Management and Optimization Methods of Music Audio-Visual Archives Resources Based on Big Data

Hongyu Liu, Henan Vocational College of Information and Statistics, China
Chenxi Lu, North University of China, China*

ABSTRACT

Protecting Oroqen folk songs is not only the only way to reproduce Chinese traditional music culture, but also the only way to rebuild its national spirit and enhance national cultural confidence. In view of the modernity problems of Oroqen folk songs in the current process of inheritance and protection, this paper puts forward the management and optimization methods of music audio-visual archives resources under the background of big data. This paper analyzes and discusses the resource management path of folk music audio-visual archives in Oroqen in the era of big data and designs a set of perfect digital music audio-visual archives resource management platform, which can not only facilitate the collection, storage, management, and utilization of paper files and electronic files in archives, but also optimize the retrieval algorithm of archives. The resource allocation algorithm based on Nash equilibrium solution is used to optimize it. The simulation results show that the proposed method reduces the information resource allocation time and improves the demand satisfaction.

KEYWORDS

Big Data, Management of Resources, Music Audio-Visual Archives, Optimize, Oroqen Folk Songs

INTRODUCTION

Oroqen folk songs area a reflection of Oroqen music culture, capturing its national spirit, cultural customs, and religious beliefs. In the era of big data, the preservation of Oroqen ethnic folk songs, however, face various challenges, including cultural decline, language loss, insufficient recordings and documentation, a shortage of professionals, cultural changes, and limited resources and support. These challenges highlight the value of existing Oroqen folk songs.

As the intangible heritage protection list grows, the Oroqen folk song database has accumulated a large amount of archival information resources. Thus, it has become difficult to identify, retrieve, and share information, requiring more effective information technology solutions. The greatest advantage of big data technology lies in its ability to quantify all data, following digital standards, and gradually innovating the preservation methods for audio-visual data. This promotes the management of data in the form of words, pictures, audio, and video (Deng, 2022).

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*Corresponding Author

By extending the approach to the management of audio-visual archive resources, we can conceptualize archives in the era of big data. Thus, all files (e.g., words, pictures, music, and videos) can use the new concept of digitization to play a greater role in preserving culture (Shoumy et al., 2020).

The modernization of archives management is a necessary measure for social and cultural advancement. Audio-visual archives management plays a pivotal role, presenting a focal point and challenge (Zhong, 2021). This article, in response to the practical problems in the management of audio-visual archives, summarizes the importance of the development of audio-visual archive management. It analyzes the optimized management measures through ideas, facilities, and technology.

Regarding the design of information resource management platforms for music's intangible archives, the literature analyzes the requirements of blockchain technology in the design of information resource management platforms for music's intangible archives. It proposes an information resource management platform design for music's intangible archives based on blockchain technology (Adeel et al., 2020). Additionally, the literature explores the management path of music audio-visual archive resources in the era of big data, laying the foundation for the development of archive management (Cheng, 2022). It also analyzes the use of submodules through a general business overview and offers detailed descriptions (Pouyanfar et al., 2018).

In addition, the nonfunctional requirements of music education and teaching management systems in higher education are analyzed (Wang et al., 2020). The literature implements music-related recommendations, collected by experts or through expert feedback (Kang & Ampornstira, 2020). This highly credible approach can ensure seamless song transitions, effectively improving recommendations and accuracy.

The literature proposes using social media data to improve the accuracy of music recommendation algorithms, such as user relationships withing music social platforms (Ma, 2017). It also introduces the mixed mode technology (B/S and C/S), based on a multilayer technology. Net architecture, an online educational administration system suitable for colleges and universities, utilizes a combination of the university educational administration process and computer technology. Thus, it meets the information and technological needs of the educational administration (Tang et al., 2022).

In view of the prominent contradictions of court archives management, the literature promotes JAVA language development combined with B/S and C/S dual architecture technology. This approach realizes the sharing of information platforms and improves archive utilization efficiency (Phan et al., 2022).

The inheritance and preservation of any culture is linked to its people. This is profound to the Oroqen people. Their folk songs are passed down by word of mouth, making the role of the inheritors even more vital (Schmarzo, 2013). However, a strong sense of depression is evident when looking at the situation of Oroqen folk song inheritors. The emergence of new storage technology and audio-visual repair techniques holds significant practical importance for the preservation and recovery of archives.

The advent of the era of big data has brought a new development opportunity to the management of music audio-visual archive resources. In this case, it is particularly important to strengthen the preservation of information. Effective storage, management, and accessibility of audio-visual archives can maximize their societal benefits. Therefore, based on the analysis of music audio-visual archive management system requirements, this study carefully designed the digitalization of archive management and proposed a parallel allocation optimization method of big data information resources within the underlying network, leveraging the Nash equilibrium solution.

