IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 28 April 2024, accepted 20 June 2024, date of publication 24 June 2024, date of current version 15 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3418578

RESEARCH ARTICLE

Design of a Digital Exhibition Service System Under the Deep Belief Network Models

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This work was supported by the Ministry of Education's Industry School Cooperation Collaborative Education Project under Grant 220605635220438.

ABSTRACT This work aims to optimize the classification efficiency of the digital exhibition service system and achieve optimization of booth layout and visitor route planning. This work combines the Deep Belief Network (DBN) model with Reinforcement Learning (RL) algorithms and Random Forest (RF) algorithms to design and construct a digital exhibition service system. This work utilizes publicly available exhibition promotion and display channels, selecting four common types of exhibitions such as industry exhibitions. Each type chooses 10 different time periods and content formats of exhibition data, which are scattered and arranged into five exhibition datasets. The work introduces the RF algorithm as an auxiliary classifier, extracts the features through the DBN model, and uses quantitative indicators to evaluate the robustness of the model and the accuracy and personalization of the recommended results. Meanwhile, the learned features and patterns are input into the RL algorithm to verify the system's decision optimization effect. Results demonstrate that 1) Under perturbed data conditions, the system's accuracy average differs by only 0.4% from the original data conditions; the average F1 score differs by 0.003; and the average recall rate differs by only 0.1%. This indicates that the system exhibits good robustness when facing perturbed environments. 2) Cross-validation results show that the system maintains stable classification efficiency across different folds, with accuracy ranging from 82% to 89%. The average time consumption for each fold does not exceed 10ms, indicating that the system can efficiently classify different types of exhibition data. 3) Variance analysis results show that the p-values corresponding to five indicators—recommendation accuracy, recommendation coverage rate, personalized recommendation effect score, recommendation click-through rate, and user satisfaction—are 0.036, 0.027, 0.037, 0.046, and 0.039, respectively. They are all less than 0.05, indicating that the system has significant value in use and performs superiorly in personalized recommendations. 4) Decision-effect verification results show that the system's decision accuracy is highest at 96.1% for consumer goods exhibitions, with a reduction rate of 71.2%. The decision effects of the other three types of exhibitions have also been significantly optimized, indicating that while maintaining relatively high accuracy, the system can improve decision optimization by effectively reducing key errors. This work aims to ensure real-time decision-making strategies and improve the accuracy of personalized matching in digital exhibition service systems, providing more accurate and efficient service experiences for participants of different types of exhibitions.

INDEX TERMS Deep belief network model, reinforcement learning algorithm, random forest algorithm, digital exhibition service system, decision optimization.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

In the modern digital era, the exhibition industry, serving as a bridge connecting business, culture, and technology, plays an increasingly vital role [1]. However, traditional exhibition service models often encounter numerous challenges, such as low information transmission efficiency, subpar participant experiences, and underutilized resources. These issues hinder the further development of the exhibition industry [2].

Against this backdrop, this work aims to leverage cutting-edge technologies like Deep Belief Network (DBN)

The associate editor coordinating the review of this manuscript and approving it for publication was Xueqin Jiang.

models and Reinforcement Learning (RL) to construct a digital exhibition service system. By analyzing and mining data from public channels regarding exhibitors and attendees, the system aims to intelligently classify, precisely recommend, and optimize decisions regarding exhibition information. This endeavor ultimately aims to enhance the overall exhibition experience and benefits, thereby promoting the healthy development of the exhibition industry.

B. RESEARCH OBJECTIVES

In addition to achieving the fundamental task of information classification, the digital exhibition service system under the application of DBN models can also perform more precise recommendations and matching, while dynamically adjusting layouts and planning for decision optimization [5]. This work utilizes DBN models to learn latent features and patterns from the collected data [6]. These learned features and patterns are then input into RL algorithms, leveraging Q-learning and deep Q-networks, to train a digital service decision-making agent. This agent optimizes decisions, dynamically adjusts layouts and plans, and adapts to changes on the exhibition floor and the needs of participants in real-time, thereby enhancing the overall effectiveness and experience of the exhibition. In order to enhance the classification efficiency during the matching process, the Random Forest (RF) algorithm is introduced as a supplementary method. It's utilized to handle the complex features and patterns within the exhibition data, enabling better comprehension of the key factors within the data. This, in turn, further improves the accuracy and efficiency of decision-making.

