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Research article

Application of DMSFNN-COA technique for brand image design

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A R T I C L E I N F O

Keywords:
Brand image design
Mnist data set
Deep multi-scale fusion neural network
Cheetah optimization algorithm
Master-slave adaptive notch filter
Automatic image classification
Stylish and natural product colour brand image

A B S T R A C T

Color plays a pivotal role in product design, as it can evoke emotional responses from users. Understanding these emotional needs is crucial for effective brand image design. This paper introduces a novel approach, the Brand Image Design using Deep Multi-Scale Fusion Neural Network optimized with Cheetah Optimization Algorithm (BID-DMSFNN-COA), for classifying product color brand images as “Stylish” and “Natural”. By leveraging deep learning techniques and optimization algorithms, the proposed method aims to enhance brand image accuracy and address existing challenges in product color trend forecasting research. Initially, data are collected from the Mnist Data Set. The data are then supplied into the pre-processing section. In the pre-processing segment, it removes the noise and enhances the input image utilizing master slave adaptive notch filter. The Deep Multi-Scale Fusion Neural Network optimized with cheetah optimization algorithm effectively classifies the product colour brand image as “Stylish” and “Natural”. Implemented on the MATLAB platform, the BID-DMSFNN-COA technique achieves remarkable accuracy rates of 99 % for both “Natural” and “Stylish” classifications. In comparison, existing methods such as BID-GNN, BID-ANN, and BID-CNN yield lower accuracy rates ranging from 65 % to 85 % for “Stylish” and 65 %–70 % for “Natural” product color brand image design. The simulation outcomes reveal the superior performance of the BID-DMSFNN-COA technique across various metrics including accuracy, F-score, precision, recall, sensitivity, specificity, and ROC analysis. Notably, the proposed method consistently outperforms existing approaches, providing higher values across all evaluation criteria. These findings underscore the effectiveness of the BID-DMSFNN-COA technique in enhancing brand image design through accurate product color classification.

1. Introduction

The significance of brand design has evolved beyond mere logo creation, extending towards a structured approach for brand visual identification [1]. Today, a consumer’s perception of a brand, termed as its “brand image,” encompasses more than just its logo; it encapsulates memories and associations with the brand [2]. These associations are pivotal in shaping consumer preferences and perceptions [3], influencing their purchasing decisions and brand loyalty [4].

A crucial element influencing brand perception is product design, encompassing factors like color and quality [5]. The choice of color, in particular, plays a significant role in evoking emotions and perceptions among consumers [6]. However, existing methods for predicting color trends often rely on subjective expertise, lacking accuracy in reflecting evolving user preferences [7]. As businesses navigate the challenges of the “novel retail” era, effective brand image design becomes imperative for enhancing consumer loyalty and brand perception [8].

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In this work, the challenges associated with product color design for brand image classification are addressed. Specifically, a novel approach, the Brand Image Design using Deep Multi-Scale Fusion Neural Network with Cheetah Optimization Algorithm (BID-DMSFNN-COA), is proposed for categorizing product color brand images as “Stylish” and “Natural” with enhanced accuracy. The methodology involves data collection from the Mnist Data Set and the utilization of pre-processing techniques to refine input images [9]. A deep multi-scale fusion neural network optimized with the Cheetah Optimization Algorithm is employed to effectively classify brand images based on their color attributes.

“The following is an outline of the paper’s main contributions:"

- Introduction of the BID-DMSFNN-COA technique for precise classification of product color brand images.
- Utilization of advanced pre-processing techniques to enhance image quality and reduce noise.
- Evaluation of the proposed technique’s efficacy through comprehensive performance metrics analysis.
- Comparison of the proposed approach with existing methods, including BID-GNN, BID-ANN, and IMI-CNN, highlighting its superiority in brand image classification accuracy.
- This work’s originality lies in its use of a deep multi-scale fusion neural network optimized with the cheetah optimization algorithm (BID-DMSFNN-COA) to classify product color brand images as “Stylish” and “Natural.” This approach enhances brand image accuracy and outperforms existing methods, offering a more effective solution for product color trend forecasting.

Through this research, a robust framework for product color design is provided, aligning with evolving consumer preferences, thereby enhancing brand perception and competitiveness in the market. The rest of the manuscript is organized as follows, part 2 explains a survey of literature, the proposed technique is described in part, part 4 explains the result and discussion, and part 5 concludes the paper.

2. Literature survey

In this section, some of the most recent studies on deep learning-based brand image creation were evaluated.

Zhang et al. [10], have introduced the Grey theory and Kansei engineering, based on the product colour brand image whichwere utilized to examine both broad and specific aspects of the product colour design judgment process. The outcomes demonstrated that the created approach may be utilized to direct the product’s colour scheme in order to fully and swiftly met the user’s emotional requirements. The technique fixed issues with the existing method of forecasting product colour trends and improved the correlative analysis’s accuracy among the product colour design elements and brand image. In order to demonstrate practicality of the research strategy and the color scheme of the mid-range car were used as an examples. It provides high accuracy. It resulted in higher error rate.

