scientific reports

OPEN

The analysis of international communication value assessment of Chinese mythology themed animated films in belt and road under BPNN algorithm

Nan Zhang[1,2] & Ellen Zhu[3]✉

Chinese mythology-themed animated films are critical carriers of cultural communication. With the promotion of the "Belt and Road" initiative, how to scientifically assess their international communication value has become a current research hotspot. The innovation of this work lies in integrating the Backpropagation Neural Network (BPNN) algorithm from artificial intelligence techniques with the Bidirectional Long Short-Term Memory (BiLSTM) algorithm. This work proposes a cultural feature recognition model based on the BPNN-BiLSTM fusion. This innovative approach effectively handles the complex nonlinear features in film content and captures long-term dependencies and semantic information within text sequences through the BiLSTM algorithm. The approach improves the recognition accuracy of cultural features in Chinese mythological animated films. Experimental results show that the model achieves an accuracy of 94.39% on the test set, with the loss value maintained at around 0.60, demonstrating high performance and accuracy. Compared to traditional evaluation methods, the proposed fusion algorithm improves the efficiency of the evaluation. Also, it provides a new technical path for accurately identifying cultural features. Thus, this approach has significant theoretical value and practical significance. Meanwhile, it can effectively promote the international dissemination of Chinese mythological animated films in the context of the "Belt and Road" initiative.

Keywords Artificial intelligence, Animated films, Back propagation neural network, Chinese mythology, Cultural communication

Research background and motivations

Chinese mythology-themed animated films have become critical carriers of distinctive cultural symbols amid China's growing global cultural influence. These cinematic works now play a vital role in international Chinese cultural dissemination through their unique symbolic representation[1,2]. Concurrently, with the introduction and advancement of the Belt and Road Initiative, the popularity of Chinese mythology-themed animated films has been on the rise domestically and internationally in recent years. This presents an unprecedented historical opportunity for Chinese culture to enhance mutual understanding and friendship among people of different nations, requiring various forms of cultural products for international communication[3–5]. However, there is currently limited research on the international communication value of Chinese mythology-themed animated films, especially lacking systematic evaluation methods and tools. Therefore, in-depth assessment and research on the international communication value of these films have become a focal point for scholars in the relevant field.

The Back Propagation Neural Network (BPNN) algorithm represents a widely-used neural network approach that employs backpropagation for weight adjustment. This mechanism continuously optimizes network parameters to minimize the discrepancy between output and target values[6]. It is applied to extract and analyze relevant features of Chinese mythology-themed animated films, including aspects such as the film's theme, plot, character portrayal, and visual effects. This allows for a thorough understanding of these films'

[1]School of Film, Jilin Animation Institute, Changchun 130013, China. [2]School of Theater, Film and Television, Communication University of China, Beijing 100024, China. [3]Academy of Arts and Design, Tsinghua University, Beijing 100084, China. ✉email: el_zhu@163.com

cultural connotations and artistic value, providing insights into their attractiveness and competitive advantages in international communication[7–9]. Simultaneously, the analysis results from the BPNN algorithm model can be used to adjust film promotion strategies, international market positioning, and other aspects. Thus, the competitiveness and influence of these films in the international market can be enhanced.

Research objectives and main contributions

This work aims to assess the international communication value of Chinese mythology-themed animated films using the BPNN algorithm from artificial intelligence (AI). It provides theoretical support and practical guidance for the dissemination and development of these films within the framework of the "Belt and Road" initiative. The innovation of this work lies in its first attempt to conduct a quantitative analysis of the international communication effects of Chinese mythology-themed animated films in the context of the "Belt and Road" initiative. The specific contributions include:

(1) A BPNN-based evaluation model is proposed and established to quantitatively assess the international communication value of Chinese mythology-themed animated films, providing a scientific framework for the international dissemination of cultural products.
(2) This work reveals the practical role and potential of Chinese mythology-themed animated films in promoting cultural exchange, enhancing international friendship, and improving cultural understanding. It offers new perspectives and insights for the film industry and cultural communication strategies.
(3) The work explores the application of the BPNN algorithm in evaluating the international communication value of cultural products. It enriches the theoretical framework and methodological system in the field of cultural communication and promotes the technological and precise development of cultural communication research.
(4) This work strategically supports the international promotion and marketing of Chinese mythology-themed animated films. Meanwhile, it lays a theoretical foundation for enhancing the competitiveness and influence of Chinese cultural products in the international market.

Literature review

Chinese mythology-themed animated films inherit ancient Chinese mythological stories and folk legends, promoting the essence of Chinese culture and providing robust support for the international dissemination of Chinese culture. Numerous scholars have researched the development of Chinese mythology-themed animated films. Tang and Gong (2021)[10] examined the inheritance relationship between classical Chinese mythology and the production of Chinese animated films. They analyzed the application of classical mythological elements in Chinese animated films, highlighting the historical development and cultural significance of Chinese mythology-themed animated films. Zhao and Zheng (2023)[11] discussed the representation of traditional Chinese mythology in animation art. They explored how animation art portrayed traditional Chinese mythological stories and the impact of these myths on the development of Chinese animated films. Deng (2023)[12] analyzed elements of the ancient Chinese mythological animated film "Shan Hai Jing." They emphasized the influence of Chinese mythological culture on animated film creation and explored the representation of "Shan Hai Jing" in animated films. Shafira and Rui (2023)[13] conducted a semiotic analysis of the representation of Chinese culture in Sony Pictures Animation's film "Wish Dragon." They studied how Chinese culture was portrayed through animated films, highlighting the expression and dissemination of Chinese culture through Chinese mythology-themed animated films. Chen et al. (2024)[14] explored the innovative expression of traditional Chinese cultural prototypes in animated films. They investigated how animated films established reliable, respectable, and respectful images of China, emphasizing the importance of Chinese mythology-themed animated films in shaping the image of Chinese culture.

