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Research Article

Research on Intelligent Customization of Cross-Border E-Commerce Based on Deep Learning

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Cross-border e-commerce has become an important way of "New Infrastructure for Foreign Trade" and "Online Silk Road construction." Utilizing intelligent technology to energize cross-border e-commerce can improve the quality and efficiency of the whole industrial chain. Cross-border e-commerce enterprises generally face the problem of product customization and development due to the large difference in international market demand. This study first analyzes the research status and technical underpinnings of intelligent customization of cross-border e-commerce, then establishes the technical framework of intelligent customization of cross-border e-commerce based on in-depth learning, and subsequently trains, tests, and analyzes the model, and the intelligent customization model has achieved a higher learning level. Finally, it puts forward the promotion and application strategy of cross-border e-commerce intelligent customization based on deep learning. It has theoretical significance and practical value for intelligently identifying changes in international market demand, helping cross-border e-commerce enterprises select products, and optimizing cross-border e-commerce product development.

1. Introduction

Affected by COVID-19, online trade in China and even the world has developed rapidly. Cross-border e-commerce has become an important way of "New Infrastructure for Foreign Trade," which has more room for energizing agriculture, manufacturing, and service industries. With the help of new digital technologies, it can effectively solve the problem of supply and demand matching between the upstream and downstream of the cross-border e-commerce industry chain. First, digitalization can enable upstream manufacturers of the supply chain, help them open overseas markets, provide integrated and one-stop services for international sales, and facilitate the accumulation and precipitation of better business big data to help fully understand the overseas market demand. Secondly, digital technology can better serve downstream distributors. Based on the accumulation of big data of cross-border e-commerce, it can accurately identify consumers' needs, train intelligent models to help cross-border e-commerce sellers select products and deliver goods, integrate global manufacturing, logistics, marketing, services, and other resources, and effectively solve a series of problems from production to after-sales.

The needs and shopping habits of consumers in the international market vary greatly. Therefore, the important problems faced by cross-border e-commerce enterprises are product development and product selection. In the cross-border e-commerce industry, the business idea of "7 points by selection and 3 points by operation" is widely spread. To accurately identify the needs of customers in the cross-border e-commerce market, it provides the best personalized consumption experience and timely cooperates with enterprises in the supply chain to prepare production capacity and service capabilities. Cross-border e-commerce enterprises must have a certain big data foundation, be able to dynamically optimize and process these data in real time, and utilize artificial intelligence technology to assist product customization and development. Intelligent customization,

on-demand production, catering to consumers' preferences, and promoting the upgrading of both supply side and demand side at the same time, all these features mark the evolution of cross-border e-commerce industry to enter a higher level of intelligence era.

Cross-border e-commerce enterprises urgently need to solve three major problems by virtue of intelligent customization technology. First, we accurately study and judge the international market demand. The deep neural network has a detailed feature recognition capability. It can detect subtle changes in the demand of the cross-border e-commerce market, respond to the information, and quickly take the lead in the international market of cross-border e-commerce. Second, we help cross-border e-commerce sellers select products. The artificial intelligence model can assist in business prognosis and decision-making, recommend products suitable for customization and development, help predict demand accurately, make product design, creativity, and development more in line with consumer preferences of the target market, leverage the advantage of scale to gain bargaining position, and reasonably arrange supply chain and logistics resources. Third, we optimize the product development of cross-border e-commerce manufacturers. Digitalization promotes the rapidity, integration, and visualization of the whole transaction chain and supply chain of cross-border e-commerce, makes the cross-border e-commerce industry more capable of resource integration, and helps product manufacturers build flexible production systems and upgrade intelligent customized production. It also assists to reduce procurement and manufacturing costs, improves the fairness and order of supply chain operations, and brings better shopping experience to cross-border e-commerce consumers.

2. Literature Review

The literatures review for this work is explained in the following sections.

2.1. Connotation of Intelligent Customization. There has always been a contradiction between high efficiency and low cost of standardized production and personalized customization with high added value and high cost that low cost and differentiation competition strategy cannot balance. In 1970, Toffler [1] first proposed the idea of using the efficiency advantage of mass production to meet the personalized needs of consumers. In 1987, Davis [2] referred to this production mode with both personalized production and moderate cost as mass customization. In 1993, Pine and Kotha [3] conducted in-depth research on mass customization system from the perspective of new business competition strategies, thus opening the floodgate of mass customization research.

Dell and Toyota were early practitioners of the strategy of mass customization, where product diversification and low cost were achieved through the synergy between the modular design ideas and delayed manufacturing strategies. Strictly speaking, this customization mode belongs to the manufacturer-oriented "semicustomization," which has not realized the true sense of intelligent customization based on digital technology, with consumers as the center and wide participation in the whole process [4]. Whereas the innovation of digital business model and open organizational structure is promoting the deepening of the enterprise customization model, which can better meet the needs of customers, promote the construction of global innovation network, and strengthen the innovation ability of enterprises [5].

The traditional customization research mainly focuses on mass customization, which integrates low cost and differentiated competitive advantages in the aspects of strategy, flow, process, technology, and organization. It also includes some research on moderate scale customization and small batch customization. In the large environments of digitalization, intelligence, and globalization of cross-border e-commerce, intelligent customization has become a new research hotspot. Smart customization is driven by big data and aims to increase the value creation provided to customers [6]. With the aid of Internet platforms and intelligent information technology, it can attract more consumers and enterprises to participate in customization activities, accurately identify and meet consumers' personalized needs, and integrate supply chain resources for production at prices acceptable to customers. Intelligent customization requires dynamic, rapid, and accurate accumulation and collection of product and consumption information. With the help of a highly flexible intelligent manufacturing system, intelligent supply chain system can be built from order acceptance, task decomposition, raw material procurement, production and manufacturing, and rapid distribution, which is very different from traditional customization.

