Hybrid Attention-SVM Based Product Recommendation with Grey Wolf Optimization for E-Commerce Platforms

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With the rapid development of the e-commerce industry, personalized product recommendation models have received increasing attention. Traditional recommendation systems have shortcomings in capturing user interest features. This study proposes a product recommendation model based on a hybrid attention mechanism and Support Vector Machine (SVM), which makes recommendations more accurate and personalized. This model combines three attention mechanisms: Spatial attention automatically identifies the product image areas that users are concerned about; Channel attention dynamically adjusts the importance of feature channels to highlight the features that influence user decisions; Frequency attention optimization focuses on the detailed features of the product. Based on feature extraction, this study uses an SVM classifier for product recognition and classification and introduces a grey wolf optimization algorithm to adaptively adjust the core parameters of SVM, improving classification accuracy and robustness. The experimental results showed that the mean square error of the model was 0.19 in the training set and 0.07 in the validation set. Compared with the K-means clustering algorithm and backpropagation neural network, this algorithm has improved by 0.06 and 0.04. Meanwhile, the accuracy rate of personalized recommendation reached 0.702, which was 0.059 and 0.026 higher than that of K-means clustering and backpropagation neural networks. The operation time of the model was 1.04 seconds, demonstrating high practicability and efficiency. The research model has improved the depth and accuracy of feature extraction, consistent recommendation ability, and computational efficiency. This study provides a new practical personalized recommendation strategy for e-commerce platforms, which has broad application potential and economic value.

Povzetek: Hibridni priporočilni model za e-trgovino združuje tri mehanizme pozornosti (prostorsko/STN, kanalno/SE in frekvenčno/FAM) za bogat zajem slikovnih in numeričnih značilnosti izdelkov, nato pa uporablja SVM (RBF), katerega hiperparametre (C, γ) samodejno optimizira Grey Wolf Optimization (GWO).

1 Introduction

The advancement of e-commerce has made online shopping an indispensable part of consumers' daily lives. Consumers often face difficulties in making choices due to a large amount of product information, and Personalized Recommendation Systems (PRS) are designed to help users find products that highly match their preferences among the vast amount of information [1]. PRS can improve user satisfaction and assist e-commerce platforms in increasing conversion rates and sales revenue. Traditional recommendation algorithms are mostly based on collaborative filtering and content filtering, but there are certain limitations in capturing users' potential needs and preferences. For example, recommendations based on user historical behavior often overlook real-time changes in user interests, while recommendations based on product features lack effective integration of multimodal information [2-3]. In current research, many scholars optimize the PRS of products. Wu et al. conducted a comprehensive review of PRS, addressing its core issues from a fresh perspective and discussing key issues for PRS improvement, providing the latest and most comprehensive perspectives for PRS [4]. Fu et al. proposed a flexible multi-branch sub-interest matching network framework for personalized recommendation. This method first aggregated the compatibility scores output by multiple Interest Matching Branches (IMBs) using the max operator and then fused them with the output of the total IMB to estimate the user's affinity with the project. This study validated the method with a benchmark dataset and demonstrated its good recommendation performance [5]. Fan et al. proposed a multiple Attention Mechanism (AM) deep learning method for recommending MOOCs to students. This recommendation model combined learning record attention, word level review attention, sentence level review attention, and course description attention. This model has achieved good results in MOOC recommendation platforms [6]. Hien N L H proposed a method combining Convolutional Neural Networks (CNN) and matrix factorization to address the issue of information overload. This method improved the information accuracy and contextual understanding ability of the recommendation system, achieving higher recommendation accuracy. This method had potential application value in improving recommendation effectiveness [7]. Wu J proposed an adaptive value method based on a combination of distributed computing framework and topology structure. This method aims to solve the problems of untimely and inaccurate data updates in e-commerce operations, to improve the collection speed of user purchasing behavior data and increase the revenue of e-commerce operations. The improved algorithm, under the control of the topological structure, achieved an accuracy rate of over 94% for the product, with the highest reaching 98%. Compared with other algorithms, it had higher accuracy. To sum up, the improved algorithm performed excellently in stability, accuracy, and application error control, and had a better application prospect for data mining of user purchasing behavior [8]. Latha Y M et al. proposed a recommendation framework based on deep learning to address the issue of sales improvement on e-commerce websites. They obtained the results of an average recall rate of 94.80%, an accuracy rate of 93.64%, and a precision rate of 96.92% on the Amazon product review database, indicating that this enhanced CNN model outperformed traditional models in product sentiment analysis. This method improved the convenience and computational efficiency of data interpretation through the preprocessing of text information, and further extracted feature values through TF-IDF technology, providing a more accurate basis for sentiment analysis [9]. The literature review is specifically shown in Table 1.

Table 1: Literature review table

Literature	Model type	Model advantages	Limitations
Wu C et al. [4]	A Review of PRSs	It provides a broad theoretical basis to help understand the core issues of recommendation systems	Insufficient universality, no detailed analysis was conducted for specific models
Fu Z et al. [5]	Multi-branch interest matching network framework	It has high flexibility and can effectively match multiple interest branches	The exploration of multimodal data is lacking
Fan J et al. [6]	Deep learning multi-AM	It emphasizes the combination of different AMs and has strong adaptability	Insufficient consideration was given to the application scenarios of e-commerce
Hien N L H [7]	The combination of CNN and matrix factorization	The accuracy of information has been enhanced and the ability to understand the context has been improved	Dynamic information has not been fully utilized
Wu J [8]	Distributed computing and topological structure	The speed of data collection and the ability to generate operational revenue have been enhanced	The influence of changes in user behavior on the model was not considered
Latha Y M et al. [9]	Deep learning recommendat ion framework	Efficient feature extraction and sentiment analysis, superior to traditional models	Reliance on feature extraction may lead to performance degradation

In the above-mentioned literature, although many studies have provided valuable insights in the aspect of PRSs, there are still some deficiencies. Firstly, although review studies provide a broad theoretical foundation, they fail to conduct in-depth analysis of the applicability of specific models, making it difficult to provide precise guidance in practical applications. Secondly, although the network framework based on multi-branch sub-interest matching is flexible, it lacks integration of multimodal data, which limits its application in information rich e-commerce scenarios. The method based on the multi-AM of deep learning performs well in MOOC recommendation. However, due to its deficiency in e-commerce applications, it cannot make full use of the unique user behavior characteristics of e-commerce. In addition, although research based on CNN and matrix factorization enhances contextual understanding, it does not fully consider the dynamic nature of user behavior, which may lead to a decrease in recommendation accuracy in actual recommendation scenarios. Overall, these literatures have certain limitations in terms of feature extraction capability, timeliness of user behavior, and integration of multimodal information. In response to the above deficiencies, a product recommendation model combining the Hybrid Attention Mechanism (HAM) and Support Vector Machine (SVM) is proposed in the study. The innovation of the research method lies in introducing a deep context aware mechanism to analyze user behavior changes in real-time, making the recommendation system more adaptable. A multi-level feedback mechanism is designed to enhance user interaction by analyzing users' feedback on the recommendation results. The contribution lies in constructing an e-commerce product recommendation model with a more flexible structure and stronger adaptability. The innovative fusion of feature extraction and classification methods provides new ideas for PRS.