The Belt and Road Initiative, as a major national strategy proposed by China, aims to promote economic cooperation and cultural exchange among countries along the route. Scholars have explored cultural communication and dissemination under this initiative through various approaches, with Chinese mythology-themed animated films receiving widespread attention as a crucial cultural product. Qian (2022)[15] researched the relationship between the Silk Road and China's Belt and Road Initiative. Their study explored the inheritance and development of Silk Road cultural heritage under this initiative, highlighting the significant role of the initiative in the development of cultural exchange and communication. Sigley (2023)[16] discussed the connection between tea culture and the Belt and Road Initiative. The analysis focused on the role of tea culture in contemporary Chinese cultural policies, emphasizing this initiative's function in the protection and inheritance of traditional cultural routes. Ding (2024)[17] studied the innovative path of precise dissemination of Chinese martial arts under the Belt and Road context. The research focused on the dissemination methods and effects of Chinese martial arts in Belt and Road countries, proposing innovative paths to strengthen the international dissemination of traditional Chinese culture. Sattar et al. (2024)[18] researched whether Chinese education and cultural diplomacy promoted economic growth in Belt and Road countries. They analyzed the economic impact of Chinese education and cultural diplomacy on these countries, highlighting the close relationship between cultural exchange and economic cooperation.

In recent years, the application of AI has been deepening across various fields. For instance, Zhao et al. (2022)[19] proposed an intelligent prediction method for hydrogen pipeline leakage fires based on the Finite Ridgelet Neural Network. Despite the different application scenarios, both studies rely on deep neural networks (DNNs) to handle complex nonlinear problems and improve prediction accuracy. Therefore, their research provided theoretical support for using deep learning (DL) methods in film cultural feature recognition. Zhao et al. (2020)[20] introduced a maintenance risk assessment method for refining units using a fuzzy second-generation wavelet neural network. Their research demonstrated the wide application of neural networks in risk assessment, offering theoretical support and showing that neural networks could recognize cultural features and perform efficient evaluations in other fields. Similarly, Zhao & Song (2021)[21] proposed a fuzzy Shannon wavelet finite element method for analyzing coupled heat transfer in leakage flow gaps of single-screw compressors. The DL framework and the ability to handle complex data in this method share similarities with the application of cultural feature recognition here.

With the continuous advancement and application of AI technology, it can quantitatively analyze and evaluate the dissemination effects of cultural products through methods such as big data analysis and machine learning (ML). For instance, Mantello et al. (2023)[22] studied the attitude of emotional AI in the workplace. The research highlighted the cultural communication effects of AI technology and emphasized the impact of emotional AI on employee attitudes in different cultural backgrounds. Depounti et al. (2023)[23] explored gender stereotypes in cultural products using AI technology, emphasizing the influence of AI technology on the dissemination of cultural products. Tzirakis et al. (2023)[24] employed DL to reveal the content expressed in speech bursts in different cultures. They discussed the application of DL technology in cultural communication and highlighted the dissemination effects of speech signals in diverse cultural environments. Wei et al. (2023)[25] researched the impact of tourist experience at the attribute level on satisfaction through cross-cultural analysis. They used DL technology to analyze the impact of tourist experience on satisfaction, highlighting the application of AI technology in studying the dissemination effects of cultural products. Tasneem et al. (2024)[26] applied machine learning and DL to analyze the application of AI technology in the environmental field, highlighting its diversity and universality in the study of the dissemination effects of cultural products.

However, although Chinese mythology-themed animated films have become a vital medium for cultural communication, there remains a gap in research on evaluating the effectiveness of cultural communication in this field. Existing studies have explored how traditional cultural elements are represented in animated films. However, there is still a lack of research on how to quantitatively analyze the dissemination effects of these cultural elements and evaluate the effectiveness of different types of cultural products. Therefore, this work addresses this gap. By leveraging AI technology, particularly DL methods, this work proposes a new model for identifying the cultural features of Chinese mythology-themed animated films. This study employs machine learning techniques, integrating DNNs including BPNN and BiLSTM, to automate the identification and evaluation of cultural features. This computational approach enables quantitative analysis of Chinese cultural products' communication effectiveness, representing a methodological advancement beyond traditional qualitative assessment methods.

Additionally, existing literature primarily focuses on the artistic expression of cultural communication, with limited exploration of AI technology applications in cultural communication. This work introduces DL methods and, by incorporating the advancements of AI technology, improves the accuracy of cultural feature recognition and enables further analysis of cultural communication effectiveness. In the future, this approach can be extended to the study of the dissemination of various types of cultural products. Within the context of the "Belt and Road" initiative, exploring AI technology can promote the transnational dissemination of more cultural products, thus enhancing the global influence of Chinese culture. Therefore, this work fills the gap in AI technology in the quantitative evaluation of the cultural communication effectiveness of Chinese mythology-themed animated films. Meanwhile, it expands the depth of research on the analysis of cultural products' communication effectiveness, providing a theoretical basis for the future optimization of cultural product dissemination.