II. LITERATURE REVIEW

Researchers have conducted various studies on the design of digital service systems supported by DBN models. Xu et al. explored the application of neural network algorithms in the design of 3D simulations and metaverse space ecological scene design in interactive multisensory systems. They found that, based on mixed features, the network model's performance with DBN features showed a slight improvement, with performance increases of 2.59% and 2.77% in different sensory modules. DBN can enhance the performance of ecological scene design in digital spaces through the design of mixed features and biomimetic mechanisms [8]. Sridhar et al. discussed a content-based movie recommendation model based on Facebook user profiles, using the butterfly optimization algorithm and DBN model for hybrid model construction. The results showed that the hybrid model had an average absolute error of 0.716, a root mean square error of 0.915, and accuracy and recall rates of 97.35% and 96.60%, respectively. It demonstrated the superiority and stability of the hybrid model [9]. Kumar and Murugan proposed an innovative model based on DBN and the cuckoo search method for human activity recognition (HAR). The model relies on DBN to effectively identify and classify different types of human activities. The results showed excellent performance of the innovative model in classifying six different types of human activities, with recognition rates significantly improved and the lowest recognition rate being 96.6% [10]. Farhadipour and Veisi investigated the effect of using DBN for feature extraction in a language verification system. The results showed that feature optimization using DBN could reduce the error rejection rate from 15.24% to 10.97% in the language system. Additionally, it effectively improved the system's response speed by reducing feature dimensions, demonstrating the effectiveness of DBN in improving acoustic modeling methods [11].

These studies demonstrate the significant achievements of DBN in various fields such as information recommendation, HAR, speech verification systems, and metaverse space ecological scene design. However, there are still some shortcomings in current research, such as the need for improvement in handling more challenging datasets and increasing system response speed. Furthermore, the pure DBN model may have limitations in digital exhibition service system design, such as limited ability to model complex nonlinear relationships and challenges in handling real-time data and adapting to environmental changes. Therefore, this work introduces RL algorithms and RF algorithms to enhance the model's capabilities in handling real-time data, adapting to environmental changes, and optimizing decisions.

III. RESEARCH MODEL

A. DBN MODEL

The DBN model is a type of deep learning model composed of multiple stacked Restricted Boltzmann Machines (RBMs) [11]. DBN can perform unsupervised learning on each layer's RBM units, maximizing the likelihood function of observed data to learn the distribution characteristics and patterns of the data [14]. Ultimately, these learned features and patterns are utilized for classification, prediction, or generating new data [17].

Figure 1 illustrates the implementation principle of DBN.

The main computational steps of DBN can be represented as follows:

1) ENERGY FUNCTION

$$E(v, h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_i \sum_j v_i w_{ij} h_j \quad (1)$$

$E(v, h)$ represents the energy of the joint state composed of visible units v and hidden units h; a_i represents the bias of visible unit v_i; b_j represents the bias of hidden unit h_j; w_{ij} represents the connection weight between visible unit v_i and hidden unit h_j [22].

2) ACTIVATION FUNCTION

$$P(h_j = 1|v) = \sigma(b_j + \sum_i v_i w_{ij}) \quad (2)$$

where $P(h_j = 1|v)$ represents the probability of a hidden unit h_j being activated given the visible unit state v; $\sigma()$ represents the logistic sigmoid function [23].