2 Methods and materials

2.1 Construction of product feature extraction model based on HAM

The study focuses on exploring the performance of the product recommendation model combining the HAM and SVM in accuracy and efficiency. The specific research question is whether the model combining HAM and SVM can surpass the product recommendation effect using only deep learning methods. To verify this issue, the following two hypotheses are proposed. Hypothesis 1: SVM optimized by Grey Wolf Optimization (GWO) outperforms unoptimized standard SVM in classification accuracy and runtime. Hypothesis 2: Product feature extraction based on the HAM can significantly improve the personalized recommendation level of the model, thereby greatly enhancing user satisfaction. These research questions and hypotheses provide a clear direction for the subsequent model construction and experimental design.

AM is a technique that enables models to better focus on input data-related information. This technology can significantly improve the effectiveness of product recommendations on e-commerce platforms. Using AM can automatically identify the core features of user interests and highlight the product features preferred by users. By focusing on different features in different time periods or contexts, AM can dynamically adjust recommended content based on users' real-time behavior. The e-commerce platforms often involve various kinds of data like images, text, and user ratings. AM can establish connections between different modalities, enabling recommendation models to comprehensively consider various information [10]. Therefore, this study will introduce three types of AMs into the PRM, namely Spatial Transformer Network (STN), Squeeze-and-Excitation (SE), and Frequency Attention Mechanism (FAM). Among them, STN better identifies the product image areas that users are interested in in in e-commerce product recommendations. STN can perform geometric transformations on input images to maintain visual continuity when manually selecting product images. The structure of STN is shown in Figure 1.

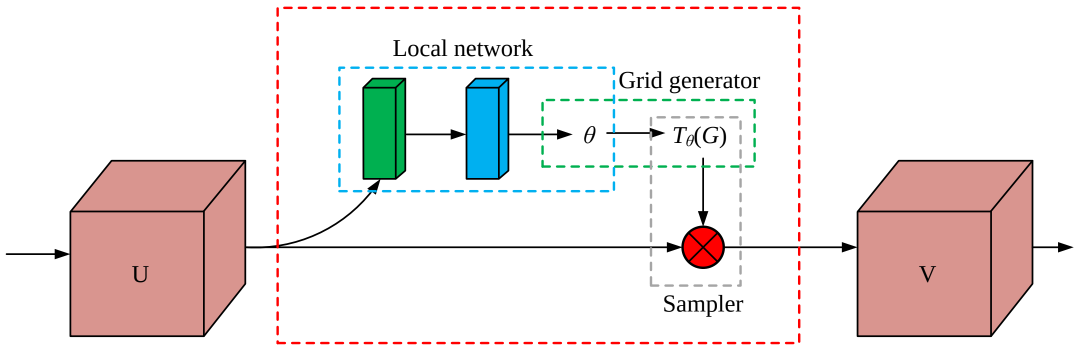


Figure 1: STN network structure

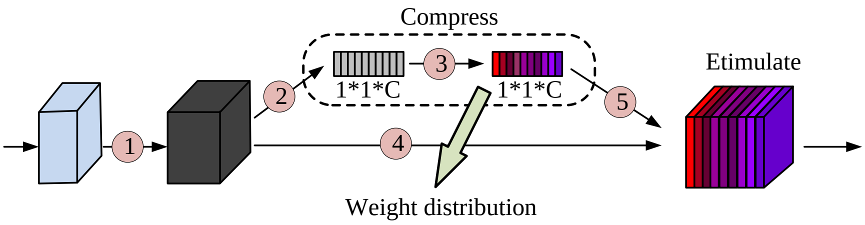


Figure 2: SE structure

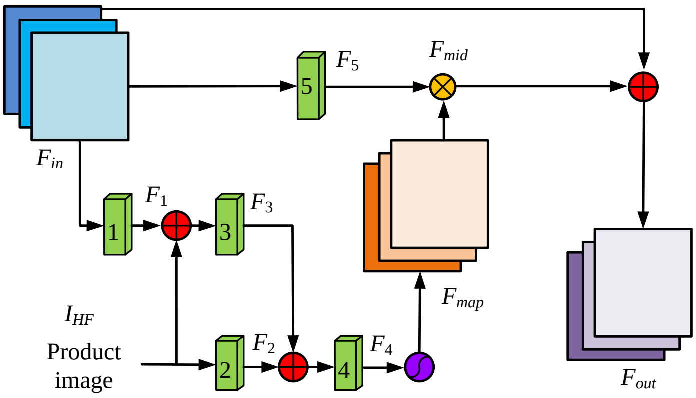


Figure 3: FAM structure diagram

Figure 1 shows the basic architecture of STN, including three main steps: feature extraction, weight calculation, and weight fusion. In the feature extraction stage, the input image is processed through convolutional layers, and the size of the convolutional kernels is usually 3×3 or 5×5. Subsequently, activation functions (such as ReLU) are used to introduce nonlinear transformations. The weight calculation part adopts a fully connected layer to map the feature vectors obtained after convolution to a weight space. Finally, in the weight fusion stage, the extracted feature vectors will be multiplied element by element with the calculated weight vectors, thereby generating the final weighted feature output. This data flow process ensures that the key areas of the product image can be highlighted, thereby enhancing the accuracy of the recommendation model [11]. SE can enhance features that have a significant impact on user purchasing decisions in e-commerce recommendations. SE can dynamically adjust the significance of feature channels to each user based on their historical behavior or preferences, providing more personalized recommendations. Figure 2 shows the SE structure.