The purpose of this study is to use a CNN model to contribute to the preservation of Oroqen folk songs in the era of big data. It focuses on the unified management of records, documents, audio, and other materials. The overarching goal is to realize the efficient retrieval of documents and the inheritance of ethnic cultures.

RESEARCH METHOD

Music Audio-Visual Archive Resource Management

There is a vast amount of data resources within the realm of big data. Meeting the corresponding demands requires high data storage and data processing capabilities. Therefore, there is a pressing need for archives to improve their capacities and efficiently manage or back up archival resources.

To ensure the effective implementation of music audio-visual archives management, we should strengthen managerial awareness and improve management proficiency. This is key to ensuring the improvement of audio-visual archive management, underscoring the value of data preservation to managers. In addition, we must improve management techniques of enterprise managers to ensure the effective implementation of audio-visual data, improving the confidentiality and authenticity of these resources.

Diversification is a main characteristic of China's current stage of social development. To meet the various and personalized needs of users, archive departments at all levels in China have made great efforts to diversify their collection structure. This includes accelerating the construction of their own collections in areas like people's livelihood archives, celebrity archives, and archives on local characteristic. However, the existing platform sharing mode is highly decentralized, closed, and uniform, lacking cooperation within and outside the industry. It cannot effectively connect the shared archive information from various regions to form a cohesive whole (Kusiak, 2023).

Oroqen folk songs, one of the protected elements within the intangible cultural heritage, are recognized as living cultural expressions. This is similar to other concepts of intangible cultural forms, with the protection folk songs viewed as a form of live transmission (Vryzas et al., 2020). The use of big data technology for the management of audio-visual materials aligns with current needs and new industry trends. Thus, it is important to strengthen and update the management perspectives of stakeholders, with leaders emphasizing its great importance. A concerted effort should be made to actively seek more human and material support, gradually expanding capital investments toward the management of audio-visual materials.

Using scientific classification and database management to catalog archive contents is an indispensable innovation in the management of audio-visual archives in the era of big data. Therefore, all relevant departments must participate in archive management, foster inter-departmental collaboration, actively carry out electronic archive management, and improve the standard of archive management.

Ontology is a conceptual modeling tool with the capability to reveal semantic and knowledge levels, making it a powerful tool for organizing knowledge. This is achieved by building semantic ontologies for digital archive resources and describing metadata in digital archive resources. This involves semantic association and semantic description of metadata in different formats. Through metadata ontology, certain metadata elements are converted into RDF triples, facilitating the association and mapping between ontologies for metadata of different formats. Finally, this approach achieves semantic interoperability and association of metadata of RDF triples with different semantics (Alkurd et al., 2020).

There are two main knowledge innovation modes for digital music audio-visual archive resources based on semantic ontology (Khaleel & Al-Raweshidy, 2018). The first mode involves knowledge through semantic reasoning within the field of digital archive resources. This mode focuses on the rediscovery and excavation of hidden knowledge within the identified digital archive resources. The second mode links knowledge outside the domain through data association technologies, influencing external knowledge through association, inductive reasoning, and data mining technology. This process results in the generation of new knowledge within the domain.

This external knowledge can come from sources other than digital archive resources, including empirical knowledge within the human brain. Therefore, in the knowledge application layer, efforts should be made to expand and enrich the existing domain knowledge. This serves to enrich the ontology library of digital archive resources, which is conducive to improving users' satisfaction in the utilization of these resources.

In summary, we can draw the overall knowledge management model diagram of digital archive resources, as shown in Figure 1.

As deep learning techniques continue to advance in areas like speech recognition and natural language processing, various neural network models, especially the circular neural network models, are being used to measure text similarity. Thus, recurrent neural networks, known for their advantages in processing time series data, prove to be suitable for text data analysis.

Convolutional neural networks (CNNs) contain convolution calculations and has a deep structure. By adopting weight sharing and local connections, they can directly obtain meaningful representations from the original data and automatically capture local data features. The long short-term memory (LSTM) network is also an important model in deep learning, designed to learn data by simulating processes within the human brain. LSTM builds on RNN (Recurrent Neural Network), overcoming the gradient disappearance issue related to RNN when dealing with long-term series data. This enhances its ability to deal with long-term series thanks to the forget gate (responsible for selectively forgetting historical information), input gate (responsible for preserving the fusion of current time information and historical information), and output gate (responsible for determining the output state of the hidden layer) (Abdessamad et al., 2020).