2.2. Implementation Pathway of Intelligent Customization. Cui and Pan [7] believe that e-commerce can be utilized to implement resource sharing, coordination, and optimal allocation and promote the realization of intelligent customization. Intelligent customization needs to integrate networked, digital, and intelligent technologies, realize the deep cooperation of the whole supply chain, all resource elements, and the whole industry chain, and fulfill the collaborative symbiosis of human, machine, material, law, and environment [8]. Senyo et al. [9] propose that digital innovation has fundamentally changed the way of cooperation and competition among enterprises, and a new collaborative value creation network for construction of digital business ecosystem is the focus of digital innovation. Zhang and Hua [10] analyzed the resource operation and found that resource theories such as dynamic capability, entrepreneurial bricolage, and resource arrangement all focus on using industrial big data resources to gain enterprise competitive advantage. In the context of industrial Internet, the effective means for enterprises to implement C2M (customer to manufacturing) mass customization include intellectualization of product design, digitalization of marketing mode, flexibility of production and manufacturing, and the wisdom of logistics services [11]. The garment

supply chain has distinct industry characteristics, especially under the requirement of consumer sovereignty, so the demand for rapid change, short cycle, and flexibility is particularly strong. The embedment of artificial intelligence provides an innovative management mode for the fashion supply chain system [12]. Active use of commercial big data technology and machine learning algorithm can effectively improve the intelligence level of supply chain [13]. Chen and Liu [14] believe that digital intelligent technology is driving supply chain reform from both the supply side and the demand side. In order to meet the personalized needs of customers, it provides an integrated digital, service, and product package with open and expanded functions.

2.3. Digital Empowerment of Intelligent Customization. Digitalization can expand the breadth and depth of resource allocation, create competitive advantages for marketing activities at different stages of the product life cycle, and profoundly affect the ability to create value for customers [15]. Intelligent customization and production is a data-driven flexible manufacturing mode. Based on the basic environment of digitalization, networking, and standardization, it constantly strengthens the sharing, integration, and circulation of data so that the data can be directly embedded in the links of organization, production, operation, and trading, realizing the automatic integration of resources and reducing the hysteresis of the supply chain [16]. Gunther et al.[17] argue that the interconnection and portability of data are fundamental to the realization of the value of big data. Customer, enterprise, and technology orientation, as well as development culture, are key to improving big data capabilities [18]. Cross-border e-commerce enterprises use big data to match supply and demand and integrate EOQ system, sales forecasting system, and inventory control system so as to help enterprises realize scientific and efficient utilization of overseas warehouses [19]. Data empowerment is the key to the digital transformation of enterprises. The development of data technology and analysis technology has enhanced the power of data empowerment [20]. Intelligent customization connects both ends of the supply chain, and meanwhile, enables differentiated demand mining at the front end and personalized manufacturing at the back end [21]. The integrated application of Internet of Things (IoT), Cyber Physical Systems (CPS), big data technology, and blockchain will enhance the efficiency, security, and transparency of operations and push for the implementation of customer-oriented customized models [22]. Chen et al.[23] mainly explored the methods of intelligent decision optimization and efficiency improvement in demand analysis, product development, pricing decision, warehousing logistics, supply chain management, and others. Liu et al.[24] built a 4C model of big data value mining, including data collaboration, computing collaboration, analysis collaboration, and human-computer collaboration. Jiao and Liu [25] studied the moderate scale intelligent customization mode based on digital technology and believed that this mode required the close combination of the dual-layer system of "core resources-product development-value co-creation" and "connection pathway-process reengineering-ecological construction." Zhang et al. [26] deem that enabling client is the premise of C2M reverse customization mode innovation, and the path of data enabling is to "build portfolios of data resources, bundle resources to form data capabilities, and use capabilities to create data value."

Overall, from the perspective of intelligent customization research, there are three levels. First, at the manufacturing level, scholars follow the ideas of Toffler, Davis, and Pine, integrating the low cost of mass production and the added high value of personalized customization into the production and manufacturing, which involves the innovation of equipment, technology, and process. Second, at the strategic level, mass customization is regarded as a new Internet-based business model and an important way for enterprises to implement differentiation strategy, where the contents of the research include business model reform and digital operations' innovation. Third, at the organizational level, it integrates internal and external resources of the enterprise through large-scale formulation, especially the integration of global consumer and innovation resources, so as to improve the organization and management ability to meet the individual needs of consumers. The research's contents include customer value co-creation, dynamic capability evolution, supply chain collaboration, and value chain improvement. However, specific technology construction, data analysis, deployment, and implementation of intelligent customization are rarely involved. From the perspective of research methods of intelligent customization, the traditional case analysis, econometric analysis, and structural equation model are mainly used to deeply explain the definition, connotation, influencing factors, and significance, while the basic theory and specific application of artificial intelligence technology in intelligent customization are almost blank. Therefore, the research of intelligent customization must carry out interdisciplinary research and intelligent technology must be introduced to promote the development of the double link between theoretical exploration and application practice.

3. Intelligent Customization Technology Framework for Cross-Border E-Commerce Based on Deep Learning

The intelligent customization technology framework for cross-order e-commerce based on deep learning is described as follows.

3.1. Deep Learning Principles. Deep learning simulates the activities of biological neurons. A neuron has one or more dendrites, and each dendrite receives the stimulation signal (input pulse) transmitted by the previous layer of neurons. Each of the dendrites receives signals with a different sensitivity. After the neuron accumulates all received real signals, it is activated when the accumulated signal value exceeds its potential threshold, thus converting the signal into an output pulse and transmitting it to other neurons in the next layer.

