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RESEARCH ARTICLE

Empowering Retail Through Advanced Consumer Product Recognition Using Aquila Optimization Algorithm With Deep Learning

MOHAMMED ALGHAMDI[1], HANAN ABDULLAH MENGASH[2], MOHAMMED ALJEBREEN[3], MOHAMMED MARAY[4], ABDULBASIT A. DAREM[5], (Member, IEEE), AND AHMED S. SALAMA[6]

[1]Department of Information and Technology Systems, College of Computer Science and Engineering, University of Jeddah, Jeddah 21959, Saudi Arabia
[2]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
[3]Department of Computer Science, Community College, King Saud University, Riyadh 11437, Saudi Arabia
[4]Department of Information Systems, College of Computer Science, King Khalid University, Abha 61421, Saudi Arabia
[5]Department of Computer Science, College of Science, Northern Border University, Arar 76321, Saudi Arabia
[6]Department of Electrical Engineering, Faculty of Engineering and Technology, Future University in Egypt, New Cairo 11845, Egypt

Corresponding author: Abdulbasit A. Darem (basit.darem@nbu.edu.sa)

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ABSTRACT Recently, consumer product recognition comprises harnessing cutting-edge technologies namely artificial intelligence (AI) and computer vision (CV) to develop the purchasing expedition. This technology allows retailers to utilize robust product recognition systems that precisely identify and categorize products in real time. The comprehension of automatic product identification becomes of major importance for both social and economic improvement since it is more reliable and time-consuming than manual function. Product detection through images is a complex task in the domain of CV. This can be obtained the improving consideration because of the excellent application viewpoint like visually impaired assistance, stock tracking, automatic checkout, and planogram compliance. Currently, deep learning (DL) prefers a successful progression with great achievements in object detection and image classification. Therefore, this study presents Advanced Consumer Product Recognition using the Aquila Optimization Algorithm with Deep Learning (ACPR-AOADL) technique. The proposed ACPR-AOADL model utilizes hyperparameter-tuned DL concepts for the identification of consumer products. To achieve this, the ACPR-AOADL model first pre-processes the input data utilizing a Wiener filter (WF) to improve the image quality. Besides, the YOLO-v8 model with a deep residual network (DRN) as a backbone network can be applied for the product detection process. For product classification, the deep belief network (DBN) approach can be used. To boost the complete product detection process, the ACPR-AOADL technique involves AOA based hyperparameter selection process. The performance analysis of the ACPR-AOADL method can be examined under the Product-10K dataset. Wide-ranging results stated that the ACPR-AOADL technique reaches enhanced classification performance over other compared approaches.

INDEX TERMS Product recognition, Aquila optimization algorithm, deep learning, Wiener filter, computer vision.

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I. INTRODUCTION

n our everyday lives, products are the most normal objects and are connected to everybody through commercial actions. Identifying daily products by snapping a picture is one of the most important issues in pattern detection for both industry and academia [1]. The main goal of product recognition is to simplify the organization of marketing products and enhance purchasing expeditions for customers. In the current scenario, recognition of barcodes is one of the most commonly utilized techniques in research and in businesses where automated designation of merchandise is employed [2]. When scanning barcode labels on every product package, the product organization can be effortlessly assisted. Generally, all items on the marketplace have their related barcode label. However, owing to the insecurity of printing barcode position, this needs sufficient time to physically discover the barcode and help the device recognize the barcode at the counter checkout [3]. In grocery stores, executing automatic product detection through images has an important influence on the trade industry. Initially, it will profit from the planogram compliance of items. For instance, product recognition can be able to classify which objects have vanished from the rack to remember the store employee to replace the objects instantly [4]. Mostly, recognition of retail product issues can be defined as complicated models connected to image identification and object recognition problems. Image processing (IP) relates to the change and inspection of visual information. Whereas, the regular case of an IP is to improve the image until its personal appears to be most attractive [5].

Currently, difficulties like product detection for commercial online contacts are highly challenging and these are resolved by IP and machine learning (ML) techniques [6]. The ML applications belong to the artificial intelligence (AI) methods which can learn and develop the system from the experiences without a clear program. Its applications mainly concentrate on the improvement of computer programs that can able to obtain data and employ it to absorb personally [7]. During the last year, deep learning (DL) particularly in the area of computer vision (CV) has attained wonderful achievement and become the fundamental solution for object recognition and image identification [8]. The main alteration among DL and customary pattern detection techniques is can previously acquire features in image data directly instead of utilizing physically intended features [9]. An additional main cause for the sturdy capability of DL is the deep layers which can remove exact features than the customary neural networks. The aforementioned benefits permit DL models to take new concepts to resolve some significant CV issues like key point recognition and image segmentation [10].

This study presents Advanced Consumer Product Recognition using the Aquila Optimization Algorithm with Deep Learning (ACPR-AOADL) approach. To achieve this, the ACPR-AOADL system first pre-processes the input data utilizing a Wiener filter (WF) to improve the image quality. Besides, the YOLO-v8 model with a deep residual network (DRN) as a backbone network can be applied for the product detection process. For product classification, the deep belief network (DBN) system can be used. To boost the complete product detection process, the ACPR-AOADL technique involves AOA based hyperparameter selection process. The performance analysis of the ACPR-AOADL system is inspected under the Product-10K dataset.

II. LITERATURE WORKS

Saqlain et al. [11] developed a DL and CV-based hybrid method termed Hyb-SMPC. The Hyb-SMPC technique contains dual units: The first unit identifies fine-grained trade products by employing a one-stage DL detector. For the recognition portion, the contrast of 3 DL-based detectors namely YOLOR, YOLO-V4, and YOLO-V5 will be delivered and the best outcome will be picked. In [12], a rapid and effectual product identification structure has been presented, which is dependent upon a new effort that inserts the innovative concept of humans in ML techniques. It is assumed that a customer modeling mode depends upon the DL methods, and a consumer data deduction technique relies on the Motivation Design Model (MDM) that computes multi-level consumer features in the restricted data. Amirifar et al. [13] measured a method that contains three stages. Stage 1 forecasts the complete grade by feeding the common product features to 3 dissimilar DL techniques: radial basis function NNs (RBFNNs), probabilistic neural networks (PNNs), and deep feedforward neural networks (DFFNNs) methods. Stage 2 recognizes other features that clients caution named entity recognition (NER) procedure to the client online analyses. At last, Stage 3 feeds the mixture of the common and habit features to similar DL methods.

Gothai et al. [14] concentrated on product display organization. DL is employed to define and recognize each item. The technique is created in II-phases. For product detection, the study utilized YOLOV5, and the size and shape features besides the colour feature to decrease the wrong product recognition. Panda et al. [15] intended to categorize customer favourites while assuming ads for BoP clients. Four kinds of user favourites (like, most like, most dislike, and dislike) are categorized while picturing dissimilar ads. A sturdy long short-term memory (LSTM) model-based DNN technique has been proposed for categorizing user favorites by executing the signal of EEG. In [16], a multichannel electroencephalography (EEG)-based DL technique has been presented. The multi-taper spectral study technique was employed to remove the feature vectors. Employing the removed feature vectors, the acts of bi-directional LSTM (BiLSTM) DL, SVM, and K-NN ML methods were equated.