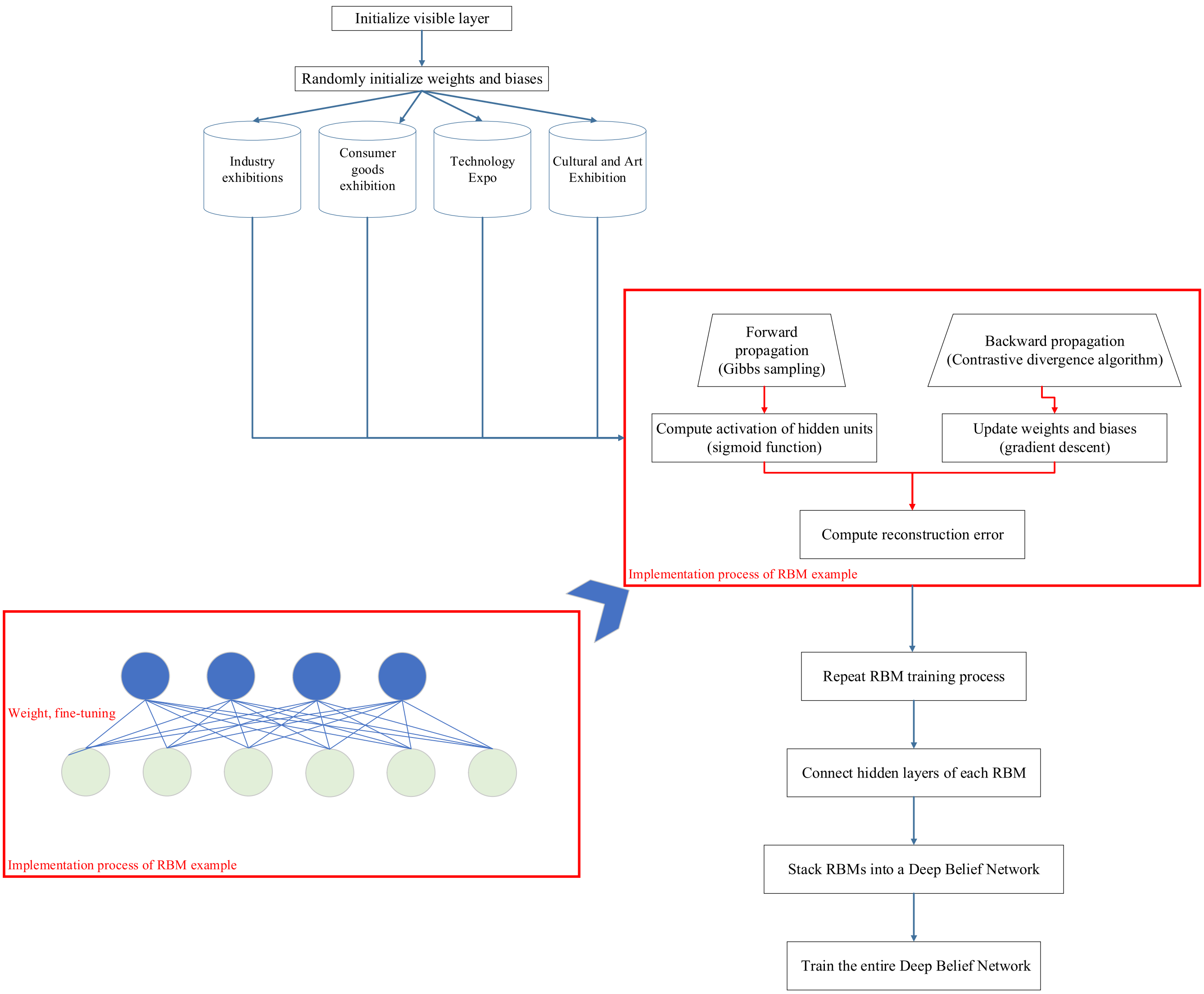

FIGURE 1. Diagram illustrating the implementation principle of the DBN model.

3) RECONSTRUCTIVE ERROR

$$\mathcal{L}(v, v') = -\sum_i (v_i \log v'_i + (1 - v_i) \log (1 - v'_i)) \quad (3)$$

$\mathcal{L}(v, v')$ represents the reconstruction error; v'_i represents the reconstruction value of the visible unit.

4) NEGATIVE PHASE

$$\Delta w_{ij} = \epsilon \left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{model}\right) \quad (4)$$

Δw_{ij} represents the update amount of connection weight; ϵ represents the learning rate; $\langle v_i h_j \rangle_{data}$ represents the expectation on the real data distribution; $\langle v_i h_j \rangle_{model}$ represents the expectation on the model distribution.

5) POSITIVE PHASE

$$\Delta w_{ij} = \epsilon \left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{recon}\right) \quad (5)$$

where $\langle v_i h_j \rangle_{recon}$ represents the expectation on the reconstruction data distribution.

6) GIBBS SAMPLING

$$P(v_i = 1|h) = \sigma(a_i + \sum_j h_j w_{ij}) \quad (6)$$

where $P(v_i = 1|h)$ represents the probability of visible unit v_i being activated given the hidden unit state h [24].

7) PARAMETER UPDATE

$$w_{ij} \leftarrow w_{ij} + \Delta w_{ij} \quad (7)$$

where Δw_{ij} represents the updated amount of connection weight.

B. RL ALGORITHM

RL algorithms aim to utilize agents interacting with the environment to learn optimal behavioral policies, to maximize cumulative rewards [25]. Upon receiving actions from the agent, the environment transitions to a new state and provides the agent with a reward signal indicating the quality of the action [12]. Based on this reward signal, the agent adjusts its behavioral policies, continuously updating these functions through trial and error and learning to optimize the agent's behavioral strategy [12].

Its key computations can be represented as follows:

1) POLICY EVALUATION

$$V^{\pi}(s) = \sum_{a} \pi(a|s) \sum_{s',r} P(s', r|s, a)[r + \gamma V^{\pi}(s')] \tag{8}$$

where $V^{\pi}(s)$ represents the value function of state s under policy π; $P(s', r|s, a)$ represents the state transition probability; r represents the reward; γ represents the discount factor [32].

2) POLICY IMPROVEMENT

$$\pi'(s) = \arg\max_{a} \sum_{s',r} P(s', r|s, a)[r + \gamma V^{\pi}(s')] \tag{9}$$

where $\pi'(s)$ represents the improved policy; $\arg\max\limits_{a}$ represents taking the action that maximizes [33].

3) ITERATION OF Q-LEARNING VALUE

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha \left[r + \gamma \max_{a'} Q(s', a') \right] \tag{10}$$

where $Q(s, a)$ represents the Q-learning value of the state-action pair (s, a); α represents the learning rate; s' represents the next state; a' represents the next action [34].

4) POLICY GRADIENT UPDATE

$$\nabla J(\theta) = \mathbb{E}_{\pi}[\nabla log\pi(a|s)Q(s, a)] \tag{11}$$

where $J(\theta)$ represents the performance measure of policy π; θ represents the policy parameters.