Nufer and Muth [11], have introduced a brand image measurement application of artificial neural networks. The research methodology that is being provided analyses the implementation of artificial neural networks in this specific application environment while taking into account the intricate nature of brand image measurement. The implementations of the learning algorithm were considered since it enables the modelling of complicated non-linear and multilayer interactions, which are crucial for management and require profound insights into a brand’s image. Adidas is used as an empirical example to demonstrate the conceptual approach that is presented in the paper. Utilizing numerical survey data, a multilayer ANN was created that links ratings of certain brand attributes with opinions of the brand as a whole. The value of various brand qualities is measured, based on a review of the connection weights of the neurons in the ANN. It provided high precision and computation time.

Wang and Chen [12], have presented type identity and product design are essential to a brands basic values. However, the opinion of a human specialist is crucial for developing the style and individuality. Due to the recent development of deep learning for picture identification as a quick process, the utilization of brand style and design aspects holds potential. By practicing a convolutional neural network, this study examined the development of car styling for the Dodge and Jaguar car brands. Deep learning heat map analysis was used as a part of the method, which also included statistical techniques. The datasets used in this study were the one that included automotive design features and the other that included car style photos. It provides better generalization ability, smaller error and low accuracy.

Zhang and Li [13], have presented a network image assortment method that combines text assistance with image fusion. The likelihood of each and every category of an image was obtained by combining support vector machine (SVM) classification and visual feature extraction through artificial decision algorithms. In an effort to increase the effectiveness of network image classification, we also weigh the relevant text category on the page where the image is located using keyword correlation. Real-time interactive 3D environments for print advertisements, cross compilation approaches for visual information simulation, and print advertisement visual optimization design in a CAD virtual reality simulation environment are all being done. It provides high specificity and low precision.

Wu [14], has recommended a creative brand perception design based on 5G IoTera. This article positions the consumer group as the target audience, is made to defining the brand’s basic values, and integrates consumer emotional personality psychology into logical brand strategy. An efficient assurance to promote and improve brand development is to create excellent brand recognition and precise brand development tracking. The combination of Chinese and English is the typical font used for the design. The benefit of combining Chinese and English is found on the cosmopolitanism and nationalism combination. In addition to being a brand-new phenomenon in culture, it also has robust operability, which satisfies the desires for internationalizing design. In addition to corporate image, self-consistency, and product image, the model explanatory power increases. It provides low computation time and low RoC.

Fu [15], has presented a brand image design in a global setting. The Internet of everything is a feature of the globalization period. In addition to encouraging global economic growth, it challenges the conventional strategy for brand building in all industries promoted through modernization of established brands and gives rise to a sizable count of next-generation online brands. The brand visual design is the graphical representation of the complete advertising strategies for brands. In the complete type identification system, statement and attraction are the most straightforward then precise. Media and modern techniques of brand communication are more prevalent as a result of the growth of platforms, the use of the Internet, the substitution of mobile devices, and the quick change of new media technologies. Brand value is improved when the brand image reflects the cultural norms and adopts a spiritual perspective. It provides high RoC and low accuracy.

Chen [16], have suggested using a human–computer interaction (HCI) methodology to establish a brand for the Hakka culture. The presented paper describes the brand concept, the components of culturally and creatively produced goods, and the relation between Hakka cultural, creative businesses and travel-related enterprises. This method is being used here to conducts a thorough investigation of the Gannan region's innovative Hakka cultural tourist brand. The First step is to analyse the meaning of the brand and the fundamental elements of brand's culture and inventive products. The next part is to analyse looks at how culturally and creatively designed products under the Hakka tourism brand are related. Hakka culture is employed in branded creative and cultural works, and it covers the acquisition and advancement of Hakka culture. Analyzing the design process used by the Hakka cultural tourist brand to create artistic and cultural items in Gannan is the third phase.

Kim et al. [17], have examined the use of online games in China and Korea, the two largest Asian marketplaces, to see whether relationships exist between brand perception, perceived game quality, country of origin (COO), and online game beliefs. Service quality, Product quality and pleasure quality are the three dimensions of perceived game quality. According to the authors survey of 355 Chinese and Korean online gamers, brand image effects quality assessments either indirectly or directly through brand belief. The impact of COO on decisions of game quality appears to be more indirect and less significant than that of brand image. There are some cross-country variations found by the multi group research organization. In China, the COO has a significant impact on beliefs, but not in Korea. Compared to China, brand image has a greater influence on brand beliefs in Korea. The COO should be highlighted with other product details by the game developer to indicate to Chinese users excellent product or service quality. Considering that Koreans respond more favourably to corporate identity, brand personality, and brand content. To attract Korean players, game makers have to accentuate the symbolic elements of their brand image.