Hafez et al. [17] proposed a solution to mechanically classify the altering product record into a 3-level food classification. The proposal studies 3 dissimilar techniques such as traditional ML methods, DNNs, and a score-based ranking method. Therefore, the technique offers 4 dissimilar classifiers to be more effectual and few fault-prone preservations of provisions lists. Sun et al. [18] project a rapid and actual product identification method depending upon the DL technique. This structure contains 3 parts: the target customer modeling model depends on the DL model; the consumer feature closed loop relies on the Motivation procedure framework (MPF); weighted fusion slightly solutions an iterative identification effect that integrates a user viewpoint with a producer side. The technique employs the customer data reasoning method.

III. THE PROPOSED MODEL

In this article, we have presented an advanced ACPR-AOADL technique. The proposed ACPR-AOADL model utilizes hyperparameter-tuned DL concepts for the recognition and classification of consumer products. Fig. 1 establishes the whole process of the presented ACPR-AOADL algorithm.

A. IMAGE PROCESSING

The WF is a leading tool in image pre-processing that goals to increase the quality of images by decreasing noise and enhancing overall clarity [19]. Functioning in the frequency domain, the WF differentiates between the wanted signal and undesirable noise, implementing various levels of filtering that are dependent upon their individual properties. By leveraging statistical data about the noise and signal, the WF reduces distortions, making it mainly efficient in conditions where the characteristics of the noise have been perceived. Extensively utilized in image restoration and improvement applications, the WF offers to generate visually greater images by intelligently balancing noise reduction and protecting significant details of images.

B. PRODUCT DETECTION: YOLO-V8

YOLOv8 is an effective single-shot detector applied for the detection and classification method [20]. The YOLO-v8 algorithm has been employed for consumer product detection. Moreover, it needs less number of parameters for training. The C2f exchanges the C3 modules dependent upon the CSP concept, while the YOLO-v8 backbone is similar to the YOLO-v5 backbone. The C2f integrates C3 and ELAN for creating the C2f component, based on the ELAN model from YOLO-v7, thus YOLO-v8 continues that movable but attaining gradient data flow. The SPPF model was used at the finish of the backbone, and a 3 Max-pool of 5 × 5 size was applied sequentially before being combined to certify the accuracy of entities of different measures.

The feature fusion method used by YOLO-v8 within the neck section is PAN-FPN which enhances the usage and fusion of feature layer data at different measures. The neck component is constructed by fusing the two upsampling, the last decoupled head structure, and many C2f elements. The last module of the neck in YOLO-v8 was made up of a similar perception as the head in YOLOx. With the help of fusing regression and confidence boxes, this increases the accuracy of the model. Furthermore, it can be an anchor-free architecture that could be identified center of the object. A complex post-processing stage that categories over potential recognition after inference, anchor-free recognition drops the amount of box predictions to accelerate Non-Maximum Suppression (NMS).

C. BACKBONE NETWORK: DRN MODEL

At this stage, the YOLO-v8 model with DRN as a backbone network can be applied for the product detection process. DRN is mainly used to estimate the quality of food as it postures the ability to classify the milk with minimal error and better accuracy [21]. Furthermore, DRN effectually prevents over-fitting issues and delivers the highest computation efficacy. The accuracy of classification is improved by developing the layer amount, but outcomes in a gradient vanishing and explosion. Now, the highest efficiency must be attained by improving the depth of the system than the width. The DRN contains a layers count like a pooling layer, activation layer, batch normalization (BN) layer, and convolutional (conv) layer.

1) CONV LAYER

It is a major important layer in DRN, where input data can be perused by the conv kernel and later conv has been implemented to extract the feature facts. At present, kernel signifies the sequence of filters that can be used to handle the input data. Conv process is definite as follows:

$$R_k^{z+1} = v\left(\sum_{y\in E_k} r_k^Z * p_{y,k}^{z+1} + w_k^z\right) \tag{1}$$

Here, v denotes the activation function, and R_k^{z+1} defines the kth feature map of the $(z+1)th$ conv layer that can be provided by input $r_k^z.p$ states the conv kernel, E signifies the mapping feature set and w denotes the bias. The function of activation has been utilized to attain a novel feature map.

2) POOLING LAYER

It executes down-sampling to diminish the size of the feature map, evading over-fitting problems. The max pooling is a normally employed technique due to its high efficacy and simple process.

3) RESIDUAL BLOCKS

It builds the primary DRN that permits a straight link of input and output blocks in a state of size. The mentioned formula signifies the residual blocks.

$$q = V\left(r, \{U_i\}\right) + r \tag{2}$$

$$V = U_2\beta(U_1 r) = q - r \tag{3}$$

Here, q specifies the output r refers to the input, V $(r, \{U_i\})$ directs the residual mapping to be learned, β denotes the function of Rectified Linear Unit (ReLU), U_1 states the weight of layer 1 and U_2 denotes the weight of layer 2. The target output has been prepared to reach $y + r$ by the learning procedure in the sub-elements with short-cut links.