Figure 2 illustrates its implementation process:

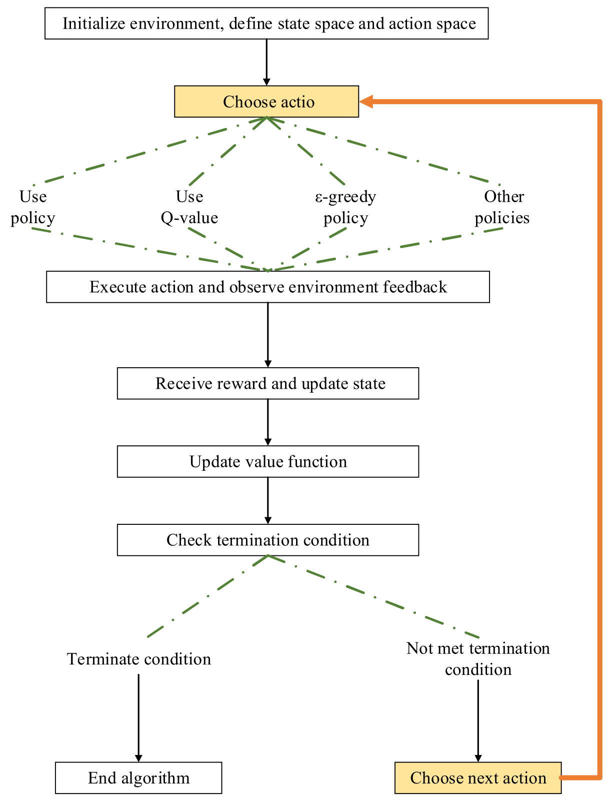

FIGURE 2. Flowchart of RL algorithm implementation.

C. RF ALGORITHM

The RF algorithm constructs multiple decision trees by randomly selecting samples and features, and integrates the results of these decision trees to reduce overfitting risks and improve the model's generalization ability [36]. Its relevant equations are as follows:

1) BASIC FORM OF DECISION TREE

$$h(x_i; \Theta_j) = \sum_{m=1}^{M} \mathbb{I}(x_i \in R_{jm})c_m \tag{12}$$

where $h(x_i; \Theta_j)$ represents the prediction result of decision tree j for the sample x_i; Θ_j represents the parameters of the decision tree [39].

2) IMPURITY OF DECISION TREE NODES

$$G(t) = 1 - \sum_{i=1}^{K} p(i|t)^2 \tag{13}$$

where $G(t)$ represents the impurity of decision tree node t; $p(i|t)$ represents the proportion of samples belonging to class i in node t.

3) EXPRESSION OF RANDOMNESS IN DECISION TREE GENERATION PROCESS

$$\Theta_j = \{(X_j, Y_j), \Theta_{j0}\} \tag{14}$$

where Θ_j represents the parameter set of decision tree j, including input features X_j, output labels Y_j, and other parameters Θ_{j0}.

4) RF PREDICTION

$$\hat{f}_{RF}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{f}_b(x) \tag{15}$$

where $\hat{f}_{RF}(x)$ represents the prediction result of RF for sample x; $\hat{f}_b(x)$ represents the prediction result of the b-th decision tree; B represents the number of decision trees in RF.

Figure 3 illustrates its implementation process.

