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An intelligent deep learning based product image recommendation and classification system

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***Abstract*---**Recently, recommendation system (RS) has gained significant attention in several industries and business sectors. At the same time, image recommendation is also found helpful to determine the relevant objects that exist in the form of image. It is mainly based on the extraction of different features and utilize it to get recommended outcomes. The recently developed deep learning (DL) models can be applied to design effective product image recommendation and classification systems. In this aspect, this paper designs an intelligent deep learning enabled product image recommendation and classification (IDL-PIRC) system. The proposed IDL-PIRC technique aims to examine the input image to recommend and classify products based on the user query. In addition, the proposed IDL-PIRC technique involves Gaussian filtering (GF) based pre-processing to eradicate the existence of noise exist in it. Moreover, the fusion-based feature extraction technique uses the Grey-Level Run Length Matrix (GLRLM) and Residual Network (ResNet152) models. Furthermore, the kNN based ranking approach is employed for product recommendation and cascaded neural network (CNN) is utilized for product classification. A wide range of simulations take place and the results are inspected interms of different evaluation parameters. The experimental results showcased that the IDL-PIRC technique is found to be a proficient tool for product image recommendation and classification.

***Keywords*---**Image classification, Recommendation system, Product recommendation, Deep learning, Fusion model, Machine learning

1. Introduction

In recent times, the adaption of e-commerce has brought many satisfactions to the consumer and led to high profitability for the merchants [1]. Also, it positively

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impacted the economy of countries around the work by enhancing Gross Domestic Product (GDP). For the first time in history, The PricewaterhouseCoopers (PwC) in South Africa have stated that user online retail shopping sales exceeded a trillion Rand (South Africa currency) that is improved to 1.46 trillion Rand in 2016 [2]. Moreover, similar sources stated that because of the global rise in e-commerce, the collective GDP of Africa continent is anticipated for increasing by US $1trillion in 2020, i.e., US$1.6 trillion by 2010.

E-commerce plays a significant part in global economic growth and it is necessary to keep satisfying customers could not be over emphasized [3]. But, large amount of e-commerce data in the past few years became a severe problem to the customers, due to the inherent difficulties in data finding. This leads to the advent of recommendation system to support a user in the data found [4]. The source of recommendation system could be traced to method in approximation theory, information retrieval, management science, and cognitive science that is employed in different human endeavours [5].

In the field of e-commerce applications, several principles and methods were employed for implementing recommendation systems that classification method has been recognized as significant components [6]. Product classification includes the relationship of class with correlated products in huge amount of merchants, which is the major processing task of content-based recommendation system. Besides user profiling [7], classification method has been considered to be advantageous in various recommendation applications like product taxonomy browsing, increase scalability, product image retrieval, and enhanced whole recommendation performance [8].

Seo and Shin [9] projected to employ Hierarchical Convolution Neural Network (H ___CNN) on apparel classification. This work was contributed to employing hierarchical classification of apparel with CNN and is importance from the presented method which is a knowledge embedded classifier outputting hierarchical data. Yu et al. [10] present the aesthetic data that is very appropriate with user preferences, into clothing recommender system. To attain this, they initially propose aesthetic features extracted by a pretrained NN, i.e., a brain-inspired deep structure trained for the aesthetic evaluation process.

Chen et al. [11] described a recommendation by emphasizing certain areas of an image. For learning the attention mechanism, they present user review data as weaker supervision signals to gather further detailed user preferences. In this method, the textual and visual features are coupled seamlessly by a multi-modal attention mechanism. Moreira et al. [12] proposed one of the winning solutions for the Recommendation method of the SIGIR 2021 Workshop on E-commerce Data Challenge. These solutions were stimulated by NLP methods and contain an ensemble of 2 Transformer frameworks - XLNet and -Transformer-XL trained with autoencoding and autoregressive methods.

Li et al. [13] designed a retrieval system and hierarchical commodity classification. A class decision layer is employed for determining the class of commodity images and later accurately retrieving the respective class of commodity image features. Haihan et al. [14], constructed a shopping recommendation mechanism-based DL method. The shopping recommendation and user data crawling models are designed primarily. Initially, we get significant product data and user review data from Jingdong Mall through python crawler and construct a user data crawling model. Next, a shopping recommendation model was built according to the DL method, integrated with recommendation system.

Guan et al. [15] designed multi-view models, such as, Deep Multi-view Information iNtEgration (Deep-MINE), various sources of contents (viz., review texts, product images, and descriptions) are considered and develop an end-to-end recommendation algorithm. In that way, SAE network is positioned to map Multiview data into a unified latent space, cognition layers are included to represent consumer heterogeneous cognition models and an incorporation model is presented for reflecting the interactions of Multiview latent depictions.

This paper designs an intelligent deep learning enabled product image recommendation and classification (IDL-PIRC) system. The proposed IDL-PIRC technique to aims to examine the input image to recommend and classify products based on the user query. In addition, the proposed IDL-PIRC technique involves Gaussian filtering (GF) based pre-processing to eradicate the existence of noise exist in it. Moreover, the fusion-based feature extraction technique uses the Grey-Level Run Length Matrix (GLRLM) and Residual Network (ResNet152) models. Furthermore, the kNN based ranking approach is employed for product recommendation and cascaded neural network (CNN) is utilized for product classification. A wide range of simulations take place and the results are inspected interms of different evaluation parameters.

2. The Proposed Model

In this study, a novel IDL-PIRC technique has been developed for effective product image recommendation and classification. The proposed IDL-PIRC technique encompasses GF based pre-processing, fusion based feature extraction, kNN ranking based recommendation, and CNN based classification. Fig. 1 illustrates the overall working process of proposed IDL-PIRC model. The detailed working of these processes is discussed in the succeeding sections.

