed many features such as colours, patterns, texture, and shape in the product images[5], [6].

Most of the solutions involved semi-image-based approaches or text-based searches, and those image-based approaches solution have low the performance and provide inaccurate recommendation. Most of these systems use textual meta-data of products such as attributes, descriptions, and purchase histories of the different users. This text-based search requires specifying the description of each product, which may or may not cover the entire item.

Hence, a picture of any product should clarify the user's expectations about its appearance, usage, and brand. In spite of the maturation of computer vision and image processing, applications of image features for product retrieval using machine learning in online shopping are mostly still unexplored. In order to achieve this, it is also necessary to group similar items or images together with Clustering algorithms which use feature vectors extracted from images to group similar images together. It is essential and most challenging to select the right clustering algorithm for image classification dataset optimization.

To come up with a solution to those problems based on user interaction and interests, to search the products efficiently in an online shopping system using image-based searching techniques, which is giving an input image rather than text description. In other words, a user provides or insert an input image, and similar products (images) are presented to the user. we propose a machine learning based approach for a similar image recommendation system.objective of the study is to experiment and design an image-based recommendation system model for similar products on e-commerce websites that will help buyers find the alternative they're looking for.

2. Literature Review

Recommender systems filter information, providing personalized content, to reduce user effort and time. However, satisfaction decreases with more difficult selections, as noted by Iyengar et al. [7].

Recommender systems are algorithms that offer personalized recommendations based on user preferences. They involve users and items, who rate items based on their experiences. These systems can be content-based, collaborative, or hybrid, and their choice depends on the available data. Collaborative filtering is a suitable approach for historical interaction data. Content and context filtering techniques enhance recommendation accuracy by assessing user characteristics and item properties. These methods aim to predict user preferences and anticipate future interactions. The success of a recommender system depends on its ability to leverage diverse data sources and advanced algorithms to deliver personalized, relevant recommendations in real-time. Collaborative filtering is useful for past interactions.

➢ Content-based Recommendation System

A content-based recommendation system categorizes data items based on user preferences or past searches, enabling structured similarity judgments between products.

Salter et al.'s [8] study highlights the limitations of content-based recommendation systems, which primarily recommend items related to previously evaluated ones, limiting diversity in recommended content, despite their crucial role in user profiles.

Content-based recommendation systems use advanced technologies like text mining, Semantic Analysis, TF-IDF, Neural Network, Naive Bayes, and SVM to effectively derive user preferences. The MMP method reduces dimensionality in image retrieval, enhancing the margin between negative and positive examples.

➢ Collaborative recommendation

A collaborative recommender system uses user evaluations to generate recommendations based on similar interests. It constructs a user's preference database and predicts items that match a user's tastes. By starting with a user, it finds similar users in neighbourhoods, and recommends items to the user. The efficiency of a collaborative algorithm depends on its accuracy in finding the target user's preferences and interests.

A collaborative recommender system uses user evaluations to create a preference database, predicting items that match a user's preferences, as per Miller et al. and Hars et al.[9].

There are two types of collaborative recommendation system: memory-based approach and model-based approach [8]. Memory-based collaborative approach suggests new items based on surrounding preferences, using technologies like Pearson correlation, vector cosine correlation, and KNN to create similar groups among users. It can be further segmented into User-Based Collaborative recommendation and Item-Based

Collaborative recommendation systems. Model-based collaborative approach predicts user ratings for unrated items using data mining and machine learning algorithms, extracting features from the dataset.