Comparing neural networks with biological neurons, x_0, x_1, x_2 represent various stimulus signals received by the dendrites of a neuron, where the neural network represents the input, indicating that the data sample includes three attributes: x_0, x_1, x_2. w_0, w_1, w_2 represent the sensitivity of each dendrite of a neuron to signal strength, and after the inputs x_0, x_1, x_2 are boosted with sensitivity, the signals become $w_0 * x_0, w_1 * x_1, w_2 * x_2$, where w_0, w_1, w_2 are called weights in the neural network, that is, the parameters to be trained and predicted. $w_0 * x_0 + w_1 * x_1 + w_2 * x_2$ is the accumulation of signals received by the neuron, and b is the offset. The activation behavior of the biological neuron structure is completed by the activation function, and the activation function is denoted by f in the neural network; $f(\sum w_i x_i + b)$ indicates the output signal transmitted after the ^{i}neuron is activated as shown in Figure 1.

The more widely used activation functions are $\text{sigmoid}(x) = 1/1 + e^{-x}$ and $\tanh(x) = 1 - e^{-2x}/1 + e^{-2x}$ function, where the tanh function corresponds to the translation of sigmoid: $\tanh(x) = 2\text{sigmoid}(2x) - 1$. These activation functions, as the second half of the nonlinear neurons and the first half of the linear neurons, constitute a complete neuron with excellent fitting characteristics. The sigmoid function outputs values between (0,1) that may represent probabilities or can be used for normalization of input data, while the tanh function can convert any input to a value between−1 and 1. The defect of sigmoid function and tanh function lies in the soft saturation, and its derivative is $f'(x) = f(x)(1 - f(x))$, while with the extension of x to both ends, $f(x)$ gradually tends to a straight line, and its derivative gradually tends to 0. Therefore, the gradient transmitted backward becomes very small, and it gets closer and closer to zero. Without gradient, the parameters of the neural network cannot be effectively trained in this case, resulting in the disappearance of the gradient. In order to solve the problem of gradient disappearance caused by sigmoid and tanh functions, ReLU function is often utilized in combination with neural networks. ReLU is short for rectified linear unit, and $\text{Re}LU(x) = \max(x, 0)$ is a modified linear element, which does not have gradient attenuation and disappearance problems when $x > 0$. The three activation function curves are shown in Figure 2.

A multilayer neural network includes many hidden layers, each of which contains a large number of neurons, and there are enormous weights to be estimated among neurons. Therefore, multilayer neural network is also called deep neural network, and the process of using deep neural network for artificial intelligence learning is called deep learning. According to the large number of input characteristic variable X and label variable Y (true value), the deep neural network is trained, where the weight w is the parameter to be estimated in the mapping $Y' = g(X \mid w)$ between X and Y' (a predicted value). By minimizing the loss function $\min Loss = \min (Y - Y')^2$ for the true value Y and the predicted value Y', the estimates of w are deduced inversely, and based on these estimates, the output of the new input is predicted. Deep learning has made great progress and breakthroughs in intelligent recognition and decision-making, especially in graph processing, but it lags behind in management theory and practice. The market globalization and business digitalization of cross-border e-commerce provide a broad space for the theoretical and practical development of artificial intelligence and big data in the field of management and decision-making.

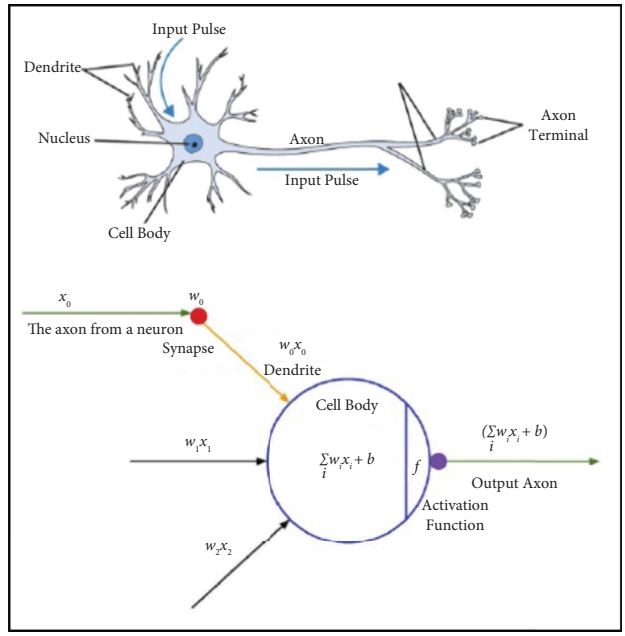

Figure 1: Biological neurons and neural network structure.

3.2. Data Sources. Taking the dress market on the cross-border e-commerce platform as an example, this study collected the sales records of 862 dresses in 2020, thus forming the dress sales dataset. The dataset consists of 13 tag attributes, Dress_ID , Style, Price, Rating, Size, Season, NeckLine, SleeveLength, Waistline, Material, FabricType (to simplify the in-store experience of clothing products, Amazon merged the existing properties of Material and FabricType into FabricType properties starting from 8/20/2021), Decoration, and PatternType, and one characteristic attribute, Recommendation. The specific attributes and attribute values of this dataset are shown in Table 1.

3.3. Model Building. With the rapid development of cross-border e-commerce, sales enterprises expect to be able to accurately predict sales and reasonably customize products so as to gain greater profits, attract more investment, and bring better experience. Many studies only make time-series predictions based on the sales or sales volume of products sold by cross-border e-commerce. Some other studies extract the customer evaluation of cross-border e-commerce products and identify the emotional characteristics of consumers by the LSTM method [27]. Custom forecasting is widely used in industry, factories, trade, and so on. Predictions using deep learning methods perform better than machine learning methods [28]. Due to the increasingly fierce competition in the global market, most manufacturing industries are facing the transformation of mass