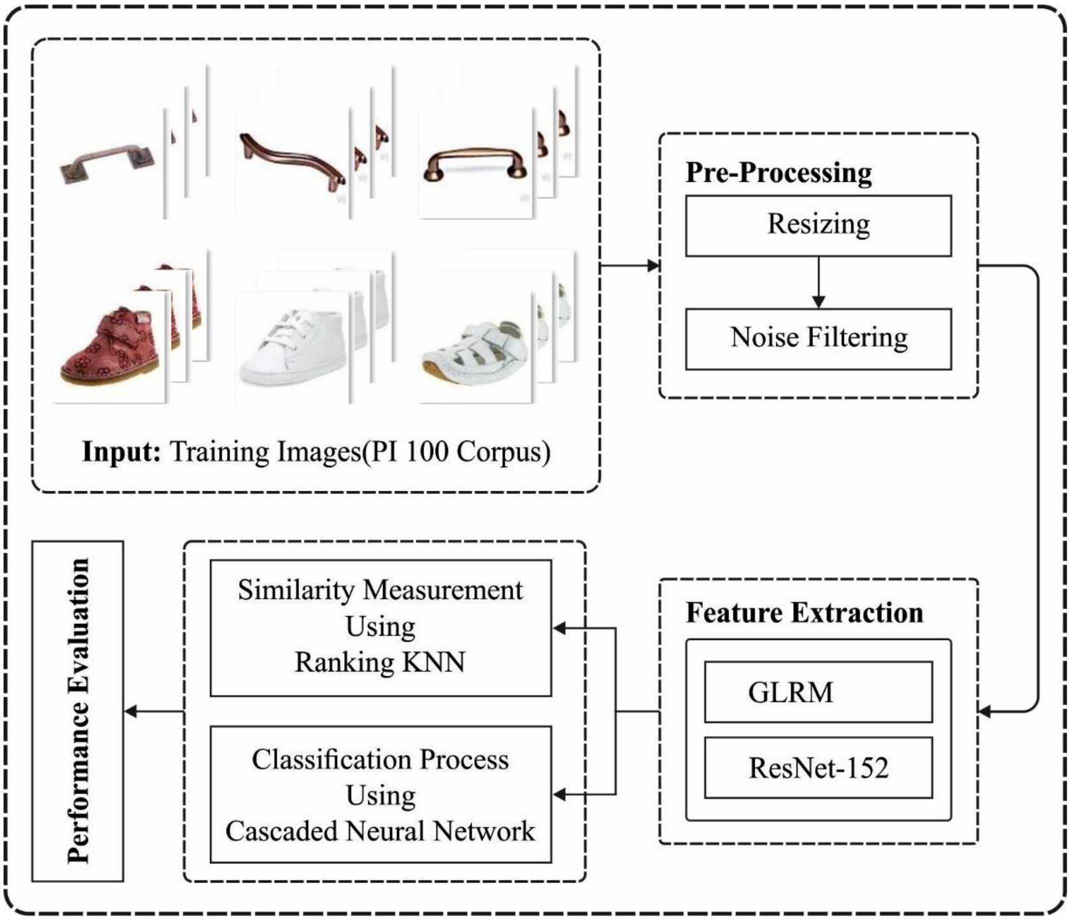

Fig. 1. Overall process of IDL-PIRC model

2.1. Image Pre-processing

A lot of researches like medicine, astronomy, geography, etc, have been prominently employed in digital image processing. This model requires efficient real-time results. The execution of two-dimensional Gaussian filters is widely used with the aim of noise removal and smoothing [16]. The traditional operator is Gaussian and the process of Gaussian smoothing is achieved by convolution. The Gaussian operator in 1D can be formulated by:

$$G_{1D}(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{x^2}{2\sigma^2}\right)}. \tag{1}$$

An efficient smoothing filter for an image is fitted in several spatial and frequency domains, in which it fulfills the uncertain relationships as follows:

$$\Delta x \Delta \omega \geq \frac{1}{2}. \tag{2}$$

The Gaussian operator in *two dimensional* (circularly symmetric) is described by:

$$G_{2D}(x,y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}, \tag{3}$$

whereas σ (Sigma) denotes the SD of Gaussian function. The maximal value has been attained by high smoothing effects. (x, y) indicates the Cartesian coordinate of an image which characterizes the window dimension. These filters are made up of multiplication and summation operations amongst a kernel and image, where the image is positioned in a matrix form within 0 to 255 (8 bits). The kernel ensures standardization of the square matrix (among zero & one). After that, the kernel is represented as a number of bits.

2.2. Feature Extraction using Fusion Model

During feature extraction process, the features from the pre-processed product images are extracted.

2.2.1. GLRM Features

In GLRLM, the dimensions of homogeneous run to graylevels. It is determined with texture indices and directions achieved from the matrixes such as a long run, short run, run-length non-uniformity, graylevel non-uniformity, lower graylevel run, run ratio, short run high graylevel, Long run high graylevel short run low graylevel, higher graylevel run, and long run low graylevel. The (a, b) modules of GLRLM equivalents homogeneous run of b pixel with intensity a from images like GLRLM(a, b). Consider the GLRM matrix with features as determined before. The directions and features are attained from each image [17].
While Q a denotes a gray level, $(\mathrm{a, b})$illustrates a GLRM matrix, S depicts sum of whole values in GLRM matrix, and b indicates run length.

$$Short\ run = \sum_a \sum_b (\,Q(a, b)/b^2)/S \tag{4}$$

$$Long\ run = \sum_a \sum_b 0^2\, Q(a, b)\,)\ /S \tag{5}$$

$$Graylevel\ non\text{-}\ uniformity = \sum_a, \left(\sum_b Q\,(a, b) \right)^2 /S \tag{6}$$

$$Run\ length\ non\text{-}\ uniformity = \sum_b, \left(\sum_a Q\,(a, b) \right)^2 /S \tag{7}$$

$$Run\ ratio = \sum_a \sum_b S\ /bQ(a, b) \tag{8}$$

$$Low\ gray\ level\ run = \sum_a \sum_b Q\,(a, b)/Sa^2 \tag{9}$$

$$High\ gray\ level\ run = \sum_a \sum_b a^2\, Q(a, b)/S \tag{10}$$

$$Short\ run\ low\ gray\ level = \sum_a \sum_b Q\,(a, b)/Sb^2 a^2 \tag{11}$$

$$Short\ run\ high\ gray\ level = \sum_a \sum_b a^2\, Q(a, b)/Sb^2 \tag{12}$$

$$Long\ run\ low\ gray\ level = \sum_a \sum_b b^2\, Q(a,b)/Sa^2 \tag{13}$$

2.2.2. ResNet152

ResNet presented as a family of many DNN methods with analogous structures but distinct depths. ResNet presents a framework named residual learning unit to mitigate the degradation of DNN. This unit structure is an FFNN with a shortcut connection that adds novel inputs into the networks and generates novel output. The major advantage of this unit is that it generates improved classification performance without expanding the difficulty of the method. They choose ResNet152 since it attains the optimal accuracy amongst ResNet family members [18].

2.2.3. Fusion based Feature Extraction

The fusion of features plays an important role in the image classification method which intends to incorporate at worst 2 feature vectors. Currently, the feature is combined based on the entropy. As mentioned in the previous section, LBP and ResNet 152 comprised in the fusion process are given in the following.

$$f_{R_{1\times n}} = \{R_{1\times 1}, R_{1\times 2}, R_{1\times 3}, \cdots, R_{1\times n}\} \tag{14}$$

$$f_{G_{1\times m}} = \{G_{1\times 1}, G_{1\times 2}, \cdots, G_{1\times m}\} \tag{15}$$

Moreover, extracted feature is combined in a single vector.

$$Fused(feature\ vector)_{1\times q} = \sum_{i=1}^{2} \{fR_{1\times n}, fG_{1\times m}\} \tag{16}$$

Let f be a fused vector.

2.3. k-NN Ranking based Recommendation

At this stage, the recommendation of products takes place using the fused features. The k-NN technique is utilized as easy ranking technique. In that drive, regard the feature spaces $\mathbb{R}^p$ and represents with $d_2(f,g) = \|f-g\|_2$ the Euclidean distance of 2 feature vectors. Assume that $\{f_1, \dots, f_m\}$ is trained group of feature vectors. The k- NN technique then resolves few regression/classification tasks at $f \in \mathbb{R}^p$ utilizing the k neighboring trained features. It can be executed by primary computing an enumeration $\pi(f): \{1,2,\dots,m\} \to \{1,2,\dots,m\}$ satisfying $d_2(f, f_{\pi(f)(i)}) \leq d_2(f, f_{\pi(f)(i+1)})$. It utilized the permutation $\pi(f)$ as ranking outcome to the input feature f. For reducing memory requirement of k-NN ranking [19], it can be utilized an execution which utilizes a balltree search.