3. Proposed methodology

The BID-DMSFNN-COA methodology follows a structured approach for automatic image classification. It begins with the acquisition of input data, which in this case involves obtaining the Mnist dataset of handwritten digits. The data undergoes preprocessing steps, including the application of an adaptive notch filter to enhance its quality. Subsequently, features are extracted from the preprocessed data using deep multi-scale fusion neural networks. These features capture relevant characteristics of the input data

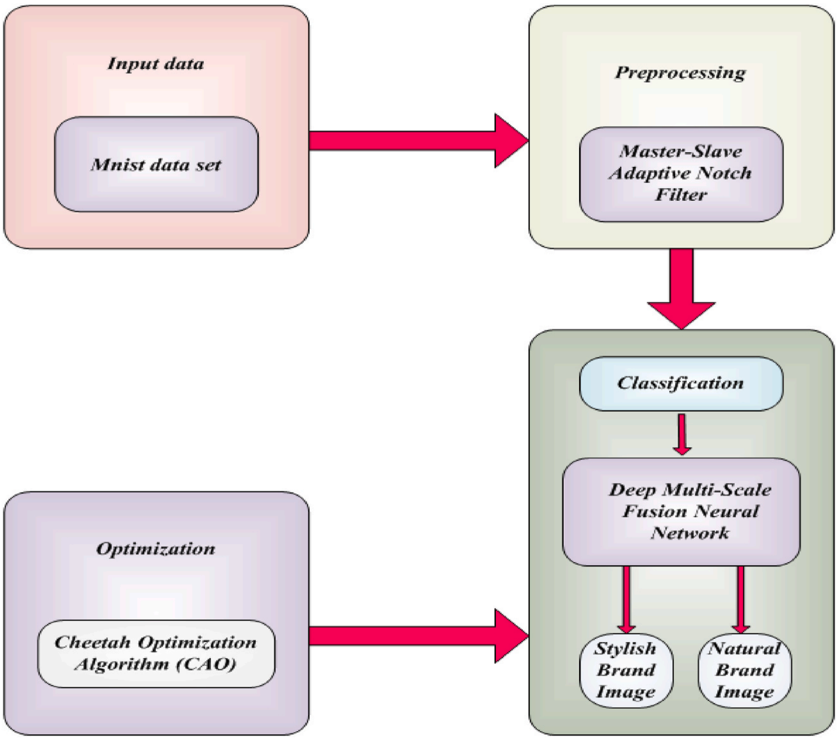

Fig. 1. The block diagram of proposed BID-DMSFNN-COA approach.

necessary for classification. The classification process itself employs the deep multi-scale fusion neural network, assigning input data to appropriate classes based on the extracted features. To optimize the classification process, the Cheetah Optimization Algorithm is utilized, fine-tuning parameters to enhance performance. The methodology aims to produce accurate classification results, contributing to the design of brand images. Each step's comprehensive description may be found below. Fig. 1 that the block diagram of proposed BID-DMSFNN-COA approach.

3.1. Data acquisition

The MNIST dataset is a widely recognized benchmark dataset utilized for handwritten digit recognition tasks. With 10,000 cases in the test set and 60,000 instances in the training set, it is divided into 4 files. The "train-images-idx3-ubyte.gz" file contains grayscale images of handwritten digits in the training set, with each image represented as a 28x28 pixel array. Correspondingly, the "train-labels-idx1-ubyte.gz" file provides the labels for the training set images, indicating the digit (0 through 9) represented in each image. Similarly, the "t10k-images-idx3-ubyte.gz" and "t10k-labels-idx1-ubyte.gz" files contain images and labels, respectively, for the test set. This dataset serves as a standardized and well-labeled resource for training and evaluating machine learning models, facilitating research, benchmarking, and comparison efforts in the field of handwritten digit recognition [18].

3.1.1. Connecting handwritten digits to product color branding

While seemingly disparate, the MNIST dataset, originally intended for handwritten digit recognition, holds relevance to product color branding through shared principles of image classification. Leveraging CNNs and transfer learning techniques, features learned from handwritten digits can be repurposed to classify product color brand images. By aligning methodologies and leveraging pre-existing datasets, such as MNIST, for feature extraction and model training, this approach bridges the gap between handwritten digit recognition and product color branding tasks, enhancing brand perception and consumer engagement.

3.2. Data pre-processing using master-slave adaptive notch filter (MSANF)

Here the pre-processing is attained by the use of MSANF. By using the MSANF, the noise in the product colour brand image is removed [19].

The differential equation of the ANF is followed in equation (1)

$$\begin{cases} \ddot{b} + \hat{\omega}^2 b = 2\xi\hat{\omega}\varepsilon(k) \\ \hat{\omega} = -\lambda b\hat{\omega}\varepsilon(k) \\ \varepsilon(k) = f_s - b \end{cases} \tag{1}$$

where f_s is the input product colour brand image, λ represents bandwidth, $\hat{\omega}$ represents fundamental frequency as shown in equations (2) and (3)

$$B_1(t)\left(t^2+\omega_1^2\right) = 2\xi\omega_1(D_s(t) - tB_1(t) - tB_3(t)) \tag{2}$$

$$B_1(t)\left(t^2+9\omega_1^2\right) = 2\xi\omega_1(D_s(t) - tB_1(t) - tB_3(t)) \tag{3}$$

where t implicates Laplace operator, μ implicates bandwidth, s implicates harmonic order $\omega_t = t\omega_1$ and ω_t refers frequency of the fundamental wave and is determined in equations (4) and (5)

$$B_3(t) = \frac{2\xi\omega_1(B_s(t) - tB_1(t))}{t^2 + 2\xi\omega_1 t + 9\omega_1^2} \tag{4}$$

$$tB_1 = \frac{2\xi\omega_1 t\left(t^2+9\omega_1^2\right)}{(t^2+\omega_1^2)(t^2+2\xi\omega_1 t + 9\omega_1^2)| + 2\xi\omega_1 t(t^2+9\omega_1^2)} B_s(t) \tag{5}$$

From this equation $t = j\omega_1$, gain as1 and $t = j3\omega_1$, gain as 0.