Research model

Analysis of the BPNN algorithm and its optimization

Cultural communication involves a large amount of data, including various forms of information such as text, images, and videos. As one of the AI technologies, the BPNN algorithm can handle large-scale data efficiently. It can extract key features from massive data, enabling the identification of important patterns and trends in cultural communication[27,28]. In the context of film feature recognition, the BPNN algorithm can capture implicit relationships among features such as plot, characters, and scenes in a film. This allows for a comprehensive and accurate portrayal of the characteristics and style of the film. The network structure of the BPNN algorithm illustrates the typical three-layer structure when applying the BPNN algorithm to extract features from Chinese mythology-themed films. This structure comprises the input, hidden, and output layers. Neurons between adjacent layers are fully connected, while neurons within the same layer cannot connect. In the BPNN algorithm, there are two processes, including the forward propagation of signals and the backward propagation of errors. During the BPNN algorithm's computation, the first process is the forward propagation of signals. The input to the jth node in the hidden layer is denoted as net_j, as shown in Eq. (1):

$$net_j = \sum_{i=1}^{n} w_{ji} x_i \tag{1}$$

x_i refers to the input of the ith node in the input layer, where $i = 1,2,\ldots,n$; w_{ji} represents the weights between the jth node in the hidden layer and the ith node in the input layer. The output z_j of the jth node in the hidden layer is given by Eq. (2):

$$z_j = f\left(net_j\right) = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{2}$$

The input net_q to the qth node in the output layer is:

$$net_q = \sum_{j=1}^{p} v_{qj} z_j = \sum_{j=1}^{p} v_{qj} f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{3}$$

v_{qj} represents the weight between the qth node in the output layer and the jth node in the hidden layer. $q = 1, 2, \cdots, m$.

The output y_q of the qth node in the output layer reads:

$$y_q = f\left(net_q\right) = f\left(\sum_{j=1}^{p} v_{qj} f\left(\sum_{i=1}^{n} w_{ji} x_i\right)\right) \tag{4}$$

Next is the process of backward propagation of errors. In this stage, when the actual output does not match the expected output, the output error values for each layer's nodes are calculated starting from the output layer. Then, using the gradient descent method and the computed error values, adjustments are made to the weights and thresholds between the network's layers until the actual output values meet the desired expectations. For the quadratic error criterion function for a single sample p, denoted as E_p, it is expressed in Eq. (5):

$$E_p = \frac{1}{2} \sum_{q=1}^{m} \left(T_q - y_q\right)^2 \tag{5}$$

The total error criterion function E for the system over P training samples reads:

$$E = \frac{1}{2P} \sum_{p=1}^{P} \sum_{q=1}^{m} \left(T_q^p - y_q^p\right)^2 \tag{6}$$

T_q^p andy_q^prefer to the expected and actual output of the pth sample. This error calculation method, during the training process of each sample, adjusts the weights each time. However, this correction method does not comprehensively consider whether errors are also decreasing during the training of other samples, inevitably leading to an increase in the number of training iterations. Global error is the reduction of error values overall from all samples. The system's global error for P training samples is:

$$E = \frac{1}{2} \sum_{p=1}^{P} \sum_{q=1}^{m} \left(T_q^p - y_q^p\right)^2 = \sum_{p=1}^{P} E_p \tag{7}$$

The mean square error (MSE) can reduce individual training errors and truly improve the overall training error. It combines the advantages of the two previous algorithms, addressing their shortcomings. It is more suitable to be chosen as the network training error. The system's MSE[29] is defined as:

$$MSE = \frac{1}{P} \sum_{p=1}^{P} \sum_{q=1}^{m} \left(T_q^p - y_q^p\right)^2 \tag{8}$$

Analysis of the construction of a cultural feature recognition model for Chinese mythology-themed animated films based on the fusion of BPNN and bidirectional long short-term memory (BiLSTM) algorithms

To enhance the cultural communication effectiveness of Chinese mythology-themed animated films, this work employs the BPNN algorithm to handle the nonlinear relationships between features. Meanwhile, the BiLSTM algorithm is combined to capture long-term dependencies and semantic information within the text[30]. By integrating BPNN with BiLSTM, a cultural feature recognition model is constructed (as shown in Fig. 1). The rationale for selecting these two algorithms lies in their complementary strengths. BPNN excels at extracting global information from multiple dimensions, while BiLSTM effectively captures the temporal dependencies within textual data. The cultural features in Chinese mythology-themed films, such as the complex relationships between plot, themes, and characters, are well-suited for modeling with BPNN. In contrast, BiLSTM can effectively process the correlations of these cultural elements at different time points through forward and backward learning.

This combination allows the model to handle the film's static features (e.g., title, director, production company) and dynamic features (e.g., plot development and character interaction), thereby improving the accuracy of cultural feature recognition. Moreover, this approach effectively addresses the gradient vanishing issue that traditional neural networks may encounter when processing long sequences, ensuring that the model retains long-term contextual information.

Therefore, BPNN is highly effective in extracting static information related to film culture, while BiLSTM supports understanding dynamic information. When integrated, these two models allow for feature fusion across a broader range, reducing bias from relying on a single algorithm and enhancing the model's generalization