In Figure 2, the SE module presents its multi-layer structure, including five steps: input feature extraction, feature mapping, weight calculation, weighting processing, and feature integration. In the input feature extraction stage, the size of the convolution kernels applied in the convolutional layer is also 3×3 or 5×5. Subsequently, the feature channels are mapped to the low-dimensional space to reduce the computational complexity. The weight calculation part determines the importance of each channel through the fully connected layer and generates the weight values through the Sigmoid activation function. In the weighting processing stage, the original feature vectors are multiplied by the corresponding weights, and finally integrated to obtain the feature tensor composed of the weighted feature vectors. The design of this data flow enables the model to effectively adjust the recommendation process based on the user's historical preferences [12]. FAM can help models identify detailed features in product recommendations, and by optimizing feature selection, the FAM mechanism helps provide more accurate product detail descriptions. Figure 3 shows the framework of FAM.

Figure 3 shows the structure diagram of FAM. In the input stage, the image features processed by the convolutional layer are introduced, where the convolution kernels are usually 3×3. After multiple layers of convolution, a set of frequency-domain features is generated. These features are then sent to activation functions (such as Sigmoid) to calculate the frequency attention weights to identify high-frequency details in the image. Next, the attention weights and feature maps are subjected to element-by-element product operations to generate the intermediate features of the focus features. These data stream processing steps enhance the model's focus on product details and improve the accuracy and effectiveness of recommendations.

The feature map inputs of FAM are F_{in} and I_{HF}, where F_{in} is the output value of the image feature. I_{HF} is the high-frequency feature of the product image. F_n is the feature map output by the convolutional layer. F_{map} is the frequency attention weight, F_{map} is generated by the activation function Sigmoid, and its expression is shown in formula (1) [13].

$$F_{map} = \sigma(Conv(Conv(Conv(F_{in}) \oplus I_{HF}) + Conv(I_{HF}))) \tag{1}$$

In formula (6), σ is the Sigmoid function. $Conv$ is a convolution operation with a convolution kernel of 1×1 and a stride size of 1. $\oplus$ is an element wise addition. Multiply F_5 by weight F_{map} element by element to obtain the intermediate feature F_{mid}. Finally, the element weighting method is adopted to weight the feature map, and the weighted result is fused with F_{in} to obtain the final output F_{out} of the module. The expression for generating F_{out} is shown in formula (2).

$$F_{out} = F_{in} \oplus (Conv(F_{in}) \otimes F_{map}) \tag{2}$$

In formula (2), $\otimes$ stands for "element-by-element multiplication", which is used to weight the feature map and the frequency attention weight map (Fmap) generated by the convolution operation. In this process, the input feature map F_{in} is first convolved to obtain a rich feature map. Then, this feature map is combined with the weighted Fmap generated by the FAM through element-by-element multiplication to highlight the responses of important features. Finally, the weighted Fmap is fused with the original feature map F_{in} through element-by-element addition to generate the final output feature map F_{out}. By focusing on the high-frequency detail features of the product through formula (1) and integrating feature representation through formula (2), the model can care more about the detail features that user are interested in, enhancing the effectiveness of feature representation.

In the above content, the study has explored in detail the role of the HAM in product feature extraction, as well as how to utilize spatial attention, channel attention, and frequency attention to improve the accuracy of feature recognition. Through this multimodal feature extraction scheme, the model can capture and highlight the interest features of users more effectively, laying a solid foundation for subsequent product classification and recommendation. Therefore, the following research will focus on introducing how to apply the extracted features to the SVM classifier to achieve accurate product identification and personalized recommendation.

2.2 Construction of recommendation model based on SVM and AM

In the construction of the above model, this study introduces HAM to extract product features and further enhance their characteristics. Now it is necessary to identify and classify the processed product features to complete product recommendations that meet user needs. The commonly used method in the recognition and classification module is the SVM classifier. This method has good generalization ability, adaptability to high-dimensional feature space, and robustness to outliers, and can achieve more accurate and personalized recommendations in PRMs [14-16]. The performance of the SVM classifier mainly relies on the choice of Kernel Function (KF). Different KFs and parameters can affect the classification accuracy. The KF can map product characteristics to a sufficiently high dimensional space, which is beneficial for SVM to construct the optimal hyperplane for classification. Among them, the high-dimensional mapping method of the KF is shown in Figure 4.

In Figure 4, the schematic diagram of the high-dimensional mapping of the KF of SVM shows how low-dimensional data is mapped to the high-dimensional space through the kernel function. During this process, the striving matrix and functions used are responsible for transforming the original features into forms that are more suitable for linear classification. The actions in the figure show the arrangement changes of the data samples after mapping, ensuring that the optimal hyperplane can be found for classification with the help of SVM. During this process, different KF parameters will directly affect the classification performance and complexity of the model. KFs have different types, including linear KFs, polynomial KFs, Sigmoid KFs, and Gaussian Radial Basis Function (RBF). In this study, RBF is selected as the function for the research model based on the characteristics of the KF, as shown in formula (3) [17].

