An efficient method for retrieving fashion images based on low-level and high-level features

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Abstract

This research focuses on improving the efficiency of fashion image retrieval by utilizing both low-level and high-level features. The main objectives are to reduce retrieval time and enhance retrieval accuracy. High-level features, specifically shape features, are extracted using the RESNET algorithm, while color features are obtained through the Dominant Color Histogram algorithm. To further reduce retrieval time, an indexing method is applied. Images are retrieved using the Dominant Color Histogram distance metric, ensuring both speed and accuracy in the retrieval process. The proposed approach demonstrates significant improvements in retrieval efficiency, making it highly suitable for large-scale fashion image databases.

Keywords: Dominant Color Histogram; similarity measurement, Deep learning, indexing method, low and high level features.

طريقة فعالة لاسترجاع صور الأزياء بناء على الميزات منخفضة وعالية المستوى.

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الملخص

تركز هذه الدراسة على تحسين كفاءة استرجاع صور الأزياء من خلال الاستفادة من كل من الميزات منخفضة المستوى والميزات عالية المستوى. تتمثل الأهداف الرئيسية في تقليل زمن الاسترجاع وتعزيز دقة الاسترجاع. تستخلص الميزات عالية المستوى، وبشكل خاص ميزات الشكل، باستخدام خوارزمية RESNET، في حين تستخرج ميزات اللون عبر خوارزمية مخطط اللون السائد (Dominant Color Histogram). ولتقليل زمن الاسترجاع بشكل أكبر، يتم تطبيق طريقة الفهرسة. تسترجع الصور باستخدام مقياس المسافة لمخطط اللون السائد، مما يضمن تحقيق كل من السرعة والدقة في عملية الاسترجاع. تظهر المنهجية المقترحة تحسينات كبيرة في كفاءة الاسترجاع، مما يجعلها مناسبة للغاية لقواعد بيانات صور الأزياء واسعة النطاق.

الكلمات المفتاحية: مخطط اللون السائد؛ قياس التشابه؛ التعلم العميق؛ طريقة الفهرسة؛ الميزات منخفضة وعالية المستوى.

Introduction

Large image collections, or image libraries, have emerged as a result of the quick expansion of digital images and the accessibility of enormous storage capacity [١]. These digital image archives have grown considerably over the Internet as transmission methods have advanced. However, consumers now face a significant difficulty in finding particular photographs among such vast collections. Digital image databases, which are typically organized around two core research concepts—indexing and retrieval—need to be managed and organized effectively in order to address this problem.

The processes used to search for photos and how they are kept in the database (or in other ways) are referred to as indexing. Retrieval, on the other hand, is the process of obtaining and presenting photos from the database that are pertinent to a specific query image [٢].

Images can be retrieved from digital libraries using two main methods [٢]: The first is text-based image retrieval (TBIR), in which a user queries the system with a text description. After analyzing the supplied text, the system returns the appropriate images. However, this approach has two major drawbacks. The first step is to annotate every image in the database, which is a laborious and time-consuming process.

Second, because various users may use different terms or phrases to describe the same image, the annotation process is frequently subjective and inconsistent. The second method is called content-based image retrieval (CBIR), where the user submits an image as the query and the system uses the database to find related images. The query image's visual contents, which are represented by a collection of extracted features like color, shape, and texture, are examined by the system. Descriptors are used to calculate these features. For instance, the Dominant Color Descriptor (DCD) is a frequently used descriptor for color-based feature extraction.

Using a similarity measure, the retrieval process finds and shows the database photos that are most similar to the query image. It is possible to evaluate similarity in two ways:

classification-based similarity, in which a Convolutional Neural Network (CNN) is used to assign a label to the query image that corresponds to one of many predetermined image categories.

distance-based similarity, in which the Euclidean distance—or the distance between the feature vectors of each database picture (DB) and the query image (Feature Vector, or FV)—is used to determine the degree of similarity.

The ١٩٩٠s saw the first appearance of CBIR systems. The QBIC system [٣], which retrieves photos based on their visual content, is among the first and most prominent instances. CBIR systems have been adopted in a variety of fields, including security, commercial, and medical applications, among others, due to their ease of use and the positive outcomes they provide.

In this work, we concentrate on CBIR systems in the fashion industry, which has emerged as a vibrant field of study [٤]. Opening and running virtual storefronts anywhere in the world is now feasible thanks to the COVID-١٩ epidemic, which has further pushed the worldwide trend toward online buying. However, because of things like the large number and variety of products, as well as linguistic and cultural barriers, consumers frequently struggle to choose appropriate fashion items while making purchases online. During the online buying process, CBIR technologies can help customers make better decisions and choose clothing items more efficiently [٥].

