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Retraction

Retracted: Intelligent Evaluation of Product Form Design Based on Deep Neural Network Model

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. Wang and Q. Wu, “Intelligent Evaluation of Product Form Design Based on Deep Neural Network Model,” *Mathematical Problems in Engineering*, vol. 2022, Article ID 3140489, 7 pages, 2022.

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Research Article

Intelligent Evaluation of Product Form Design Based on Deep Neural Network Model

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In order to evaluate the product morphological design, a method of applying BP neural network to evaluate the product morphological design is proposed based on the analysis of the principle of artificial neural network. In such method, the advantages of the BP neural network with self-learning, self-organization, self-adaptation, and nonlinear dynamic processing are applied to effectively evaluate the product morphological design. Specifically, 13 product morphological design solutions of the automotive evaluation data set are selected as samples, 15 out of 18 solutions are used to train the evaluation system, and the remaining 3 solutions are used to validate the trained system. The validation results show that the relative errors between the simulated and actual values are 3.6%, −1.7%, and 2.8%, respectively. Such results also show high accuracy and simultaneously can reflect the effectiveness of our proposed system for evaluating the design solutions.

1. Introduction

Product form design is an emerging edge discipline involving science and aesthetics, technology, and art, with product design as the main object, which contains 3 basic elements: product function, material and technical conditions, and form image [1]. Product form design not only requires the determination of the product's appearance quality but also considers the structure, function, and materials that affect the interests of producers and users, and its basic contents include product ergonomic design, product form design, product color design, and other product design [2–4]. Morphological design is an important part of product design and a major part of the product life cycle, which directly determines the performance of the product. Therefore, how to effectively evaluate the product form design is particularly important. At the same time, with the development of science and technology and the complexity of the design object, the product design has put forward higher requirements, so you can not rely on intuition, experience to evaluate the product form design, but should use advanced theory and methods to make a comprehensive and scientific evaluation of product form design [5–9].

Product form design evaluation is to evaluate the product design scheme, select the best design scheme, and provide theoretical basis for product form design, which is related to the survival and development of products, and guide the direction of product design and development in the future [10–14]. Therefore, it is of great importance to design the product image and make a comprehensive and scientific evaluation of its form.

In recent years, many scholars have conducted a lot of research on the application of neural networks in the evaluation of product form design. The authors in [15] established a three-layer network model to evaluate it based on the investigation and successfully used the legacy algorithm to optimize the product morphology design of cell phones. The authors in [16] used a combination of partial least squares and neural networks to develop a design support system for the appearance morphology design of running shoes and evaluated the solution; theauthors in [17] collected data with the concept of perceptual engineering through an experimental study of cell phones, and the authors in [18] introduced BP neural network into the evaluation of product morphological design and established an evaluation model, which showed that the method could evaluate the product morphological design more accurately; Khan et al. [19] established an RBF neural network model evaluation system for the evaluation of refrigerator morphological design, and the results showed that, compared with the BP algorithm, the RBF neural network model prediction has higher accuracy and faster convergence speed than the BP algorithm.

With the rapid development of artificial intelligence, several swarm intelligence algorithms have been developed to optimize neural networks for their powerful global optimisation capability and faster convergence speed to improve the generalization performance of networks [20].

In view of this, this paper applies the deep neural network phase to the evaluation of laptop computer morphology design.

2. Deep Neural Network Model

Product evaluation project structure analysis is divided into product evaluation and structure analysis, in which only the product evaluation item as an object is analyzed, and intersentence product evaluation item structure analysis, in which only the product evaluation item as an object is analyzed, while the latter includes the part of the product evaluation item outside the sentence as an object in the analysis object.

2.1. Deep Duplex Model. In the DRM study, a deep regression model based on the model of [10] was used as a baseline. The DRM is illustrated in Figure 1. The DRM is composed of the following: (1) input layer: an intermediate layer that receives sequences consisting of prime maps; (2) an output layer that uses a bivariate; and (3) RNN: a multivalued classification using a soft maximal function.