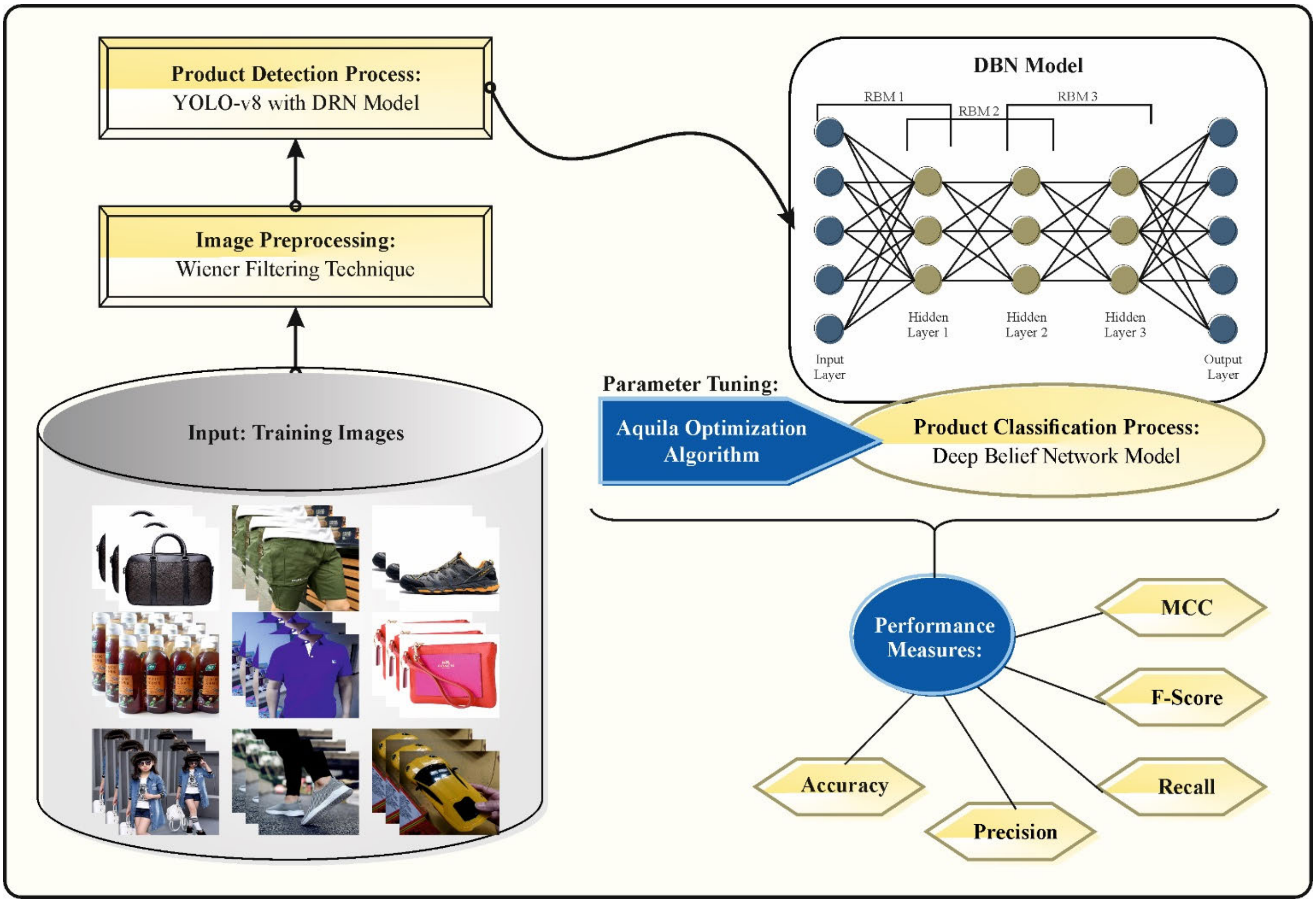

FIGURE 1. Overall function of the ACPR-AOADL technique.

4) BATCH NORMALIZATION (BN)

This layer is included for regularizing outputs by creating the alteration and mean as (1, 0). BN efficiently reduces the trained epochs and creates the learning procedure even. The procedure of BN is signified as follows:

$$\mu_B = \frac{1}{s}\sum_{j=1}^{s} r_j \cdot \sigma_B = \frac{1}{s}\sum_{j=1}^{s}(r_j - \mu_B)^2 \tag{4}$$

$$r_j^* = \frac{r_j - \mu_B}{\sqrt{\sigma_B^2 + e}}; \quad q_j = \lambda r_j^* + \eta \tag{5}$$

Here, $R = \{r_1, r_2, \ldots, r_s\}$ denotes the batch of input with size s, whereas μ_B denotes the mean and σ_B^2 states the variance that could be assessed in forward propagation, and e is used to prevent the situation in the training of $\sigma_B^2 = 0$, λ and η is implemented in the backward propagation.

λ denotes the parameter of scaling and η signifies the offset. L refers to the achieved output.

D. PRODUCT CLASSIFICATION: DBN MODEL

For product classification, the DBN model can be applied. DBNs are a multi-layered probability-based technique that contains many parameters for model learning [22]. Every layer holds the simplest un-directed graphs termed RBMs. RBM layers are of dual kinds such as visible layers (VL) and hidden layers (HL). The VL is said to be the bottom layer, and HL is the top layer. HL models the distribution of the probability of the noticeable variables and is fully bi-directionally linked with symmetric weight. The layers are not combined in RBMs. An RBM encrypts the joint distribution of probability through energy function in Eq. (6), whereas v denotes the VL data, h signifies the HL data, w refers to the weight, and $= \left(w, b^{(v)}, b^{(h)}\right)$. The set joint probability is measured in Eq. (7):

$$E(v, h, \theta) = -\sum_i \sum_j w_{ij} v_i h_j - \sum_i b_i^{(v)} v_i - \sum_j b_j^{(h)} h_j \tag{6}$$

$$p(v, h \mid \theta) = \frac{\exp(-E(v, h{:}\theta))}{\Sigma_{v'} \Sigma_{h'}, exp(-E(v', h', \theta))}. \tag{7}$$

These instructions are derivate to upgrade the preliminary state, every upgrade provides a low energy state and finally relaxes into equilibrium. In Eqs. (8) and (9), $\sigma(x) = 1/(1 + exp(-x))$, where the function of the sigmoid is perceived as follows:

$$p\left(v_i=1 \mid h, \theta\right)=\sigma\left(\sum_j w_{ij} h_j+b_i^{(v)}\right) \tag{8}$$

$$p\left(h_i=1 \mid v, \theta\right)=\sigma\left(\sum_i w_{ij} v_i+b_j^{(h)}\right) \tag{9}$$

To train RBMs, the VL is delivered with input data. Now, the learning is to adjust the parameter θ as a distribution of probability in Eq. (7) converts maximum parallel to the true rates, this indicates that it can increase the log-likelihood of every group of the detected data. A contrastive divergence (CD) procedure examples the novel values for every HL similar to the present input to provide a complete example (v, h_{data}). Also, it makes an example for the VL, and then examples of the HL again. Then, we acquire the example from the method as (v_{model}, h_{model}). The weights are upgraded according to Eq. (10).

$$\Delta w_{ij}=\eta\left(v_{i,data} h_{j,data}-v_{i,model} h_{j,model}\right). \tag{10}$$

E. HYPERPARAMETER TUNING: AOA

Finally, the ACPR-AOADL technique involves AOA based hyperparameter selection process. The AO is a new SI model that consists of four different hunting plans of Aquila for dissimilar kinds of bait [23]. Like other MH techniques, AO has ERP and EIP which perform the optimizer algorithm using the above dual stages to resolve these problems. Indeed, AO searches the Search Space (SS) to find the optimum performances locally and globally through ERP and EIP and lastly converge towards the last optimum performance. The steps of the AO technique are briefly described in the following:

Step 1: Extensive ERP:

$$X(t+1)=X_{best}(t) \times\left(1-\frac{t}{T}\right) + \left(X_{avg}(t)-X_{best}(t) \times rand\right) \tag{11}$$

$$X_{avg}(t)=\frac{1}{N1} \sum_{k=1}^{N1} X_k(t) \tag{12}$$

where $X_{best}(t)$ denotes the optimum location obtained, and $X_{avg}(t)$ indicates the average position of Aquila in the existing iteration, t, and T denote the present rounds and maximum iterations count, correspondingly, $N1$ and $rand$ are the size of the population and arbitrary integer within [0, 1].

Step 2: The position upgrade in ERP as:

$$X(t+1)=X_{best}(t) \times lf(Dim)+X_R(t) + (y-x) \times rand \tag{13}$$

In the equation, $X_R(t)$ denotes the random location of Aquila, Dim shows the dimension size and $lf(Dim)$ indicates the levy flight (lf) function:

$$lf(Dim)=s \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \tag{14}$$

$$\sigma=\left[\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right] \tag{15}$$

where u and v denotes random values amongst zero and one, $s=0.01$ and $\beta=1.5$ are constant values:

$$\begin{cases} x=r \times sin(\theta) \\ y=r \times cos(\theta) \\ r=r_1+0.00565 \times Dim_1 \\ \theta=-w \times Dim_1+\dfrac{3 \times \pi}{2} \end{cases} \tag{16}$$

where r_1 is the amount of search cycles within [1,20], Dim_1 ranges from 1 to the size of dimensional (Dim) and is equivalent to 0.005.