RELETED WORK

Distance-based similarity techniques and classification-based similarity approaches are the two basic categories into which research on content-based image retrieval (CBIR) systems in the fashion industry can be generally separated.

General feature extraction algorithms, like the Dominant Color Descriptor (DCH) or Color Histogram, are used in distance-based methods to extract visual qualities from fashion photos. Following the extraction of these features, the photos that are most similar to the query image are found and retrieved using a variety of distance metrics, such as the Manhattan and Euclidean distances.

On the other hand, classification-based techniques harvest and learn information from fashion photos using specialized algorithms like Convolutional Neural Networks (CNNs) [٩-١١]. More semantically relevant retrieval results are obtained with these methods, which first identify the category or class to which the query image belongs before retrieving photos that belong to the same class.

Accuracy and retrieval time are two important criteria that often affect CBIR system performance. The user experience can be adversely affected by delays in displaying results, which makes the time issue especially important in online applications. Large picture databases frequently yield slow results from sequential searches; consequently, a variety of indexing strategies have been developed to get around this restriction and increase retrieval performance.

Numerous noteworthy studies have investigated various indexing and feature extraction techniques:

The R-tree structure was used in Study [٦] to prevent consecutive searching, and the LEADER clustering technique was used to extract color features.

The R-tree* was used to speed up image retrieval in Study [٧], while the Mean Shift technique was used to extract color characteristics.

In Study [٨], researchers adopted a lattice structure to improve retrieval performance and utilized the General Lloyd algorithm to collect color characteristics.

Wavelet Transformation, K-means clustering, and a B+-tree were utilized in Study [٩] to extract features and cut down on search time.

Some researchers suggested innovative indexing techniques to further enhance retrieval performance. Two effective indexing techniques were presented in one study:

The RGB color space is necessary for the Dominant Color-Based Indexing Method for Quick Content-Based Image Retrieval.

The Luv color space is used in the Content-Based Image Retrieval Using Uniform Color Space.

Both techniques, which are based on the final five bits of each pixel, work well across major color descriptors. A three-level matrix makes up their internal structure, with the final three bits represented at the first level, the fourth and third bits represented at the second and third levels, and a B+ tree structuring the fourth level.

In order to improve faster picture retrieval, Study [١٠] used the Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) descriptors to extract image features. A Support Vector Machine (SVM) was then used for classification.

The Radix Trie (RT) approach was used to increase efficiency even more.

Proposed method

In this paper, we propose an improved method for retrieving fashion images based on shape and color features. This proposed method is characterized by high accuracy and speed in retrieving fashion images. The proposed method consists of five main sequential operations:

Shape feature extraction

color feature extraction & Distance measure

Connect the shape feature and the color feature.

Indexing method

Shape feature extraction

By defining the shape of the article of clothing, a category is identified from the dataset of photos to which the query image belongs. In this paper, we developed a model based on convolutional neural networks to identify the shape of an article of clothing. The following make up the model:

- Data download.
- Data scaling.

- Data split.
- Improving and training the ResNet (Residual Neural Network.

Data download

The process of downloading data is the first step in training the model, as it was obtained from the Kaggle website [١٣]. The dataset includes a total of ٣٠,١٤٤ clothing images, divided into seven categories. Here are the categories of the dataset:

•Dresses (٦,٢٣٦) images

•Jackets Coats (١,٨٩٥) images

•Pants (١,٨٠٤) images

•Shorts (٣,٤٨٦) images

•Skirts (٢,٠٤٢) images

•Sweaters (٣,٠٣٦) images

•Shirt (١١,٦٤٢) images

The size of each image in the dataset is (٢٥٦×٢٥٦×٣) pixels in JPEG format.

Data Sizing

The uploaded dataset is ready for direct use without any pre-processing. Only the size of the images is changed from (٢٥٦ x ٢٥٦ x ٣) to (٢٢٤ x ٢٢٤ x ٣) in order to fit the size required by the RESNET model used.

Data Splitting

The researcher divided the original dataset into two parts:

•Training dataset: It is the data through which the model is trained, as the images and the category to which each image belongs are passed to the model. Data percentage amount (٨٠٪).