In the input layer (Input Layer) of Figure 1, the prime vector xH is given for each product evaluation word andrH is assigned to the input sentence; in the intermediate layer (RNN Laver). In the output layer, a softmax function is used to predict the label for each product evaluation word. DRM is a model for product evaluation to predict whether a product evaluation word is an item, so in the case that the text contains multiple product evaluations, DRM is prepared separately for each product evaluation. As an example, the table in Figure 2 represents the labels of the input sentences and predicted objects after being segmented by product evaluation words. No labels are given to the product evaluation words that are not related to items. Thus, the predicted set of labels consists of three lattice labels, denoting not GA, M0, NI, product evaluation label PRED, or item, respectively. The aim is to add a label to each product evaluation word from these five labels. In the subsequent sections, these network structures are described in detail.

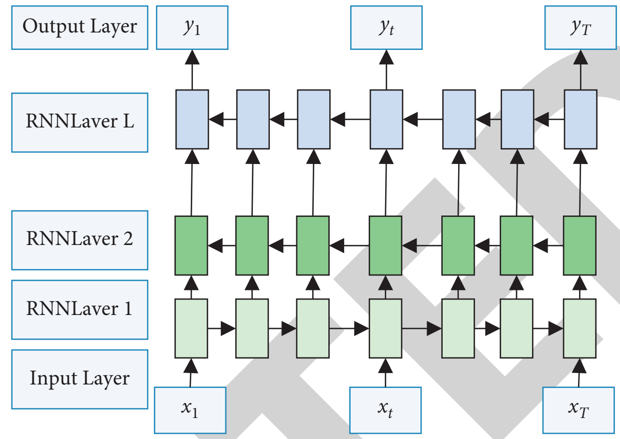

Figure 1: Deep regression model.

2.2. Input Layer. After the product evaluation words are segmented in the input sentence, the origin of each product evaluation word is extracted, and a vector of the plainness is made based on the extracted plainness. The prime extracted in Figure 2 indicates the example of prime extracted for each product evaluation word. The following four types are defined:

(i) *Arg*: candidate words
(ii) *Pred*: product evaluation words for product evaluation
(iii) *Pred Context*: product evaluation words around the product evaluation
(iv) *Mark*: whether or not to enter the Pred Context

Arg and Pred are the product evaluation words for this candidate product evaluation. For example, in the example sentence of Figure 3, the Arg prime of the product evaluation word "she" is "she" and the Pred prime is "ate." C is a hyperparameter, which is set to $C = 1$ in Figure 3, and Mark is a binary prime with 0 or 1 to indicate whether it is included in the set of product evaluation words that match the Pred Context prime. As an example, consider the Mark origin of the product evaluation word "she." On the other hand, considering the Mark origin of the product evaluation word "she," which is not one of the three product evaluation words, the Mark origin is 0. On the other hand, considering the Mark origin of the product evaluation word "she," which is one of the three product evaluation words, the Mark origin is 1, and the Mark prime is 1.

Based on the extracted plainness of the plain vector, the plainness vector is made. It is a matrix of dimensional product evaluation word vectors. The three Arg Pred Contexts (origins associated with the product evaluation words) are subdivided into each column vector of this matrix. Therefore, the vectors associated with each product evaluation word are extracted from this matrix, and as with the vectors used for prime, the "Mark Emb" in Figure 2 is a matrix of Md. It is a matrix of dimensional graphs. The column vectors associated with each Mark are extracted and used for the prime vector. The extracted vectors (six vectors