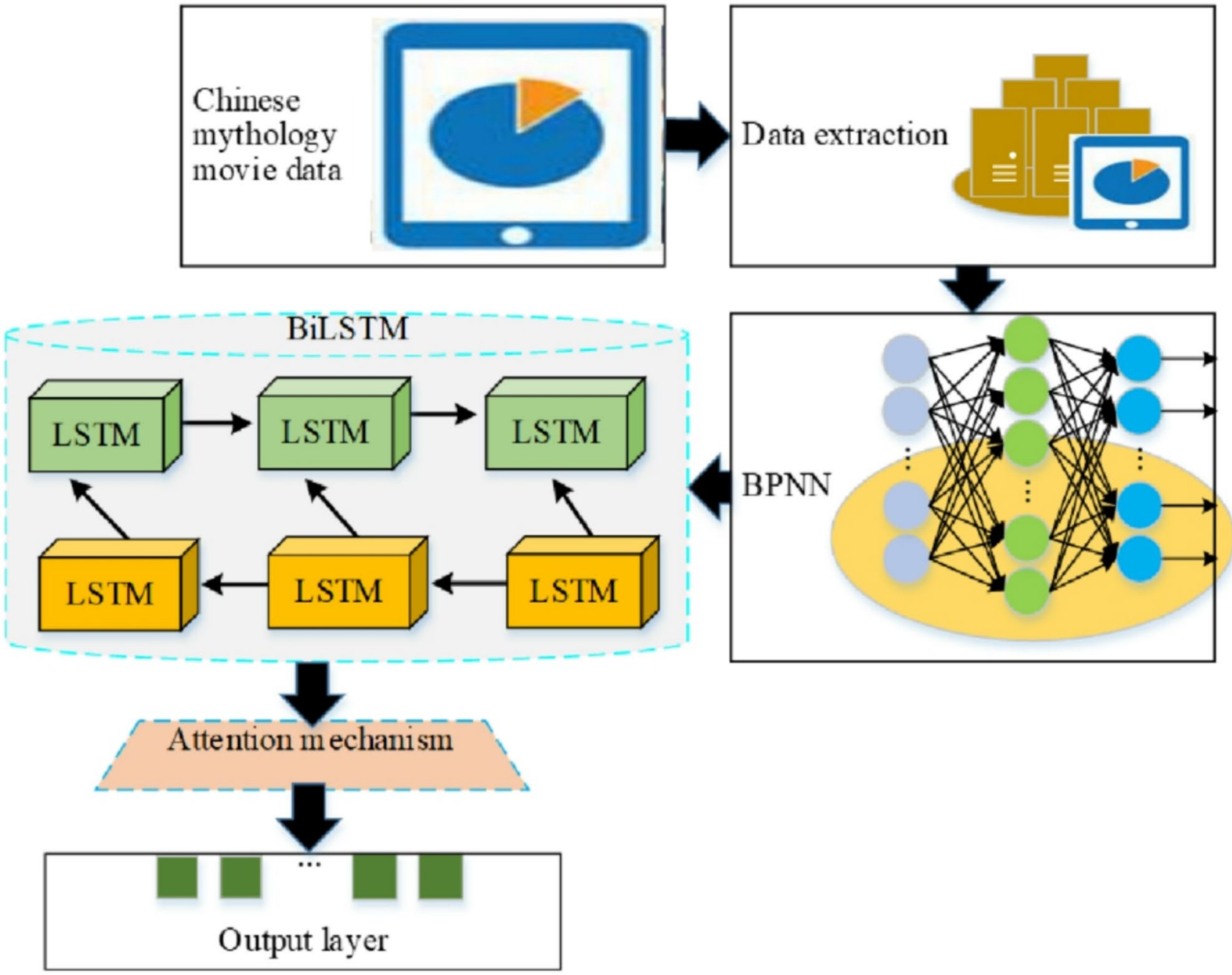

Fig. 1. Schematic diagram of the cultural feature recognition model for Chinese mythology-themed animated films based on the fusion of BPNN and BiLSTM algorithms.

ability. Fusioning BPNN's global information modeling capability with BiLSTM's ability to model temporal relationships significantly improves cultural feature recognition accuracy and reduces model error.

Figure 1 illustrates the model's initial phase of data collection and organization for Chinese mythology-themed animated films. This preparatory stage systematically compiles key film attributes including titles, directors, production companies, plot synopses, thematic elements, character profiles, and associated cultural features. Following data collection, preprocessing steps are applied, involving noise removal, handling missing values, and feature encoding, ensuring data quality and usability. Subsequently, the extracted cultural features are transformed into a numerical representation for computer processing, facilitating subsequent modeling and analysis.

This work designs specific feature selection and extraction methods to accurately identify the cultural features of Chinese mythology-themed animated films, incorporating cross-cultural communication and cultural reception theories. These theories provide a solid theoretical foundation for determining which cultural features are most effective in international communication and how they resonate with audiences from different cultural backgrounds.

Firstly, several cultural features are selected for model training, and Hofstede's Cultural Dimensions Theory is applied to ensure the cross-cultural adaptability of the features. (1) Plot elements: By analyzing the film's storyline, key phrases, and central themes, cultural features reflecting Chinese traditional culture and mythology are extracted. This aligns with the concept of cultural proximity, which suggests that familiar narrative structures enhance audience engagement in cross-cultural contexts. (2) Character traits: The main characters in the film, including mythological figures, heroes, or villains, are analyzed to extract their cultural symbolism and personality traits. These features are crucial in cultural semiotics, where symbolic expressions influence the audience's understanding and acceptance of culture. (3) Visual symbols: DL techniques extract visual features from the film, such as traditional symbols, costumes, and architectural styles, which reflect the uniqueness of Chinese culture. According to Hall's High-Context vs. Low-Context Communication Theory, Chinese culture, as a high-context culture, relies on symbolic visual communication, making these features significant in international communication. (4) Language and dialogue: Text analysis techniques are applied to extract dialogue and narrative language from the film, analyzing its significance in cultural communication. According to Narrative Transportation Theory, culturally rich and compelling dialogue enhances the audience's immersion and facilitates cultural adaptation. 5)Music and sound effects: This includes elements related to traditional Chinese music, such as folk music and traditional instruments, which play a crucial role in emotional resonance and cultural communication.

During the feature selection process, relevant literature is reviewed, and discussions with cultural communication experts help identify which cultural features effectively represent the uniqueness of Chinese mythology-themed animated films. Subsequently, methods such as sentiment analysis and topic modeling are used to extract keywords and emotional tones from the film script, which serve as representatives of the cultural features. Next, visual feature extraction methods are applied, focusing on symbols related to Chinese culture. To reduce redundant information, dimensionality reduction techniques are employed, ensuring that the selected features effectively represent the cultural content. The basis for selecting these cultural features is their strong cultural representativeness, enabling them to fully reflect the cultural connotations of Chinese mythology-themed animated films. Moreover, the feature selection process considers their potential in international communication, prioritizing features that resonate with international audiences. Finally, it is ensured that the selected features can be reliably extracted from existing data sources, with high data quality and wide coverage.