2.4. CNN based Product Classification

At last, the CNN model is utilized to classify e-commerce products into different categories. In FFNN connection i.e., created among input and output is indirect relation whereas, perceptron connection created among input and output is a kind of direct relationship. The association is non-linear in shape over activation function from the hidden layer. When the linking formed on perceptron and multi-layer networks are fused, later the network with direct connections among the input and output layers are created, as well the indirect connection. The network created from these connection patterns is named CNN. The equation is created from the CNN method is expressed by:

$$y=\sum_{i=1}^{n} f^{i}\,\omega_{i}^{i} x_{i}+f^{o}\left(\sum_{j=1}^{k} \omega_{j}^{o}\, f_{j}^{h}\left(\sum_{i=1}^{n} \omega_{ji}^{h}\, x_{i}\right)\right) \tag{17}$$

In which f denotes the activation function from the input-output layers and ω_i^i indicates weight from the input-output layers [20]. When a bias is included in the input layer and the activation function of all the neurons from the hidden layer are f^h then becomes

$$y=\sum_{i=1}^{n} f^{i}\,\omega_{i}^{i} x_{i}+f^{o}\left(\omega^{b}+\sum_{j=1}^{k} \omega_{j}^{o}\, f^{h}\left(\omega_{j}^{b}+\sum_{i=1}^{n} \omega_{ji}^{h}\, x_{i}\right)\right) \tag{18}$$

In this work, the CFNN method is employed in time series information. By this means, the neuron in the input layer is the lags of time series information $X_{t-1}, X_{t-2}, \ldots, X_{t-p}$, where the output is the present information X_t.

3. Experimental Validation

The experimental validation of the IDL-PIRC technique takes place against a dataset, comprising 10000 low-resolution color images of e-commerce products, which falls into 100 class labels. Fig. 2 depicts the sample set of images chosen from the ten class labels of the PI100 dataset [21]. The class labels include hiking backpack, nutrition, cowboy-hat, helmet, baby shoe, jacket, earring, flower, can, and briefcase.

Fig. 2. Sample Images

Fig. 3 illustrates the confusion matrix offered by the IDL-PIRC technique on the applied dataset under test run-1. The figure depicted that the IDL-PIRC technique has categorized 18 images into Baby shoe, 19 images into Jacket, 18 images into

Nutrition, 17 images into Cowboy Hat, 19 images into Earing, 19 images into Flower, 19 images into Can, 20 images into Helmet, 19 images into Hiking Backpack, and 19 images into Brief case.

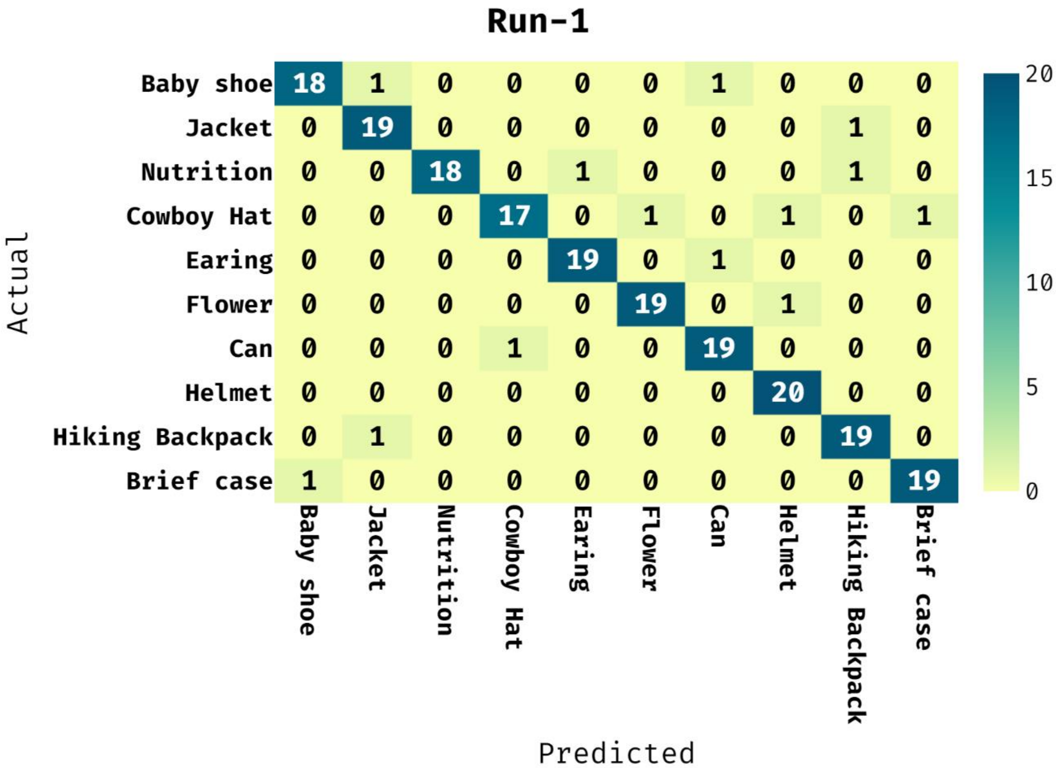

Fig. 3. Confusion matrix analysis of IDL-PIRC model under run-1

The classification results analysis of the IDL-PIRC technique is examined under test run-1 in Table 1 and Fig. 4. The results show that the IDL-PIRC technique has attained improved classification performance on distinct class labels. For instance, with baby shoe class, the IDL-PIRC technique has reached to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 0.9474, 0.9000, 0.9850, 0.9231, and 0.9151 respectively. In addition, with Flower class, the IDL-PIRC approach has attained to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 0.9500, 0.9500, 0.9900, 0.9500, and 0.9444 respectively. Similarly, with helmet class, the IDL-PIRC system has gained to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 0.9091, 1.0000, 0.9900, 0.9524, and 0.9482 respectively.

Table 1 Result analysis of IDL-PIRC model with distinct measures under run-1

Methods	Precision	Recall	Accuracy	F-Score	MCC	Kappa
Baby shoe	0.9474	0.9000	0.9850	0.9231	0.9151	-
Jacket	0.9048	0.9500	0.9850	0.9268	0.9188	-
Nutrition	1.0000	0.9000	0.9900	0.9474	0.9435	-
Cowboy Hat	0.9444	0.8500	0.9800	0.8947	0.8852	-
Earing	0.9500	0.9500	0.9900	0.9500	0.9444	-

Flower	0.9500	0.9500	0.9900	0.9500	0.9444	-
Can	0.9048	0.9500	0.9850	0.9268	0.9188	-
Helmet	0.9091	1.0000	0.9900	0.9524	0.9482	-
Hiking Backpack	0.9048	0.9500	0.9850	0.9268	0.9188	-
Brief case	0.9500	0.9500	0.9900	0.9500	0.9444	-
Average	**0.9365**	**0.9350**	**0.9870**	**0.9348**	**0.9282**	**0.9278**