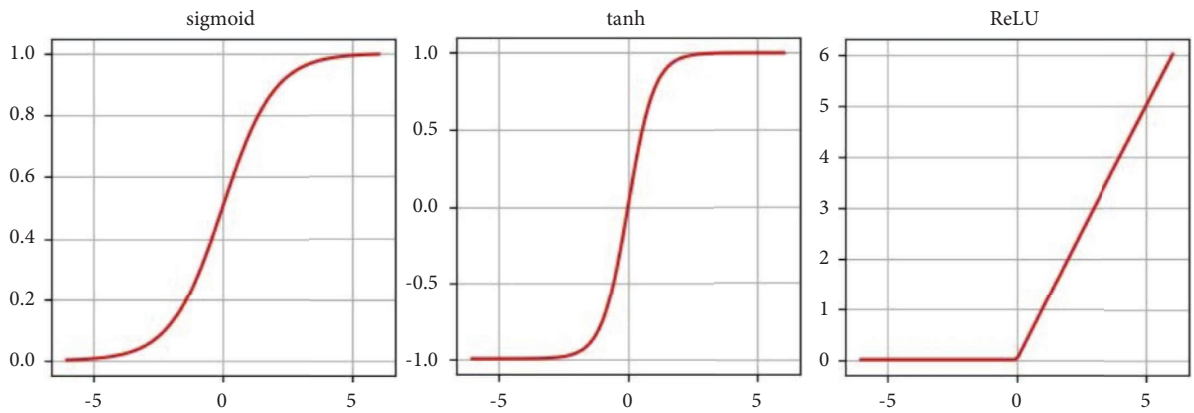

Figure 2: Three activation function curves.

Table 1: Cross-border e-commerce dress sales dataset attributes.

Attribute classification	Attribute code	Attribute name	Attribute value
Tag attributes	$X1$	Dress_ID	
	$X2$	Style	1-Bohemian, 2-brief, 3-casual, 4-cute, 5-fashion, 6-flare, 7-novelty, 8-OL party, 9-sexy, 10-vintage, and 11-work
	$X3$	Price	1-low, 2-average, 3-medium, 4-high, and 5-very high
	$X4$	Rating	1, 2, 3, 4, and 5
	$X5$	Size	1-small, 2-S, 3-M, 4-L, 5-XL, and 6-free
	$X6$	Season	1-autumn, 2-winter, 3-spring, and 4-summer
	$X7$	NeckLine	1-O neck, 2-backless, 3-boat neck, 4-bowneck, 5-halter, 6-mandarin collar, 7-open, 8-peterpan collar, 9-ruffled, 10-scoop, 11-slash neck, 12-square collar, 13-sweetheart, 14-turndown collar, and 15-V neck
	$X8$	SleeveLength	1-full, 2-half sleeve, 3-butterfly, 4-sleveless, 5-short, 6-three quarter, 7-turndown, and 8-cap sleeves
	$X9$	Waistline	1-dropped, 2-empire, 3-natural, 4-princess, and 5-null
	$X10$	Material	1-cotton, 2-wool, 3-microfiber, 4-polyester, 5-silk, 6-chiffon fabric, 7-nylon, 8-linen, 9-rayon, 10-lycra, 11-milk silk, 12-acrylic, 13-spandex, 14-mix, 15-cashmere, 16-knitting, 17-chiffon, 18-viscos, 19-lace, 20-modal, and 21-other
	$X11$	FabricType	1-chiffon, 2-broadcloth, 3-Jersey, 4-batik, 5-worsted, 6-woolen, 7-satin, 8-flannel, 9-poplin, 10-dobby, 11-knitting, 12-flannel, 13-tulle, 14-satin, 15-organza, 16-lace, 17-corduroy, 18-terry, and 19-none
	$X12$	Decoration	1-ruffles, 2-embroidery, 3-bow, 4-lace, 5-beading, 6-sashes, 7-hollow out, 8-pockets, 9-sequined, 10-applique, 11-button, 12-tiered, 13-rivet, 14-feathers, 15-flowers, 16-pearls, 17-pleat, 18-crystal, 19-ruched, 20-draped, 21-tassel, 22-plain, 23-cascading, and 24-none
	$X13$	PatternType	1-animal, 2-print, 3-dot, 4-solid, 5-patchwork, 6-striped, 7-geometric, 8-plaid, 9-leopard, 10-floral, 11-character, 12-splice, 13-leopard, and 14-none
Characteristic attributes	Y	Recommendation	0, 1

customization. The implementation of intelligent customized products can better adapt to complex production environment conditions, and it is more economical and effective [29]. The traditional method does not consider the complex properties of the products and market characteristics, and the prediction is time-consuming and labor-intensive, and the accuracy is not high enough. Deep learning provides a powerful way to identify and predict which can deal with complex environments of cross-border e-commerce customization. In this study, an effective deep learning framework is constructed to extract complex features of cross-border e-commerce products and markets by using deep neural networks and to predict whether the customized results are suitable for market demand.

The Keras deep learning framework is adopted to complete the model development, and the sequential mode is selected for research. First, a fully connected layer, dense_1, is constructed as the input layer, and the ReLU activation function is used to transform 12-dimensional input into 128-dimensional output in this layer which generates 1664 parameters w to be estimated. There are too many parameters in the network, and the neural network has very strong memory ability. To overcome the overfitting phenomenon in the process of machine learning, a random

dropout layer dropout_1 is added. During the learning process, 20% of the input neuron connections are randomly disconnected and every time parameters are updated, and some nodes are discarded so that they neither input nor output data. Subsequently, a fully connected layer, dense_2, is established, and ReLU activation function is used to transform 128-dimensional inputs into 32-dimensional outputs, at which time 4218 parameters w are generated to be estimated. Finally, the fully connected layer dense_3 is established, and the sigmoid function is used to transform the 32-dimensional input into the 2-dimensional output Y', as shown in Figure 3.

In the process of training, the characteristic attribute is used as the input X, and the training round epoch, the learning rate η, and other hyperparameters are set. The output value Y' is calculated according to the feedforward training by initializing the weight w and bias b, and then, the feedback training is carried out according to the loss function constructed by the real value Y and the output value Y' to minimize the loss function $L = \sum_{n=1}^{N} (Y - Y')^2$ and to obtain the optimal weight w and bias b. See Table 2, for a specific solution algorithms.