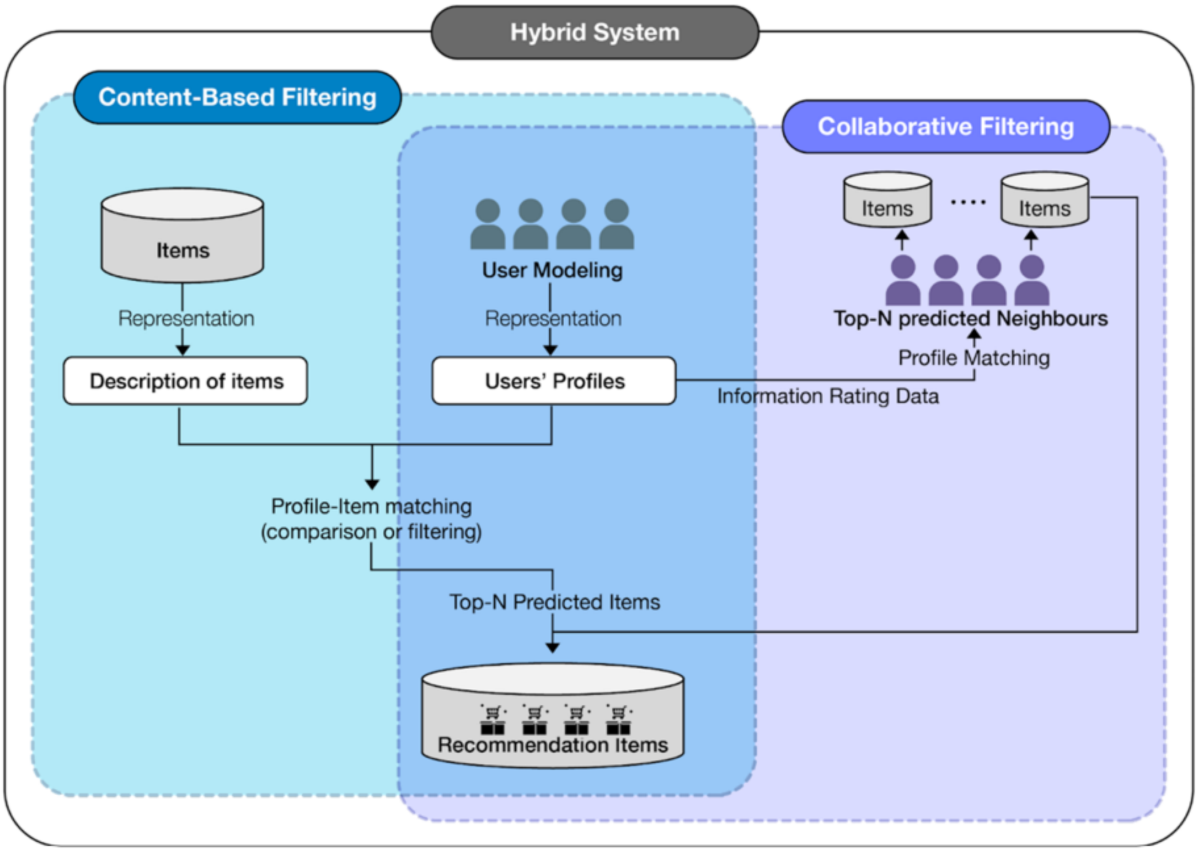


Figure 1 process of general recommendation system model[10].

With respect to empirical works, there are a couple of attempts that considered content and collaborative recommendations. Younus et al. [11] proposed a content-based image retrieval system using PSO and K-means, comparing it to existing methods. The system performed better than existing methods, based on histograms, co-occurrence matrix, color, and wavelet moments.

Facultyrurrozi et al.[12]developed a fruit query system using fuzzy-based feature extraction, color histogram, and K-means clustering. They tested their model on 1075 images, achieving 89.5% accuracy and 90% accuracy for single and multi-object fruits.

A road-based travel recommendation system is developed in [13]using geo-tagged images. The proposed approach recommends the most famous landmarks and travel routs. The proposed algorithm is implemented and tested with Flickr photos in Munich, Germany. Totally, 45,950 images were acquired via Flickr API (http://www.flickr.com/services/api/). And they filter out unnecessary images whose tags are not related to tourism Consequently, 31,335 geotagged images taken by 2422 users were finally chosen as the study data in this paper. the total test accuracies of these study were rather good (approximately 80%).

Farz. Jouyandeh, P. Zadeh et al. [14] developed an Image-based Personalized Advertisement Recommendation System using social media analysis. They evaluated the system using Flickr 8K dataset and Twitter API, finding that 74.166% of selected users were related to associated images with a score above 0.50.