$$K(x_i, x_j) = \exp(-g\left\|x_i - x_j\right\|^2) \tag{3}$$

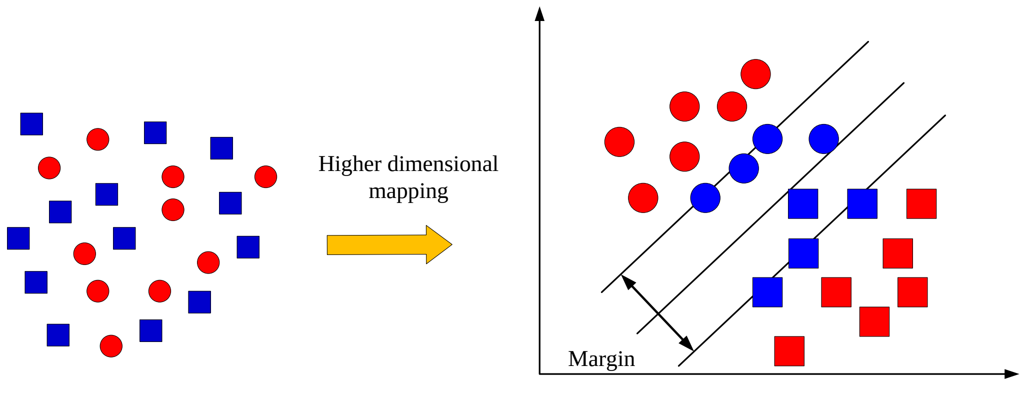


Figure 4: High dimensional mapping of KF

In formula (3), g is the distribution of sample points in the kernel space. There are two very important parameters in the RBF function, namely the Error Penalty Coefficient (EPC) and the Kernel Parameter (KP). EPC is used to balance the classification accuracy and model complexity in training data. If the EPC value is large, the model will focus more on the correct classification of the training data, but it can easily cause overfitting. If the EPC value is small, the model may allow for some misclassification and have better generalization ability, but overall, it will affect the accuracy of classification. In product recommendation systems, the adjustment of EPC can help the model more accurately understand the correlation between user purchasing behavior and products. KP mainly affects the width of the Gaussian function, and a smaller KP will reduce the range of influence of the KF, which is beneficial for more focused local feature training. A larger KP will increase the range of influence of the KF, which is beneficial for wider feature training of the model [18-20]. In product recommendation, appropriate KP can help the model learn the similarity between products and fully supplement user preference details. However, adjusting the value of the KF has a high level of difficulty, and it requires a significant amount of work to continuously confirm through experiments. Therefore, this study adopts GWO to adaptively adjust the value of KP. The GWO algorithm is a biomimetic algorithm that simulates the hunting behavior of gray wolves by updating their positions. Other solutions in the search space are considered as the position of the wolf, and the objective function is considered as the prey. The wolf will approach the prey by constantly updating its position. This study assumes that the number of iterations of the model is t, the position vector of the prey is denoted as X_p, and the position vector of the wolf pack is X. Therefore, the straight-line distance between the prey and the wolf pack can be expressed by formula (4) [21-23].

$$D = \left| CX_p(t) - X(t) \right| \tag{4}$$

In formula (4), C is the coefficient vector. The calculation process of distance helps the model find the optimal solution position in the high-dimensional parameter space, that is, to improve the accuracy of feature classification through the optimal SVM parameters. The update of grey wolf position is shown in formula (5).

$$X(t+1) = X_p(t) - AD \tag{5}$$

Formula (5) is the rule for updating the position between different gray wolves, where also represents the coefficient vector. The calculation of vectors A and C with different coefficients is shown in formula (6).

$$\begin{cases} A = 2ar_1 - a \\ C = 2r_2 \end{cases} \tag{6}$$

In formula (6), r_1 and r_1 are random vectors with values ranging from [0,1]. a is the convergence factor, whose value is inversely proportional to the number of iterations. The calculation of a is shown in formula (7).

$$a = 2 - 2\left(\frac{t}{t_{\max}}\right) \tag{7}$$

This study uses formulas (5) to (7) to calculate the distance between the wolf pack's position and prey, and simulates the position adjustment of the leader wolf, subordinate wolves, and executing wolves with other wolf pack positions, thereby achieving local and global search. The chart of the updated position of wolf packs when hunting prey is shown in Figure 5.

Figure 5 shows the process of pack position update in the GWO, where wolves of different roles approach their prey through displacement adjustment. During this process, the position information of each wolf includes its coordinates in a high-dimensional parameter space. The update rules depend on the current distance and strategy from the prey. This data stream indicates that through the dynamic adjustment of position updates, the wolf pack can effectively explore the search space, thereby finding the optimal SVM parameters and achieving the optimization and accurate classification of the model.

In Figure 5, α refers to the leading wolf, β is the subordinate wolf, γ is the executing wolf, and D is the distance from the wolf pack to the prey. When the vector coefficients are large, wolf packs are more exploratory in the search process and are suitable for discovering potential global optimal solutions. Smaller values help with detailed search and local optimization, improving convergence speed. According to hunting behavior, the position of the leader wolf is updated as shown in formula (8).

$$\begin{cases} D_\alpha = \left| CX_\alpha(t) - X(t) \right| \\ X_1 = X_\alpha(t) - A_1 * D_\alpha \end{cases} \tag{8}$$

In formula (8), X_1 represents the position of the head Wolf. Similarly, the update of the position of the subordinate wolf is shown in formula (9).

$$\begin{cases} D_\beta = \left| CX_\beta(t) - X(t) \right| \\ X_2 = X_\beta(t) - A_2 * D_\beta \end{cases} \tag{9}$$

The update of the execute wolf's position is shown in formula (10).

$$\begin{cases} D_\gamma = \left| CX_\gamma(t) - X(t) \right| \\ X_3 = X_\gamma(t) - A_3 * D_\gamma \end{cases} \tag{10}$$

The updated wolf pack position obtained through formulas (8) to (10) is shown in formula (11).