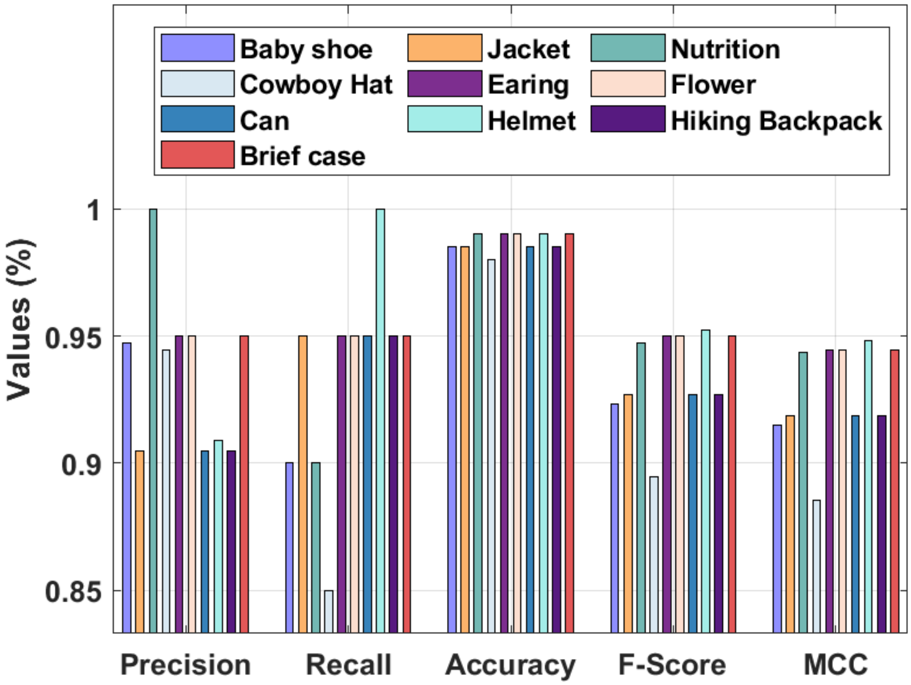

Fig. 4. Result analysis of IDL-PIRC model under run-1

Fig. 5 depicts the ROC analysis of the IDL-PIRC technique under test run-1. The results portrayed that the IDL-PIRC technique has resulted in an increased ROC of 99.8717%.

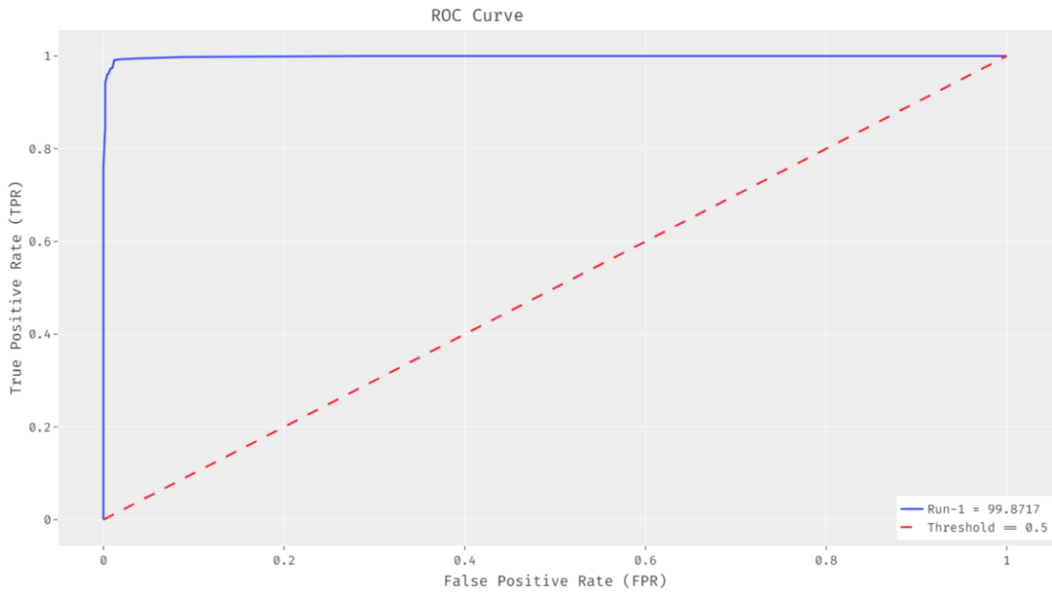

Fig. 5. ROC analysis IDL-PIRC model under run-1

Fig. 6 depicts the confusion matrix presented by the IDL-PIRC system on the applied dataset under test run-2. The figure demonstrated that the IDL-PIRC approach has categorized 19 images into Baby shoe, 19 images into Jacket, 18 images into Nutrition, 18 images into Cowboy Hat, 19 images into Earing, 19 images into Flower, 19 images into Can, 20 images into Helmet, 19 images into Hiking Backpack, and 19 images into Brief case.

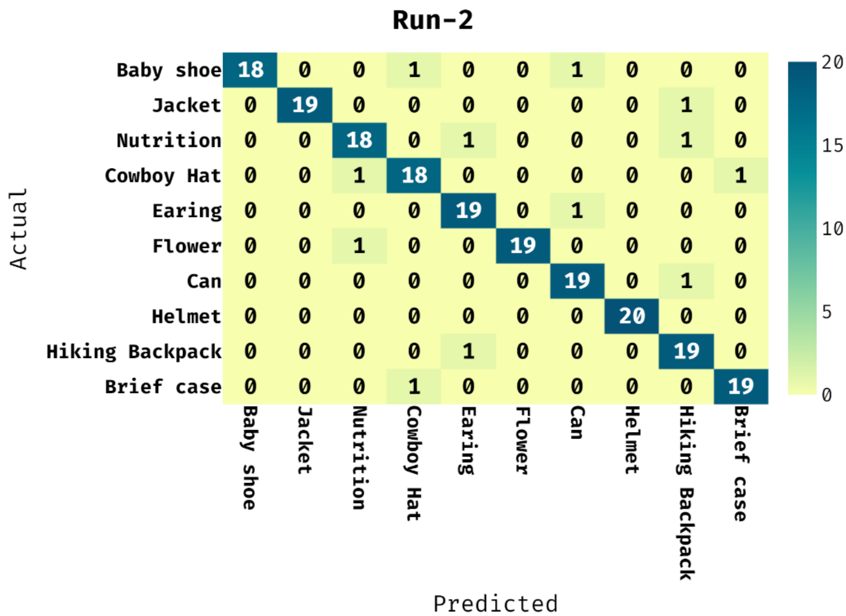

Fig. 6. Confusion matrix analysis of IDL-PIRC model under run-2

The classification outcomes analysis of the IDL-PIRC system is examined under test run-2 in Table 2 and Fig. 7. The outcomes exhibited that the IDL-PIRC technique has attained enhanced classification performance on different class labels.