4. Analysis and Test of Cross-Border E-Commerce Intelligent Customization Based on Deep Learning

The analysis and test of cross-border e-commerce intelligent customization based on deep learning is explained in the following sections.

4.1. Data Cleaning and Segmentation. Data cleansing is the process of reexamining and verifying datasets to remove repeated information, correct errors, and provide data consistency. A consistency check is based on the reasonable value range and relationship of each variable to check whether the data meet the requirements and find data that are out of the normal range, logically unreasonable, or contradictory. The processing of invalid and missing values is due to survey, coding, and entry errors. There may be some invalid and missing values in the data, which need to be corrected as necessary. In general, the collected data may not be standardized and complete; therefore, it is necessary to conduct preliminary analysis and exploration of data, thus processing and cleaning the data well. By showing the first 5 items of dress sales data (as shown in Figure 4), it can be found that the attribute values are all English characters, and these unprocessed data cannot be used for machine learning.

First, the text of the attribute value is converted according to the corresponding numbers in Table 1. The first five records in the converted dataset are shown in Figure 5. Meanwhile, the Dress_ID attribute does not affect intelligent customization decisions, so, in the process of intelligent learning, we delete the Dress_ID attribute value.

Then, by observing the attribute distribution of the dress sales dataset (Figure 6), we can see the distribution characteristics of its attribute values and find that there is no missing data. In this way, the data cleaning and preprocessing work are completed, and machine learning sales datasets containing 13 attributes and 862 records are formed. Finally, data segmentation is completed, and 862 records are divided into two mutually exclusive sets by the method of reservation, in which 80% data are used as training data (including 689 data) and 20% data are used as test data (including 173 data).

4.2. Model Training and Testing. Mass customization aims to provide goods and services that meet the needs of each customer at an efficiency level close to that of mass production. It is a key business strategy for enterprises that expect to gain competitive advantages in cross-border e-commerce. Existing customization methods require consumers to choose from a predetermined list of attributes or component alternatives. However, if customers do not have the necessary domain knowledge about the product, they are confused in the product selection. The effectiveness of consumer selection and participation is also a huge challenge, with greater time consuming and cost increases. In this study, deep neural network and adaptive optimization Adam technology were used to configure the model, and the most appropriate hyperparameters were automatically selected for the model. Compared with the traditional methods, it was more automatic and intelligent, and the decision could be completed in a short time. A new data optimization model was introduced to continuously improve the accuracy of prediction. The study used the dataset as "Cross-border e-commerce_attributes_customization.csv," which is the dress sales dataset established by the author, including 14 variables and 862 pieces of data. The detailed platform configuration is Windows10, Anaconda3, Python3.7, Tensorflow-gpu 1.15, Keras2.4, and java1.8.0.

The selection of the optimizer is essential for the accuracy of model training. Because the traditional gradient descent method is sensitive to the superparameter of learning rate η, problems such as flatness, saddle point, and cliffs often occur in high-dimensional space and multilayer neural networks, making the effect of the traditional gradient descent method not ideal. Adam of an adaptive optimizer of RMSprop with momentum term is used here, which can estimate the learning rate of dynamically adjusted parameters by using the first and second moments of the gradient, which greatly improves the smoothness of parameters and the accuracy of learning. Since there is a certain gap between the attribute values of the dataset, the attribute values are normalized before the training, (X-mean)/std, so that all data are concentrated near −1 to 1 according to variance 1. The Keras learning framework and Adam optimizer are used to conduct 500 rounds of training for the model, and the results are shown in Figure 7. At the 500th training round, the training loss decreases from 0.2538 to 0.0442, and the training accuracy increases from 0.9020 to 0.9826, reaching a high learning level.

We test the trained model with test data, and the test results are shown in Table 3. The test loss is 0.8188, the test accuracy is 0.8092, and the test effect is good.

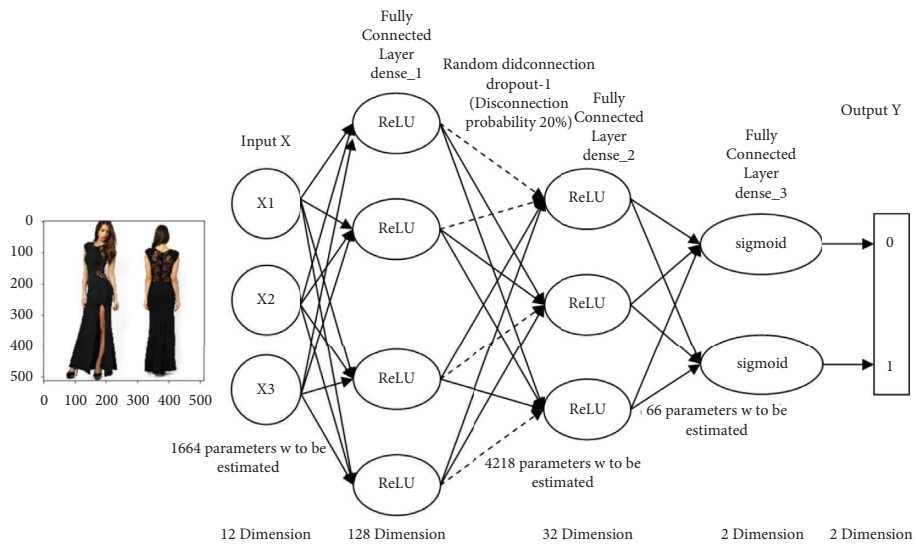

Figure 3: Cross-border e-commerce intelligent customization deep learning model.

Table 2: Deep learning solution algorithm.