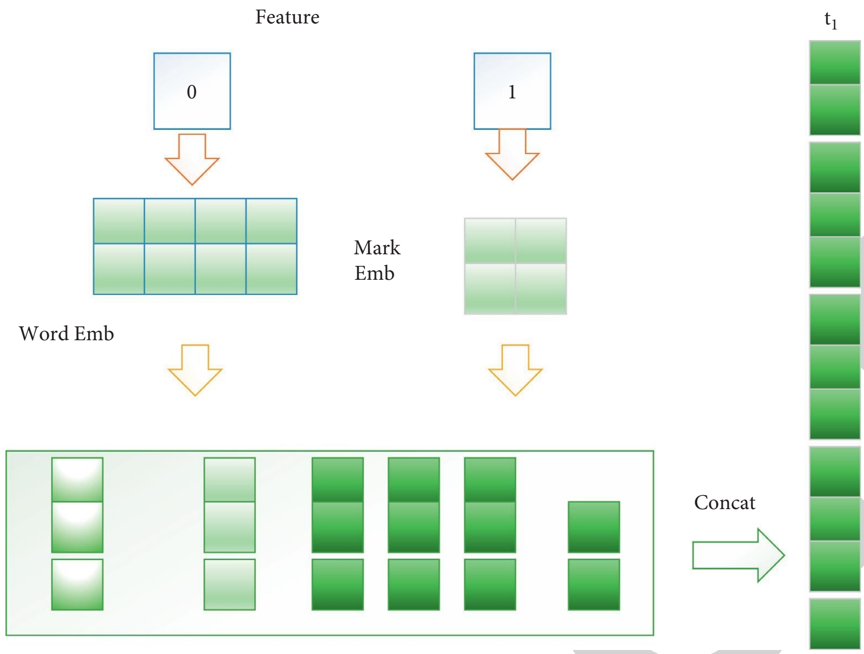

Figure 2: Example of how vectors are made.

Word	GA	NONE	WO	NONE	PRED	NONE

Feature				
1	Arg	Pred	Pred Context	Mark
2	GA	Ate	Have breakfast	0
3	NONE	Ate	Have breakfast	0
4	WO	Ate	Have breakfast	1
5	PRED	Ate	Have breakfast	1

Figure 3: Example.

in the lower part of Figure 2) are combined together as the basic vector *x*. This vector of prime is given as the input to the Bi-RNN of the middle layer.

2.3. Middle Layer. In the intermediate layers, the computation of the prime vector is then performed in multiple layers (RNN Layer) using RNN. The RNN layers use Bi-RNN, where the odd-numbered bits process the sequence from left to right and the even-numbered ones from right to left. By overlapping these RNN layers, the depth of the network structure can be changed.

3. Model Training Algorithm and Steps

In this paper, the network input is represented as vector $X = (x_1, x_2, \cdots, x_n)$, and n corresponds to the number of neurons in the input layer. The activation function is chosen as a hyperbolic tangent S-shaped function, also called hyperpolar Sigmoid function, $f(u) = \tanh(\theta u) = e^{\theta u} - e^{-\theta u}/e^{\theta u} + e^{-\theta u}$, where θ is the slope parameter of the function. The error propagation algorithm of this network is used to obtain the corresponding prediction error.

$$y^K = \sigma\left(y^{(k-1)} W^{(k)}\right). \tag{1}$$

Then, the error is back-propagated from back to forward based on equations (2), (3), and (4), and the weights are updated layer by layer.

$$\delta^{(k)} = R^{(k)} h\left(y^k\right), \tag{2}$$

$$E^{(k)} = \left(W^{(k)}\right) T \delta^k, \tag{3}$$

$$W^{(k)} = W^{(k)} + \eta\left(y^{(k-1)}\right)^T \delta^k. \tag{4}$$

4. Simulation Experiments

4.1. Data Processing. The simulation experiment uses the open-source car evaluation dataset on UCI, which has a total of 1728 pieces of data, including four car service quality evaluation levels, and the proportion of each level is shown in Figure 4. Each data has six attributes, and the attribute values are a discrete mixture of numerical and qualitative descriptions. Based on the discrete characteristics of the dataset, in order to make the nonbiased attribute values not biased and to make them equally spaced to the round points. One-hot encoding is used for data preprocessing, the discrete attribute fetching is extended to a point in the Euclidean space, and the distance calculation between features is applied to the model algorithm processing. The features encoded in the automotive evaluation dataset can be regarded as continuous type features for reasonable processing [21–23].

4.2. Model Results and Analysis. The 1728 data items of the car evaluation data set are divided into two groups according to 3:7, 1210 of them are taken as the training data set, and the learning rate is 0.006. The data signal processed by one-hot encoding is forward propagated through the input layer, implicit layer, and output layer, and then the Adam optimizer is selected to update the weight parameters and bias parameters by backward propagation from backward to forward layer by layer, and the weights of each node are adjusted by multiple iterations to reduce the error and make the predicted value closer to the real value, while the regularization method is used to avoid overfitting. Finally, through 500 iterations of training, the model tends to be stable and the training error loss curve is shown in Figure 5. 518 data are selected to test the product service quality evaluation model, and the fit between the car service quality evaluation grade and the actual data grade is obtained by neural network model prediction, as shown in Figure 6.