Table 2 Result analysis of IDL-PIRC model with distinct measures under run-2

Methods	Precision	Recall	Accuracy	F-Score	MCC	Kappa
Baby shoe	1.0000	0.9000	0.9900	0.9474	0.9435	-
Jacket	1.0000	0.9500	0.9950	0.9744	0.9720	-
Nutrition	0.9000	0.9000	0.9800	0.9000	0.8889	-
Cowboy Hat	0.9000	0.9000	0.9800	0.9000	0.8889	-
Earing	0.9048	0.9500	0.9850	0.9268	0.9188	-
Flower	1.0000	0.9500	0.9950	0.9744	0.9720	-
Can	0.9048	0.9500	0.9850	0.9268	0.9188	-
Helmet	1.0000	1.0000	1.0000	1.0000	1.0000	-
Hiking Backpack	0.8636	0.9500	0.9800	0.9048	0.8949	-
Brief case	0.9500	0.9500	0.9900	0.9500	0.9444	-
Average	0.9423	0.9400	0.9880	0.9405	0.9342	0.9333

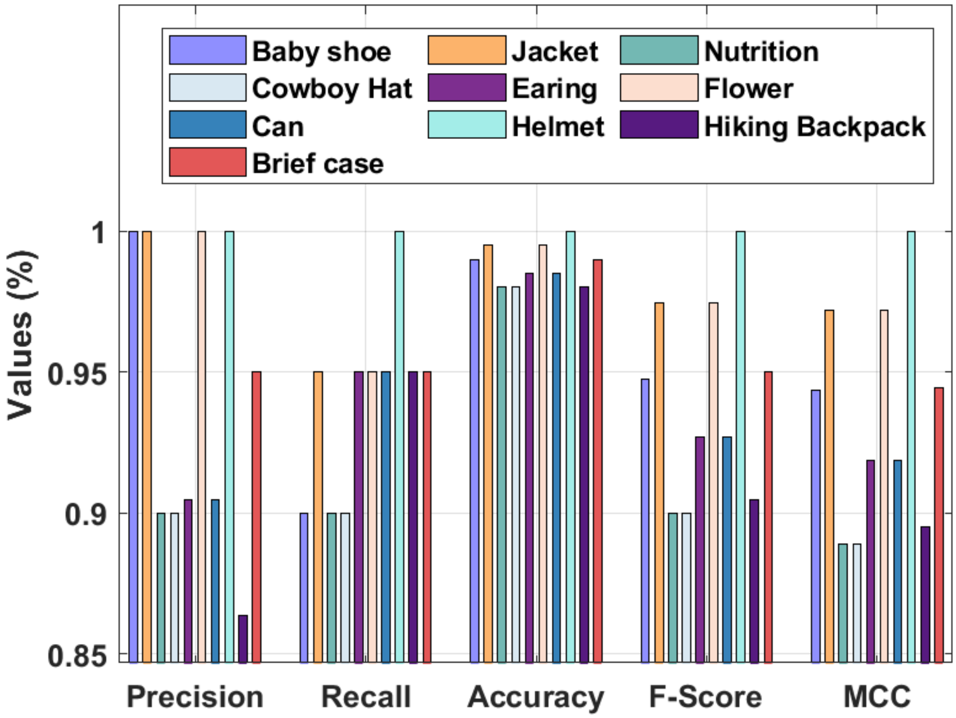

Fig. 7. Result analysis of IDL-PIRC model under run-2

For instance, with baby shoe class, the IDL-PIRC methodology has achieved to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 1.0000, 0.9000, 0.9900, 0.9474, and 0.9435 correspondingly. Besides, with Flower class, the IDL-PIRC algorithm has reached to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 1.0000, 0.9500, 0.9850, 0.9268, and 0.9188 respectively. Besides, with helmet class, the IDL-PIRC manner has achieved to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 1.0000, 1.0000, 1.0000, 1.0000, and 1.0000 correspondingly.

Fig. 8 showcases the ROC analysis of the IDL-PIRC approach under test run-2. The outcomes outperformed that the IDL-PIRC technique has resulted in a higher ROC of 99.7605%.

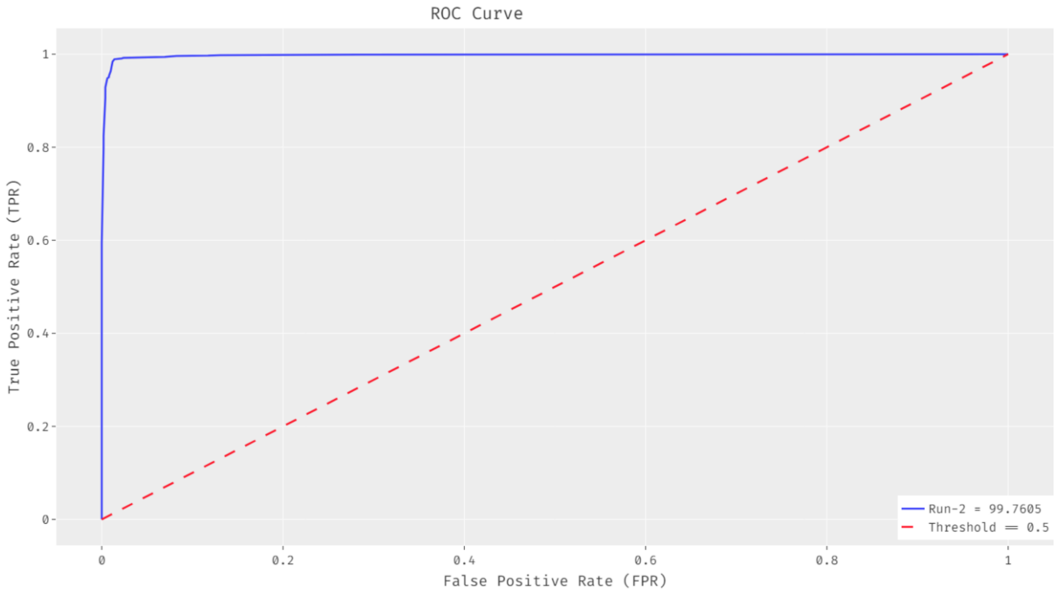

Fig. 8. ROC analysis IDL-PIRC model under run-2

Fig. 9 portrays the confusion matrix offered by the IDL-PIRC approach on the applied dataset under test run-3. The figure depicted that the IDL-PIRC system has categorized 19 images into Baby shoe, 19 images into Jacket, 19 images into Nutrition, 18 images into Cowboy Hat, 19 images into Earing, 19 images into Flower, 19 images into Can, 20 images into Helmet, 20 images into Hiking Backpack, and 19 images into Brief case.