This approach constructs a feature set to comprehensively reflect the cultural connotations of Chinese mythology-themed animated films, providing rich input data for subsequent model training. These features effectively support the cultural feature recognition task and practically support the international dissemination of the films. After data preprocessing, these features are converted into numerical forms and used to train and test a model that integrates the BPNN and BiLSTM algorithms. This process helps to identify the films' core cultural features, further enhancing their dissemination effects in the international market.

During the feature extraction phase, the BPNN algorithm is initially employed to handle the nonlinear relationships and complex mapping between features. A multilayer perceptron (MLP) is constructed as the foundational structure of the BPNN. To optimize the BPNN algorithm, gradient descent is applied to adjust the weights and threshold of the network's output and hidden layers. The correction values for the output and hidden layer weights are denoted as Δv_{qj} and Δw_{ji}, and for their thresholds as $\Delta \alpha_q$ and Δh_j. Typically, each correction value is proportional to the gradient descent of the error and can be expressed as follows:

$$\begin{cases} \Delta v_{qj} = -\eta \frac{\partial E}{\partial v_{qj}} \\ \Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \\ \Delta \alpha_q = -\eta \frac{\partial E}{\partial \alpha_q} \\ \Delta h_j = -\eta \frac{\partial E}{\partial h_j} \end{cases} \tag{9}$$

In Eq. (9), the negative sign indicates gradient descent; *E* represents the computed error; η denotes the learning rate.

Therefore, the adjustment Δv_{qj} of the output layer weights reads:

$$\Delta v_{qj} = -\eta \frac{\partial E}{\partial v_{qj}} = -\eta \frac{\partial E}{\partial net_q} \frac{\partial net_q}{\partial v_{qj}} = -\eta \frac{\partial E}{\partial y_q} \frac{\partial y_q}{\partial net_q} \frac{\partial net_q}{\partial v_{qj}} \tag{10}$$

The adjustment Δw_{ji} of hidden layer weights is:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = -\eta \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial w_{ji}} = -\eta \frac{\partial E}{\partial z_j} \frac{\partial z_j}{\partial net_j} \frac{\partial net_j}{\partial w_{ji}} \tag{11}$$

The adjustment $\Delta \alpha_q$ of the output layer threshold reads:

$$\Delta \alpha_q = -\eta \frac{\partial E}{\partial \alpha_q} = -\eta \frac{\partial E}{\partial net_q} \frac{\partial net_q}{\partial \alpha_q} = -\eta \frac{\partial E}{\partial y_q} \frac{\partial y_q}{\partial net_q} \frac{\partial net_q}{\partial \alpha_q} \tag{12}$$

The hidden layer threshold's adjustment $\Delta h_j$is:

$$\Delta h_j = -\eta \frac{\partial E}{\partial h_j} = -\eta \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial h_j} = -\eta \frac{\partial E}{\partial z_j} \frac{\partial z_j}{\partial net_j} \frac{\partial net_j}{\partial h_j} \tag{13}$$

Also, due to the existence of Equations (14) to (18):

$$\begin{cases} \frac{\partial net_q}{\partial v_{qj}} = z_j \\ \frac{\partial net_j}{\partial w_{ji}} = x_i \\ \frac{\partial net_q}{\partial \alpha_q} = 1 \\ \frac{\partial net_j}{\partial h_j} = 1 \end{cases} \tag{14}$$

$$\frac{\partial E}{\partial y_q} = -\sum_{p=1}^{P}\sum_{q=1}^{m}\left(T_q^p - y_q^p\right) \tag{15}$$

$$\frac{\partial E}{\partial z_j} = -\sum_{p=1}^{P}\sum_{q=1}^{m}\left(T_q^p - y_q^p\right) f'\left(net_q\right) v_{qj} \tag{16}$$

$$\frac{\partial y_q}{\partial net_q} = f'\left(net_q\right) = y_q\left(1 - y_q\right) \tag{17}$$

$$\frac{\partial z_j}{\partial net_j} = f'\left(net_j\right) = z_j\left(1 - z_j\right) \tag{18}$$

The adjustment quantity Δv_{qj} of the output layer weights can be written as Eq. (19):

$$\Delta v_{qj} = \eta\sum_{p=1}^{P}\sum_{q=1}^{m}\left(T_q^p - y_q^p\right) y_q\left(1 - y_q\right) z_j \tag{19}$$

The hidden layer weights' adjustment quantity $\Delta w_{ji}$is:

$$\Delta w_{ji} = \eta\sum_{p=1}^{P}\sum_{q=1}^{m}\left(T_q^p - y_q^p\right) y_q\left(1 - y_q\right) v_{qj} z_j\left(1 - z_j\right) x_i \tag{20}$$

The adjustment quantity $\Delta\alpha_q$ of the output layer threshold is given in Eq. (21):

$$\Delta\alpha_q = \eta\sum_{p=1}^{P}\sum_{q=1}^{m}\left(T_q^p - y_q^p\right) y_q\left(1 - y_q\right) \tag{21}$$

The hidden layer threshold's adjustment quantity Δh_jcan be obtained as given in Eq. (22):

$$\Delta h_j = \eta\sum_{p=1}^{P}\sum_{q=1}^{m}\left(T_q^p - y_q^p\right) y_q\left(1 - y_q\right) v_{qj} z_j\left(1 - z_j\right) \tag{22}$$