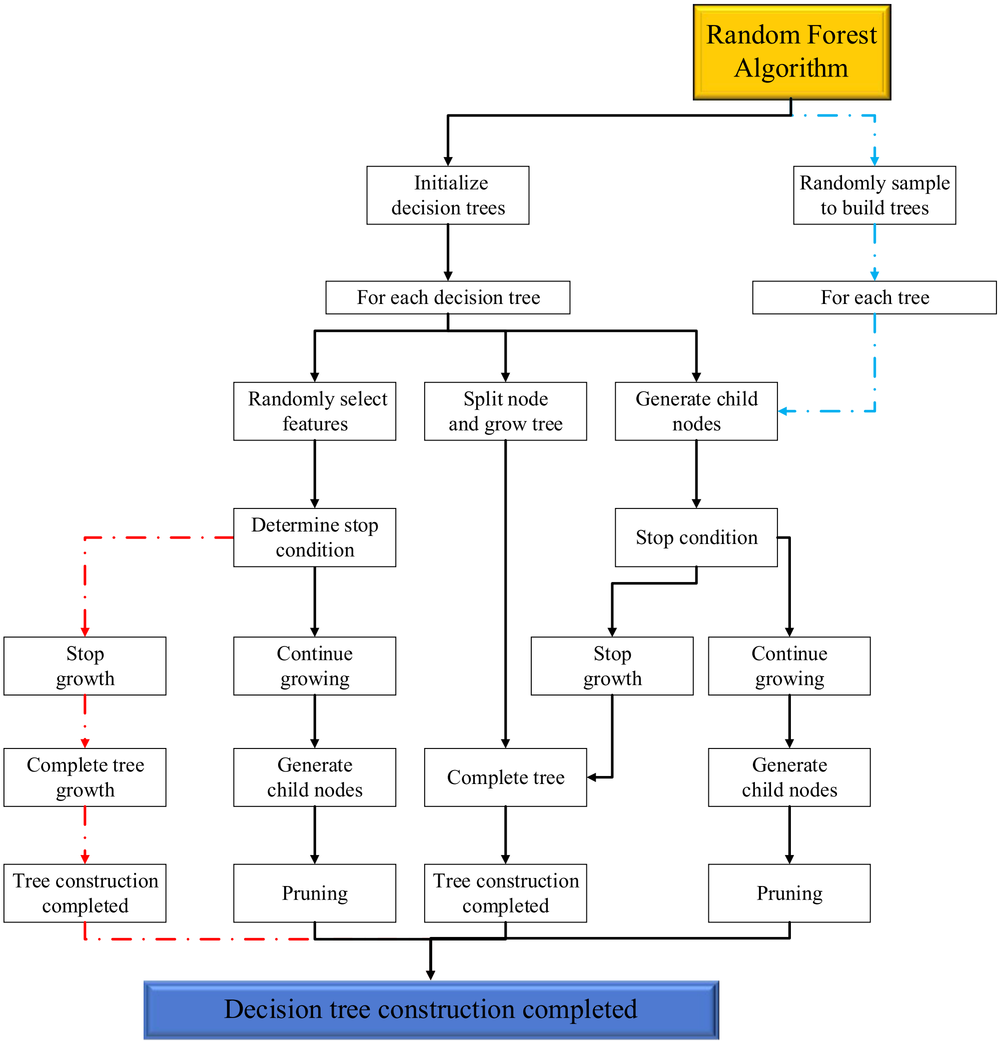

FIGURE 3. Flowchart of RF algorithm implementation.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

The design of the digital exhibition service system primarily utilizes the combination of the DBN model, RL algorithm, and RF algorithm. The work adopts the DBN model as the foundational model for design. It conducts layer-wise pre-training of the DBN through unsupervised learning. Additionally, the RF algorithm is introduced as an auxiliary classifier to enhance the system's understanding of the data. By leveraging the multi-layered hidden structure of the DBN model, the system gradually extracts high-level features from the data and comprehends the inherent patterns in exhibition data.

In order to better improve the overall benefits and participant satisfaction of different types of exhibitions, the RL algorithm is incorporated to optimize the layout of exhibitors' booths and the planning of visitor routes, modeling it as an RL problem. Specifically, the state space is defined first, followed by the definition of the action space, which includes operations such as adjusting booth layouts and visitor routes. Then, a reward function is defined to evaluate the quality of actions in each state, considering factors such as visitor dwell time and exhibitor sales. Finally, a digital service decision-making agent is trained using RL algorithms like Q-learning and deep Q-networks to select the optimal actions based on the current state, aiming to maximize cumulative rewards and enable exhibitors and visitors to achieve their goals more efficiently.

A. DATASETS COLLECTION

This work obtains data from publicly available exhibition promotion and display channels for four common types of exhibitions, including industry exhibitions, from 2020 to 2023. For each type, 10 exhibition data with different time periods and content forms are selected. These data are dispersed and arranged into 5 datasets. After removing missing and outlier values, a total of 11,360 complete data entries are obtained.

Table 1 presents the information about the datasets:

TABLE 1. Information of the dataset used.

Dataset	Exhibition Type	Number of Exhibitors	Number of Visitors	Number of Booths	Duration (days)	Exhibitor Satisfaction (score form 0-1)	Visitor Satisfaction (score form 0-1)
Dataset 1	Industry Exhibition	100-150	2000-3000	100-200	3-4	0.7-0.8	0.6-0.8
	Consumer Goods Exhibition	80-120	2500-3500	80-150	2-3	0.6-0.9	0.6-0.9
	Technology Expo	130-150	1800-2200	180-200	3-4	0.8-0.9	0.8-1.0
	Cultural and Art Exhibition	90-110	1500-1700	80-100	1-2	0.6-0.8	0.7-0.9
Dataset 2	Industry Exhibition	100-140	2500-3500	120-160	3-4	0.7-0.9	0.7-0.8
	Consumer Goods Exhibition	85-95	3000-3700	100-130	2-3	0.6-0.9	0.6-0.8
	Technology Expo	120-140	1800-2200	180-200	3-4	0.6-0.9	0.7-1.0
	Cultural and Art Exhibition	100-120	1700-2000	90-110	1-2	0.7-0.8	0.7-0.8
Dataset 3	Industry Exhibition	110-130	2600-3000	150-170	4-5	0.6-0.8	0.7-0.9
	Consumer Goods Exhibition	80-110	3200-3700	100-130	2-3	0.7-0.9	0.7-0.8
	Technology Expo	130-140	1900-2200	190-200	3-4	0.6-0.9	0.7-0.8
	Cultural and Art Exhibition	110-130	1700-1900	90-110	1-2	0.6-0.9	0.7-0.9
Dataset 4	Industry Exhibition	120-140	2700-3000	160-180	4-8	0.8-1.0	0.7-0.8
	Consumer Goods Exhibition	90-100	3300-3700	120-140	3-4	0.6-0.9	0.8-0.9
	Technology Expo	120-130	1800-2100	190-210	4-5	0.7-0.9	0.7-0.8
	Cultural and Art Exhibition	120-140	1900-2000	100-120	3-6	0.7-0.8	0.7-0.8
Dataset 5	Industry Exhibition	130-150	2600-3000	170-190	2-6	0.7-0.8	0.7-0.9
	Consumer	95-100	3000-3500	130-150	3-4	0.8-0.9	0.7-0.8