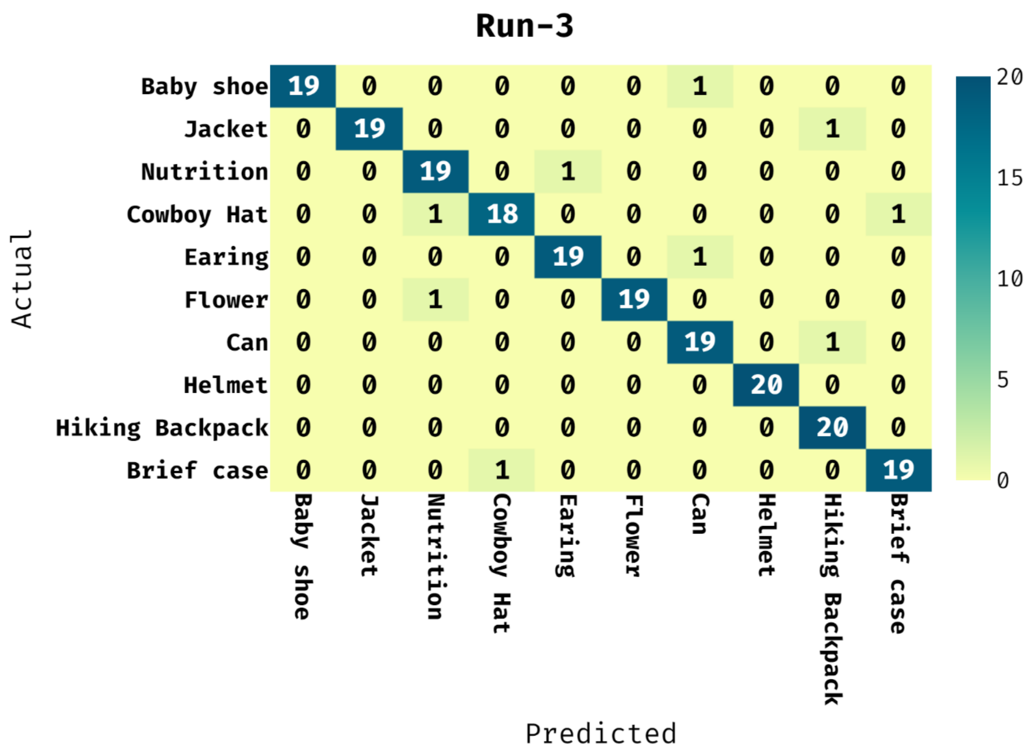

Fig. 9. Confusion matrix analysis of IDL-PIRC model under run-3

The classification outcomes analysis of the IDL-PIRC algorithm is examined under test run-3 in Table 3 and Fig. 10. The results show that the IDL-PIRC manner has gained improved classification performance on distinct class labels. For instance, with baby shoe class, the IDL-PIRC method has achieved to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 1.0000, 0.9500, 0.9950, 0.9744, and 0.9720 correspondingly. Likewise, with Flower class, the IDL-PIRC technique has obtained to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 1.0000, 0.9500, 0.9950, 0.9744, and 0.9720 correspondingly. Finally, with helmet class, the IDL-PIRC methodology has gained to $prec_n$, rec_l, acc_y, F_{score}, and MCC of 1.0000, 1.0000, 1.0000, 1.0000, and 1.0000 correspondingly.

Table 3 Result analysis of IDL-PIRC model with distinct measures under run-3

Methods	Precision	Recall	Accuracy	F-Score	MCC	Kappa
Baby shoe	1.0000	0.9500	0.9950	0.9744	0.9720	-
Jacket	1.0000	0.9500	0.9950	0.9744	0.9720	-
Nutrition	0.9048	0.9500	0.9850	0.9268	0.9188	-
Cowboy Hat	0.9474	0.9000	0.9850	0.9231	0.9151	-
Earing	0.9500	0.9500	0.9900	0.9500	0.9444	-
Flower	1.0000	0.9500	0.9950	0.9744	0.9720	-
Can	0.9048	0.9500	0.9850	0.9268	0.9188	-

Helmet	1.0000	1.0000	1.0000	1.0000	1.0000	-
Hiking Backpack	0.9091	1.0000	0.9900	0.9524	0.9482	-
Brief case	0.9500	0.9500	0.9900	0.9500	0.9444	-
Average	**0.9566**	**0.9550**	**0.9910**	**0.9552**	**0.9506**	**0.9500**

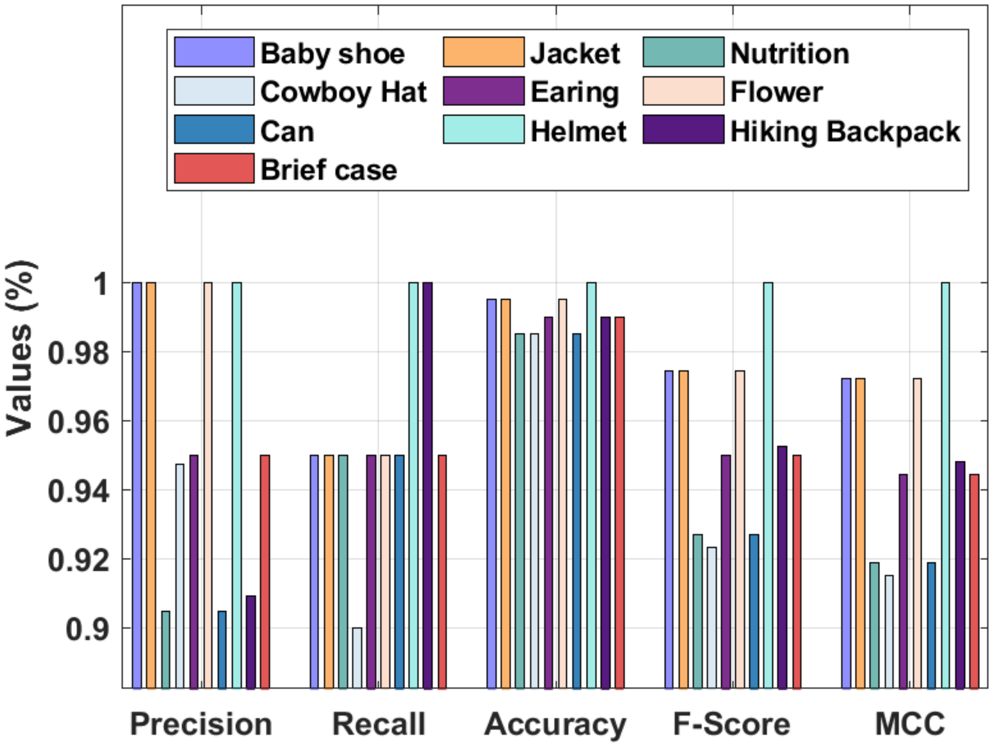

Fig. 10. Result analysis of IDL-PIRC model under run-3

Fig. 11 demonstrates the ROC analysis of the IDL-PIRC methodology under test run-3. The outcomes showcased that the IDL-PIRC algorithm has resulted in an improved ROC of 99.9815%.