Based on the above graphical information, this neural network model converges quickly and with high error accuracy in the training phase, and its optimal and average errors have convergence consistency, thus improving the reliability of convergence; the model accuracy can reach 95.40%. The comparative experimental analysis is conducted, and the model accuracy comparison is shown in Table 1. It is proved that the service quality evaluation model of this product under the same circumstances is better than the traditional quality evaluation models such as logistic regression, KNN, and SVM. Therefore, the service quality evaluation model based on the neural network has better application and research prospects.

Option 1 in Figure 7 is an optimised solution for product 1. With the addition of the information display, users can quickly switch between channels by clicking on the next channel in addition to the “next” button. Product 2 has too many levels. Problem 4 has a right-handed button layout, and question 6 has an incomprehensible entry style, and Problem 7 has small text. Problems 6 and 7 are less frequent and therefore have a lower priority for optimisation. For Problem 2, where the depth of the hierarchy affects the ease of use for participants, Option 2 removes the entry button, increases the hierarchy of the page, and places the pointer bar below the channel. To address the issue in question 4 where the layout of the buttons affected participants’ perception of the buttons when completing tasks, and therefore their selection preferences, option 3 was proposed to move the buttons from the right to the left [24–26].

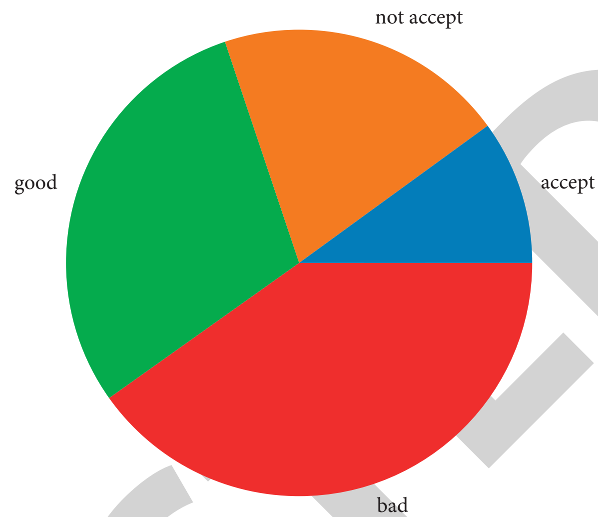

Figure 4: Data level share chart.

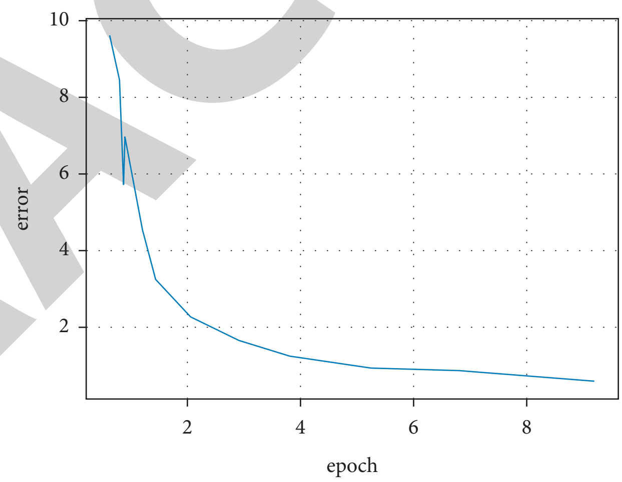

Figure 5: Training error graph.