The study by Gan et al. [15] developed StyleNet, a trainable framework for creating captions for photos and videos using the FlickrStyle10K dataset. The framework, which combines Deep Learning techniques and statistical methods, was favoured by over 80% of judges.

Karthikeyan and Aruna [16] developed a probabilistic text and image-based semi-supervised clustering approach using 2000 documents from five categories. Their method outperformed two existing algorithms and outperformed CBIR (content-based image retrieval) and signature-based approaches. They also compared their method to K-means and Dbscan.

3. Methods and Materials

The study employs quantitative experimental research, using unsupervised machine learning techniques like PCA-SVD for dimensionality reduction and K-means ++ for clustering and distance measures between top-K product image recommendations. This study uses data from Kaggle, an online community platform for data scientists and machine learning enthusiasts, to analyse product images. The dataset includes 44446 high-resolution images with ten attributes and two additional attributes. The images are 25 GB in size and include various product categories and 45 subcategories, including apparel, accessories, footwear, personal care, and sporting goods. As with the pre-processing data stage, seven thousand three hundred thirty-three 7333 images are sampled out using Random sampling technique.

The experiment involves training and testing anaconda python 3.12 on an Acer Swift 3 laptop with a 11th Gen Intel Core i7-1165G7 @2.80GHZ with 8.00GBRAM and 500 GB hard disk and Microsoft Windows 10 64-bit operating system. Data is collected and processed using Python libraries like NumPy, pandas, matplotlip, and scikit-learn. The initial step is to compute PCA singular values and compute the K-means++ clustering approach for the sampled dataset. The paper also calculates the cluster's inertia and distance measure using Manhattan distance measure. The experiment includes 45 subcategories of various product images.

The model is trained on training and testing images using feature engineering and machine learning techniques like Principal Component Analysis, SVD, similar distance measure, and Probabilistic PCA. The best recommendations are determined using distance from the origin to the database.

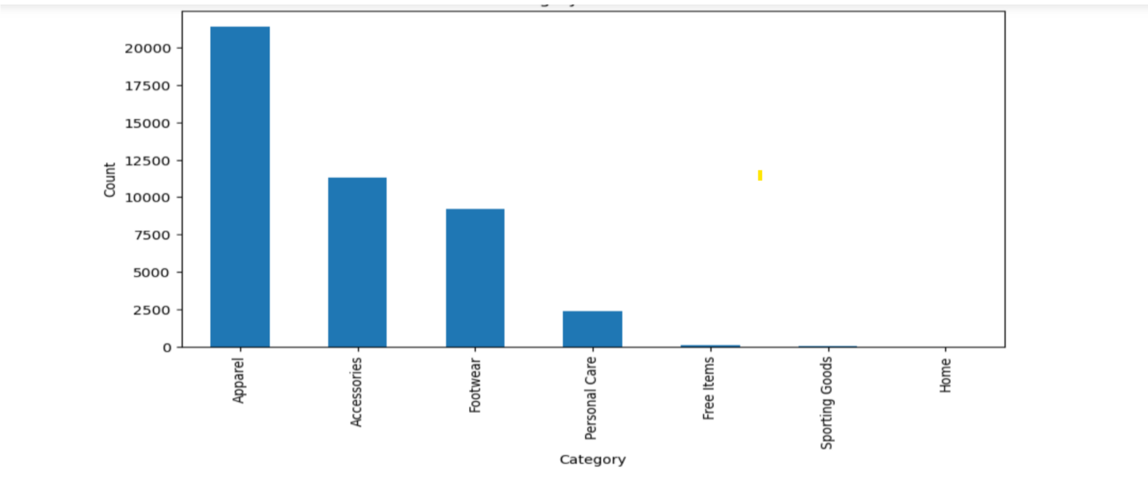


Figure 2 Major category distribution.