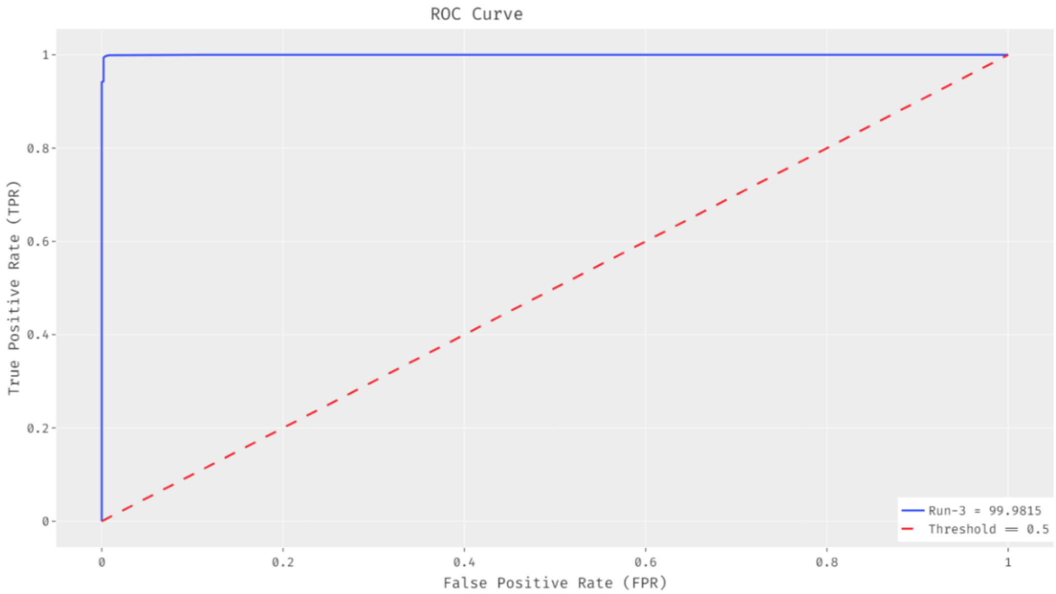

Fig. 11. ROC analysis IDL-PIRC model under run-3

Table 4 and Fig. 12 offer the overall classification results analysis of the IDL-PIRC technique. On the test run-1, the IDL-PIRC technique has gained $prec_n$, rec_l, acc_y, F_{score}, MCC, and kappa of 0.9365, 0.9350, 0.9870, 0.9348, 0.9282, and 0.9278 respectively. Simultaneously, on the test run-2, the IDL-PIRC manner has reached $prec_n$, rec_l, acc_y, F_{score}, MCC, and kappa of 0.9423, 0.9400, 0.9880, 0.9405, 0.9342, and 0.9330 correspondingly. Concurrently, on the test run-3, the IDL-PIRC algorithm has attained $prec_n$, rec_l, acc_y, F_{score}, MCC, and kappa of 0.9566, 0.9550, 0.9910, 0.9552, 0.9506, and 0.9500 correspondingly.

Table 4 Comparative analysis of IDL-PIRC model under 3 runs

Measures	Run-1	Run-2	Run-3	Average
Precision	0.9365	0.9423	0.9566	**0.9451**
Recall	0.9350	0.9400	0.9550	**0.9433**
Accuracy	0.9870	0.9880	0.9910	**0.9887**
F-Score	0.9348	0.9405	0.9552	**0.9435**
MCC	0.9282	0.9342	0.9506	**0.9377**
Kappa	0.9278	0.9330	0.9500	**0.9369**

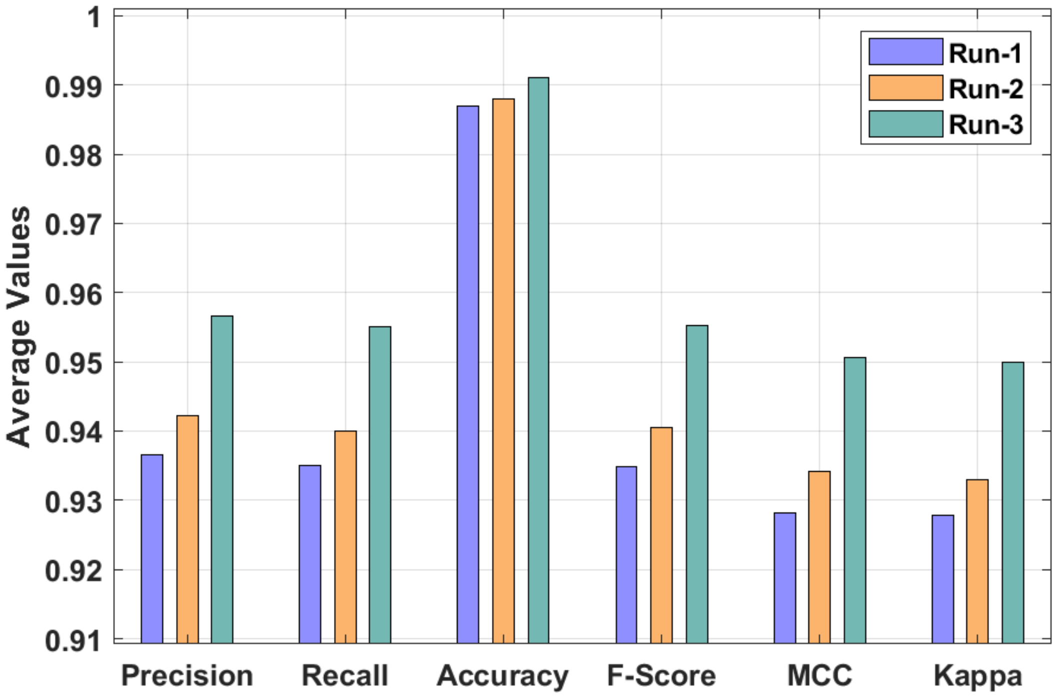

Fig. 12. Comparative analysis of IDL-PIRC model under 3 runs

Finally, a brief comparative accuracy analysis of the IDL-PIRC technique takes place with recent methods in Table 5 and Fig. 13 [22]. The figure portrayed that the SVM-ANN Single/cULBP-ECF and SVM-ANN Ensemble/cHOG-ECF techniques have resulted to lower accuracy of 51% and 52.11% respectively. Followed by, the other methods obtained moderately closer accuracy values. However, the proposed IDL-PIRC technique has resulted in a higher accuracy of 98.87%. Therefore, the proposed IDL-PIRC technique can be utilized as an effective technique over the recent approaches.

Table 5 Accuracy of Proposed with Existing Methods

S. No	Methods	Accuracy
1	Proposed Method	98.87
2	DCNN-CBFM	89.00
3	MLP-ANN Single /cHOG-ECF	83.20
4	MLP-ANN Ensemble /cHOG-ECF	87.20
5	MLP-ANN Single/cULBP-ECF	67.10
6	MLP-ANN Ensemble/cHOG-ECF	76.14
7	SVM-ANN Single /cHOG-ECF	83.50
8	SVM-ANN Ensemble /cHOG-ECF	84.00
9	SVM-ANN Single/cULBP-ECF	51.00
10	SVM-ANN Ensemble/cHOG-ECF	52.11