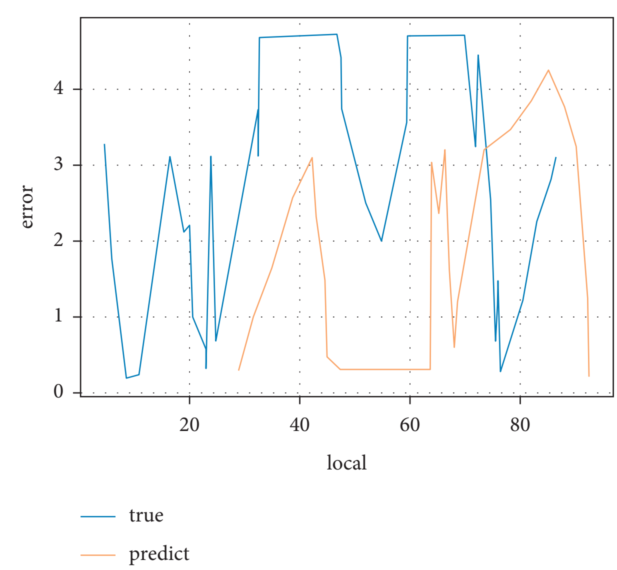

Figure 6: Actual and predicted values of car service quality level.

Table 1: Comparison of model accuracy.

Model	Accuracy (%)
Neural network	95.40
Logistic regression	69.60
KNN	83.92
SVM	90.51

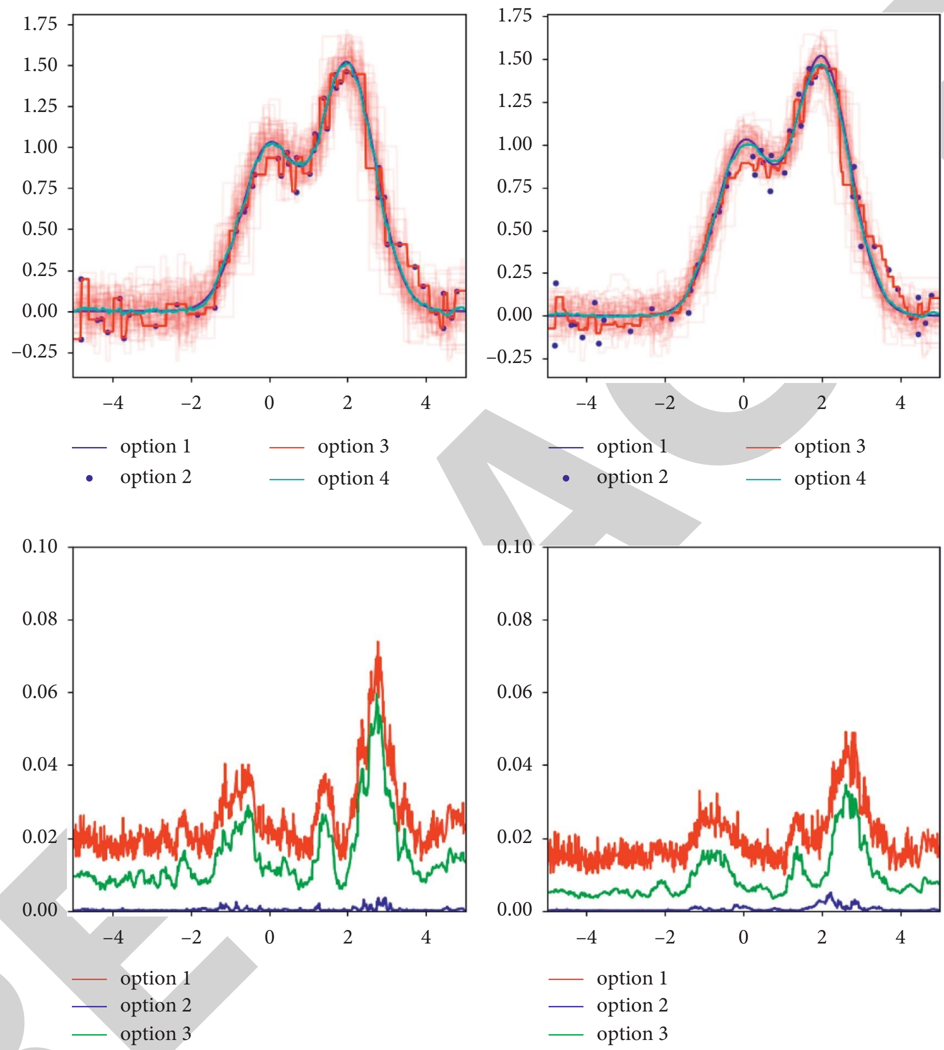

Figure 7: Design optimisation options for the Internet of things.