4. Dataset and Experimentation

Techniques like data cleaning, normalization, balancing, and numericalization are used to prepare data for analysis. These techniques are used to map symbolic and non-numerical values to numerical values, ensuring data is semi-prepared for analysis. Accordimg to this removing incorrect, incomplete, irrelevant, duplicated, or improperly formatted data. In this research, three irrelevant data values are dropped from a Data Frame with 12 attributes. machine learning algorithms to function properly, only numerical values are required as inputs or matrix values should be input values for machine learning algorithms. Therefore, the non-numeric features, such as ‘gender’, ‘masterCategory’, 'subCategory', 'articleType', 'baseColour', 'season', 'usage' and 'productDisplayName' features are converted into numeric values using a One-hot encoding scheme, which converts each category into a binary column and returns a sparse matrix or dense array. Once the dataset features are numerically analyzed, they have different values in different ranges/scales. In this case, the collected datasets failed to yield appropriate results, and the learning algorithm was unable to be effective. Therefore, a data normalization technique is applied to transform dataset features into a common range, so that larger numeric feature values do not dominate smaller numeric feature values. After all these processes we seat list of the configuration setup to be carried out for the experiments.

Table 1 *List of experimental settings to be conducted*

<table>
<tr><td rowspan="2">Number of experiments</td><td>Algorithm to be used</td><td>Data to be used</td><td>Method for finding optimal K value</td><td>Cluster distance measurement</td><td>Performance metrics to be used</td></tr>
<tr><td colspan="4">PCA_SVD to be computed first</td><td></td></tr>
<tr><td>Experiment 1</td><td>K-means ++</td><td rowspan="4">PSVD transformed image</td><td rowspan="4">Elbow with 8-16 Range of K value</td><td rowspan="4">Manhattan</td><td rowspan="4">SC index, CH index and DB index</td></tr>
<tr><td>Experiment 2</td><td>K Medoids</td></tr>
<tr><td>Experiment 3</td><td>DBSCAN</td></tr>
<tr><td>Experiment 4</td><td>Agglomerative Clustering</td></tr>
</table>

The experiment begins with applying the PSVD method for dimensionality reduction to identify determinant features and principal components. A 92% explained variance threshold is set, and PCA singular values are calculated on a sampled dataset and resulting in 2900 final principal components.in other word the PCA singular values were calculated using the PSVD process on a sampled dataset, resulting in 2900 final principal components after reducing the dimensionality to 92.01%. The elbow method determines the optimal K value for clustering algorithms by assigning a range of values to k, resulting in the optimal K value of 12. This process is followed by the four clustering algorithm using these optimal k values. By comparing data points based upon their similarity.