TABLE 1. ***(Continued.)*** **Information of the dataset used.**

Goods Exhibition						
Technology Expo	100-110	1900-2200	200-210	1-4	0.5-0.8	0.6-0.9
Cultural and Art Exhibition	130-140	1700-1900	110-130	2-5	0.7-0.9	0.7-0.8

B. EXPERIMENTAL ENVIRONMENT

TABLE 2 is the environmental parameters used.

TABLE 2. **Key environmental parameters.**

Indicator	Parameter
Deep Learning Framework	TensorFlow 2.5
RL Library	Stable Baselines 3.0
Other Libraries	Scikit-learn 0.24, Pandas 1.2, NumPy 1.20

C. PARAMETERS SETTING

When conducting cross-validation, personalized matching verification, and decision effect validation, a system robustness test is conducted first. The robustness test aims to simulate and validate the stable performance of the system when facing noise, outliers, and other disturbance conditions in real-world scenarios.

In order to achieve this, the work introduces perturbed data. Perturbed data are generated using random number generators and manual operations to introduce noise or outliers, simulating the uncertainty in real data environments.

The work conducts a total of 5 robustness tests. Table 3 illustrates the perturbation parameters under 5 conditions:

In order to demonstrate that the system can handle the issue of dispersed data and inconsistent data quality in multi-scenario backgrounds, the system will conduct relevant classification based on the input data. Table 4 shows the parameter selection for cross-validation.

In practical applications, the rewards obtained by the system based on different environmental states and behavioral feedback influence the overall learning and decision-making process. As the feedback results vary, besides common metrics like efficiency and accuracy, less commonly used indicators such as prediction errors have also been assigned significance.

Table 5 shows the parameter selection values and ranges for these less commonly used indicators.

D. PERFORMANCE EVALUATION

Figure 4 shows the results of robustness testing.

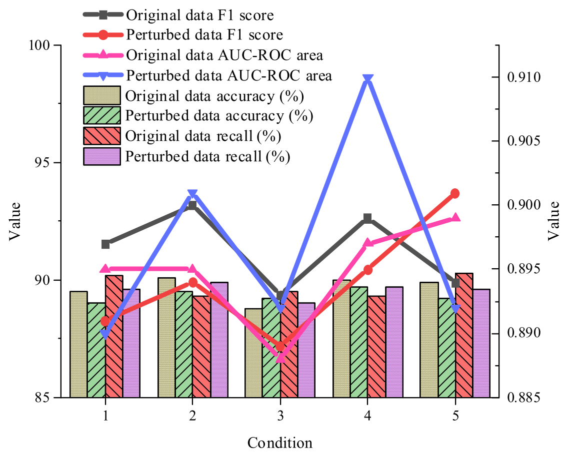

FIGURE 4. **The results of system robustness testing.**

Based on the results in Figure 4, the mean and mean differences are calculated separately, as shown in Table 6:

Combining the results of mean and mean difference, it can be observed that there are only minimal differences on the accuracy, recall, and F1-score between the original and perturbed data. The average difference in accuracy between the perturbed and original data is 0.4%; the average difference in F1-score is 0.003; the average difference in the recall is only 0.1%; and the average difference in the Area Under the Receiver Operating Characteristic (AUC-ROC) curve is only 0.002. This indicates that the system proposed exhibits good robustness when facing perturbed environments.

Figure 5 shows the results of cross-validation for classification efficiency.

Figure 5 reveals that the system's accuracy ranges from 82% to 89% across different folds, with recall rates ranging from 81% to 86%, precision ranging from 88% to 91%, F1 scores ranging between 0.84 and 0.89, and AUC-ROC values ranging from 0.9 to 0.93. This indicates that the system maintains overall stability across different folds, with minimal variation in scores across different evaluation indicators. Relatively higher classification efficiency is observed in the 1st, 4th, and 5th folds. Although there is a slight decrease in accuracy in the 2nd and 3rd folds, it still remains between 82% and 84%, while recall rates, precision, F1 scores, and AUC-ROC values remain at high levels. Additionally, the