This demonstrates that while the specific harmonic is completely erased, the fundamental wave is carefully tracked. The filter's reaction speed is determined by its time domain (ξ), and a larger ξ value is selected to achieve a faster response. Finally, the pre-processed data is supplied to the classification process.

3.3. Automatic image classification using deep multi-scale fusion neural network (DMSFNN)

The use of DMSFNN to automatically identify each image and reveal hidden connections between visual components and brand engagement is discussed in this section [20]. The classification task at ILSVRC showed that the InceptionV3 model established the lowest error rate. The deep multi-scale fusion neural network (DMSFNN) has shown robust performance for the types of image classification. The final prediction task was carried out using a multilayer classification, with a binary class for each category. Equation (6) was used to modify all of the chosen models, in addition to adding one fully connected layer, so that the final output layer contained only one neuron.

$$R = Con\left(g_{e_1}, g_{e_2}\right) \tag{6}$$

here *Con* represents the concatenation operation, R expresses the fusion feature map and g_{e_1}, g_{e_2} means the multiple scale-specific features. Then the spatial attention component helps to mining the discriminative characteristics and thus improves the performance. Here the global feature map is acquired by performing the global average pooling operation is expressed in equation (7)

$$D_u = \frac{1}{t}\sum_{l=1}^{d} R_{u,l} \tag{7}$$

here D represents the global feature map, u means the spatial location, t expresses the channels and l represents the variables. Then the spatial attention map h_{att} is produced using the sigmoid function to D is expressed in equation (8)

$$h_{att} = \sigma(Y * D + a) \tag{8}$$

here $\sigma(.)$ represents the sigmoid function, a represents the features. Thus the global feature map by performing one by one convolution is expressed in equation (9)

$$D = D + h_{att} \otimes D \tag{9}$$

here $\otimes$ indicates the channel-wise product operation. Then the feature integration from various convolution channels and features dimension compression is attained by the global pooling layer. The fusion feature maps are then pooled using maximum and average pooling in the proposed technique. Max-pooling is used to extract specific information, whereas average-pooling is used to obtain global information. This can be denoted in equation (10)

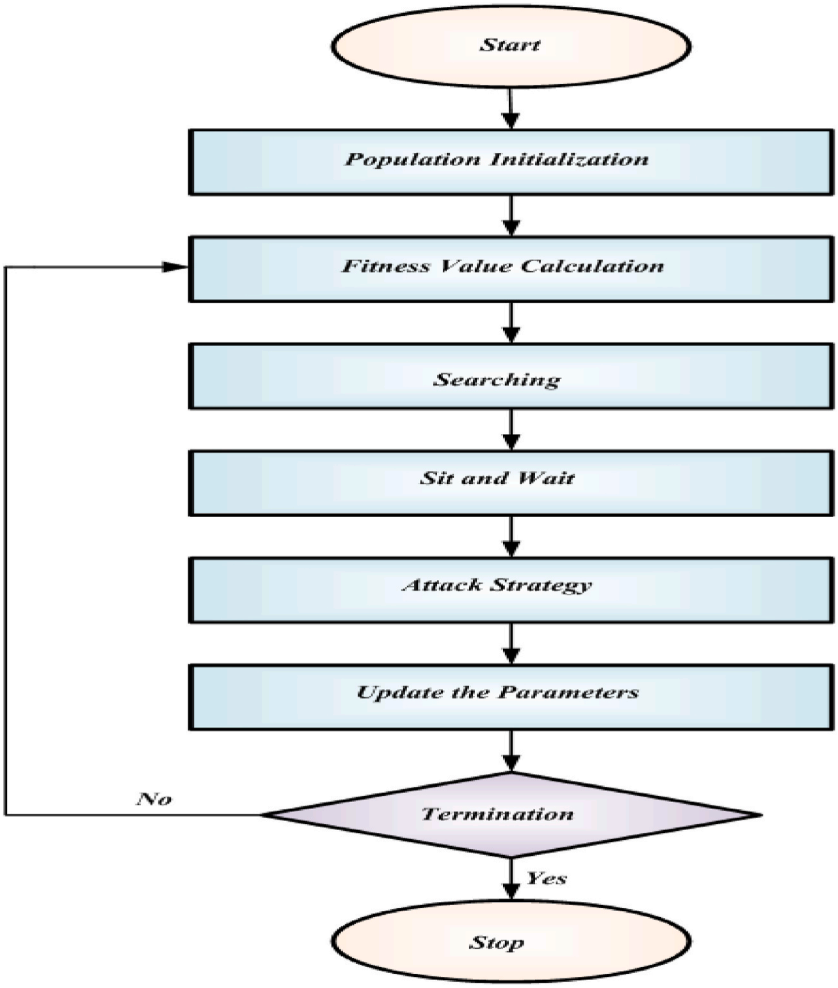

Fig. 2. Flowchart of COA

$$x_{c_g} = h_m(R) + h_a(R) \tag{10}$$

here h_a refers the average pooling operation, h_m represents the max-pooling, x_{c_g} epitome the features used for prediction. The soft max classification loss which is assumed as the objective function is expressed in equation (11)

$$H_{c_g} = -\frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{R} J\{x_j = i\}\log q(x_{c_g}) \tag{11}$$

here H_{c_g} represents the loss function, M, R represents the total parameters, i, j, q represents the variables and J means the soft max coefficient. Finally, the Deep Multi-Scale Fusion Neural Network (DMSFNN) classifies the product colour brand image as stylish colour images and natural colour images.