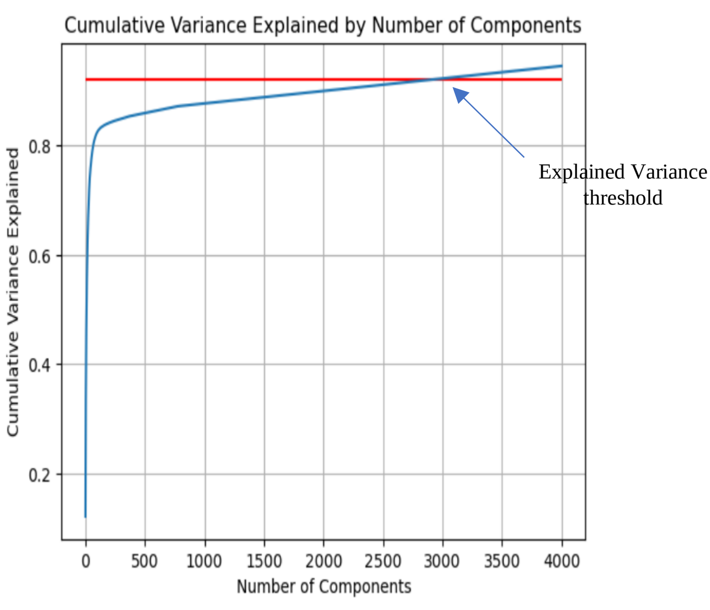


Figure 3 Cumulative Variance

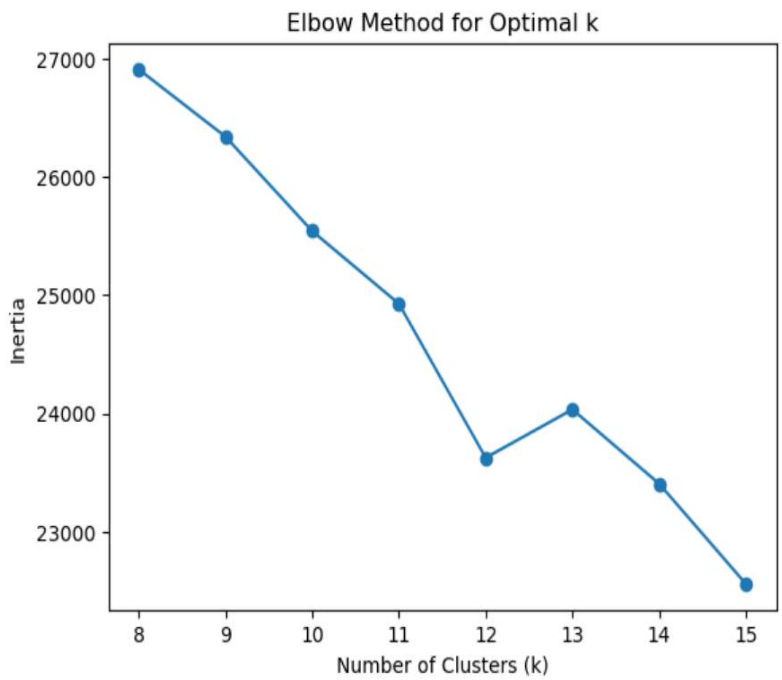


Figure 4 Elbow Method for finding optimal K value.

5. Result and Discussion

The experimental results show that using four types of clustering approaches on PSVD-transformed images of 2900 final principal components significantly reduces the size of the dataset. This research analyzed cluster performance metrics to improve recommendations for unsupervised learning techniques. Cluster performance metrics are crucial for evaluating the quality of clustering algorithms, as they help identify distinct similar clusters within a dataset. Cluster evaluation measures homogeneity and separation between groups using metrics like the Silhouette Score. It helps identify hidden patterns in data for optimization.

The experiment computed several cluster performance metrics, including the Silhouette coefficient (SC), Calinski-Harabaz Index (CH), and Davies-Bouldin Index (DB). The k-means++ clustering algorithm performed better than the other three, demonstrating better separation between clusters and shorter execution time. These metrics, along with the Calinski-Harabasz index and Silhouette coefficient, contribute to better clustering quality.

Table 2 *Performance comparison of clustering algorithms using PSVD transformed image.*

Type of Algorithm	Cluster performance metrics			Execution time in seconds.
	SC index	**CH index**	**DB index**	
K-means ++	0.1377	436.6845	2.2896	0.4104
DBSCAN	0.0893	292.3833	2.1351	159.6118
K medoid	-0.0253	8.8513	27.1432	1.9689
Agglomerative Clustering	0.1267	425.6170	2.3566	46.3894

This experiment uses Manhattan distance to measure distance between clusterd images in a grid or vector space. Top similar images are selected using K-means ++ clustering, and the absolute difference between coordinates is calculated. Based on Manhattan distance results, the top 5 similar images are recommended, providing a comprehensive overview of similarity analysis results.