•Testing dataset: It is the data that is passed to the model without specifying the category to which it belongs in order for the model to recognize it and to know the extent of the model's performance in determining the images of the piece of clothing. Data percentage amount (٢٠٪).

Improving and training the RESNET model.

The RESNET model is considered one of the ready-made models that can be used, with the last layer changing according to the data set used. represents the general structure of the RESNET model.

The values that are set and given to the model in order to train the data entered into the model differ from one model to another. Here are the values that are set and given to the form:

Epoch: means the number of times to train and test the model; in this research, it was assigned a value of ٦٤, meaning that the model will be trained on the training data set and tested on the test data set ٦٤ times.

Patch size is set to ٦٤. The larger the batch size, the more memory space is used for training .

The learning rate was set at ٠,٠١٪ for the neural network.

When the value adjustment process was completed without any modifications to RESNET [١٤], the model was trained on the training and test data sets .

The researcher faced a problem called over fitting. This problem is common in deep learning models and can be defined as "the large difference in both the value of the loss function and the accuracy of the model between the training data and the test data. That is, the value of the loss function in the model is small and the accuracy of the model is high on the training data, while the value of the loss function is large and the accuracy of the model is small on the test data. In order to overcome this problem, data augmentation and dropout technology were added to the RESNET model. The following is an explanation of these additions that the researcher included in order to improve the performance of the model:

١. Data augmentation is the process of artificially increasing the size of data using transformation methods on images of clothing. The purpose of data augmentation is to reduce the problem of model over fitting[١٥]. In this paper, the following methods were used:

•Rotation: rotation of the image

•Height shift range: Shift the image horizontally.

•shear: crop the image.

•Zoom range: Zoom in on the image.

•horizontal flip: flip the image horizontally.

•Fill mode=nearest: Fill in the blank spaces in the image and make them equal to the nearest pixel.

٢. Dropout: It is a technique used to reduce the problem of over fitting by randomly deleting the artificial cells (neurons) along with the cell links of the RESNET neural network in each iteration during the training process in each of the layers. The form is as shown in Figure ٣-٣. The value of the deletion ratio is passed to the model [١٦].

Dominant Color Histogram (DCH)

present in an image. Instead of using all pixel colors, DCH reduces the color space to a limited number of **dominant colors** KKK, usually between ٣–٨, which significantly simplifies image comparison and retrieval. This technique is widely used in **Content-Based Image Retrieval (CBIR)** systems to compare images based on color similarity [١٧].

Convert the input image into a suitable color space, such as RGB, HSV, or LUV, denoted as:

I={p١,p٢,...,pN},pi∈R٣

Where pip_ipi is the color vector of the iii-th pixel, and NNN is the total number of pixels.

Clustering Colors:

Group the pixels into KKK clusters representing the **dominant colors** using clustering algorithms such as **K-Means**, **Mean Shift**, or **Octree Quantization**. The cluster centers CkC_kCk represent the dominant colors:

Ck=١|Sk|∑pi∈Skpi,k=١,...,KC_k = \frac{١}{|S_k|} \sum_{p_i \in S_k} p_i, \quad k=١,...,KCk=|Sk|١pi∈Sk∑pi,k=١,...,K

Where SkS_kSk is the set of pixels belonging to cluster kkk, and |Sk||S_k||Sk| is the number of pixels in that cluster [١٧].

Histogram Construction:

Compute the **frequency or proportion** of each dominant color:

H(Ck)=|Sk|N,k=١,...,KH(C_k) = \frac{|S_k|}{N}, \quad k=١,...,KH(Ck)=N|Sk| ,k=١,...,K

Here, H(Ck)H(C_k)H(Ck) is the normalized value representing the fraction of the image occupied by dominant color CkC_kCk.

Histogram Representation:

The histogram HHH is a vector containing the dominant colors and their relative weights:

H=[(C١,H(C١)),(C٢,H(C٢)),...,(CK,H(CK))]H = [(C_١, H(C_١)), (C_٢, H(C_٢)), ..., (C_K, H(C_K))]H=[(C١,H(C١)),(C٢,H(C٢)),...,(CK,H(CK))]

Similarity Measurement Between Images:

Given two images with dominant color histograms HAH_AHA and HBH_BHB, similarity can be computed using various metrics:

Histogram Intersection:

DI(HA,HB)=∑k=١Kmin(H(CkA),H(CkB))D_{I}(H_A, H_B) = \sum_{k=١}^{K} \min(H(C_k^A), H(C_k^B))DI(HA,HB)=k=١∑Kmin(H(CkA),H(CkB))

Indexing method

To overcome the issue of sequential searching in large image databases, which often results in slow retrieval, an indexing method called Dominant Color-Based Indexing Method (DCBIM) was proposed by Abdul Amir [٢] for the RGB color space. This method works by reducing the search space or constructing a new search space containing images similar to the query image. Instead of searching the entire database, only a subset of relevant images is examined, which significantly accelerates the retrieval of clothing images. DCBIM is compatible with all major color descriptors.