Step 3: Extensive EIP as:

$$X(t+1)=\left(X_{best}(t)-X_{avg}(t)\right) \times \alpha-rand + ((upb-lob) \times rand+lob) \times \delta \tag{17}$$

where α and δ are the adjustment parameters of EIP set as 0.1, upb and lob are the upper and lower bounds.

Step 4: Limited EIP as:

$$X(t+1)=QF \times X_{best}(t)-\left(G_1 \times X(t)\right) \times rand - G_2 \times lf(Dim)+rand \times G_1 \tag{18}$$

$$QF(t)=t^{\left(\frac{2 \times rand-1}{(1-T)^2}\right)} \tag{19}$$

$$G_1=2 \times rand-1 \tag{20}$$

$$G_2=2 \times\left(1-\frac{t}{T}\right) \tag{21}$$

where G_1 refers to the movement parameter of Aquila while chasing the bait that is a random value within [−1,1], G_2 refers to the flight slope but tracing bait that linearly dropped from 2 to 0.$A(t)$ is the existing location and $QF(t)$ is the quality function value which balances the search approach. Until the termination criteria are satisfied, the process of improving the solution is done. Fig. 2 depicts the steps included in AOA. The AOA system gives a fitness function (FF) to accomplish increased classifier performance. This defines an optimistic number for signifying the candidate solution's great performance. In this paper, the decrease in classifier error rate can be measured as FF represented in Eq. (22).

$$\begin{aligned} fitness\left(x_i\right) &= ClassifierErrorRate\left(x_i\right) \\ &= \frac{No.\ of\ misclassified\ instances}{Total\ no.\ of\ instances} * 100 \end{aligned} \tag{22}$$

IV. EXPERIMENTAL VALIDATION

The presented methodology was simulated utilizing the Python 3.8.5 tool on PC i5-8600k, 16GB RAM, GeForce 1050Ti 4GB, 1TB HDD, and 250GB SSD. The parameter settings are provided as follows: batch size: 5, rate of learning: 0.01, activation: ReLU, dropout: 0.5, and epoch count: 50. In this section, the consumer product recognition results of the ACPR-AOADL system have been tested using the

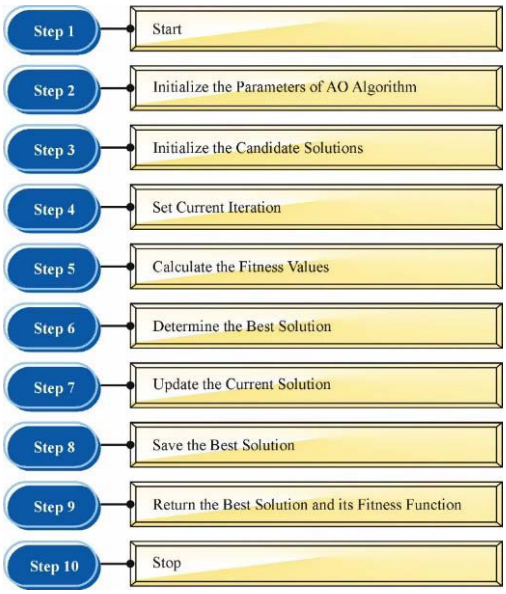

FIGURE 2. Steps involved in AOA.

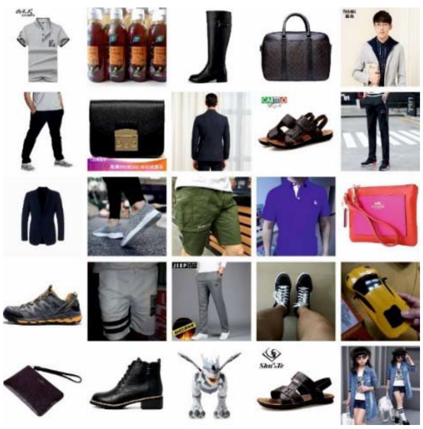

FIGURE 3. Sample images.

TABLE 1. Details of the dataset.

Classes	No. of Instances
Top	250
Bottom	250
Footwear	250
Case and Bag	250
Digital	250
Food and Drink	250
Toy	250
Home	250
Total Instances	**2000**

Product-10K dataset [24]. A sample of 2000 images with 8 classes is considered into account as defined in Table 1. Fig. 3 portrays the sample imageries.

Fig. 4 shows the confusion matrices generated by the ACPR-AOADL method with distinct epochs. The experimental outcomes display the efficient recognition and classification of eight classes correctly.

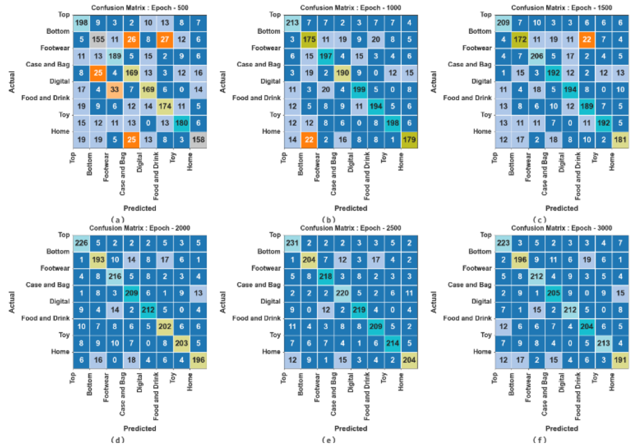

FIGURE 4. (a-f) Confusion matrices of ACPR-AOADL technique under Epochs 500-3000.

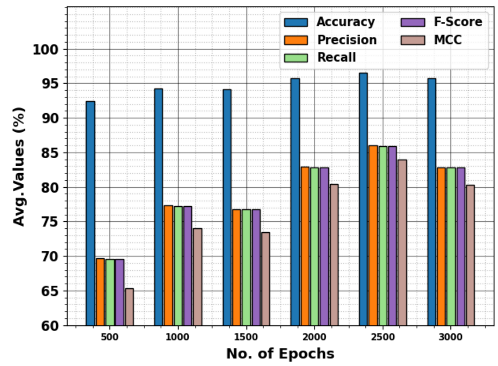

FIGURE 5. Average of ACPR-AOADL technique under diverse epochs.

The product identification results of the ACPR-AOADL technique can be examined under varying epochs in Table 2 and Fig. 5. The results stated that the ACPR-AOADL approach reaches enhanced performance with maximum classification results. It is also noticed that the proposed model reaches effective results under various epochs.

The $accu_y$ curves for training (TRA) and validation (VL) shown in Fig. 6 for the ACPR-AOADL system give esteemed insights into its efficacy under varied epochs. Mainly, it can be a reliable promotion at both TRA and TES $accu_y$ with enlarged epochs, signifying the proficiencies of the learning model and pattern detection from both data. The increasing trend in TES $accu_y$ emphasizes the flexibility of the method to the dataset of TRA and the capability to generate correct forecasts on unnoticed data, emphasizing robust generalization.