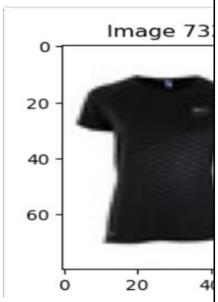
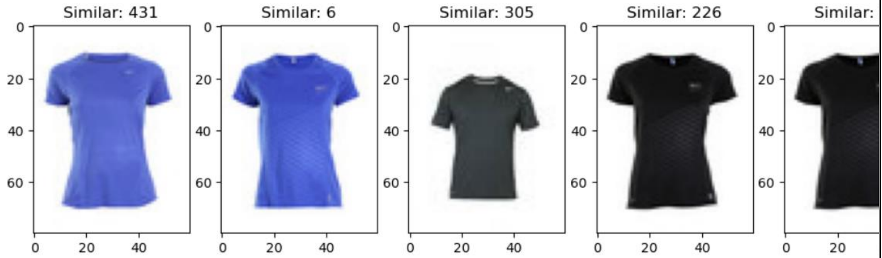
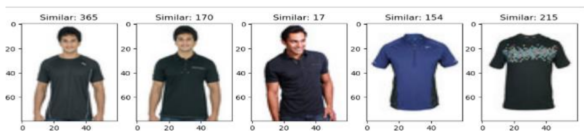
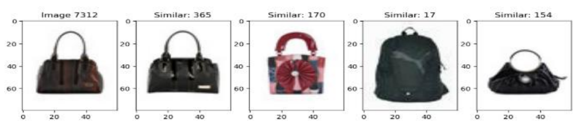
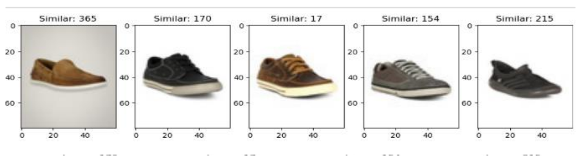
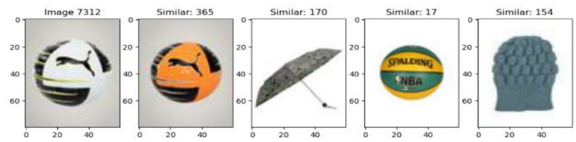
Input Image	Top 5 Recommended image
	
	

Figure 5 Final similar image recommended

The system's effectiveness should be thoroughly evaluated using various methods. A test case was used to verify the solution's workability. Clustering performance evaluation techniques were used to measure cluster separation and similarity. The system's precision and correctness were assessed using various test cases. MasterCatagory values were used as a test case to ensure accurate performance.

Table 3 *System Performance Evaluation*

Test case		Expected output	Actual output	Remark
master Category	Article Type			
Apparel	T-shirts	Top 5 similar T-shirts		Accurate performance "5/5"
Accessories	Handbags	Top 5 similar Handbags		Poor Performance "1/5"

Footwear	Casual Shoes	Top 5 similar Casual Shoes		Accurate Performance “5/5”
Sporting Goods	Basketballs	Top 5 similar Basketballs		Poor Performance “2/5”

This study investigates clustering algorithms to develop a product recommendation model for an e-commerce platform based on images. The goal is to provide users with knowledgeable product recommendations, aiding their decision-making process. Nine features were tested, with two being more determinate: master category and subcategory. Poor performance results are evaluated using masterCatagory values as a test case, ensuring accurate performance. It has been shown in other studies that their image-based recommendation system uses three features: texture, color, and shape[4], [17][18].The research identifies k-means++ clustering as the most suitable algorithm for accurately identifying similar images, as demonstrated in experiments comparing four methods. The k-means++ clustering method was used for recommending systems in [19], [20]and showed better performance.

6. Conclusion

The research aims to simplify searching for products on an e-commerce platform by suggesting similar images using Kaggle datasets, focusing on bringing the desired product to the customer. The experiment uses unsupervised machine learning to produce similar product images for e-commerce platforms. It uses 44446 images from Kaggle and uses K-means++ clustering algorithms. Anaconda Jupiter notebooks simulate experiments, and accuracy and execution time are calculated using clustering performance metrics. The study used PSVD dimensionality reduction on a product image dataset, achieving a 92.00% variance. The images were then clustered using K-means++. Compared to other clustering algorithms, PSVD-K-means++ scored well on similarity coefficients and CH scores, but lacked in DB index score. This suggests that similar image recommendation algorithms work well. The study identifies determinant features for optimizing item search in ecommerce systems, including gender, masterCategory, subcatagory, articleType, baseColour, season, year, and usage attributes. MasterCategory and subcategory are the most significant determinant variables. K-means ++ is found effective.

The results obtained from this experiment can be considered a very effective result. However, a lot of work can be done to improve performance of the proposed system. In order to improve the effectiveness of image-based recommenders, continuous experimentation and research are essential. For more accurate image feature extraction and training for similar image recommendations, it is suggested that using image data augmentation techniques and deep learning approaches (CNNs) is better

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