The method relies on the last five bits of each dominant color. For each dominant color, the last five bits of the three channels (R, G, B) are extracted and converted into three dimensions using the “Extract_Index_Dimensions” algorithm:

First dimension: represents the last three bits of each color channel, with values ranging from ٠ to ٥١٢.

Second dimension: represents the fourth bit, with values from ٠ to ٨.

Third dimension: represents the third bit, also ranging from ٠ to ٨.

The overall structure of the method is organized as a fixed-size four-level matrix:

First level: corresponds to the first dimension.

Second level: corresponds to the second dimension.

Third level: corresponds to the third dimension.

Fourth level: serves to exclude images that are not similar based on the percentages of the indexed dominant colors. Images showing large differences in dominant color percentages are removed from the search space.

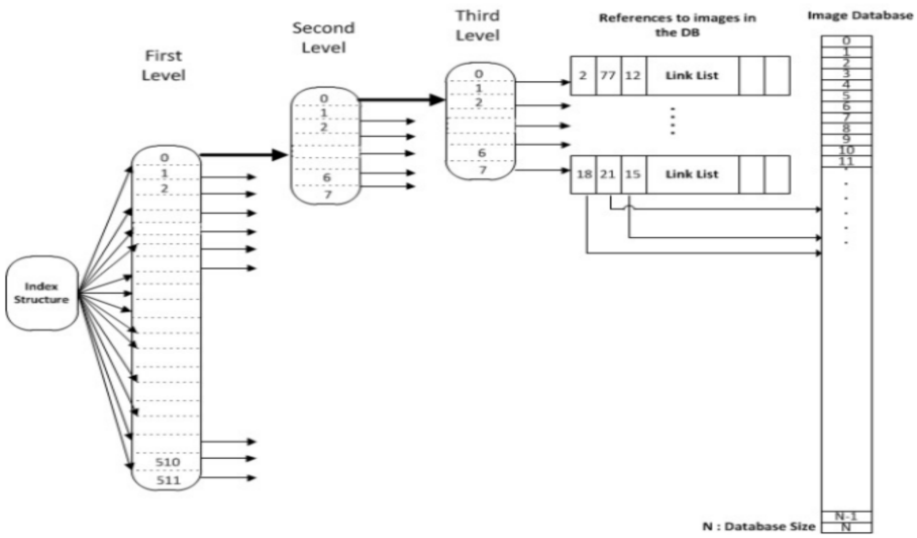
The fourth level is implemented using a B+-tree consisting of four nodes with predefined percentage limits:

Node ١: ٠–٠,٢٥

Node ٢: ٠,٢٥–٠,٥

Node ٣: ٠,٥–٠,٧٥

Node ٤: ٠,٧٥–١,٠٠



DCBIM method

Additionally, the method incorporates a tolerance mechanism for the indexed colors in the second and third dimensions. Colors are considered similar within a limited range (٠–٨–٢٤), which ensures that images resembling the query image are included in the new search space, further improving retrieval accuracy and efficiency.

Experiment results

We examine the performance outcomes of the suggested system in this section. We'll evaluate the outcomes of each of the following:

- performance of the RESNET
- Performance of the indexing method.
- Performance of similarity measure.

Every procedure listed above has a unique performance evaluation statistic. Additionally, ١٠ samples will be selected at random from each dataset group. Additionally, random samples from each step are distinct from one another .

Sect. ٣,١ mentions the dataset that was used to assess the RESNET model's performance. Three categories from the same dataset—skirts, shorts, and coats—

were used to assess how well the indexing approach and the dissimilarity metric performed.