$$X(t+1) = \left| {X_1 + X_2 + X_3} \middle/ 3 \right| \tag{11}$$

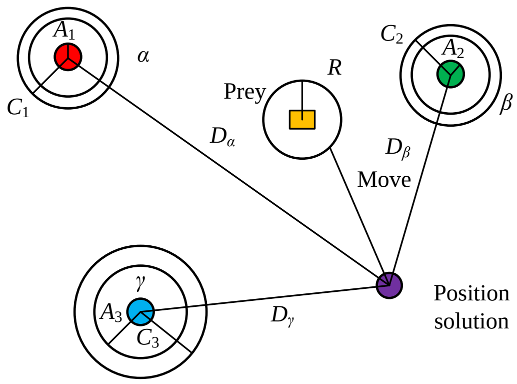


Figure 5: Wolf pack position update map

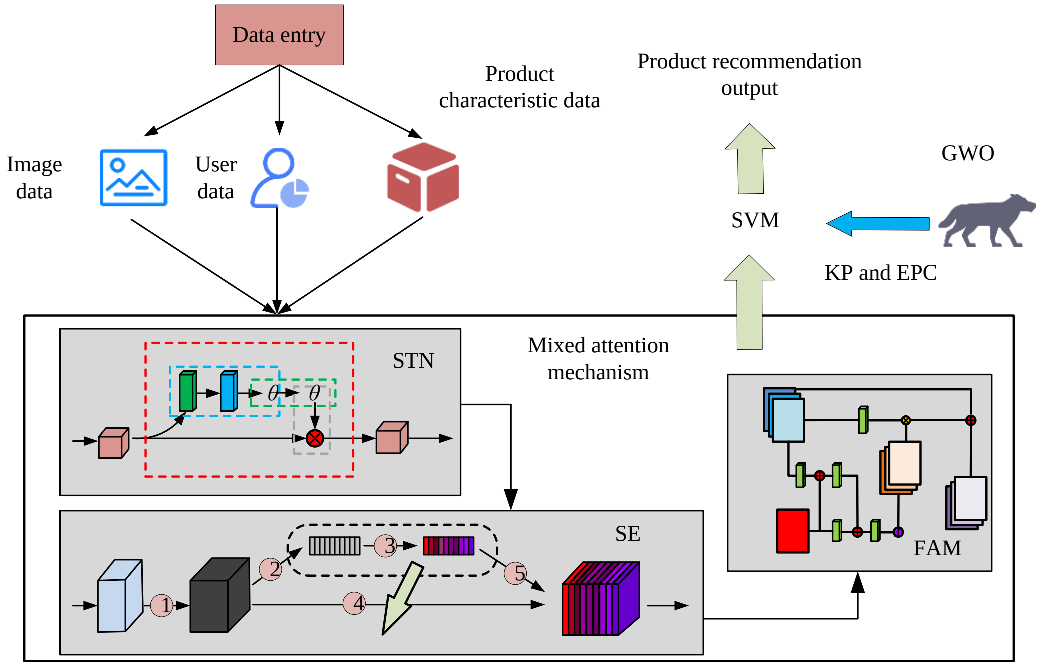


Figure 6: E-commerce platform PRM based on SVM and AM

Through the dynamic location updates mentioned above, the exploratory and random nature of the wolf pack enables it to have global search capabilities. The following and support of subordinate wolves enhance the efficiency of search. The execution wolf focuses on the current local area. This structure enables GWO to search effectively in complex solution spaces. The framework of the constructed e-commerce platform PRM is shown in Figure 6.

Figure 6 shows the framework of the e-commerce product recommendation model constructed by combining the SVM algorithm and the HAM, emphasizing the data flow between each module. On the left side of the model, the basic information of the product is extracted through multiple convolutional layers to extract key features. The size of the convolutional kernels is 3×3. After feature extraction, it enters the HAM for the refinement of multimodal features. STN, as the pre-module, is responsible for performing spatial transformation on the input data and correcting the geometric changes of the input samples to obtain a more consistent feature representation. The feature maps corrected by STN will be input into the SE module. SE dynamically adjusts the weights of each feature channel by learning the dependencies between channels, emphasizing important features and suppressing redundant features. The features weighted by SE then enter FAM. FAM further enhances the expression ability and selectivity of key features through deep learning of the correlation between features. Subsequently, the extracted features flow into the SVM classifier, and the RBF kernel function is selected for high-dimensional mapping to achieve nonlinear classification. Finally, the study uses GWO to precisely optimize the KP and misclassification penalty parameters (EPC) of SVM, and realizes the search for the global optimal solution by simulating the hunting behavior of gray wolves. GWO initializes a group of "gray wolf" individuals, each representing a specific set of values for KP and EPC. Based on the fitness value of each individual, the gray wolf group will constantly update its position. Among them, the leader approaches the best solution, while the followers explore new areas according to the position of the leader. In each iteration, GWO will guide the search process based on the fitness function, optimize KP and EPC, thereby ensuring that SVM selects the most suitable kernel function parameters during training, maximizes classification performance, and effectively reduces the risk of misclassification. The design of this model structure and data flow enhances the accuracy and efficiency of the recommendation system and effectively captures the personalized needs of users.

Based on the extracted product features, the study will further explore how to construct an SVM recommendation model combined with a HAM. The study takes SVM as the core classifier and utilizes GWO to optimize the KP to enhance the classification effect of the model. The model can accurately identify products through this structure and provide users with more personalized recommendations. Next, this study will validate the effectiveness of the model and compare it with other traditional recommendation models to verify the effectiveness and superiority of the proposed approach.

3 Results

3.1 Analysis of product recommendation effect based on SVM and AM

To enhance the model's interpretability, the SHapley Additive exPlanations(SHAP) tool is introduced to conduct feature influence analysis on the results of the SVM model. SHAP provides users with an intuitive view of the impact of different features on recommendation results by assigning relative importance values to each feature in model prediction. This study conducts performance analysis on the proposed PRM based on SVM and AM, and uses recommendation accuracy, recall, F1 score, Mean Square Error (MSE), Absolute Value of Error (AVE), and Mean Absolute Error (MAE) as the main evaluation indicators for model performance. In the research, the experiment uses a transaction information dataset from a domestic e-commerce platform. This dataset contains 3,000 transaction records, covering various types of products and user characteristics. Unique product categories include electronic products, clothing, household items and food, etc., covering a wide range of needs in users' daily lives. The total number of users in the dataset is 1,000. The transaction records and behavioral characteristics corresponding to each user are recorded in detail, including browsing history, purchase behavior, product ratings, and personal basic information of users, etc. To ensure the training and validation effect of the model, the dataset is randomly divided into the training set, the validation set, and the test set in a ratio of 7:2:1. In the experimental setup, the training set is used for the training and feature learning of the model. The validation set is used to adjust the hyperparameters of the model. The test set is used for the final performance evaluation to compare the personalized recommendation effect of the research model with other baseline models. In the SVM model, the Gaussian RBF is selected as the kernel function to effectively handle nonlinear data. In terms of hyperparameter adjustment, the EPC C and the KP γ are optimized through the cross-validation method to ensure that the model can achieve the best classification performance when processing data. This study conducts a comparative analysis between K-means Clustering Algorithm (K-means) and Backpropagation Neural Network (BPNN) [24-25]. The MSE results are shown in Figure 7.

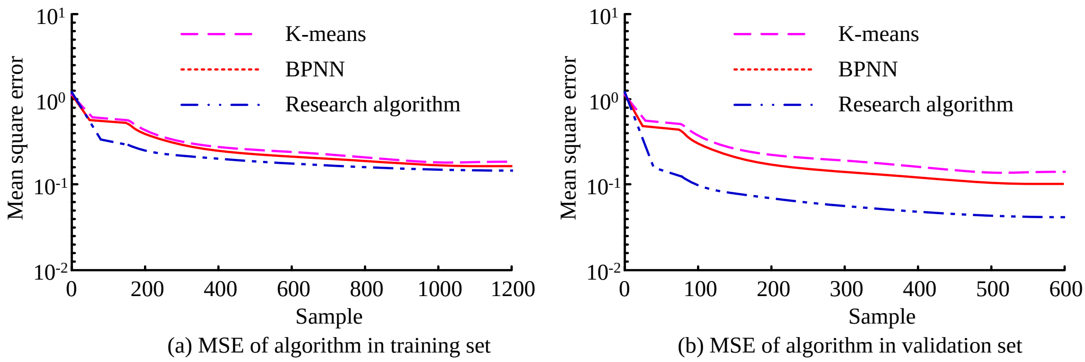
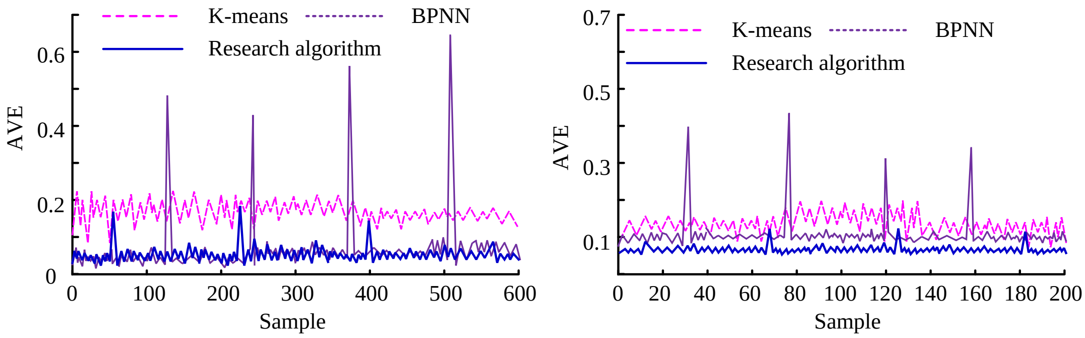