Fig. 7 exhibits a wide-ranging summary of the TRA and TES loss analysis for the ACPR-AOADL system through numerous epochs. The TRA loss consistently decreases as the model improves the weights to diminish identification errors in both data. The loss curves remarkably represent the model's position with the TRA data, highlighting

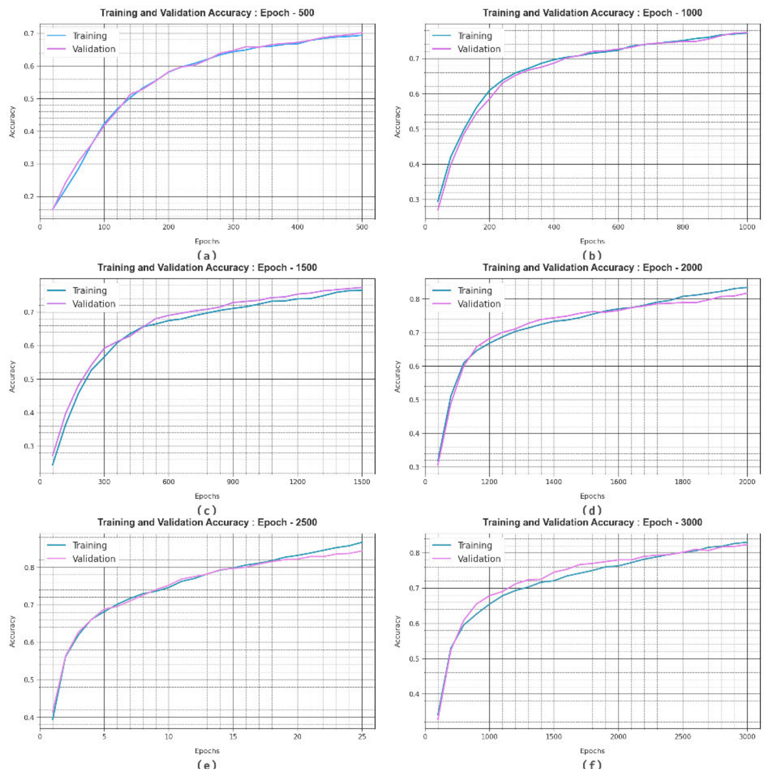

FIGURE 6. $Accu_y$ **curve of ACPR-AOADL technique (a-f) Epochs 500-3000.**

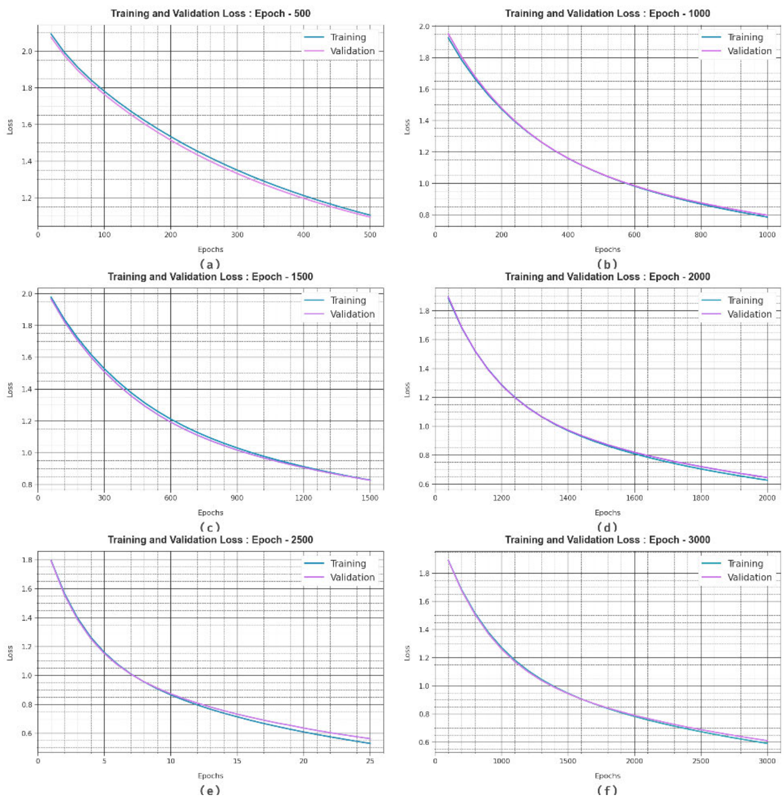

FIGURE 7. **Loss curve of ACPR-AOADL technique (a-f) Epochs 500-3000.**

its capability to take patterns effectively. Noticeably, the constant development of parameters in the ACPR-AOADL technique, targeted at diminishing differences amongst forecasts and real TRA labels.