A CNN is a feedforward neural network that combines convolution operations and depth structures (Xu et al., 2021). It extends the standard feedforward neural network by adding convolution and pooling layers. CNN consists of an input layer, convolution layer, pooling layer, and fully connected layer. A simple neural network model structure is shown in Figure 2.

For a feature graph *X* with input size *p*q*, a convolution operation is performed with convolution kernel *K* with size *m*n*. The final output result *Y* can be expressed as:

$$Y_j\left(j \in p * q\right) = f\left(\sum\nolimits_{i \in n*n} X_i * K_i + b\right) \tag{1}$$

The pooling operation requires a more detailed segmentation of the input convolution feature maps to obtain several local feature maps with smaller sizes. For the $l-1$-th output feature map α_j^{l-1} in the $l-1$-th layer, the result obtained after the pooling operation can be expressed as:

Figure 1. Knowledge management model of digital music audio-visual archive resources based on semantic ontology

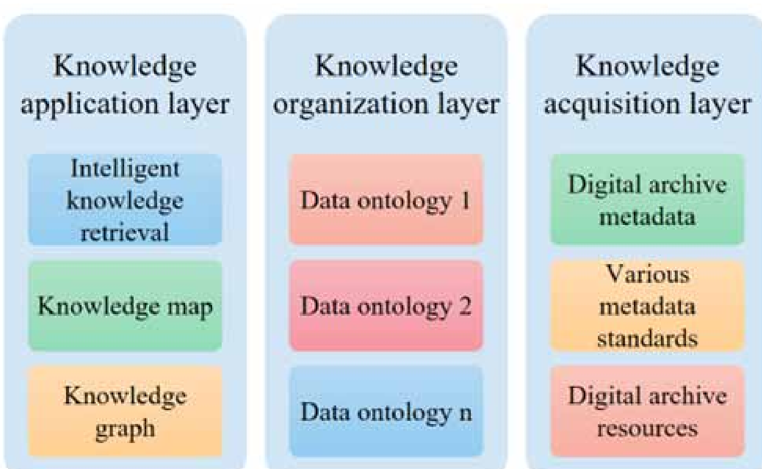
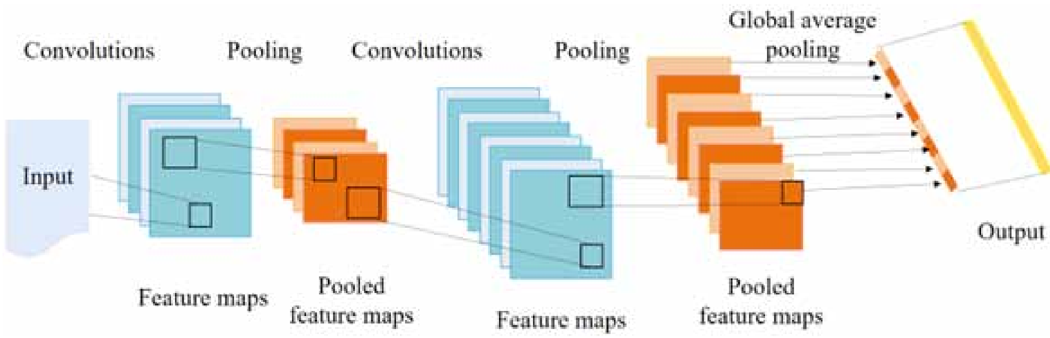


Figure 2. CNN model structure



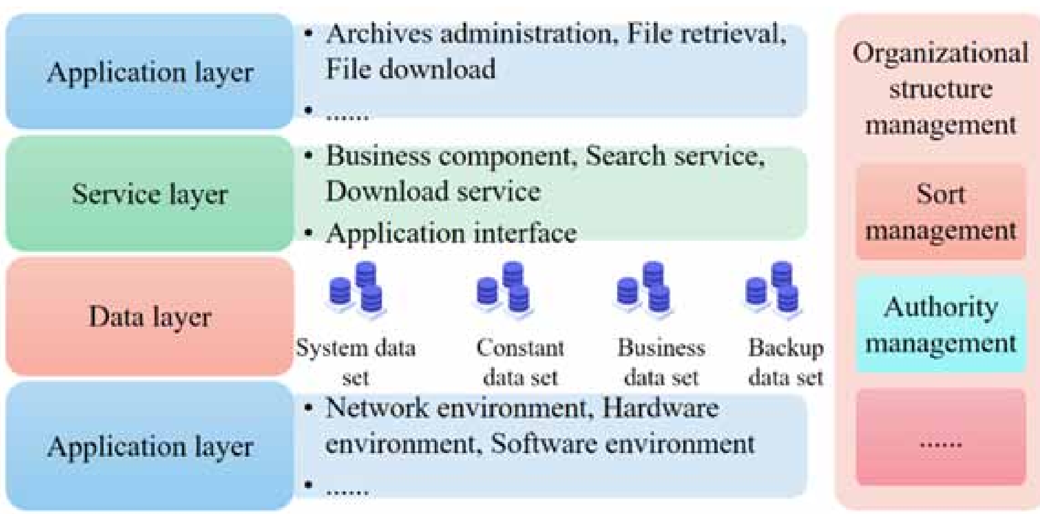
$$\alpha_j^l = f\left(down\left(\alpha_j^{l-1}\right) + b_j^l\right) \tag{2}$$