Performance results of the RESNET

We will utilize the accuracy and loss function (Categorical Cross Entropy) metric to assess the RESNET model's performance [١٢]. may be acquired using the equation that follows.

$$\textbf{Accuracy} = \frac{True_{positive}+True_{negative}}{\text{True}_{positive}+True_{negative}+\text{False}_{positive}+False_{negative}} \quad (٥)$$

$$loss = -\sum_{i=1}^{N} y_i \log(\hat{y_i}) \quad (٦)$$

We trained RESNET directly on the dataset. The results showed that the model suf-fers from an over fitting problem. This problem is explained in Section ٣،١. Here are the results of the model:

- Model results on training data

.٠٧٦٣٠ Accuracy

٠,٣٣٧٣ Loss function

- Model results on testing data

٠,٥٢٧٠ Accuracy

٣,٤٥٥٣ Loss function

After adding dropout and data augmentation technology to RESNET , the results showed a significant improvement as follows:

- Model results on training data

٠,٩٢٢ Accuracy

٠,٣٣ Loss function

- Model results on testing data

٠,٩٣٣٥ Accuracy

٠.٢٣٦ Loss function

Performance results of the indexing method

To measure the performance of the indexing method, we use two types of metrics: accuracy metrics and efficiency metrics.

Efficiency measures: The goal of the indexing method is to reduce the retrieval time of fashion images. The method used in this paper reduces retrieval time by reducing the search space. In other words, instead of searching the entire database, a group of images is searched in the database. The smaller the search area, the less time is required to retrieve images. In addition, we calculate the time it takes for the indexing method to reduce the search space. Accordingly, we will use two measures. The first measure is a measure called the search space ratio (SSR) [٢] can be obtained according to following equation.

SSR=Reduced Search Space(RSS) /Whole Search Space (WSS) (٧)

The second measure is time, using the unit millisecond.

accuracy metrics: We use two metrics to measure the accuracy of the new search space: recall and precision. Recall is a measure of the system's ability to present all similar images as shown in equation (٩). The precision measure indicates the system's ability to provide only similar images, can be obtained according to following equation [٢].

Precision=(number of relevant image retrieved)/(total number of images retrieved from the database) (٨)

Recall=(number of relevant image retrieved)/(total number of relevant images in the database) (٩)

Table ٢. Result of indexing method.

Time_DC	Time	SSR	Recall	Precision	Classes
١٥١,٤	٤	٤٥٪	٠,٣٣٣	٠,٣٧	Shorts
٧٩,٦	٣	٣٠٪	٠,٤٣	٠,٤٢	Skirts
٦٤	٤	٢٠٪	١٠,٦	٠,٢٢	Jackets Coats
٩٨,٣	٣,٦٧	٣١,٦٪	٠,٦٢	٠,٢٣٧	Average

Table ٢ includes the results of the indexing method, which represents the results of the categories of shorts, skirts, and Jackets Coats. Based on standards of accuracy and efficiency The results show that the indexing method reduces the time required compared to a sequential search by ٣١٪.Based on accuracy measures (precision and recall), about half of the resulting area is similar to the query image.

Performance results dissimilarity measure

The image retrieval process (displaying the images most similar to the query images to the user), represented by the distance measure, is considered the most important process. In this section, we evaluate the performance of the dissimilarity measure in retrieving similar images using accuracy measures, precision, and recall. The results are shown in the table.

The system has also been fully tested. In addition to evaluating the difference measure, the accuracy of a model-based RESNET in determining the shape of a piece of clothing is calculated, and the effect of the indexing method on the speed of retrieving fashion images compared to a sequential search is calculated.

Table (٣). includes the results of the proposed method with a comprehensive search on the following categories: shorts, skirt, coat. The results showed that the model achieved average results in all categories (١٠٠/١٠٠). The indexing method achieved good results in reducing the time taken to retrieve images by an average percentage of (٢٧٪). The results were also more accurate. The proposed method is more accurate and less time-consuming

Table ٣. Result of proposed method.

Time	Recall	Precision	Classification _accuracy	Method
Shorts				
٥٠	٠,٥	٠,٧٥	١٠٠/١٠٠	Proposed Method
١٧٦	٠,٥	٠,٧٤	١٠٠/١٠٠	DCH
Skirts				
٣٠	٠,٤٨	٠,٧	١٠٠/١٠٠	Proposed Method
٨٦,٢	٠,٤٥	٠,٦٨	١٠٠/١٠٠	DCH
Jackets Coats				
٢٥	٠,٦٦	٠,٨	١٠٠/١٠٠	Proposed Method
٧١	٠,٦٦	٠,٨	١٠٠/١٠٠	DCH

Conclusion

In this paper, we suggest a better approach that uses local color features and shape features to retrieve fashion images in CBIR systems. The model's performance was enhanced and the issue of overfitting was lessened by incorporating the dropout and data augmentation techniques. Additionally, using indexing technology instead of a thorough search improved accuracy and decreased the amount of time needed to retrieve fashion images. Additionally, the dissimilarity measure was successful in retrieving pictures of colorful clothing for this paper.