Deep learning solution algorithm	
Input	Input X to represent the characteristic attributes Input Y for the true value of the tag attributes
Defining hyperparameters	Training round epoch Learning rate η
Initializing weights and biases	Weight w and bias b
Defining loss function	$L = \sum_{n=1}^{N} (Y - Y')^2$
Training neural network	For i in range(epoch): Feedforward training, transferring the sample data X to the neural network $H = \sigma(wX + b)$ $Y' = \sigma(wH + b)$ Feedback training: we update the weight deviation to minimize the loss function $w = w - \eta\partial L/\partial w$ $b = b - \eta\partial L/\partial b$ Where X is the input, H is the output of the hidden layer, w is the weight, $\sigma$is the activation function, Y' is the predicted value of the output, and Y is the true value

	Dress_ID	Style	Price	Rating	Size	Season	Neck Line	Sleeve Length	Waist line	Material	Fabric Type	Decoration	Pattern Type
0	16032852	Sexy	Low	4.6	M	Summer	O-neck	Sleevless	Empire	Other	Chiffon	Ruffles	Animal
1	12122089	Casual	Low	0	L	Summer	O-neck	Halfsleeve	Natural	Microfiber	None	Ruffles	Animal
2	11900701	Vintage	High	0	L	Autumn	O-neck	Full	Natural	Polyster	None	None	Print
3	966083	Brief	Average	4.6	L	Spring	O-neck	Full	Natural	Silk	Chiffon	Embroidary	Print
4	879541	Cute	Low	4.5	M	Summer	O-neck	Butterfly	Natural	Chiffonfabric	Chiffon	Bow	Dot

Figure 4: The first 5 records of the dress sales dataset.

We take 15 cases randomly from the test sets to check the test effect (Table 4). Among the 15 records, only 380 and 623 are found to be prediction errors. The true value of recommendation in these two records is 0; that is, development and production are not recommended. The predicted value is 1, which means that it should be manufactured and put on the shelf. The rest are predicted accurately.

4.3. Conclusion and Discussion. In the sales of cross-border e-commerce products, the garment industry is often faced with greater challenges in product demand forecasting, mainly for three reasons. First, the garment industry is a field with fierce competition in cross-border e-commerce and rapid innovation and change. Second, clothing products have the characteristics of fast fashion and the life cycle is

Dress_ID	Style	Price	Rating	Size	Season	Neck Line	Sleeve Length	Waist line	Material	Fabric Type	Decoration	Pattern Type
0 16032852	9	1	4.6	3	4	1	4	2	21	1	1	1
1 12122089	3	1	0.0	4	4	1	2	3	3	19	1	1
2 11900701	10	4	0.0	4	1	1	1	3	4	19	24	2
3 966083	2	2	4.6	4	3	1	1	3	5	1	2	2
4 879541	4	1	4.5	3	4	1	3	3	6	1	3	3

Figure 5: The first 5 records after attribute value conversion of dress sales dataset.