CNN is composed of several convolution layers. As the number of convolutions increases, the data size gradually decreases. Before joining the fully connected layer, the network must extend the high-latitude data into a one-dimensional vector. Finally, the feature map abstracted from the convolution layer is projected into the space of the specified dimension through the fully connected layer (Pourshahabi et al., 2018).

The design of the digital music audio-visual archive management system is a response to the business needs of the Design and Research Institute. The system includes eight functional modules: (1) user and organization architecture management; (2) classification management; (3) data type management; (4) authority management; (5) process management; (6) archive management; (7) third-party system integration; and (8) archive utilization. Figure 3 shows the overall functional design and architectural design of the system.

This system adopts a combination of C/S and B/S architectures. The C/S component offers archive management personnel a convenient way to reorganize or organize papers and store files

Figure 3. System architecture design



(Wen et al., 2018). The B/S component is user-friendly for regular users, allowing them to store files through various criteria like online browsing, downloading of electronic files, and applying to borrow paper files.

Optimization of Archival Information Resources in a Big Data Environment

Repository resources are growing at a rapid pace due to larger archives, including resources for structured, semistructured, and unstructured data. The main idea of resource optimization is to harness big data technology to consolidate scattered archive information resources, followed by an analyze, process, and mine phase. Finally, it provides the data for utilization.

Several steps are used when developing archive databases. First, digitizing archives entails converting paper archive information into electronic formats. Second, a systematic file classification is needed to enhance the efficiency of file management. Finally, it is necessary to create a comprehensive archival database to compile all archival materials and make the database public, optimizing the utilization efficiency of the database.

Oroqen folk songs are rich in content, numerous in number, colorful in performance, and unique in their musical characteristics and aesthetic implications. In addition, music reproduction is an excellent way for its live transmission. The evolution of digital information processing technology and electronic storage methods for audio-visual data opens up technical means and possibilities for the digitalization of archival information. Using these technologies, we can “preserve” existing archival materials, including delicate or susceptible items like photographs and documents, by converting them into digital forms and ensuring their safekeeping. At the same time, managers should earnestly strengthen their expertise and knowledge, mastering new technologies and techniques that improve their work efficiency and capabilities. Their role is not limited to simply managing archives but also promoting the dissemination of audio-visual archives.

Search engines and cross-database retrieval have their own advantages and disadvantages. Search engines store local database indexes for quick retrieval; however, it can take up significant amounts of storage space with many data sources. Therefore, this article will combine the advantages of search engines and cross-database retrieval to propose a dynamic resource reorganization system model or “new model.”

The basic idea of this model involves the maintenance of a keyword list and local index database to record user inputs. This information allows the model to judge the main operation of the user, including retrieval operations and data updates. Then, it decides whether to adopt the search engine mode or the cross-database retrieval mode in response to the the user’s request.

According to the resource allocation model with quantum behavior, the Nash equilibrium algorithm is used to solve the model. Once the bottom network big data information resource allocation model is established, the next step is to solve the Nash equilibrium of the game. If each participant tries to maximize the utility value, the optimal transmission strategies of various priorities can be obtained by solving the Nash equilibrium solution of the game. According to the definition of the Nash equilibrium solution, the model satisfies the Nash equilibrium solution of the game. The optimal sending strategy P_i^* with various priorities needs to meet the following requirements:

$$\begin{cases} U_1\left(P_i^* \sim P_3^*\right) \geq U_1 \\ \vdots \\ U_3\left(P_i^* \sim P_3^*\right) \geq U_3 \end{cases} \tag{3}$$

Using the utility function to make partial differentiation of elements (Peng et al., 2018), the best utility function can be obtained:

$$\frac{\partial U_1}{\partial P_1} = u_1^t \times P_1^t + u_1^f \times P_1^t + P_1 \left(u_1^t \times \frac{\partial U_1}{\partial P_1} \right) \tag{4}$$

where $\frac{\partial U_1}{\partial P_1} = 0$ is the necessary condition for maximizing the utility function U_i. Only when the calculation conditions are met can the utility function U_i have the maximum extreme value.