In this study, the Deep Multi-Scale Fusion Neural Network (DMSFNN) classifier's optimal parameters were optimized using the Cheetah optimization algorithm. It is a revolutionary natural-inspired algorithm based on cheetah hunting techniques that serves as the inspiration for the met heuristic algorithm. The stepwise procedure of the Cheetah Optimization algorithm given below.

3.4. Cheetah optimization algorithm (COA)

An algorithm using met heuristics is the CO. The CO is based on the four primary hunting tactics used by the cheetah including search, set, wait, attack. It also employs an early converge avoidance strategy known as "leave the victim and go home," which raises the likelihood that the best answer will emerge from the search [21]. The phases of the CO algorithm are initialization, population evaluation, and updating parameters. The flow chart of COA is depicted in Fig. 2. COA method includes the following steps. The process of step is given in the following.

Step 1. Initialization

Initialize the input parameters M, R, iteration and population of cheetah.

Step 2. Random Generation

Following the initialization procedure, the input weight parameter is created random through COA method.

Step 3. Fitness Function

Using the initialized parameters, the fitness function generates a random solution. Equation is used to determine the fitness function. Equation (12) shows the fitness function.

$$\textit{Fitness Function} = \textit{optimize}\,[\sigma] \tag{12}$$

Step 4. Searching the Prey

Let, $X_{i,j}^t$ defines the current location of cheetah i ($i = 1, 2 \ldots n$) and j ($j = 1, 2 \ldots D$) in arrangement in which, n is the population size of cheetahs and the efficiency problem's dimension is D. Mathematically, characterize this searching techniques of cheetahs.

Every cheetah deals with different prey in various situations. The positions of each prey's decision variables, which correspond to the best choices, form a population in the cheetah's states (other configurations). The following equation (13) is given by updating the noval position of each cheetah in each arrangement using the current position of each and an arbitrarily large step size:

$$Y_{i,j}^{t+1} = Y_{i,j}^t + \hat{r}_{ij}^{-1}.\alpha_{ij}^t \tag{13}$$

where, $\alpha_{i,j}^t$ indicates the cheetah iin arrangement j's randomization parameter and step length; the randomization parameter and step length for cheetah *i*in arrangement *j;* $Y_{i,j}^{t+1}$ and $Y_{i,j}^t$ indicates the next current locations of cheetah *i* in arrangement *j*; $\hat{r}_{i,j}^{-1}$'*t*' denotes the current hunting duration. Random numbers from a conventional normal distribution are used in the second randomization term, where the parameter $\hat{r}_{i,j}$ is normally distributed. Given that cheetahs are slow-moving searchers, the step length ($\hat{r}_{i,j}^t > o$) can typically be set as (0.001 × t/T) as. The cheetahs could run and change its directions by meeting others (enemies). For each cheetah in multiple hunting seasons, the random number (r̂−1) is used to express such attitude in addition near/far destination search mode. $Y_{i,j}^t$ is the distance amid the cheetah *I* and his or her leader in some cases can be altered. In each arrangement of cheetahs, the direction of a cheetah is updated by assuming $Y_{i,j}^t$ equivalent to (0.001 × t/T) multiplied by the maximal step size. In this case, we consider it based on the upper limit minus the lower limit. The distinction between randomly chosen positions for cheetah *i* and multiplied to determine the positions of the other members, $Y_{i,j}^t$ of each cheetah's arrangement.

Step 5. Sit-and-Wait

During its search, the cheetah may get sight of the victim. In this circumstance, the cheetah's every step has the potential to make the victim aware of its presence and send it running. To ease this concern, the cheetah may choose to ambush in order to get sufficiently near to the victim. This means that during this stage, the cheetah keeps their distance and waits for the prey to approach which is shown in equation (14)

$$\underset{i,j}{\overset{t+1}{X}} = \underset{i,j}{\overset{t}{X}} \tag{14}$$

where $X_{i,j}^{t+1}$ and $X_{i,j}^{t}$ is denoted as current locations of cheetah *i* in arrangement *j*.

Step 6. Attack Strategy

Cheetahs use two essential characteristics when they attack their prey: speed and adaptability. When a cheetah decides to attack, it moves swiftly in the direction of its victim. The prey starts to run away. The cheetah uses its keen vision to quickly pursue its victim in the direction of the intercept. Follow the victim 'sposition; the cheetah changes its course to obstruct the victim 's passage at one point. The victim is forced to quickly change positions in order to survive after the cheetah closes in on it at peak speed. The cheetah's next position is near the victim 's previous location.