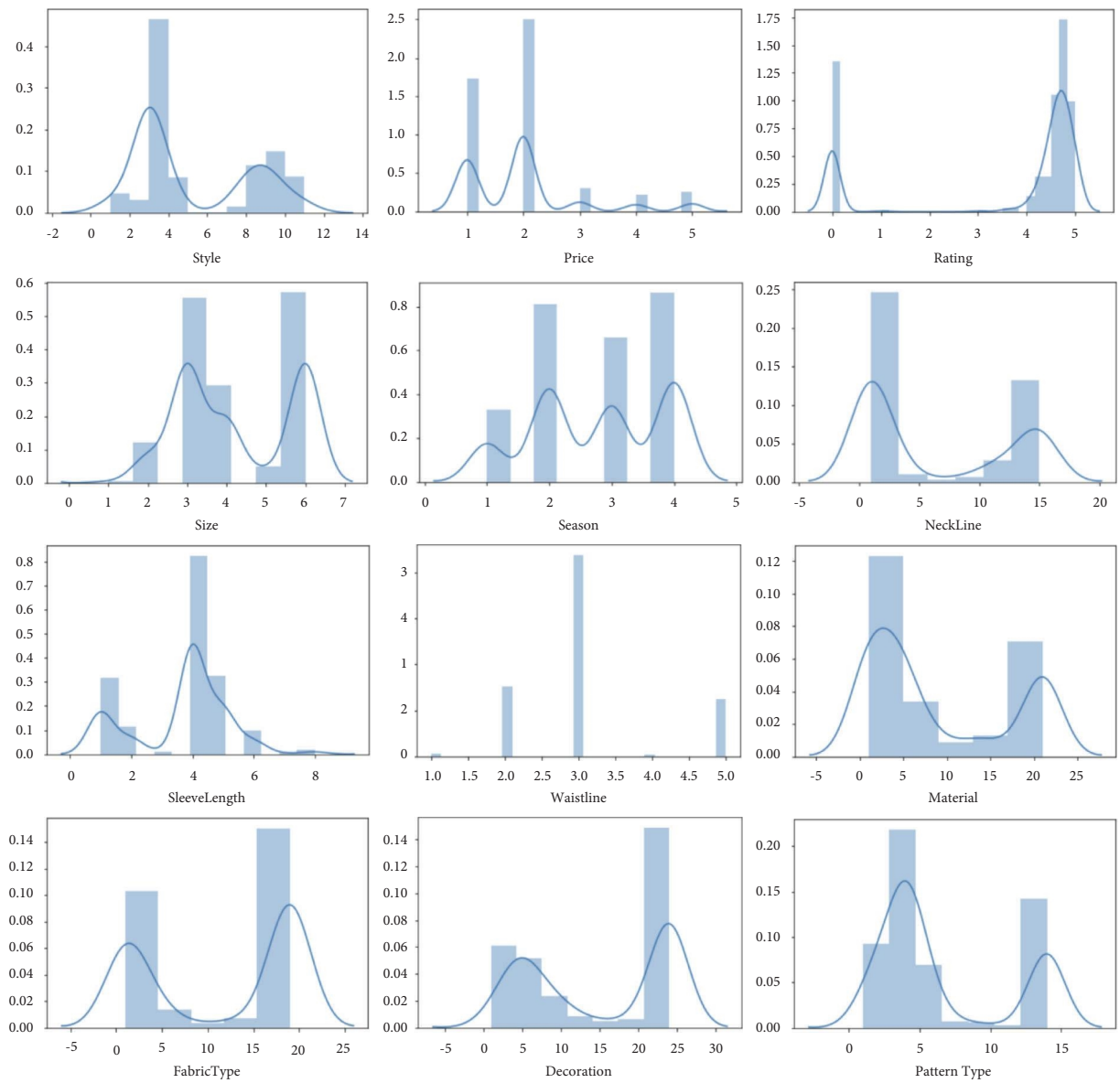

Figure 6: Attribute distribution of dress sales dataset.

relatively short. Third, the cross-border e-commerce apparel market is vast, and the international market demand is very different. To address this challenge, cross-border e-commerce fashion retailers have to place a large number of virtual product images and their features' information on their websites so that their customers can understand the fashion products and improve their buying experience. However, a large number of allocation goods dramatically

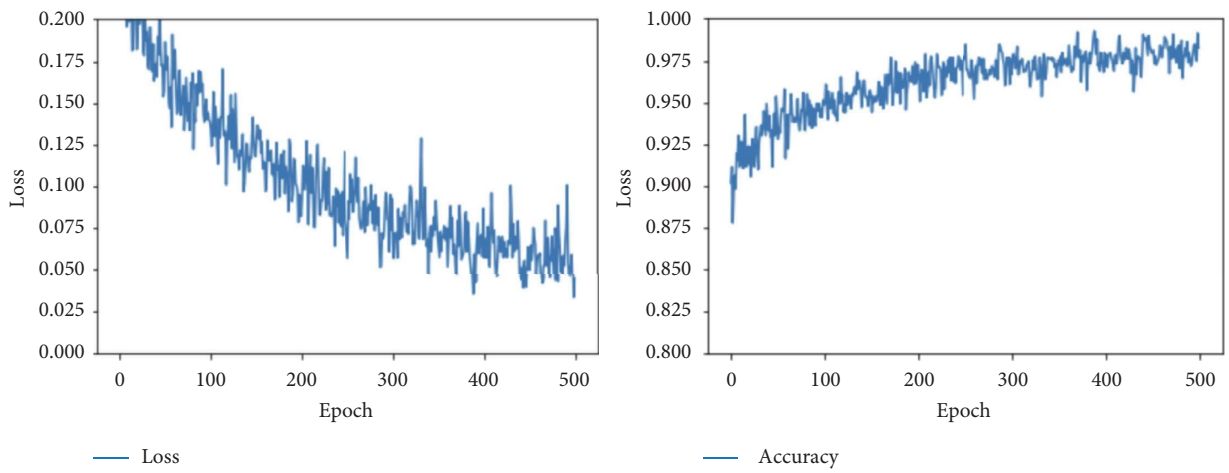

Figure 7: Cross-border e-commerce intelligent customization of deep learning training results.

Table 3: Cross-border e-commerce intelligent customization of deep learning test results.

Test sample	Test time
173/173 [==========]	-0s 202us/step
Test loss	Test accuracy
Loss = 0.818844379717215	Accuracy = 0.8092485666275024

Table 4: Cross-border e-commerce intelligent customization of deep learning test example.

Index number	Dress_ID	Style	True recommendation value	Prediction recommendation value
715	738079582	3	1	1
605	733134203	10	1	1
120	861626197	11	0	0
208	941333009	4	0	0
380	727676110	3	0	1
817	1083779666	3	0	0
575	854444464	3	0	0
266	1066740059	8	1	1
557	1083323104	9	0	0
826	1217548862	10	1	1
580	832391864	3	1	1
327	1072784739	3	0	0
623	941333009	4	0	1
365	918331326	2	0	0
765	754316257	3	0	0

increased the seller's costs. The garment industry has cross-border e-commerce systems in a large scale and a strong production and manufacturing system, but there is still a huge room for improvement in intelligent customization, which is mainly reflected in two aspects. First, the flow type cross-border e-commerce enterprises lack good product accumulation and supply chain information and cannot integrate the best supply chain resources. Second, it cannot accurately meet the consumer demand of the international market, and it is difficult to plan and design according to market preferences and key pain points.

It has become especially important for cross-border e-commerce sellers to predict consumer preferences in advance and perform intelligent customization, but they lack advanced tools to achieve this goal. Previous forecasts only take GMV as a key indicator which are far from enough to meet demand. Combined with various attributes and complex characteristics of clothing sales, this study utilized deep learning and backpropagation neural network model to assist product customization decisions. The study found that despite the small dataset, the model performed well. This method can be effectively applied to the cross-border e-commerce apparel sales industry to help more cross-border e-commerce apparel sales enterprises intelligently improve the efficiency of product selection. Through the transfer learning of other sales category data, it can also be extended to other product categories of cross-border e-commerce, which is conducive to the cross-border e-commerce operators to make correct decisions on shelve, selection, and customization. Cross-border e-commerce

more and more needs to do business. With the help of the latest information technology, the deep neural network constructed by this model can be more comprehensive, more sharp, and more in-depth insight into consumer behavior, habits, preference, characteristics, and rapid access to a large number of clothing characteristic information, which lets the brand side accurately determine which products are suitable for which market and empower the brand for the development of internationalization.

5. Promotion and Application of Cross-Border E-Commerce Intelligent Customization Based on Deep Learning

The promotion and application of cross-border e-commerce intelligent customization based on deep learning are described in the following sections.