The first step is the internal game competition stage. To ensure the best transmission probability of various priority services in the network, it is necessary to select various service data streams.

The second step is the data sending stage. In addition to winning the internal competitive business data streams, it is also necessary to compete for the information resources of external data. In the competition, it is necessary to automatically adjust the minimum competition window so that the allocation of network resources on various priority business data streams can converge to the allocation results when Nash equilibrium is solved.

By obtaining the optimal transmission rate and automatically adjusting the minimum competition window, various services can secure optimal transmission opportunities, enabling the network's performance to reach its optimal state. This, in turn, reduces collisions between network nodes and facilitates the allocation of big data information resources in the underlying network (Liu, 2022). A direct relationship exists between the data transmission probability of the station and the minimum contention window in the enhanced distributed channel access protocol.

$$P_i = \frac{2\left(1-2p_{ci}\right)}{\left(1-2p_{ci}\right)\left(w_i+1\right)+p_{ci}w_i\left(1-2p_i\right)\left(1-\left(2p_{ci}\right)^m\right)} \tag{5}$$

Among them, the node probability of each highest level of class I is represented as p_i, while the data's overlap rate is represented by p_{ci}. The lowest-level competitive units are represented by w_i. Collaborative filtering recommendation offers two advantages when compared with other personalized recommendation technologies: it can overcome the "island phenomenon" by using collective wisdom, providing users with valuable and novel items. In addition, there is no special requirement on the format or content of recommended resources, making it a suitable approach for unstructured resources like songs (Adnan & Akbar, 2019). This article proposes a multilayer collaborative filtering personalized music recommendation algorithm based on ontology modeling and tensor decomposition.

The main idea is as follows: using music ontology within the model, the similarity of user preference concepts is calculated according to the user preference values associated with concept nodes in the model. By fusing this with user background similarity, a candidate nearest neighbor for the current user can be found (Ghani et al., 2020). This approach allows personalized music recommendations to users by breaking down the predicted score of songs.

All ternary entities should be modeled with each other in a multirelated way. The scoring function can be defined as follows:

$$f_R : User \times Item \times Tag \rightarrow RelevanceScore \tag{6}$$

The consumption patterns of users may change with time. The time series model is designed to learn the time-varying patterns in data by considering the time factor, which can be described as:

$$f_R : User \times Item \times Time \rightarrow RelevanceScore \tag{7}$$

According to the user knowledge model, for the limited and relatively few concept node sets C in music ontology, the preference vector P_{ai}, P_{bi} is used to express the user's interest in concept nodes. The cosine similarity is used to measure the similarity of preference concepts among users:

$$CSim\left(a,b\right) = \frac{\sum_{i\in C} P_{ai} \times P_{bi}}{\sqrt{\sum_{i\in C} P_{ai}^2}\sqrt{\sum_{i\in C} P_{bi}^2}} \tag{8}$$

According to the quantitative representation of the user's personal information in the user knowledge model, the background similarity of user *a,b* is calculated by the cosine similarity method:

$$BSim\left(a,b\right) = \frac{\sum_{i=1}^{3} Q_{ai} Q_{bi}}{\sqrt{\sum_{i=1}^{3} Q_{ai}^2}\sqrt{\sum_{i=1}^{3} Q_{bi}^2}} \tag{9}$$

where $Q_{ai}Q_{bi}$ is the background information vector of user *a,b*.

After calculating the similarity of the preference concept and background information between the current user and other users, the similarity is linearly fused to generate the candidate neighbor set of the current user (Nack & Lindsay, 1999). The formula for calculating the fusion similarity of user *a,b* is as follows:

$$USim\left(a,b\right) = \alpha BSim\left(a,b\right) + \left(1-\alpha\right) CSim\left(a,b\right) \tag{10}$$

where $\alpha \in \left[0,1\right]$ is the adjustment factor, which is convenient to adjust the actual situation. When new users appear, due to the lack of usage records, the value of α is increased, and the similarity is calculated according to the initial information of users. When there is a considerable amount of user data, the value of α is reduced, and the similarity is calculated according to the user's behavior data.