The one cheetah, presumably, doesn't hunt in a manner completely consistent with how cheetahs normally hunt. The cheetah uses its agility and speed to catch its prey at this stage. When hunting in groups, each cheetah may adjust its position in response to escaping prey's location of the leader or nearby cheetah. Simply put all cheetah attack techniques fall into one of the following equation (15):

$$\underset{i,j}{\overset{t+1}{X}} = \underset{\beta,j}{\overset{t}{X}} + r^{ij} \cdot \underset{i,j}{\overset{t}{\beta}} \tag{15}$$

here r^{ij} *and* $\beta_{i,j}^{t}$ is denoted as the tuning and interaction factor related to the cheetah *i* in arrangement *j*and $X_{\beta,j}^{t}$ is represented as the prey's present position in arrangement j: $X_{\beta,j}^{t}$ is in attack mode, cheetahs race to their prey's location as quickly as possible by using all of their available speed. The tuning factor $\beta_{i,j}^{t}$ demonstrates how the cheetahs or their leader interacted when in the catching mode.

Step 7. Termination

Two situations are considered for this approach.

(1) The cheetah should relocate or return to its home range if it is unsuccessful in capturing its prey.
(2) If there hasn't been any successful hunting activity for a while, it can relocate to the site of the most recent prey discovered and search the area surrounding it.

Verify the stopping criteria; if the best solution is found, the procedure is over; if not, move on to step 3.

Because of its convenience and pertinence, the deep learning based optimization strategy is taken into account in the DMSFNN classifier. In this work, COA is employed to optimize the DMSFNN optimum parameter. In this case, the weight and bias parameter of the DMSFNN are adjusted using COA.

4. Result with discussion

The experimental outcome of BID-DMSFNN-COA technique is discussed. This technique is executed in MATLAB platform. The acquired outcomes of the BID-DMSFNN-COA method are analysed with the existing methods like BID-GNN [10], BID-ANN [11], and BID-CNN [12] methods respectively.

The performance matrices like sensitivity, accuracy, specificity, F-score, precision, recall analyse the performance of the approach.

- True positive (*TP*): Stylish accurately categorized as Natural.
- True negative (*TN*): Natural accurately categorized as Stylish
- False positive (*FP*): Natural inaccurately categorized as Stylish.
- False negative (*FN*): Stylish inaccurately categorized as Stylish.

4.1. Performance measures

Performance parameters such as accuracy, sensitivity F1-score, precision, and specificity are calculated in order to assess the performance.

4.1.1. Precision

It evaluates the predictive value of a samples, either negative or positive, depending on the class for which it is computed; in other words, it evaluates the samples' ability to forecast, which is represents as equation (16),

$$precision = \frac{TP}{TP + FN} \tag{16}$$

4.1.2. Accuracy

Equation (17) represents the calculation of accuracy value, which is the ratio of the count of samples correctly classified by scheme with the total count of samples.

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{17}$$

4.1.3. F-score

Equation (18) represents the F-score, a composite measure that rewards techniques with higher sensitivity and presents problems for approaches with more specificity.

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \tag{18}$$

4.1.4. Sensitivity

In order to assess the effectiveness of a method on a single class, sensitivity approximates the likelihood that the positive (negative) sample is true, which is represented in equation (19),

$$sensitivity = \frac{TP}{TP + FN} \tag{19}$$

4.1.5. Specificity

By estimating the probability that the positive sample is real, it assesses the effectiveness of the strategy on a single class, which is represented in equation (20),

$$specificity = \frac{TN}{FP + TN} \tag{20}$$

4.2. Simulation result

Figs. 3–9 shows that the simulation results of BID- COA-DMSFNN method. Then, the method BID- COA-DMSFNN is related by existing BID-GNN, BID-ANN, and BID-CNN methods.

Analyses of performance accuracy is determined in Fig. 3. The performance accuracy on different models or approaches used to analyse product colour brand image design. This could include a comparison of machine learning algorithms, statistical models, or any other techniques employed for this purpose. The proposed BID-COA-DMSFNN methods of accuracy are 99 % Natural and 99 % Stylish. The existing methods BID-GNN, BID-ANN and BID-CNN, the accuracy become 85 %, 65 %, 75 % Stylish and 65 %, 68 %, 70 % Natural product colour brand image design. The proposed method is higher accuracy value compare with other existing methods.

Performance Analyses of f-score is determined in Fig. 4. Compare the performance of different approaches for predicting product colour brand image based on their F-score values. The proposed BID-COA-DMSFNN method provides 98 % for Natural and 98 % for Stylish f-score for product colour brand image. The existing methods BID-GNN, BID-ANN and BID-CNN, the f-score become 84 %, 75 %, 83 % are Stylish and 66 %, 84 %, 80 % are Natural product colour brand image design. The proposed method is higher F-score value compare with other existing methods.