Finally, the weights and thresholds for the $N+1$th input sample are as follows:

$$v_{qj}\left(N+1\right) = v_{qj}\left(N\right) + \Delta v_{qj}\left(N\right) \tag{23}$$

$$w_{ji}\left(N+1\right) = w_{ji}\left(N\right) + \Delta w_{ji}\left(N\right) \tag{24}$$

$$\alpha_q\left(N+1\right) = \alpha_q\left(N\right) + \Delta\alpha_q\left(N\right) \tag{25}$$

$$h_j\left(N+1\right) = h_j\left(N\right) + \Delta h_j\left(N\right) \tag{26}$$

Subsequently, the BiLSTM algorithm is employed to capture long-term dependencies and semantic information within text sequences. Additionally, this work utilizes the Rectified Linear Unit (ReLU) function as the activation function. This function sparsifies the model parameters, thereby reducing overfitting. Moreover, it helps decrease the computational load of the model. The definition of the ReLU activation function is given in Eq. (27):

$$f\left(x\right) = \max\left(0, x\right) = \left\{\begin{array}{ll} 0 & x \leqslant 0 \\ x & x > 0 \end{array}\right. \tag{27}$$

Thus, the integrated BPNN-BiLSTM algorithm effectively extracts key cultural features (including plot structures, character depictions, and scene designs) from Chinese mythology-themed animated films. This extracted cultural data facilitates targeted dissemination of Chinese mythological elements along Belt and Road partner countries. Figure 2 represents the pseudocode for this model.

Construction and analysis of the film dissemination value evaluation model

Under the "Belt and Road" initiative, Chinese mythology-themed animated films not only serve as vital tools for cultural export but also showcase cultural soft power. An evaluation model is established to quantify the film's dissemination effect and its cultural value. This model includes several quantitative indicators:

(1) Cultural Spread Effect Index (CSEI): This index quantifies the dissemination effect by analyzing the film's spread range, audience feedback, and word-of-mouth effects.
(2) Audience Cultural Recognition Index (ACRI): This index quantifies cultural recognition by surveying the audience's understanding of the mythological elements in the film.

```
Start
Input: Chinese mythology movie data input
Output: Cultural characteristics recognition results of animated movies
# Define BPNN model
def build_bpnn_model(input_size, hidden_size, output_size):
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(hidden_size, activation='relu', input_shape=(input_size,)),
        tf.keras.layers.Dense(output_size, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
# Define BiLSTM model
def build_bilstm_model(input_size, hidden_size, output_size):
    model = tf.keras.Sequential([
        tf.keras.layers.Embedding(input_dim=input_size, output_dim=hidden_size),
        tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(hidden_size)),
        tf.keras.layers.Dense(output_size, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
# Define model merging function
def merge_models(bpnn_model, bilstm_model, merge_method='concat'):
    input_layer = tf.keras.layers.Input(shape=(input_size,))
    bpnn_output = bpnn_model(input_layer)
    bilstm_output = bilstm_model(input_layer)
    if merge_method == 'concat':
        merged_layer = tf.keras.layers.Concatenate()([bpnn_output, bilstm_output])
    elif merge_method == 'sum':
        merged_layer = tf.keras.layers.Add()([bpnn_output, bilstm_output])
    else:
        raise ValueError("Invalid merge method!")
    merged_model = tf.keras.Model(inputs=input_layer, outputs=merged_layer)
    return merged_model
End
```

Fig. 2. Pseudocode flowchart for the application of the BPNN fused with BiLSTM algorithm in cultural recognition of Chinese mythology-themed animated films.

(3) Cultural Influence Index (CII): This index evaluates the film's role in promoting cultural understanding and exchange, including enhancing cultural soft power.

By combining the outputs of the film's cultural feature recognition model with actual communication data, a comprehensive analysis is conducted to establish a holistic film dissemination value assessment framework. The outputs include the accuracy of cultural element recognition and feature tags, while the actual communication data is derived from audience surveys and market feedback. Figure 3 shows the specific framework of the evaluation model.

In Fig. 3, the cultural features of Chinese mythology-themed animated films are first identified using the BPNN and BiLSTM algorithms, which yield corresponding cultural element recognition results. These cultural elements include mythological characters, storylines, and more. Subsequently, the model evaluates the dissemination effect. It considers factors such as the dissemination range (like audience demographics, and media coverage) and audience feedback (like social media discussions and survey results), thereby quantifying the film's international dissemination effect. Next, the model assesses cultural recognition by calculating the Cultural Recognition Index (CRI) through surveys and audience feedback analysis. This index measures the awareness and acceptance of cultural elements in the film. Moreover, cultural influence is evaluated by analyzing data from social media trends, online discussions, and other sources to compute the Cultural Impact Index (CII) and Soft Power Index (SPI). This intends to assess the film's influence on Chinese culture during its international dissemination. Finally, all these evaluation results are combined using a weighted average method to derive the film's final dissemination value score. These results are then presented visually to facilitate analysis and comparison of different films' dissemination effects. This model provides a quantitative and systematic framework for evaluating the international communication value of Chinese mythology-themed animated films, showcasing their cultural communication potential and actual impact through multi-dimensional assessments. This evaluation model is characterized by its multi-dimensional, quantitative approach, which integrates real dissemination data and cultural feature recognition results for a comprehensive assessment. It offers significant practical value, providing a more precise and systematic method of evaluating dissemination effects compared to traditional film evaluation methods.

Adaptive mechanism of the model

Cultural features are not static in the context of the "Belt and Road" cultural dissemination. Rather, they dynamically evolve with the development of the times, the deepening of international exchanges, and the changing aesthetic trends of audiences. Therefore, when evaluating the international communication value of Chinese mythology-themed animation, the model must possess strong adaptability to ensure that its ability to recognize cultural features does not decline over time. To address this need, this work designs a dynamic adaptation mechanism based on the BPNN-BiLSTM fusion model. This ensures that the model can timely capture changes in cultural features and make effective adjustments, thus enhancing its stability and generalization ability in a dynamic cultural environment.