Figure 7: MSE results of different algorithms



(a) AVE of algorithm in validation set (b) AVE of algorithm in test set

Figure 8: AVE results of different algorithms

Figure 7 shows the MSE of three algorithms in the training set and validation set, respectively. In Figure 7 (a), the MSE value of K-means in the training set is around 0.25, BPNN is around 0.22, and the research algorithm is around 0.19. In Figure 7 (b), after training, the MSE values of K-means, BPNN, and research algorithms in the validation set are around 0.16, 0.11, and 0.07. This indicates that the research algorithm has stronger feature extraction capabilities or more effective model structures, which can optimize the model more effectively and learn the features in the data more fully. Figure 8 shows the comparison of AVE between the training and validation sets for each algorithm.

In Figure 8 (a), the AVE values of K-means, BPNN, and research algorithms in the validation set are in the ranges of 0.1 to 0.2, 0 to 0.1, and 0 to 0.1. The error curve of K-means is relatively stable, while the error curve of BPNN has significant fluctuations, and the research algorithm has a smoother curve fluctuation compared to BPNN. In Figure 8 (b), the average AVE values of K-means, BPNN, and research algorithms are 0.14, 0.08, and 0.06. The error curve of K-means in the test set is relatively stable, while BPNN may exhibit significant errors. The curve of the research algorithm is relatively stable. This indicates that K-means performs average in new data and may have limitations in its generalization ability. BPNN exhibits significant errors on the test set and has poor stability. The stable error curve of the research algorithm indicates that it has good generalization ability on unseen data and can maintain consistent performance. It can provide higher user satisfaction in practical product recommendation scenarios. The MAE results of the research algorithm in the training set are displayed in Figure 9.

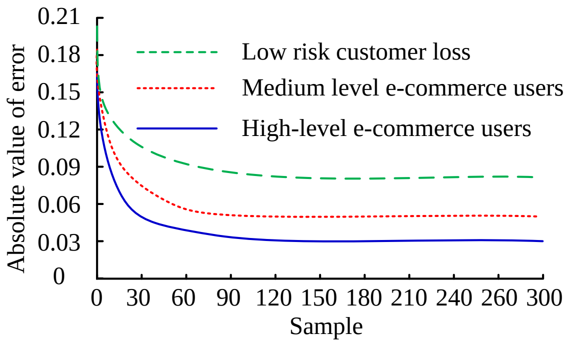


Figure 9: MAE of product recommendations for e-commerce users of different levels in the test set

Table 2: Results of HAM-GWO-SVM ablation experiments

Model Settings	Complexity analysis index	Running time (s)	Parameter quantity	Sensitivity analysis indicators	Accuracy
HAM-GWO-SVM	Low	1.04	2000	Low	0.842
SE-FAM-GWO-SVM	Medium	1.22	1800	Medium	0.652
STN-FAM-GWO-SVM	Medium	1.19	1750	Medium	0.661

STN-SE-GWO-SVM	Medium	1.16	1780	Medium	0.665
SVM	High	1.35	1500	High	0.590
HAF-SVM	Medium	1.10	1900	Medium	0.651
GWO-SVM	Medium	1.15	1600	Medium	0.670

In Figure 9, the research algorithm predicts recommended products for three levels of e-commerce users based on data. When the sample data reaches around 50, the MAE curve of high-level e-commerce users tends to stabilize, and the MAE ultimately stabilizes at 0.03. When the sample data reaches around 60, there is no significant change in the MAE curve of mid-level e-commerce users, and the MAE ultimately stabilizes at around 0.05. When the sample data reaches around 65, the MAE curve of low-level e-commerce users shows a convergence trend and eventually converges to around 0.08. The data shows that the algorithm exhibits different recommendation accuracy among e-commerce users of different levels. As the sample data increases, the MAE of users at all levels tends to stabilize, demonstrating the reliability of the model. High-level users perform the best, while the recommendation accuracy for medium and low-level users is relatively insufficient. This may be due to the low activity level of e-commerce users and weak relevant information features. To verify the effect of the mechanism introduced by the model, the study is analyzed through ablation experiments. The specific results are shown in Table 2.

Table 2 shows that the HAM-GWO-SVM model achieves a recommendation accuracy rate of 0.842, which is significantly higher than that of other models. Among them, the accuracy rate of SE-FAM-GWO-SVM without the spatial AM drops to 0.652, demonstrating the importance of this mechanism for user feature extraction. The accuracy rate of STN-FAM-GWO-SVM without the channel AM is 0.661, indicating the necessity of dynamic adjustment of channel weights. The accuracy rate of STN-SE-GWO-SVM without the FAM is 0.665, indicating the contribution of the extraction of detailed features to the recommendation effect. In contrast, the accuracy rate of the traditional SVM model is only 0.590. HAF-SVM slightly improves to 0.651, emphasizing the indispensability of the introduction of the AM. However, the 0.670 of GWO-SVM shows the limitations of parameter optimization.

The analysis of the above experimental results shows that visual features play a leading role in capturing users' immediate interests and intuitive cognition, such as the color, shape, and layout of product images. These features can effectively attract users' attention and influence their purchasing decisions. Meanwhile, numerical features play an important role in reflecting the long-term trends and behavioral patterns of user preferences, such as user ratings, browsing times, and purchase history, helping the model accurately classify users' potential preferences for products. Overall, the interaction between visual features and numerical features jointly constitutes the decision boundary of the SVM model, enabling the recommendation system to accurately capture user needs while improving the accuracy of personalized recommendations.