TABLE 3. **Perturbation data conditions.**

Condition	Noise Type	Noise Intensity	Outlier Type	Outlier Proportion	Type of Missing Data	Proportion of Missing Data	Type of Duplicate Data	Proportion of Duplicate Data
Condition 1	Gaussian Noise	0.1 - 0.5	Random Outliers	5%-10%	Random Missing	1%-5%	Duplicate Data	2% - 5%
Condition 2	Poisson Noise	0.3 - 0.7	Periodic Outliers	10%-15%	Periodic Missing	5%-10%	No	0
Condition 3	Laplace Noise	0.2 - 0.6	Outlier Outliers	15%-20%	Random Missing	3%-8%	Duplicate Data	3% - 8%
Condition 4	Uniform Noise	0.4 - 0.8	Periodic Outliers	5%-10%	Random Missing	2%-6%	Completely Duplicate Data	1% - 3%
Condition 5	Exponential Noise	0.5 - 0.9	Outlier Outliers	20%-25%	Random Missing	4%-9%	Random Duplicate Data	4% - 9%

TABLE 4. **The parameters for cross-validation.**

Parameter Name	Parameter Value
Number of Folds	5
Training Set Size	9088
Test Set Size	2272
Learning Rate	0.001
Number of Hidden Layer Nodes	100
Number of Trees	100
Maximum Depth	10
Minimum Sample Split	2
Minimum Leaf Sample Size	1

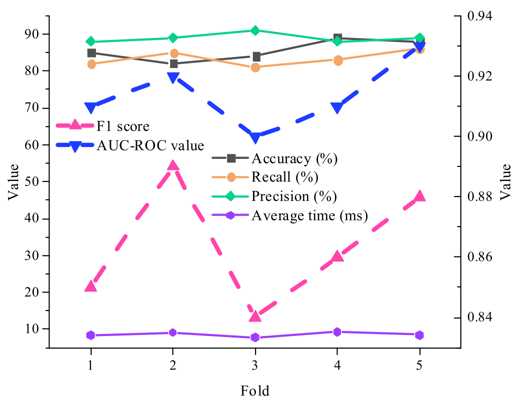

FIGURE 5. **The results of cross-validation for classification efficiency.**

average processing time for each fold is less than 10ms. This suggests that the system maintains high classification efficiency within a short time frame when dealing with multidimensional dispersed data.

TABLE 5. **Less commonly used indicators for decision optimization effect validation.**

Indicator	Parameter Range	Significance
Prediction Error	(0,1)	Lower values indicate higher prediction accuracy of the system, while higher values indicate lower prediction accuracy.
Policy Error	(0,1)	Lower values indicate that the system's decision-making strategy is more optimal, while higher values indicate suboptimal decision strategies.
Environmental Modeling Error	(0,1)	Lower values indicate stronger understanding and modeling capabilities of the system towards the environment, while higher values indicate a less accurate understanding of the environment.

In Figure 6, (a) presents the validation results of the system's personalized recommendation and matching accuracy, among other relevant indicators. In order to demonstrate the significance of each indicator, variance analysis is conducted to calculate the F-values and p-values for different types of exhibitions, as shown in (b). Figure 6 depicts the results.

Figure 6 shows the F-values of several indicators including recommendation accuracy, recommendation coverage, personalized recommendation effectiveness score, recommendation click-through rate, and user satisfaction, which

TABLE 6. Results of mean calculation for each indicator.

Indicator	Mean	Mean Difference
Original data accuracy (%)	89.7	0.4
Perturbed data accuracy (%)	89.3	
Original data recall (%)	89.7	0.1
Perturbed data recall (%)	89.6	
Original data F1 score	0.897	0.003
Perturbed data F1 score	0.894	
Original data AUC-ROC area	0.895	0.002
Perturbed data AUC-ROC area	0.897	

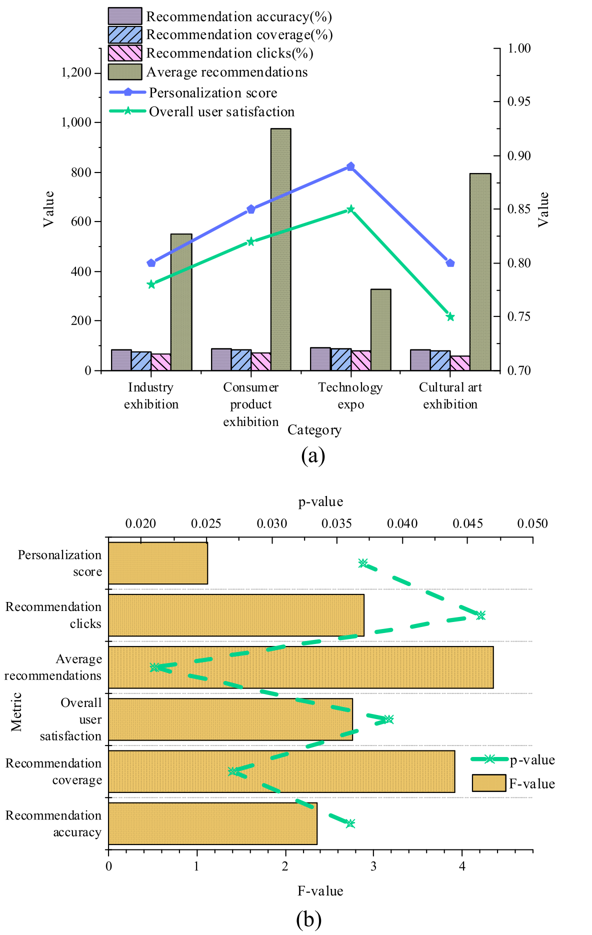

FIGURE 6. The results of personalized recommendation and matching analysis.