Nine subjects (3 males and 6 females, mean age of 24.0 years) were invited to participate in the FM console optimisation scenario driving simulator validation evaluation and the experimental results of SAGAT are shown in Figure 8 [25]. For the optimisation of product 1, the SAGAT correct rate for solution 1 was 76.67% (SD = 11.18) compared to 63.33% (SD = 15.81) for the original solution. Three of the subjects felt that this information helped them to better understand the meaning of the next button, to establish a reasonable mapping relationship, and to provide a new way of interaction. For the optimisation of product 2, the SAGAT correct rates of 76.67% (SD = 14.14) and 75.56% (SD = 15.09) were higher for both scenarios 2 and 3 than the original 68.89% (SD = 11.67), and the in-depth postexperimental interviews revealed that nine subjects thought that both optimizations were better than the original product 2; in addition, some subjects suggested that Option 1 could be combined with Option 2, i.e., reducing the FM frequency bar level to the first page of the FM and adding the first page of the FM frequency bar to the first page of the FM. In addition, it was suggested that Option 1 could be merged with Option 2 by reducing the FM frequency bar hierarchy to the FM home page and marking the FM frequency bar with nearby channels. The experimental results show that the user has a better situational awareness when driving with the optimised solution, and all three optimised solutions have a better user experience than the original solution, so the HMI evaluation and design method for

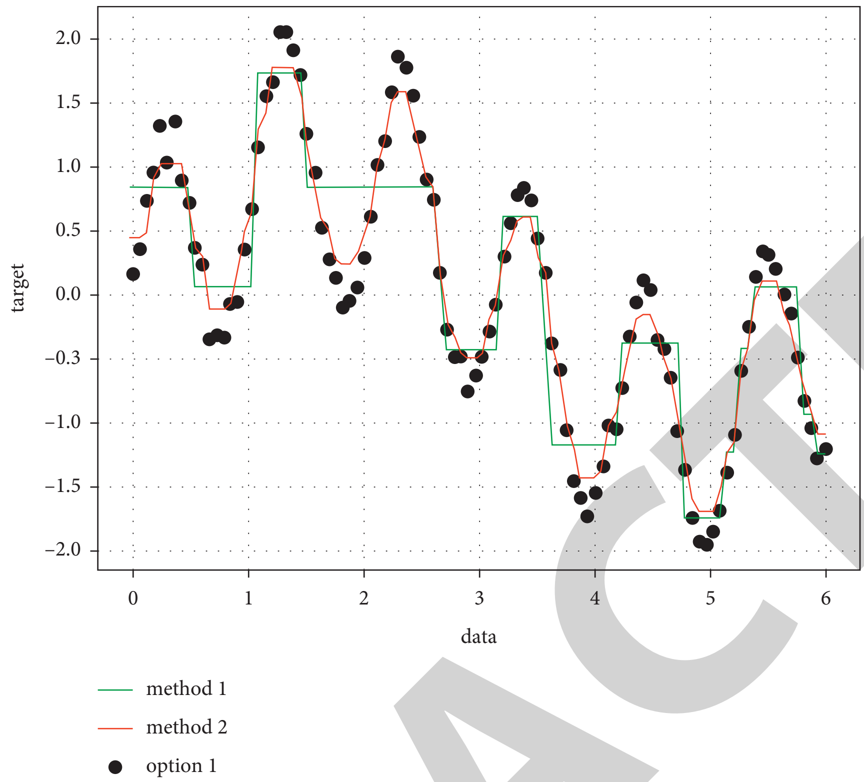

Figure 8: SAGAT correct rate for the original and optimised solutions.

automotive equipment based on team posture proposed in this paper is feasible and effective [26].

5. Conclusion

In this paper, a hybrid GA-BP product form design evaluation system is established to evaluate 18 notebook product form design solutions by combining the legacy algorithm and BP neural network. In such system, a notebook morphological design evaluation secondary index system is constructed, and 90 valid questionnaires which use a 5th-order Likert scale method are quantified simultaneously. The evaluation results show that the relative errors are 3.6%, −1.7%, and 2.8%, which indicates the effectiveness of the model.

Data Availability

The dataset used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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