Performance Analyses of precision is determined in Fig. 5. Precision is a metric, to evaluate the accuracy of a predictive model or algorithm. A metric is the proportion of occurrences correctly anticipated as positive (true positives) relative to all instances projected as positive (false positives and true positives). Reduced false positive rates are indicated by better accuracy values. This provides the model's effectiveness in identifying and predicting user behaviours accurately. The precision of proposed BID-DMSFNN-COA methods becomes 98 % Stylish and 98 % Natural. The existing methods BID-GNN, BID-ANN and BID-CNN, the precision attain 76 %, 87 %, 85 % Stylish and 65 %, 76 %, 74 % Natural product colour brand image design. The proposed method is higher Precision value compare with

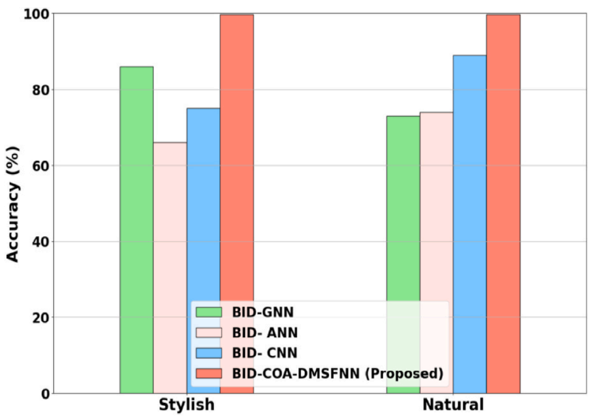

Fig. 3. Analysis of performance accuracy.

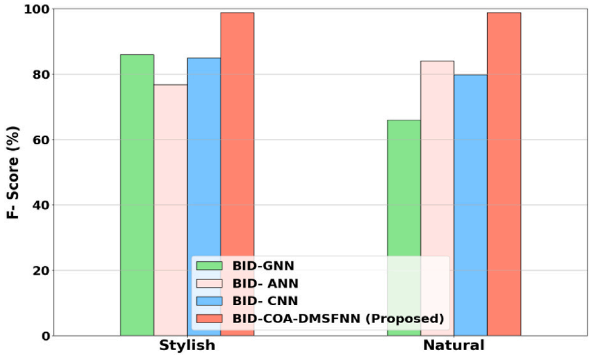

Fig. 4. Performance analyses of F-score.

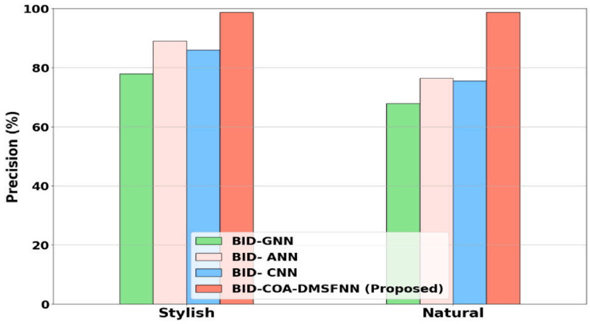

Fig. 5. Performance analyses of precision.

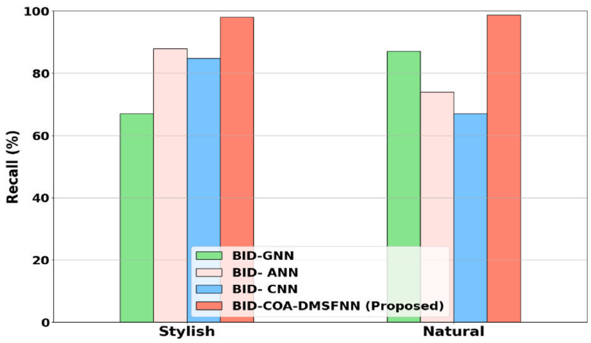

Fig. 6. Performance analyses of Recall.

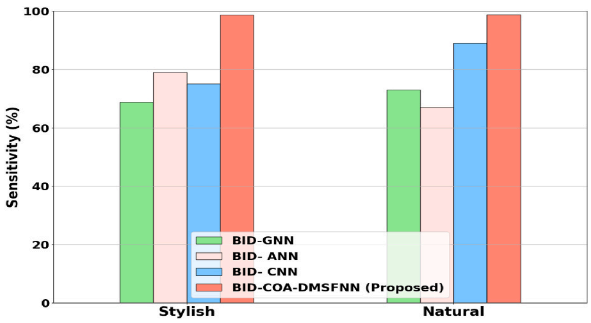

Fig. 7. Performance analyses of Sensitivity.

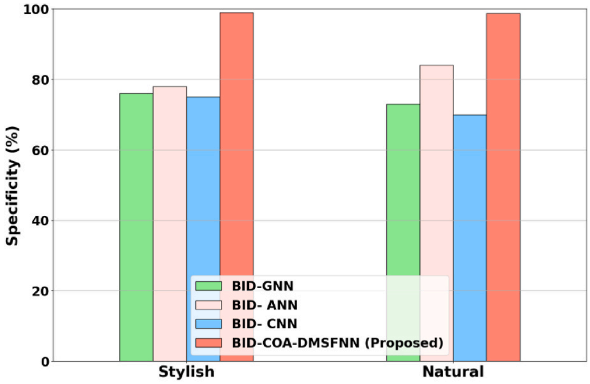

Fig. 8. Performance analyses of Specificity.