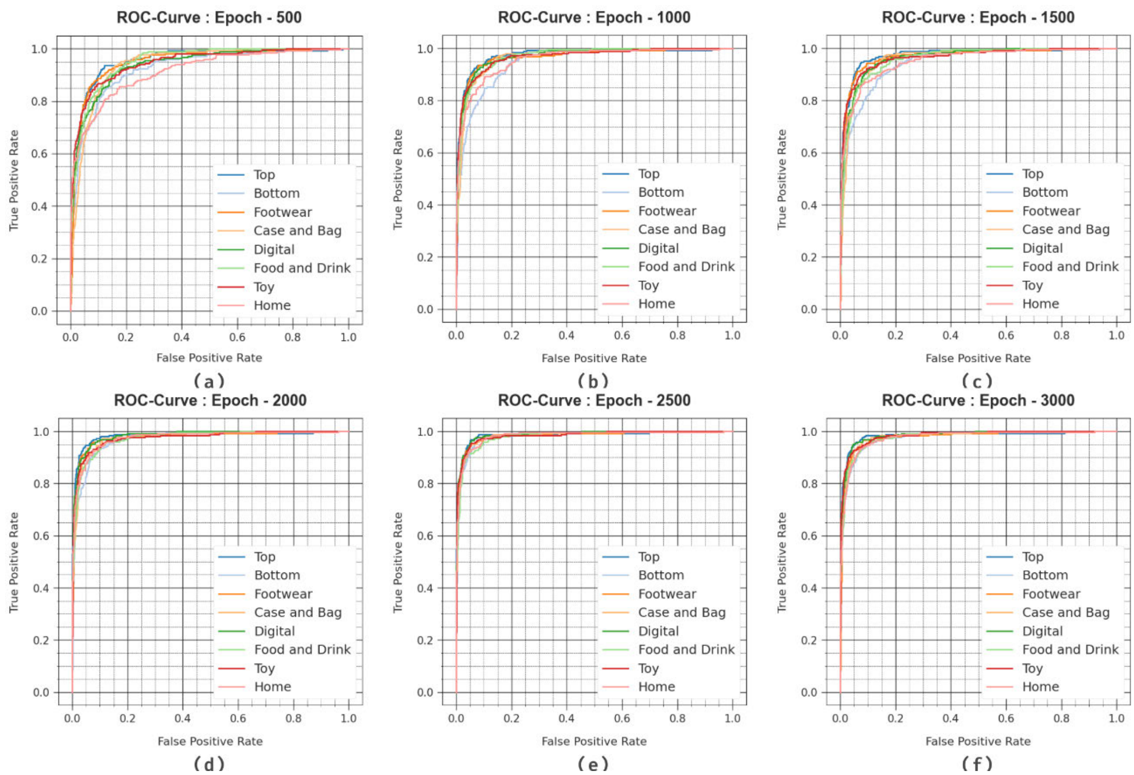

FIGURE 8. **ROC curve of ACPR-AOADL technique (a-f) Epochs 500-3000.**

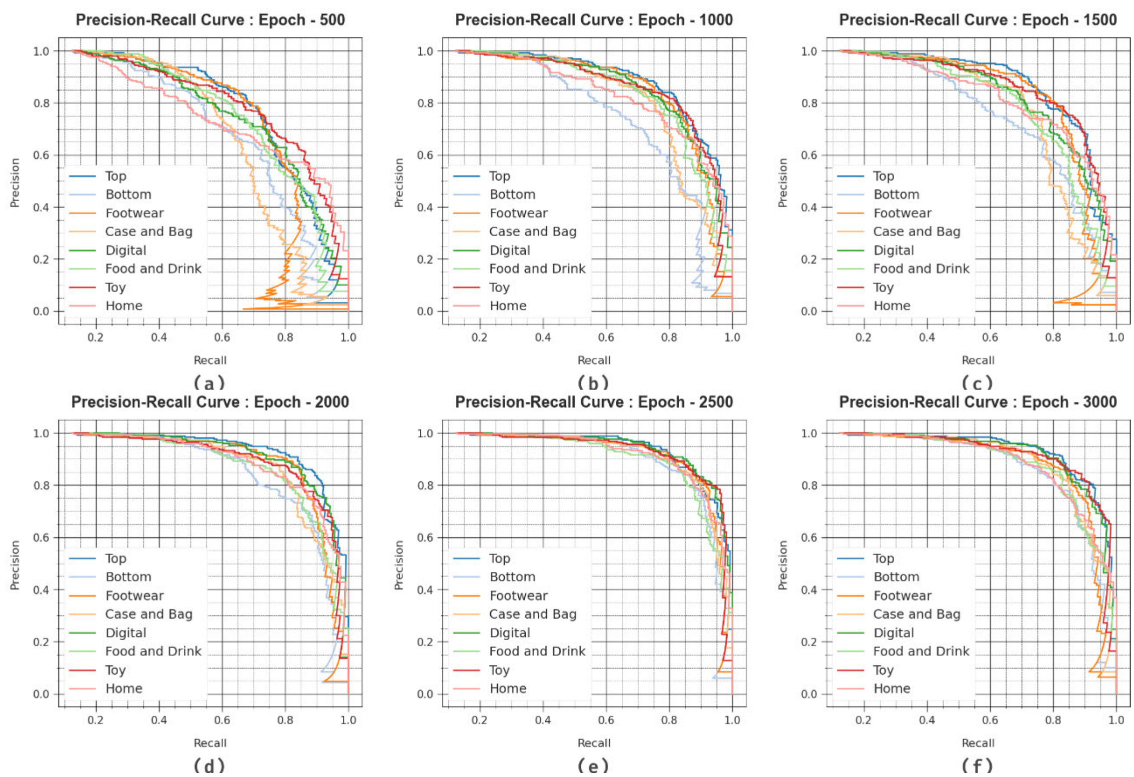

FIGURE 9. **PR curve of ACPR-AOADL technique (a-f) Epochs 500-3000.**

About the PR curve reported in Fig. 8, the findings clearly indicate that the ACPR-AOADL model under different epochs reliably accomplishes boosted PR values at every class. These results emphasize the model's efficient capacity to discriminate among various classes, underscoring its effectiveness in exactly recognizing class labels.

TABLE 2. Product identification analysis of ACPR-AOADL technique under different epochs.

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
Epoch - 500					
Top	92.70	67.81	79.20	73.06	69.15
Bottom	90.70	63.01	62.00	62.50	57.19
Footwear	93.30	72.14	75.60	73.83	70.01
Case and Bag	91.45	65.25	67.60	66.40	61.52
Digital	92.30	69.83	67.60	68.70	64.32
Food and Drink	92.60	70.73	69.60	70.16	65.94
Toy	93.75	76.60	72.00	74.23	70.72
Home	92.40	72.48	63.20	67.52	63.43
Average	**92.40**	**69.73**	**69.60**	**69.55**	**65.29**
Epoch - 1000					
Top	95.10	77.74	85.20	81.30	78.59
Bottom	92.10	67.83	70.00	68.90	64.38
Footwear	94.45	77.25	78.80	78.02	74.85
Case and Bag	94.00	76.00	76.00	76.00	72.57
Digital	94.70	78.35	79.60	78.97	75.94
Food and Drink	94.65	79.18	77.60	78.38	75.34
Toy	95.55	84.26	79.20	81.65	79.17
Home	93.95	78.17	71.60	74.74	71.40
Average	**94.31**	**77.35**	**77.25**	**77.24**	**74.03**
Epoch - 1500					
Top	95.05	78.28	83.60	80.85	78.07
Bottom	92.65	71.37	68.80	70.06	65.89
Footwear	94.75	77.15	82.40	79.69	76.73
Case and Bag	93.75	74.13	76.80	75.44	71.88
Digital	94.05	75.49	77.60	76.53	73.13
Food and Drink	93.90	75.60	75.60	75.60	72.11
Toy	95.20	83.48	76.80	80.00	77.36
Home	94.15	79.04	72.40	75.57	72.35
Average	**94.19**	**76.82**	**76.75**	**76.72**	**73.44**
Epoch - 2000					
Top	96.85	85.28	90.40	87.77	86.01
Bottom	94.30	77.20	77.20	77.20	73.94
Footwear	95.95	82.13	86.40	84.21	81.92
Case and Bag	95.25	79.47	83.60	81.48	78.79
Digital	96.45	86.53	84.80	85.66	83.64
Food and Drink	95.40	82.11	80.80	81.45	78.83
Toy	96.10	86.75	81.20	83.88	81.73
Home	95.40	83.76	78.40	80.99	78.43
Average	**95.71**	**82.90**	**82.85**	**82.83**	**80.41**
Epoch - 2500					
Top	96.70	83.09	92.40	87.50	85.77
Bottom	96.15	86.81	81.60	84.12	81.99
Footwear	96.70	86.51	87.20	86.85	84.97
Case and Bag	96.20	82.71	88.00	85.27	83.15
Digital	96.90	87.60	87.60	87.60	85.83
Food and Drink	96.05	84.62	83.60	84.10	81.85
Toy	96.95	89.54	85.60	87.53	85.82
Home	96.25	87.55	81.60	84.47	82.41
Average	**96.49**	**86.05**	**85.95**	**85.93**	**83.97**
Epoch - 3000					
Top	96.30	82.59	89.20	85.77	83.73
Bottom	94.65	78.71	78.40	78.56	75.50
Footwear	95.80	82.17	84.80	83.46	81.07
Case and Bag	95.50	82.00	82.00	82.00	79.43
Digital	96.35	85.83	84.80	85.31	83.23
Food and Drink	95.65	83.27	81.60	82.42	79.95
Toy	96.50	86.59	85.20	85.89	83.89
Home	94.85	81.28	76.40	78.76	75.88
Average	**95.70**	**82.80**	**82.80**	**82.77**	**80.34**

Likewise, in Fig. 9, we present ROC curves created by the ACPR-AOADL system under numerous epochs, indicating its ability to distinguish among classes. These curves offer valuable insights into how the trade-off among FPR and TPR varies over numerous classification thresholds and epochs. The simulation outcomes underscore the model's accurate classifier performance under various class labels, highlighting its efficiency as overwhelming diverse classification tasks