5.1. Continue to Accumulate and Improve Data. The basis of intelligent customization decision is effective and reliable big data. The lack of data has become the main obstacle to the intelligent customization of cross-border e-commerce products. In order to cope with fierce competition and rapid market changes, cross-border e-commerce enterprises must improve their own digital construction capacity and build data-driven management and operation modes. First, we keep improving the data. At the customer level, it is necessary to record the data of customer characteristics, portraits, preferences, behaviors, communication, and others. At the management level, it is necessary to store the upgrade data of potential customers, new customers, old customers, and loyal customers, as well as the maintenance data of customer complaints, customer loss, and customer recovery. At the operational level, data such as product, price, promotion, channel, payment, distribution, and after-sales service should be improved. Second, we keep accumulating the data. During the operation of the platform, a large amount of data will be generated every day, and these new data will update most of the old data. Cross-border e-commerce enterprises should have the awareness of accumulation. In this study, the dress sales figures for 2020 selected are the data saved by continuous years of operation, including more attributes in the in-depth research and application, thus forming a certain accumulation of intelligent customization analysis data.

5.2. Comprehensively Promote Data Standardization. Data generated by cross-border e-commerce operations are often complex, including structured data and unstructured data, as well as active data submitted by users and passive data generated by enterprise mining and analysis, as shown in Figure 8. The data also come in many forms, including text descriptions, numbers, picture symbols, audio, video, and others. Therefore, it is necessary to accurately select characteristic attributes based on application orientation and demand scenarios, standardize data processing, unify data standards, process default data, delete meaningless data, quantify effective data, and complete the standardized

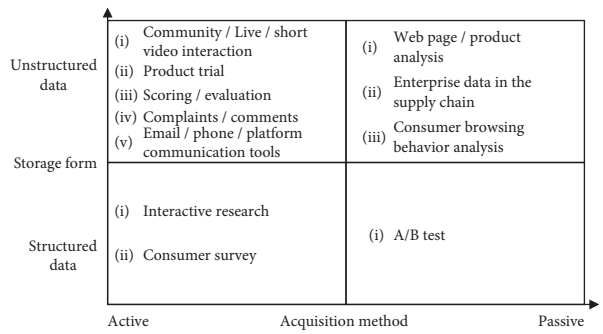

Figure 8: Data types of cross-border e-commerce.

transformation. Governance is implemented from the source to form a unified service data caliber and get through all kinds of structured and unstructured heterogeneous multisource data.

5.3. Facilitate Platform and Category Migration. Cross-border e-commerce sales enterprises tend to open shops on multiple mainstream cross-border e-commerce platforms, such as eBay, Amazon, AliExpress, Wish, and other cross-border e-commerce platforms at the same time; then, the operation data will be generated on multiple platforms. The data of the same cross-border e-commerce enterprise will be collected through planned management. The formation of large datasets with a certain scale is conducive to the realization of accurate, intelligent, and customized analysis. At the same time, the intelligent model formed by machine learning can provide auxiliary decisions for cross-border e-commerce enterprises to expand new platforms and develop products. In this study, taking the dress category of cross-border e-commerce as an example, the trained model can be used as transfer learning, and the model learned in the source field of dresses can be applied to other target fields of cross-border e-commerce market. By learning the industry data of the target category, the intelligent customization ability can be transferred to cross-border e-commerce sales enterprises of other categories, to achieve the cross-platform, cross-industry, cross-category, and cross-department application of intelligent customization.

5.4. Expand National and Regional Markets. Compared with domestic e-commerce, cross-border e-commerce has a wider market distribution, a greater demand difference, and a more prominent imbalance in development. The United States, Western Europe, and Japan have perfect network infrastructure, mature e-commerce shopping environment, mature cross-border e-commerce development, strong consumption power, and large transaction scale. Emerging markets such as Russia, South Korea, Brazil, and India enjoy strong development, relative favorable foundation for cross-border e-commerce, and great growth potential, making them new blue seas for cross-border e-commerce companies to compete for. Therefore, in the process of intelligent product customization of cross-border e-commerce, it is

necessary to fully incorporate the important variable attributes of overseas market countries and regions, such as product appearance, product color, consumer income, human culture, customs, and others. For example, the Club Factory cross-border e-commerce platform actively utilizes digital technology to enhance its competitiveness and builds an intelligent commodity management system to enter the Indian market. With the help of the intelligent customization system, it can effectively analyze the products demanded by consumers in the Indian market, accurately match the needs of overseas consumers, and guide the production of export manufacturers. Then, we cooperate with five of the largest local logistics companies in India to complete the task of commodity distribution, which reduces the operating cost of cross-border e-commerce by more than 30% on an average compared with the industry. After gaining a foothold in the Indian market, Club Factory plans to enter more countries for sale.

5.5. Enrich Intelligent Customization Tag Variables. Based on the accumulation of large amounts of cross-border e-commerce big data, richer research on intelligent customization label variables of cross-border e-commerce can be carried out. In this study, the study of tag variables mainly focuses on products; that is, artificial intelligence gives suggestions on whether a product is worth producing and putting on the shelves. Then, the next step is to give the quantity of customization, the quantity of stock in each stage, the sales price, and which price is the most profitable and optimize the supply chain and organize the production according to such a price. For example, clothing, footwear, jewelry, watches, bags, and other categories that are well sold on cross-border e-commerce platforms all have strong "fashion" attributes. With the branding construction of China's cross-border e-commerce export enterprises, more industries begin to pay attention to such characteristics and fashion attributes and pay attention to enhancing brand value through differentiation. Therefore, in the intelligent customization system, it is necessary to introduce the fashion labels for deep learning, predict the future trends according to the previous popular data, mine the popular elements of the next period, and integrate them into the intelligent customization development of products.

Data Availability

The experimental data are obtained from the enterprises and are related to the trade secret so can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

All authors contributed equally to this work. In addition, all authors have read and approved the final manuscript and gave their consent to publish the article.

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