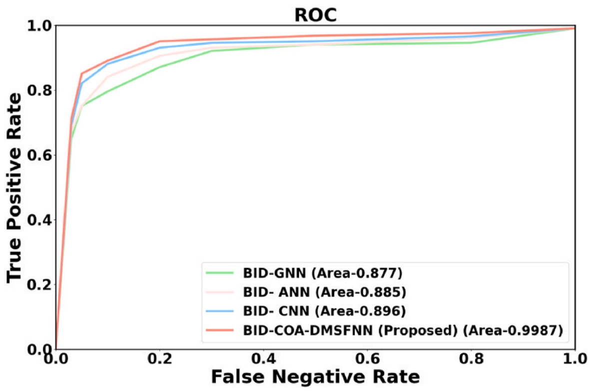

Fig. 9. Performance analyses of ROC.

other existing methods.

Performance analyses of recall is given in Fig. 6. The analysis might involve comparing the recall values for different prediction algorithms, examining the impact of various features or parameters on recall. Here, the proposed BID-DMSFNN-COA methods the recall provides 97 % Stylish and 98 % Natural product colour brand image. The existing methods BID-GNN, BID-ANN, and BID-CNN, the recall become 65 %, 85 %, 83 % Stylish and 85 %, 75 %, 65 % Natural product colour brand image. The proposed method is higher Recall value compare with other existing methods.

Performance analyses of sensitivity is given in Fig. 7. The BID- DMSFNN-COA methods the sensitivity provides 98 % Stylish and 98 % Natural product colour brand image design. The existing methods BID-GNN, BID-ANN, and BID-CNN, the sensitivity becomes 65 %, 78 %, 75 % Stylish and 70 %, 65 %, 88 % Natural product colour brand image design. The proposed method is higher Sensitivity value compare with other existing methods.

Performance analyses of Specificity is determined in Fig. 8. This graph shows the specificity of the model changes as the threshold for classification is varied. In specificity the proposed BID-DMSFNN-COA methods provide 98 % Stylish and 99 % Natural product colour brand image. The existing methods BID-GNN, BID-ANN, and BID-CNN, the specificity becomes 75 %, 78 %, 73 % Stylish and 73 %, 83 %, 69 % Natural product colour brand image design. The proposed method is higher specificity value compare with other existing methods.

Fig. 9 represents the analyses of ROC. Here, the BID-DMSFNN-COA method attains provides higher ROC than the existing approaches which include BID-GNN, BID-ANN and BID-CNN methods respectively. The value initially starts at 0.0 true positive rate and 0.0 rate of false negatives and the increases at 0.98 positive rates at 0.05 rate of false negatives and the value is constant in between the 0.98 true positive rates at 0.08 rate of false negatives. In existing GNN, the value is starts at 0.0 true positive rates at 0.0 false negative rates and the value increase at 0.9 true positive rates at 0.04 false negative rates and the value is varied in between the 0.95 true positive rates at 0.1 false negative rates to 0.93 true positive rates at 0.4 false negative rates. In ANN, the value is start at 0.2 true positive rates at 0.01 false negative rates and the value is constant in between the 0.91 true positive rates at 0.25 false negative rates to 0.91 true positive rates at 0.45 false negative rates. In CNN, the value is start at 0.0 true positive rates at 0.0 false negative rates and the value increases at 0.88 positive rates at 0.07 negative rates and value is constant in between the 0.89 true positive rates at 0.07 false negative rates to 0.89 true positive rates at 1.0 false negative rates.

4.3. Hyper parameter settings

4.3.1. DMSFNN

Learning rate: 0.001.
Batch size: 128.
Number of layers: 5.
Neurons per layer [10,128,256,512,784]: (input layer, hidden layers, output layer).
Activation functions: ReLU for hidden layers, Softmax for output layer.
Dropout rate: 0.2 (to prevent overfitting).
Optimizer: Adam.
Loss function: Categorical Crossentropy

4.3.2. COA

Population size: 50.
Maximum iterations: 100.
Convergence criteria: Stop if the fitness score does not improve for 10 iterations.
Mutation rate: 0.1.

4.4. Display training data

4.4.1. Examination of training dataset

The MNIST dataset, comprising 60,000 handwritten digit images, is utilized for training the proposed model. Each image, represented as a 28x28 pixel array, is accompanied by a corresponding label indicating the digit it represents (ranging from 0 to 9). By examining a sample subset of this training data, researchers gain insight into the characteristics and complexities of the dataset. This examination aids in establishing a connection between the handwritten digit recognition task and the subsequent brand image classification objective, laying the groundwork for the development and evaluation of the classification model.

5. Conclusion

In this section, product colour for brand image design using a deep multi-scale fusion neural network optimized with a cheetah optimization algorithm is categorizing the product colour brand image as "Stylish" and "Natural" (BID-DMSFNN-COA). The proposed BID-DMSFNN-COA approach is implemented in MATLAB utilizing the dataset from the Mnist Data Set. The performance of the proposed BID-DMSFNN-COA approach attains 50.6 %, 44.5 %, and 40.1 % higher precision for stylish brand image; and 47.8 %, 43.7 % and 37.8 % higher precision for natural brand image compared with existing BID-GNN, BID-ANN, and BID-CNN methods correspondingly.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Data availability statement

No data was used for the research described in the article.

Funding

No particular money from governmental, private, or nonprofit organizations was given to this study.

Has data associated with your study been deposited into a publicly available repository?

No.

CRediT authorship contribution statement

Lei Wei: Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financialinterestsor personal relationships that could have appeared to influence the work reported in this paper.

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