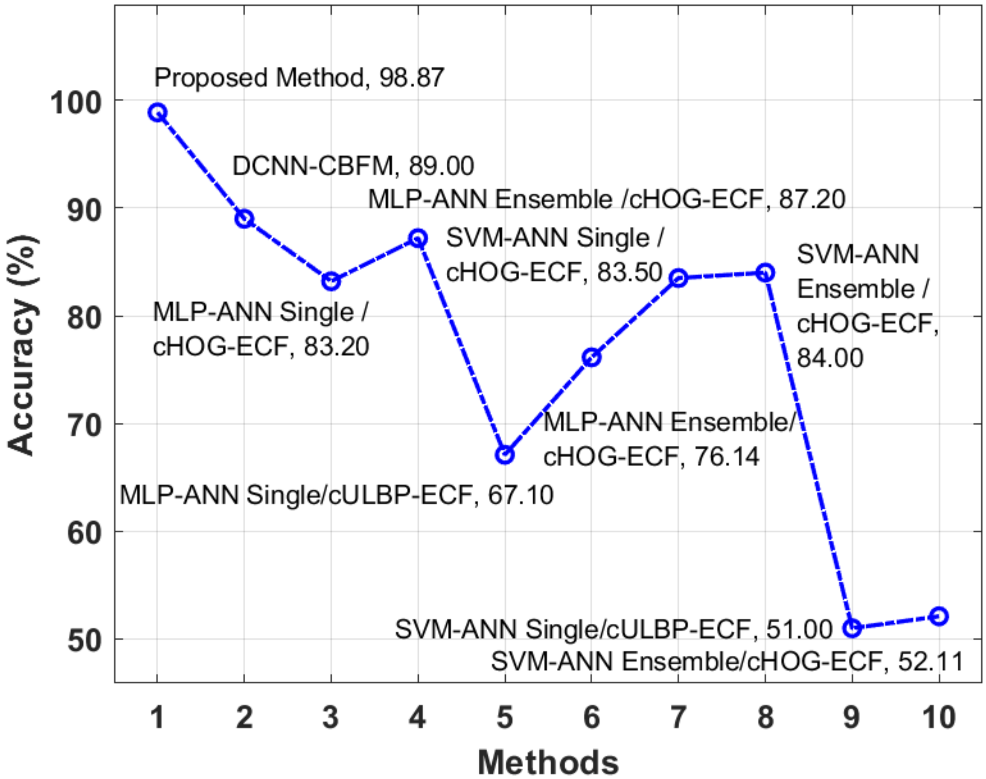

Fig. 13. Accuracy analysis of IDL-PIRC model with existing approaches

4. Conclusion

In this study, a novel IDL-PIRC technique has been developed for effective product image recommendation and classification. The proposed IDL-PIRC technique encompasses GF based pre-processing, fusion based feature extraction, kNN ranking based recommendation, and CNN based classification. The kNN based ranking approach is employed for product recommendation and CNN is utilized for product classification. A wide range of simulations take place and the results are inspected interms of different evaluation parameters. The experimental results showcased that the IDL-PIRC technique is found to be a proficient tool for product image recommendation and classification. Therefore, the proposed IDL-PIRC technique can be utilized as an effective approach for product recommendation and classification.

References

[1] Baier D, Daniel I, Frost S, Naundorf R. Image data analysis and classification in marketing. Adv Data Anal Classif 2012;6:253–76.

[2] Zhou D, Hu B, Wang Q, Hu B, Jia L, Wu Y., et al. Design of shopping guide system with image retrieval based on mobile platform. In: 2nd international symposium on computer, communication, control and automation (3CA). Atlantis Press; 2013.

[3] Bhattacharya S, Das R. Facilitating consumer satisfaction by content based product classification, ICBPEM, proceedings of international conference at national institute of technology, Rourkela, Springer; 2014.

[4] Olmo FHd, Gaudioso E. Evaluation of recommender systems: a new approach. Expert Syst Appl 2008;35(3):790–804.

[5] Olugbara OO, Ojo SO, Mphahlele MI. Exploiting image content in location based shopping recommender systems for mobile users. Int J Inform Technol Decis Making 2010;9:759–78.

[6] Han Y, Choi SM. A content recommendation system based on category correlations. Fifth international multi-conference on computing in the global information technology; 2010. p. 66–70.

[7] Ma Z, Pant G, Sheng ORL. Interest-based personalised search. ACM Trans Inform Syst (TOIS) 2007;25(1):1–38.

[8] Vailaya A, Figueiredo MAT, Jain AK, Zhang H-J. Image classification for content-based indexing. IEEE Trans Image Process 2001;10(1):117–30.

[9] Seo, Y. and Shin, K.S., 2019. Hierarchical convolutional neural networks for fashion image classification. Expert Systems with Applications, 116, pp.328-339.

[10] Yu, W., Zhang, H., He, X., Chen, X., Xiong, L. and Qin, Z., 2018, April. Aesthetic-based clothing recommendation. In Proceedings of the 2018 world wide web conference (pp. 649-658).

[11] Chen, X., Chen, H., Xu, H., Zhang, Y., Cao, Y., Qin, Z. and Zha, H., 2019, July. Personalized fashion recommendation with visual explanations based on multimodal attention network: Towards visually explainable recommendation. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 765-774).

[12] Moreira, G.D.S.P., Rabhi, S., Ak, R., Kabir, M.Y. and Oldridge, E., 2021. Transformers with multi-modal features and post-fusion context for e-commerce session-based recommendation. arXiv preprint arXiv:2107.05124.

[13] Li, B., Li, J. and Ou, X., 2021. Hybrid recommendation algorithm of cross-border e-commerce items based on artificial intelligence and multiview collaborative fusion. Neural Computing and Applications, pp.1-10.

[14] Haihan, L., Guanglei, Q., Nana, H. and Xinri, D., 2021, April. Shopping Recommendation System Design Based On Deep Learning. In 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP) (pp. 998-1001). IEEE.

[15] Guan, Y., Wei, Q. and Chen, G., 2019. Deep learning based personalized recommendation with multi-view information integration. Decision Support Systems, 118, pp.58-69.

[16] Nandan, D., Kanungo, J. and Mahajan, A., 2018. An error-efficient Gaussian filter for image processing by using the expanded operand decomposition logarithm multiplication. *Journal of ambient intelligence and humanized computing*, pp.1-8.

[17] Masino, A.J. and Folweiler, K.A., 2018. Unsupervised learning with GLRM feature selection reveals novel traumatic brain injury phenotypes. *arXiv preprint arXiv:1812.00030*.

[18] Xu, X., Li, W. and Duan, Q., 2021. Transfer learning and SE-ResNet152 networks-based for small-scale unbalanced fish species identification. *Computers and Electronics in Agriculture*, *180*, p.105878.

[19] Herliah, A., Baso, Y. S., Hidayanty, H., Syarif, S., Aminuddin, A., & Bahar, B. (2022). Effect of web-based she smart education models on adolescent girl's knowledge, attitudes, and practice about obesity. International Journal of Health & Medical Sciences, 5(1), 50-55. https://doi.org/10.21744/ijhms.v5n1.1832

[20] Tuinhof, H., Pirker, C. and Haltmeier, M., 2018, September. Image-based fashion product recommendation with deep learning. In *International Conference on Machine Learning, Optimization, and Data Science* (pp. 472-481). Springer, Cham.

[21] Rinartha, K., & Suryasa, W. (2017). Comparative study for better result on query suggestion of article searching with MySQL pattern matching and Jaccard similarity. In 2017 5th International Conference on Cyber and IT Service Management (CITSM) (pp. 1-4). IEEE.

[22] Warsito, B., Santoso, R. and Yasin, H., 2018, May. Cascade forward neural network for time series prediction. In *Journal of Physics: Conference Series* (Vol. 1025, No. 1, p. 012097). IOP Publishing.

[23] https://www.sciencedirect.com/science/article/pii/S1110866517303225

[24] Oyewole, S.A. and Olugbara, O.O., 2018. Product image classification using Eigen Colour feature with ensemble machine learning. *Egyptian Informatics Journal*, *19*(2), pp.83-100.