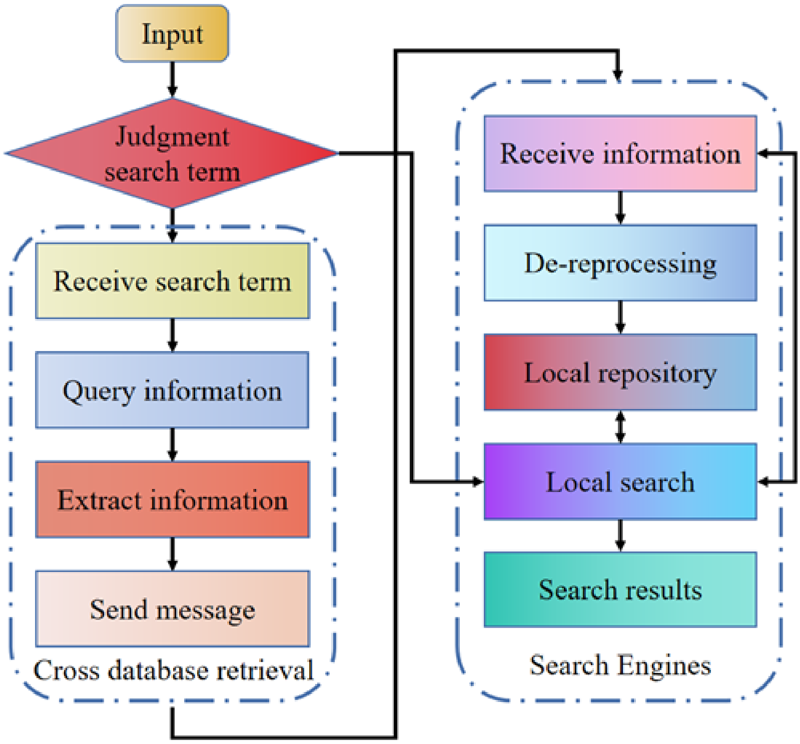
The new model can be divided into four parts: (1) user interface; (2) search engine; (3) cross-database retrieval; and (4) data update. The keyword retrieval process of the information dynamic reorganization system model is shown in Figure 4.

In terms of data size, the new model only stores information resources related to the keyword list. The search engine is tasked with storing all the information resources within the database. Therefore, the data size of the new model is small, while the search engine is large.

RESULT ANALYSIS

This article uses classified data from the old archive system to train the network model. The evaluation indicators include text search accuracy, missing values, algorithm mean absolute error (MAE) value for data source 1 and data source 2, demand satisfaction, and resource allocation time. Text data within each category and document library have high similarity. Among them, doc_1 represents document 1, doc_2 represents document 2, is_ similar represents relevance, 1 represents relevance, and 0 represents no relevance.

Figure 4. Keyword retrieval process of the information dynamic reorganization system model



CNN and LSTM models are used to conduct text similarity experiments. The CNN network integrates convolution calculations and has a deep structure. By adopting weight sharing and local connections, it can directly obtain an effective representation from the original data and automatically extract the local features of the data. On the other hand, the LSTM model in deep learning mirrors the human brain by effectively learning from data.

Experimental Comparison Between the LSTM and CNN Models

The dataset is divided into a training set and a test set with an 8:3 ratio. This training set contains 80 files, while the test set has 30 files. For this experiment, the selected training files are mainly text documents, with no information like audio or video content. Different parameters are used to compare the accuracy of the experimental results of the two models. Table 1 shows the specific parameter settings of the corresponding models. Figure 5 shows the accuracy of the two models.According to the data analysis and comparison in the figure, CNN exhibits an accuracy rate close to 90%. The LSTM accuracy rate is approximately 85%. As the threshold value increases, CNN's accuracy remains stable, whereas the LSTM accuracy declines. These findings highlight the performance of the CNN model in terms of accuracy and results.

Once the CNN model is selected for use, the ReLU function is adopted as the activation function. Subsequently, experiments are performed to assess the impact of different dropout values on loss values. The results are shown in Table 2.

The dropouts have varying values. The loss value remains close, with an average of 0.32. As the dropout increases, the loss value remains stable, indicating that the change in dropout has a limited effect on the loss value.

This article uses the Python language and MATLAB platform to realize the algorithm.

Table 1. Model experimental parameters

LSTM	Parameter	CNN	Parameter
Dim	100	Dim	100
epoch	10	epoch	10
Learning rate	0.16	Learning rate	0.19
Threshold value	0.1-1.0	Threshold value	0.1-1.0
Activation function	ReLU	Activation function	ReLU