References

[١] Attig, J., Ann, C., Michael, P.: Context and meaning: The challenges of metadata for a digital image library within the university. College & Research Libraries, vol. ٦٥, no. ٣, pp. ٢٥١-٢٦١, ٢٠٠٤.

[٢] AHMED, T. A., COLOUR-BASED IMAGE RETRIEVAL ALGORITHMS BASED ON COMPACT COLOUR DESCRIPTORS AND DOMINANT COLOUR BASED INDEXING METHODS, UNIVERSITI UTARA MALAYSIA, ٢٠١٤.

[٣] Ahmed, T., et al.: Dominant Color-Based Indexing Method for Fast Content-Based Image Retrieval. In Recent Advances in Information and Communication Technology: Proceedings of the ١٠th International Conference on Computing and Information Technology (IC٢IT٢٠١٤) (pp. ١٣٥-١٤٤). Springer International Publishing.

[٤] Niblack, C., Wayne, et al.: QBIC project: querying images by content, using color, texture, and shape, Storage and retrieval for image and video databases, ١٩٩٣.

[٥] D. Latha and Y. Jacob Vetha Raj.: Different Types of CBIR Applications, International Journal for Research in Engineering Application & Management (IJREAM), ٢٠١٩.

[٦] Gupta, M., Bhatnagar, C., & Jalal, A. S. (٢٠١٨).: Clothing image retrieval based on multiple features for smarter shopping. Procedia Computer Science, ١٢٥, ١٤٣-١٤٨.

[٧] Nasita, I., Muchtar, K., Saddami, K., & Arnia, F.: Cross-domain clothing image retrieval based on hybrid shape feature. In ٢٠١٩ IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom) (pp. ٩٨-١٠٢). IEEE. ٢٠١٩), August).

[٨] Mustaffa, M. R., Wai, G. S., Abdullah, L. N., & Nasharuddin, N. A.: Dress me up! content-based clothing image retrieval. In Proceedings of the ٣rd International Conference on Cryptography, Security and Privacy (pp. ٢٠٦-٢١٠).٢٠١٩) , January).

[٩] Mutia, C., & Akmal, M.: Content Based Image Retrieval Busana Muslimah Menggunakan Fitur Kombinasi PHOG dan DCH. (JurTI) Jurnal Teknologi Informasi, ٥(١), ٧٠-٧٦.٢٠٢١)).

[١٠] Liu, Z., Luo, P., Qiu, S., Wang, X., & Tang, X.: Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. ١٠٩٦-١١٠٤).٢٠١٦)).

[١١] Ding, Y., & Wong, W. K.: Fashion outfit style retrieval based on hashing method. In Artificial Intelligence on Fashion and Textiles: Proceedings of the Artificial Intelligence

on Fashion and Textiles (AIFT) Conference ٢٠١٨, Hong Kong, July ٣–٦, ٢٠١٨ (pp. ١٨٧- ١٩٥). Springer International Publishing.٢٠١٩) **).**

[١٢] Liu, A. A., Zhang, T., Song, D., Li, W., & Zhou, M.: FRSFN: A semantic fusion network for practical fashion retrieval. Multimedia Tools and Applications, ٨٠, ١٧١٦٩- ١٧١٨١.٢٠٢١) **).**

[١٣] Xiaochun Xu. Kaggle. [Online]. https://www.kaggle.com/datasets/xxc٠٢٥/fashiondataset

[١٤] Simonyan, K., & Zisserman, A.: Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:١٤٠٩,١٥٥٦.٢٠١٤) **).**

[١٥] Taylor, L., & Nitschke, GImproving.: deep learning with generic data augmentation. In ٢٠١٨ IEEE symposium series on computational intelligence (SSCI) (pp. ١٥٤٢-١٥٤٧). IEEE.٢٠١٨) **, November).**

[١٦] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R.: Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, ١٥(١), ١٩٢٩-١٩٥٨.٢٠١٤) **).**

[١٧] Rejito, J., Setiana, D., & Rosadi, R. (٢٠١٧). Image indexing using color histogram and k-means clustering for optimization CBIR. Int J Comput Appl Technol Res, ٦(٨), ٤٠٥-٤٠٩.