The study implements a periodic data update mechanism to enable real-time monitoring of cultural feature evolution. This system continuously collects the latest data on Chinese mythology-themed animations from multiple sources including social media platforms, international film review websites, cultural exchange forums, and multilingual news reports. Meanwhile, the study employs statistical methods including Kullback-Leibler (KL) divergence and Mahalanobis distance to evaluate cultural feature differences. These indicators quantitatively measure the distribution shift between new and existing datasets, enabling systematic comparison of cultural feature variations. When changes in the cultural feature distribution exceed a predefined threshold, it indicates that the current model may no longer accurately capture the latest cultural elements, prompting a

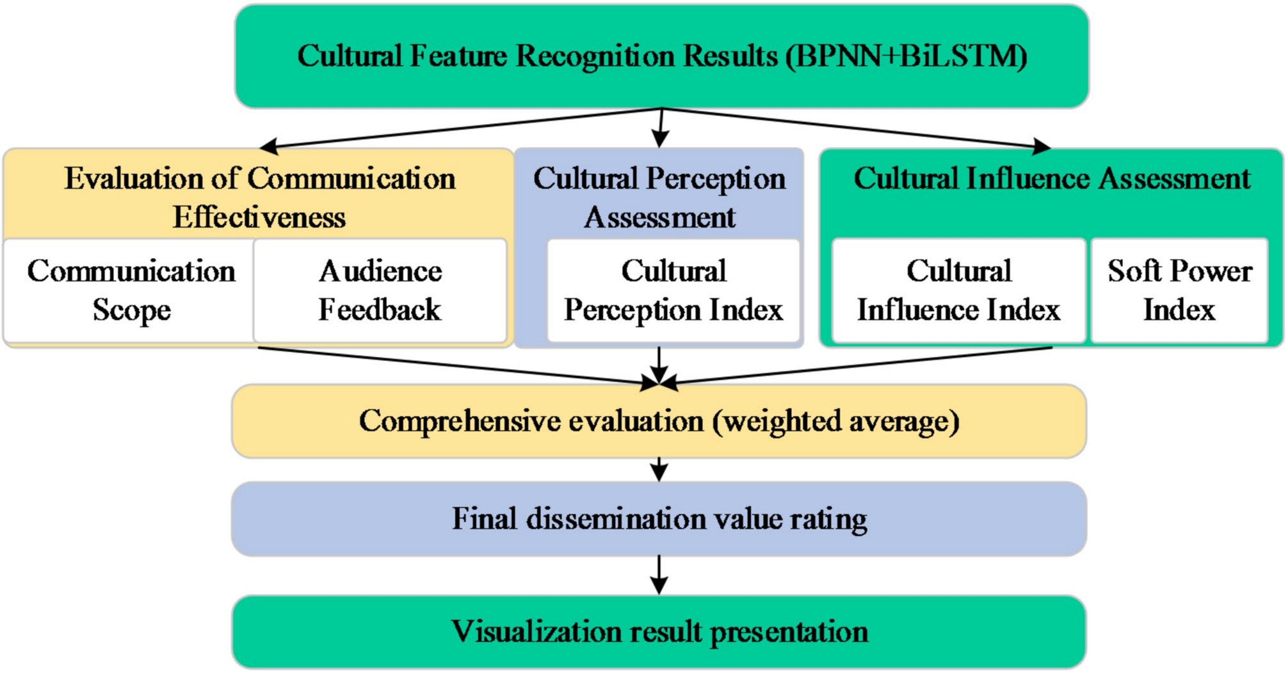

Fig. 3. Film dissemination value evaluation model.

model update. The update mechanism includes incremental training and full model retraining. Incremental training is suitable for cases where the data distribution changes slightly, applying localized updates to the model to reduce computational costs and preserve the effectiveness of existing knowledge. In contrast, when cultural feature changes are substantial, a complete model retraining is required to ensure the model adapts fully to the new cultural environment.

During model updating, the study employs a knowledge distillation method to avoid the catastrophic forgetting problem that may arise from incremental training. This method allows the newly trained student model to learn from the existing teacher model's knowledge, ensuring that the model retains its ability to recognize past cultural features while adapting to new ones. Additionally, the study incorporates a transfer learning strategy by freezing the lower semantic feature layers of the BiLSTM component during model fine-tuning. Only the higher-level fully connected layers and BPNN components undergo training in this adaptation process. This reduces computational overhead and accelerates model convergence, ensuring effective integration of new and old cultural features.

To validate the accuracy of the updated model, this work employs K-fold cross-validation (K = 5) to assess the model's adaptability to new data. Comparative experiments evaluate performance differences between updated and original models using the same test set. These analyses examine cultural feature recognition accuracy, loss values, and F1 scores as key performance indicators. This ensures that the updated model remarkably improves cultural feature recognition capabilities. Furthermore, a long-term stability testing method is used to track the model's performance across different cultural contexts, ensuring its continued adaptability to changes in cultural features within the international communication environment.

The BPNN-BiLSTM model utilizes this dynamic adaptation mechanism to automatically adjust to evolving cultural feature trends. This self-adjusting capability markedly improves the model's long-term stability and practicality for assessing the international communication value of Chinese mythology-themed animations. Compared to traditional static evaluation methods, the proposed mechanism strengthens the model's ability to adapt to dynamic cultural environments. It also provides technical support for intelligent cultural dissemination research within the context of the "Belt and Road" initiative. In the future, this mechanism could be further extended to areas such as multimodal cultural dissemination analysis and cross-cultural communication adaptability research. Such applications offer broader application possibilities for the precise identification and dynamic optimization of intelligent cultural communication.