3.2 Practical application analysis based on e-commerce PRM

In the PRM, the recommendation performance was analyzed based on the different product types and the model iterations. The recommended results are exhibited in Figure 10. Figures 10 (a)~c show the accuracy, recall, and F1 score results. As the number of recommended products increases, all three evaluation indicators show a trend of gradually increasing first and then decreasing. When the recommended quantity of products is 40 or 50, the prediction accuracy of the model reaches 0.70, the recall rate reaches 0.70, and the F1 value is 0.68. The number of iterations has a relatively small impact on the model. Figure 10 shows that when setting up a recommendation model, it is important to focus on both the number of recommended product types and the actual effectiveness to ensure that users receive highly relevant and personalized recommendations. Meanwhile, setting a reasonable number of iterations can help the model converge more stably, but increasing the number of iterations within a specific range does not necessarily improve recommendation performance. This indicates that the model can quickly learn from data and achieve good results.

This study analyzes the accuracy of personalized recommendations for e-commerce products through comparative algorithms, as shown in Figure 11. The average accuracy of K-means, BPNN, and research algorithms in the tourism information recommendation model is 0.673, 0.676, and 0.702. The recommendation accuracy of the research model has improved by 0.059 and 0.026 compared to K-means and BPNN. The research algorithm has been proven to be more effective and accurate in personalized recommendation processes, which may be related to the feature extraction mechanism. The research algorithm can better capture users' personalized needs and preferences, improving their recommendation experience and satisfaction.

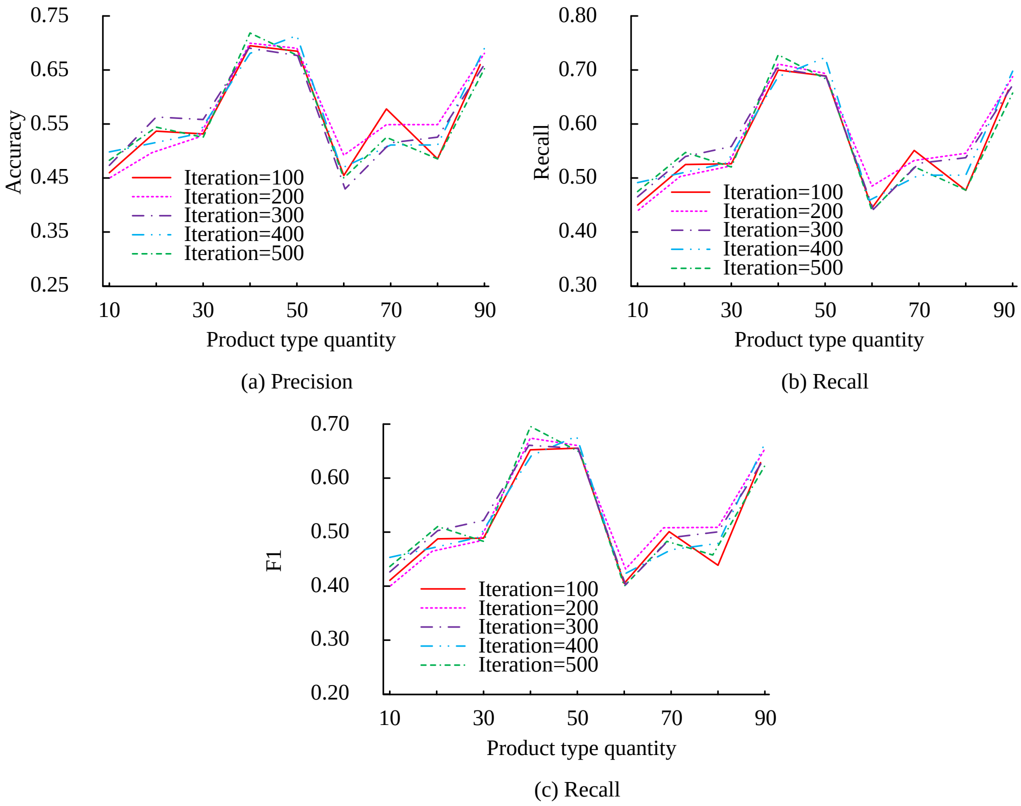


Figure 10: Analysis of model recommendation performance

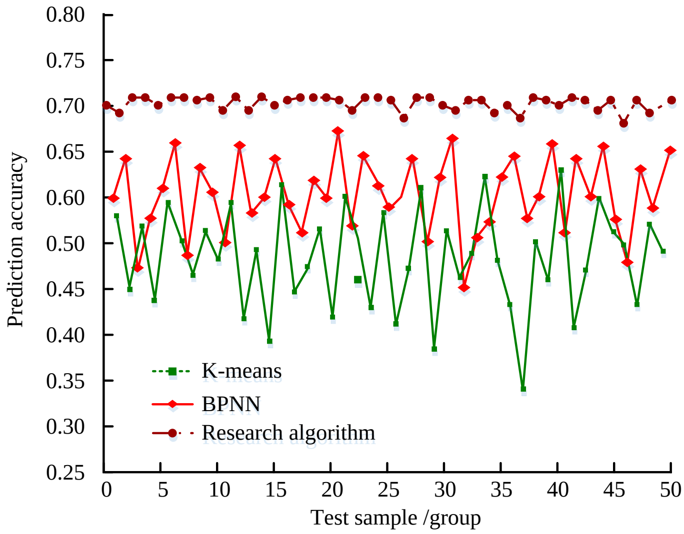


Figure 11: Personalized recommendation accuracy

Figure 12 shows the running time results in personalized recommendations of e-commerce products. The runtime of K-means in the model is around 1.33s, BPNN is around 1.18s, and the research algorithm is around 1.04s. Research algorithms can complete recommendations in a shorter time, have higher practical value, and better meet users' needs for personalized recommendations. The efficiency of research algorithms combined with high recommendation accuracy makes them more feasible and competitive in practical applications. This has positive implications for improving the service quality and user experience of e-commerce platforms.

To further verify the advancement of the method, a comparative analysis is conducted using the Deep Neural Networks (DNN) model, the Collaborative Filtering (CF), and the Graph-based Recommendation system. The evaluation indicators include ROC-AUC, Top-k accuracy rate, standard deviation, confidence interval (95%), and the average value of repeated trials. The specific results are shown in Table 3.