Figure 5. Curve of correct rate changing with threshold

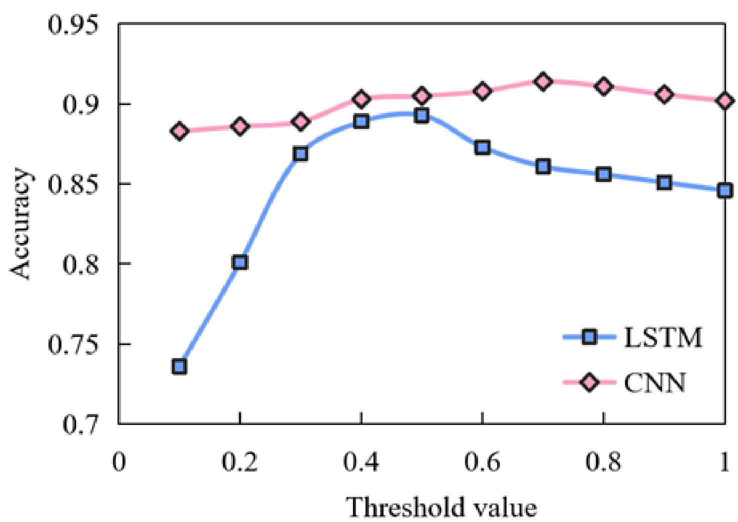


Table 2. Influence of pour value on loss

Dropout	Loss Value
0.1	0.323
0.2	0.316
0.3	0.308
0.4	0.332

Comparison of Results From Different Data Sources

The experimental data source lacks user registration information. Thus, the similarity of users' background information is ignored when calculating the similarity of fused users. Figures 6 and 7 show the MAE values of data source 1 and data source 2, respectively.

These figures show that the personalized music recommendation algorithm shown in this article, which is based on ontology and tensor decomposition, excels at recommending Chinese music. Under different nearest neighbor settings, it shows the smallest MAE value, indicating that it has superior recommendation accuracy. Thus, as the number of nearest neighbors increase, the algorithm's accuracy tends to stabilize. The MEA values of the three methods for data source 1 gradually and nearly

Figure 6. Data 1 source MAE value comparison

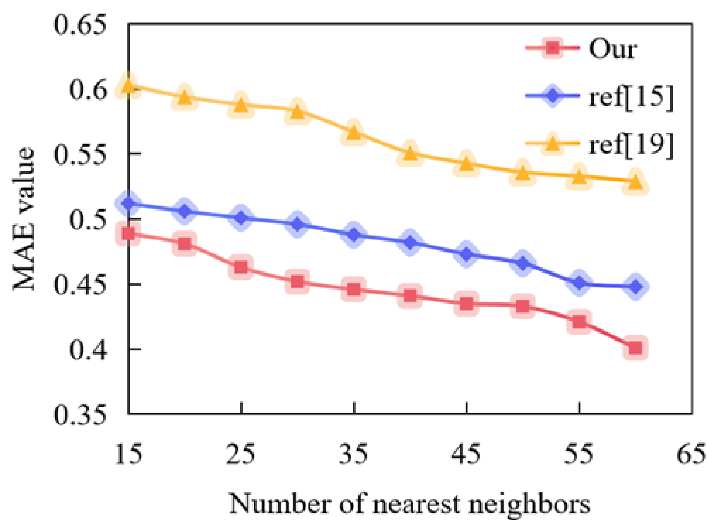
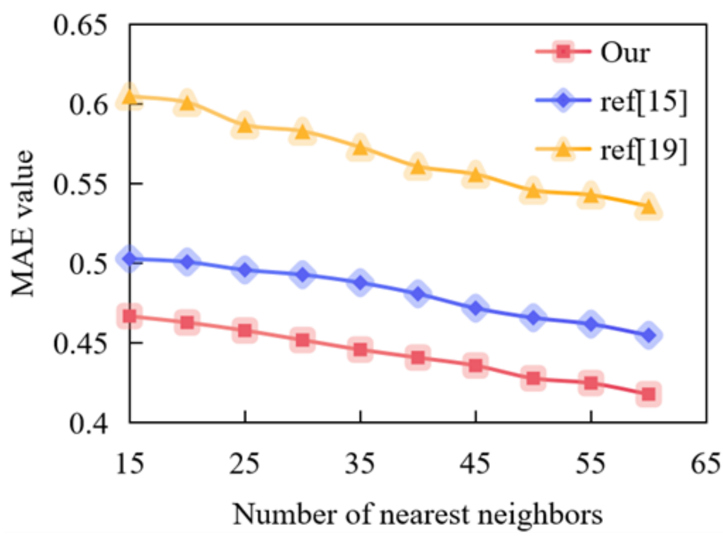


Figure 7. Data 2 source MAE value comparison



linearly decrease with the increase in the number of nearest neighbors. The algorithm introduced in this article consistently yields substantially lower MEA values compared to the other two methods.

At the same time, comparing data source 1 and data source 2, it is found that the personalized music recommendation algorithm based in ontology and tensor decomposition obtains smaller MAE values under different numbers of nearest neighbor scenarios. Thus, the recommendation accuracy is enhanced.