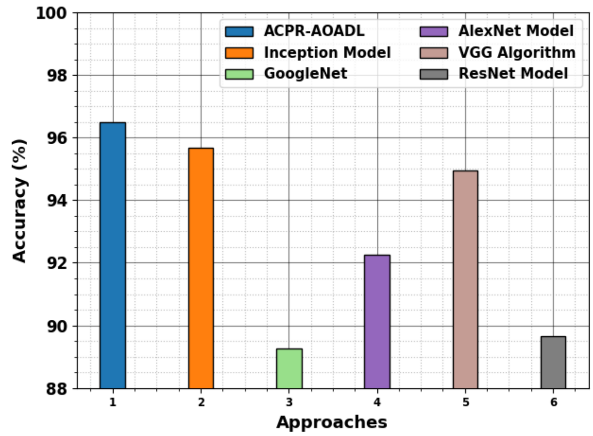

FIGURE 10. $Accu_y$ **analysis of ACPR-AOADL technique with recent methods.**

TABLE 3. Comparison analysis of the ACPR-AOADL model with other methods.

Methodologies	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
ACPR-AOADL	96.49	86.05	85.95	85.93
Inception Model	95.68	84.68	82.41	84.5
GoogleNet	89.25	82.23	83.24	84.88
AlexNet Model	92.27	84.74	80.93	83.49
VGG Algorithm	94.95	79.85	82.35	83.98
ResNet Model	89.65	83.82	80.62	84.89

To highlight the better performance of the ACPR-AOADL algorithm, a detailed set of comparative analyses is made in Table 3 [24], [25]. In Fig. 10, a comparison study of the ACPR-AOADL method is delivered in terms of $accu_y$. The experimental findings denote that the ACPR-AOADL technique achieves higher performance. According to $accu_y$, the ACPR-AOADL technique gains an increased $accu_y$ of 96.49% while the Inception, GoogleNet, AlexNet, VGG, and ResNet models obtain decreased $accu_y$ values of 95.68%, 89.25%, 92.27%, 94.95%, and 89.65%, correspondingly.

A comparison analysis of the ACPR-AOADL method can be examined for $prec_n$, $reca_l$, and F_{score} in Fig. 11. The experimental results show the ACPR-AOADL algorithm gains excellent performance. According to $prec_n$, the ACPR-AOADL system achieves boosted $prec_n$ of 86.05% whereas the Inception, GoogleNet, AlexNet, VGG, and ResNet techniques obtain diminished $prec_n$ values of 84.68%, 82.23%, 84.74%, 79.85%, and 83.82%.

Additionally, with $reca_l$, the ACPR-AOADL methodology acquires an improved $reca_l$ of 85.95% however, the

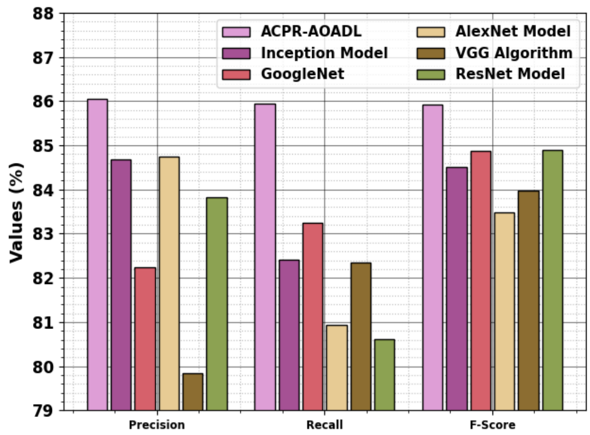

FIGURE 11. $Prec_n$, $Reca_l$, and F_{score} analysis of ACPR-AOADL model compared with other systems.

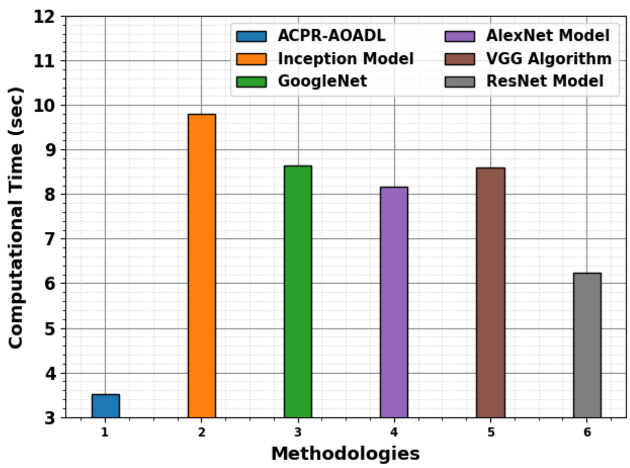

FIGURE 12. CT analysis of ACPR-AOADL technique with recent methods.

Inception, GoogleNet, AlexNet, VGG, and ResNet systems get lessened $reca_l$ values of 82.41%, 83.24%, 80.93%, 82.35%, and 80.62%, correspondingly. Lastly, on F_{score}, the ACPR-AOADL algorithm attains a higher F_{score} of 85.93% but, the Inception, GoogleNet, AlexNet, VGG, and ResNet techniques obtain minimized F_{score} values of 84.5%, 84.88%, 83.49%, 83.98%, and 84.89%, respectively.

In Table 4 and Fig. 12, a comparative computational time (CT) outcome of the ACPR-AOADL model with other approaches. The experimental findings denote that the Inception model has worse performance with higher CT values of 9.79s. Likewise, the GoogleNet, AlexNet, and VGG models have slightly better performances with CT of 8.64s, 8.16s, and 8.60s, respectively. Moreover, the ResNet technique has a moderate solution compared with other existing methods, the ACPR-AOADL model has exhibited enhanced performance with a lesser CT value of 3.52s.

Therefore, the ACPR-AOADL technique can be utilized for enhanced performance over other algorithms.

TABLE 4. CT analysis of the ACPR-AOADL model with other methods.

Methodologies	Computational Time (sec)
ACPR-AOADL	3.52
Inception Model	9.79
GoogleNet	8.64
AlexNet Model	8.16
VGG Algorithm	8.60
ResNet Model	6.23

V. CONCLUSION

In this article, we have presented an innovative ACPR-AOADL system. The proposed ACPR-AOADL model utilizes hyperparameter-tuned DL concepts for the detection and classification of consumer products. To achieve this, the ACPR-AOADL method first pre-processes the input data employing WF to enhance the image quality. Besides, the YOLO-v8 model with DRN as a backbone network can be applied for the product detection process. For product classification, the DBN model can be used. To boost the complete product detection process, the ACPR-AOADL technique involves AOA based hyperparameter selection process. The performance evaluation of the ACPR-AOADL methodology can be examined under the Product-10K dataset. Wide-ranging results stated that the ACPR-AOADL technique reaches enhanced classification performance over other compared approaches.

In future work, the combination of eXplainable Artificial Intelligence (XAI) approaches into the ACPR-AOADL system can improve method interpretability and transparency. Furthermore, exploring novel data augmentation approaches tailored to consumer product detection tasks and examining the scalability of ACPR-AOADL methodology for large-scale product databases are essential avenues for further research. In addition, measuring the ACPR-AOADL algorithm on various databases and benchmarking its performance against existing models will provide appreciated insights into its performance and generalization abilities across distinct product types and environments.