are 2.36, 3.91, 1.12, 2.89, and 2.76, respectively. The corresponding p-values are 0.036, 0.027, 0.037, 0.046, and 0.039, all satisfying $p < 0.05$, indicating statistically significant differences in these indicators among different types of exhibitions. The system demonstrates superiority in personalized recommendation and matching effectiveness, particularly in exhibition types such as the Consumer Goods Exhibition and Technology Expo. It can effectively provide personalized recommendations based on the characteristics of different exhibition types, thereby enhancing participation and satisfaction.

Figure 7 presents the evaluation of the system's decision effectiveness.

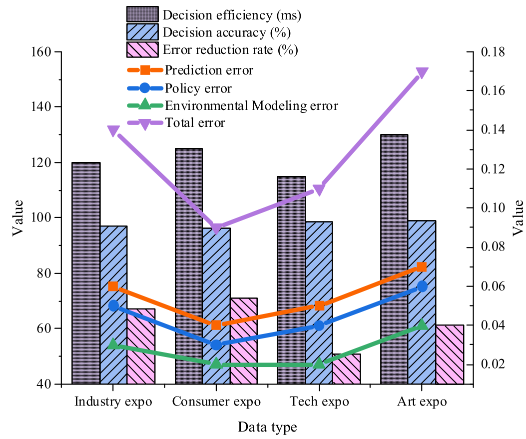

FIGURE 7. The evaluation of the system's decision effectiveness.

Figure 7 shows that there are slight differences in prediction error, policy error, and environment modeling error among different types of data, but overall they remain within relatively close ranges. In terms of decision efficiency, the Consumer Goods Exhibition and Cultural and Art Exhibition are slightly higher at 125ms and 130ms, respectively. In terms of decision accuracy, the accuracy of the Consumer Goods Exhibition is slightly higher than other data types, reaching 96.1%, while the accuracy of the Technology Expo and Cultural and Art Exhibition are 98.4% and 98.9%, respectively. In terms of error reduction rate, Consumer Goods Exhibition and Cultural and Art Exhibition have slightly higher reduction rates, at 71.2% and 61.1%, respectively. This indicates that while maintaining relatively high accuracy, the system can improve decision efficiency by effectively reducing key errors, thereby providing a more accurate and efficient service experience.

E. DISCUSSION

In summary, the system proposed demonstrates high reliability and stability in handling complex and dynamic exhibition data environments.

The innovation of this work is primarily reflected in two aspects. First, the integration of the DBN model and RL algorithm in the digital exhibition service system enables the full exploration of potential features and patterns in exhibition data. Moreover, it facilitates intelligent decision-making and real-time optimization, thereby enhancing the intelligence level and decision efficiency of exhibition services. Second, the RF algorithm is introduced as an auxiliary classifier to handle complex features and patterns in exhibition data. This multi-level data processing approach not only retains the strengths of deep learning models but also overcomes their limitations in dealing with complex data, thereby improving the system's classification efficiency and accuracy. This innovative approach can be applied to exhibition service systems. Besides, it has a certain universality and can be extended to other fields of intelligent decision-making and optimization problems, with broad application prospects and research value.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

The main contribution of this work lies in elevating the exhibition service system from traditional information classification to intelligent recommendation and decision optimization. This level of system intelligence not only better meets the personalized needs of exhibitors and visitors, enhancing their participation experience and satisfaction but also provides more accurate and efficient service management tools for exhibition organizers. Consequently, it enhances the operational efficiency and market competitiveness of the entire exhibition industry. In the practical application of digital exhibition services, this advancement holds significant real-world significance and broad social value.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

While this work has achieved some valuable outcomes, there are also some limitations to address. First, the selected types of exhibitions may not fully represent all forms of exhibitions. Second, although the RF algorithm serves as an auxiliary classifier and shows some effectiveness in handling complex features, its interpretability still needs improvement.

In order to address these issues, the work intends to collaborate with private exhibition centers to expand the breadth of the system's coverage. Within ethical constraints, real-time data streaming with deeper breadth will be introduced to optimize feature selection and dimensionality reduction processes, reducing model complexity and computational burden while enhancing interpretability. Additionally, within smaller time intervals, distributed computing and parallel processing methods will be employed to improve system computational efficiency, and dynamically update model parameters to promptly adapt to changes in the environment.

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