Table 3 shows that the HAM-GWO-SVM model performs excellently in multiple evaluation indicators, with the ROC-AUC reaching 0.92, which is significantly better than the other three comparison models. The result indicates that this model has a stronger ability to distinguish positive and negative samples. Specifically, the accuracy rate of Top-k is 0.842, which is also higher than 0.810 of the DNN, 0.761 of the CF, and 0.800 of the Graph-based recommendation system, demonstrating a higher personalized recommendation ability. Furthermore, the standard deviation of HAM-GWO-SVM is 0.013, indicating that its performance stability is superior to other models. Among them, the standard deviations of DNN and Graph-based recommendation systems are relatively high. Furthermore, the confidence interval of HAM-GWO-SVM is [0.819, 0.865], which is relatively narrow, showing high reliability. The average value of the repeated tests is 0.832, further verifying the effectiveness of this method. These results fully demonstrate the advancement and superiority of the HAM-GWO-SVM model in e-commerce product recommendation.

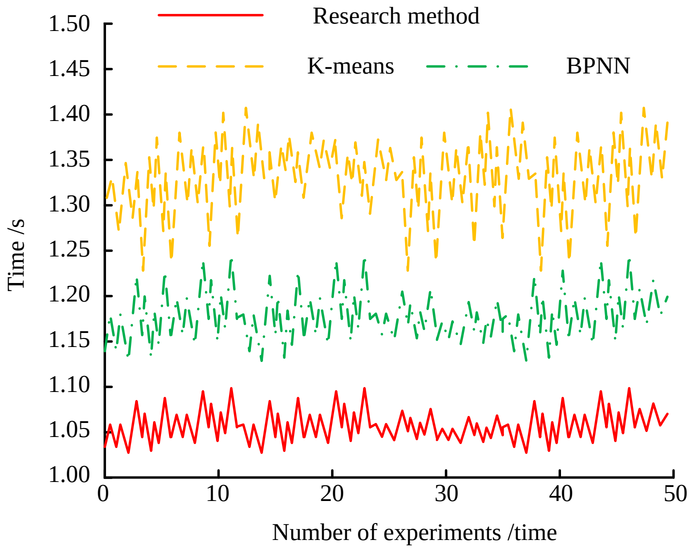


Figure 12: Personalized recommendation efficiency of the model

Table 3: Superiority test of HAM-GWO-SVM model

Model name	ROC-AUC	Top-k accuracy rate	Standard deviation	Confidence interval (95%)	Average value of repeated experiments
HAM-GWO-SVM	0.92	0.842	0.013	[0.819, 0.865]	0.832
DNN-Recommendation	0.89	0.810	0.015	[0.785, 0.835]	0.798
CF	0.85	0.761	0.018	[0.740, 0.782]	0.750
Graph-Based Recommendation	0.88	0.800	0.017	[0.777, 0.823]	0.785

4 Discussion and conclusion

In the model evaluation, this study measured the performance of the recommendation system through accuracy, recall, and F1 score. Under different recommendation quantities, the model achieved an accuracy of approximately 0.70, a recall rate of 0.70, and an F1 score of 0.68. This indicated that the model performed well in capturing user preferences. When compared with K-means and BPNN, the research model improved accuracy by 0.059 and 0.026, indicating the effectiveness of HAM's product feature extraction ability. The introduced HAM, especially STN, could accurately identify the product image areas that users are interested in, while SE and FAM enhance their recognition of key features by focusing on channel and frequency characteristics. This multi-level feature extraction method made the model more adaptable in complex data environments. In the comparison of quantitative results, the HAM-GWO-SVM model performed outstandingly in multiple key indicators. Specifically, the ROC-AUC of this model reached 0.92, and the Top-k accuracy rate was 0.842, which was significantly higher than that of the DNN (with ROC-AUC of 0.89 and Top-k accuracy rate of 0.810), the CF (with ROC-AUC of 0.85 and Top-k accuracy rate of 0.761), and the Graph-based recommendation system (with ROC-AUC of 0.88 and

Top-k accuracy rate of 0.800). In addition, the MAE of HAM-GWO-SVM was only 0.03, which was much lower than 0.08 of CF, demonstrating its accuracy in capturing user preferences. In terms of running time, this model also performed well, taking only 1.04 seconds, demonstrating an advantage in computational efficiency compared to other models. The difference in MAE among different users is due to the sparse interaction data of underlying users on the platform, which lacks sufficient historical behavior and preference information, making it difficult for the model to accurately capture users' interests. In related research, Kalakoti Y adopted an AM recommendation system and achieved good recommendation results through Transformer architecture [26]. However, this model had a high level of complexity. The research strategy of this study was to provide optimized performance more quickly in the e-commerce environment through a simple and effective combination of AM. Mamta K's research has achieved good results in behavior sequence modeling by combining deep learning models with CNN and RNN [27]. However, the feature extraction performance of this method had a strong dependence on model depth, resulting in longer training time. Compared to this study, the recommendation model based on HAM and SVM had a relatively simple structure. Unlike models that rely on global information for recommendation, research models focused more on dynamically adjusting the user's local environment, making them more flexible and practical.

On e-commerce platforms, users' demand for personalized recommendations is increasing, but traditional recommendation algorithms generally suffer from inaccurate capture of user interests. This paper aimed to perfect the performance of e-commerce product recommendation systems by introducing advanced feature extraction mechanisms and optimization algorithms. As a result, this paper constructed a recommendation model built on HAM and SVM classifiers, and adopted GWO for adaptive adjustment of KP. It combined multi-modal learning of image features to enhance the model's ability to capture personalized user needs. Through experimental analysis, the research method outperformed traditional methods in terms of accuracy and personalization, meeting the needs of e-commerce users for personalized recommendations and improving user experience. Although the e-commerce product recommendation model based on the HAM and SVM performs well in terms of accuracy and personalization, there are still several limitations. Firstly, the model may encounter performance bottlenecks when dealing with extremely sparse data, especially in the case of less user interaction. The effectiveness of feature extraction may be affected, and its recommendation accuracy for low-frequency users is insufficient. Secondly, the complexity of the model requires computational resources. Although the running time is relatively short. In large-scale e-commerce platform applications, challenges in real-time performance and computing efficiency may still be faced. Therefore, future research can explore some new deep learning architectures, such as combining graph neural networks or Transformer models, to enhance the model's ability to learn user behavior patterns and further improve the effectiveness of personalized recommendations.

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