Effectiveness Analysis of Different Allocation Optimization Methods

To prove the effectiveness of the parallel allocation optimization method for big data information resources within the underlying network, grounded in the Nash equilibrium solution, an experiment is needed. The proposed method (M1) is assessed by comparing it with the demand satisfaction of the resource allocation optimization method based on a wireless network (M2) and the information resource allocation method based on a space-time path (M3). The comparison results are shown in Table 3.

It can be seen from Table 3 that an increase in the number of iteration times leads to a gradual increase in demand satisfaction for all three methods. When the iteration count reaches 50, the M1 method achieves a demand satisfaction of 0.71, the M2 method is 0.61, and the M3 method is 0.59. The proposed method outperforms them all with a higher demand satisfaction, demonstrating a stronger capability to allocate big data information resources within the underlying network.

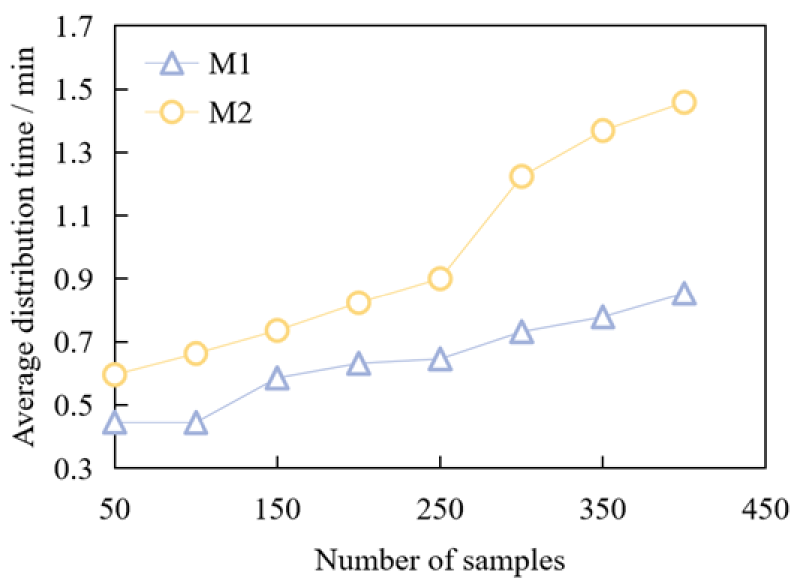
The parallel allocation time of big data information resources is compared between the M1 and M2 methods. The results are shown in Figure 8.

Figure 1 shows that the both the M1 and M2 methods experience an increase in the allocation time as the sample count rises. When the sample count reaches 150, the proposed method's average information resource allocation time stands at 0.586 minutes, while the M2 method records an average information resource allocation time of 0.736 minutes. The allocation time of the M1 method is notably shorter than that of the resource allocation optimization method based on a wireless network. The M1 method effectively reduces the average information resource allocation time through the use of Nash equilibrium.

Table 3. Comparison of different methods of demand satisfaction

Iterations	Demand Satisfaction		
	M1	M2	M3
30	0.51	0.52	0.52
40	0.63	0.55	0.56
50	0.71	0.61	0.59

Figure 8. Comparison of information resource allocation time



Regarding the management of music audio-visual data archives, we should stress the value of using the internet for effective archive management. Managers should adopt a new perspective related to file retrieval, using internet retrieval platforms to integrate information across various domains. This will help to establish a unified digital management platform for music audio-visual files, allowing users to retrieve more useful information through the platform. This approach will enhance the practicality of music audio-visual file management and avoid a situation in which files are shelved or useless.

In the era of big data, a comprehensive digital file management of music audio-visual materials in imperative. This effort will enhance management efficiency and proficiency, as well as improve its service to society.

CONCLUSION

Oroqen folk songs are an important part of China's singing culture, boasting both a long history and profound cultural heritage. In the era of big data, comprehensive digital management of Oroqen folk song audio-visual archives is vital to address the impact of operations on archive processes. This approach aims to enhance the utilization of efficient audio-visual archives and better serve society.

The current study uses classified data from the existing file system to train the network model. It employs CNN and LSTM models for text similarity experiments. In addition, the CNN model demonstrates higher accuracy and stability compared to the LSTM model.

In this study, the authors compare the proposed method (M1) with the resource allocation optimization method (M2) based on a wireless network and information resource allocation method (M3) based on a space-time path. M1 has a higher demand satisfaction and can better allocate the big data information resources within the underlying network. In addition, the timing of M1 reduces the allocation time for information resources through the Nash equilibrium.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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