In real-time execution conditions, the presented method needs substantial computational resources for inference, comprising high-end GPUs or specialized hardware accelerators that could not be easily accessible or practical in specific settings. Furthermore, the memory and processing necessities of these models cause problems for utilization on resource-constrained devices like edge devices or embedded systems. Hence, optimizing model designs, leveraging model quantization systems, and exploring effectual inference approaches are vital to making the ACPR-AOADL algorithm possible for real-time utilization in resource-constrained environments while preserving efficient execution.

Evaluating and enhancing the scalability of the ACPR-AOADL algorithm to manage huge product databases and maintain reliable performance through various product types and variations needs different considerations. Primarily, estimating the scalability of all the components individually to recognize potential bottlenecks and it is vital to optimize them accordingly. It includes increasing the performance of YOLOv8 for real-time object recognition, scaling up the DBN structure to handle huge databases, and optimizing AOA's search approach for high-dimensional parameter spaces. Moreover, deploying approaches like data augmentation, transfer learning (TL), and parallelization can improve scalability by leveraging recent knowledge and computational resources efficiently.

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REFERENCES

[1] C. M. Badgujar, P. R. Armstrong, A. R. Gerken, L. O. Pordesimo, and J. F. Campbell, "Identifying common stored product insects using automated deep learning methods," *J. Stored Products Res.*, vol. 103, Sep. 2023, Art. no. 102166.

[2] X. Yin and X. Tao, "Prediction of merchandise sales on e-commerce platforms based on data mining and deep learning," *Sci. Program.*, vol. 2021, pp. 1–9, Nov. 2021.

[3] R. Li and C. Wang, "Cultural and creative product design and image recognition based on deep learning," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–9, Jul. 2022.

[4] I. E. Parlak and E. Emel, "Deep learning-based detection of aluminum casting defects and their types," *Eng. Appl. Artif. Intell.*, vol. 118, Feb. 2023, Art. no. 105636.

[5] M. N. Mohammad, C. U. Kumari, A. S. D. Murthy, B. O. L. Jagan, and K. Saikumar, "Implementation of online and offline product selection system using FCNN deep learning: Product analysis," *Mater. Today, Proc.*, vol. 45, pp. 2171–2178, Jan. 2021.

[6] P. Rujakom, P. Takam, S. Sinthupuan, P. Khoenkaw, K. Dullayachai, and T. Chaiya, "Retail management on mobile application using product classification," in *Proc. 19th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON)*, May 2022, pp. 1–5.

[7] K. Roy, S. S. Chaudhuri, S. Pramanik, and S. Banerjee, "Deep neural network based detection and segmentation of ships for maritime surveillance," *Comput. Syst. Sci. Eng.*, vol. 44, no. 1, pp. 647–662, 2023.

[8] Y. Kim, H. J. Lee, and J. Shim, "Developing data-conscious deep learning models for product classification," *Appl. Sci.*, vol. 11, no. 12, p. 5694, Jun. 2021.

[9] J. M. Eyu, "Application development for product recognition on-shelf with deep learning," Doctoral dissertation, UTAR, 2022.

[10] H. Yang, Z. Zheng, and C. Sun, "E-commerce marketing optimization of agricultural products based on deep learning and data mining," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–11, May 2022.

[11] M. Saqlain, S. Rubab, M. M. Khan, N. Ali, and S. Ali, "Hybrid approach for shelf monitoring and planogram compliance (Hyb-SMPC) in retails using deep learning and computer vision," *Math. Problems Eng.*, vol. 2022, pp. 1–18, Jun. 2022.

[12] F. Sun, D.-B. Luh, Q. Wang, Y. Zhao, and Y. Sun, "Deep learning product classification framework based on the motivation of target customers," in *Proc. 22nd Int. Conf. Electron. Packag. Technol. (ICEPT)*, Sep. 2021, pp. 1–4.

[13] T. Amirifar, S. Lahmiri, and M. K. Zanjani, "An NLP-deep learning approach for product rating prediction based on online reviews and product features," *IEEE Trans. Computat. Social Syst.*, early access, Jul. 14, 2024, doi: 10.1109/TCSS.2023.3290558.

[14] E. Gothai, S. Bhatia, A. M. Alabdali, D. K. Sharma, B. R. Kondamudi, and P. Dadheech, "Design features of grocery product recognition using deep learning," *Intell. Autom. Soft Comput.*, vol. 34, no. 2, pp. 1231–1246, 2022.

[15] D. Panda, D. D. Chakladar, and T. Dasgupta, "Prediction of consumer preference for the bottom of the pyramid using EEG-based deep model," *Int. J. Comput. Sci. Eng.*, vol. 24, no. 5, pp. 439–449, 2021.

[16] H. Göker, "Multi-channel EEG-based classification of consumer preferences using multitaper spectral analysis and deep learning model," *Multimedia Tools Appl.*, vol. 83, no. 14, pp. 40753–40771, Oct. 2023.

[17] M. M. Hafez, A. F. Vilas, R. P. D. Redondo, and H. O. Pazó, "Classification of retail products: From probabilistic ranking to neural networks," *Appl. Sci.*, vol. 11, no. 9, p. 4117, Apr. 2021.

[18] F. Sun, D. B. Luh, Y. Zhao, and Y. Sun, "Study on the deep learning product classification based on the motivation of consumers," in *Proc. Int. Conf. Human-Comput. Interact.* Cham, Switzerland: Springer, 2022, pp. 537–545.

[19] A. A. Ismael and M. Baykara, "Image denoising based on implementing threshold techniques in multi-resolution wavelet domain and spatial domain filters," *Traitement Du Signal*, vol. 39, no. 4, pp. 1119–1131, Aug. 2022.

[20] N. Al Mudawi, A. M. Qureshi, M. Abdelhaq, A. Alshahrani, A. Alazeb, M. Alonazi, and A. Algarni, "Vehicle detection and classification via YOLOv8 and deep belief network over aerial image sequences," *Sustainability*, vol. 15, no. 19, p. 14597, Oct. 2023.

[21] N. Manisha and M. Jagadeeshwar, "BC driven IoT-based food quality traceability system for dairy product using deep learning model," *High-Confidence Comput.*, vol. 3, no. 3, Sep. 2023, Art. no. 100121.

[22] M. Javeed, M. Gochoo, A. Jalal, and K. Kim, "HF-SPHR: Hybrid features for sustainable physical healthcare pattern recognition using deep belief networks," *Sustainability*, vol. 13, no. 4, p. 1699, Feb. 2021.

[23] T. Salehnia, A. Montazerolghaem, S. Mirjalili, M. R. Khayyambashi, and L. Abualigah, "SDN-based optimal task scheduling method in Fog-IoT network using a combination of AO and WOA," in *Handbook of Whale Optimization Algorithm*, 2023.

[24] Y. Bai, Y. Chen, W. Yu, L. Wang, and W. Zhang, "Products-10K: A large-scale product recognition dataset," 2020, *arXiv:2008.10545*.

[25] Y. Wei, S. Tran, S. Xu, B. Kang, and M. Springer, "Deep learning for retail product recognition: Challenges and techniques," *Comput. Intell. Neurosci.*, 2020.