Experimental design and performance evaluation

Datasets collection

The research data are obtained using web scraping techniques to gather relevant information on Chinese mythology-themed animated films. By developing a web crawler program tailored for film-related websites, this work acquires information such as film title, director, production company, plot synopsis, themes, characters, and associated cultural feature data. In addition, several preprocessing measures are implemented during the data collection process to ensure the data quality and reliability and minimize biases and incompleteness.

Diversity and comprehensiveness of data sources

To avoid sample bias, data are collected from multiple websites and platforms during the web scraping process. This ensures that the gathered information covers various film release channels and audience groups. For example, data are collected from mainstream domestic film databases (such as Douban and Mtime). Also, the data come from overseas film websites (like IMDb, and Rotten Tomatoes) and international media platforms (such as Metacritic). Additionally, the web scraping program supports the extraction of multilingual versions of pages. It covers audience feedback from different cultural backgrounds while providing a more comprehensive view of the film's dissemination and influence globally.

Preprocessing measures: noise removal and imputation

After data collection, the data preprocessing steps are crucial to ensuring data quality. First, noise removal measures are implemented to enhance the dataset's cleanliness and reliability. Specifically, irrelevant data such as advertisements, duplicate links, and unrelated content are removed to prevent these noises from interfering with model training. Two main imputation strategies are employed for the issue of missing values. (1) Existing relevant information within the dataset is utilized to fill in the missing data. For example, if a detailed description of a cultural symbol is missing, the missing data is inferred from other related information about that symbol; (2) Missing data is supplemented through trusted external data sources (such as official reports, news reports, etc.). This approach ensures the integrity and accuracy of the data. For fields that cannot be filled by these methods, appropriate missing data markers (e.g., "NA" or "None") are used to maintain transparency and accuracy in the data processing. In addition to these basic missing value imputation methods, the study investigates data augmentation techniques and random sampling methods to enhance dataset diversity. These approaches prove particularly valuable when processing diverse cultural features, ensuring the model maintains robust adaptability across varying cultural contexts.

Sample balancing and data diversity

To avoid model bias caused by data imbalance, special attention is paid to the issues of sample balance and data diversity. In constructing the dataset for Chinese mythology-themed animation films, the distribution of different cultural feature types within the dataset is ensured to be balanced. For example, the representation of cultural symbols such as mythological characters, storylines, and cultural backgrounds is adequately reflected in the dataset. Data augmentation techniques and random sampling methods address insufficient sample sizes in specific cultural feature categories. This balancing approach prevents model bias by ensuring no single category becomes overrepresented at the expense of others. By increasing the sample size of these underrepresented categories, the model can more comprehensively learn the characteristics of various cultural symbols without showing a preference for any specific category.

The core principle of data augmentation techniques is to generate new samples by transforming and expanding the original samples, thereby increasing data diversity and enhancing the model's generalization ability. This work employs different data augmentation methods for text and image data. (1) Data augmentation: Techniques such as synonym replacement, structural variation, and sentence restructuring generate diverse text in different contexts. This approach enhances the model's understanding of cultural features, particularly in cross-cultural communication, and improves the model's adaptability to different forms of expression. (2) Data augmentation: For visual data, image transformation techniques such as rotation, scaling, cropping, and translation are used to generate new image samples, increasing the diversity of image data. This improves the model's robustness in handling various visual symbols (such as mythological characters and scenes).

The fundamental principle of random sampling involves proportionally selecting samples from imbalanced datasets based on category distributions. This approach increases the representation of minority categories while establishing more balanced sample distributions across all categories. In the implementation process, weighted random sampling is employed based on the sample size of each category. More data is extracted from categories with fewer samples to ensure a balanced sample size across categories. The implementation steps are as follows:

Step 1: The sample size of each category is calculated;

Step 2: The sampling ratio is set based on the sample size of each category;

Step 3: The dataset is subjected to weighted random sampling to ensure a balanced distribution of minority category samples.

Dataset splitting

After preprocessing, the collected text and image data are divided into a training set and a test set in an 8:2 ratio. The training set is used for model training and optimization, while the test set evaluates model performance. The data distribution in both sets is ensured to be consistent to avoid data leakage and overfitting.

Ensuring representativeness and global perspective

Given that this work focuses on the global dissemination effects of the films, it is essential to ensure that the dataset represents global audience interests and feedback. Information is collected from film platforms across different countries and languages, making the dataset internationally diverse and robust. This approach improves the model's applicability and robustness across different cultural contexts. In particular, under the "Belt and Road" framework, the dataset can accurately reflect the current status of the international dissemination of Chinese mythology-themed animated films and their cultural impact.

Experimental environment

To validate the constructed algorithm, the experimental hardware environment includes an Intel(R) Core(TM) i7-7700 Center Processing Unit, and a GTX 1080 Graphic Processing Unit (GPU). The operating system is Windows 10 Professional Edition, the programming language is Python 3.7, and the DL framework is TensorFlow GPU. The open-source toolkit Movie-net.

Parameters setting

When constructing a cultural feature recognition model based on the fusion of BPNN and BiLSTM algorithms, the choice of hyperparameters plays a crucial role in the model's performance. The subsequent analysis elaborates on the rationale for selecting each critical hyperparameter in the model architecture. It further examines how experimental tuning of these parameters optimizes training outcomes and testing performance indicators.

The input layer dimension is set to $n = 16$, meaning that each input sample contains 16 features. This dimension is chosen based on the film's cultural features (e.g., title, theme, characters, and plot). Each cultural feature is quantified and converted into a numerical representation, and selecting 16 features allows for a comprehensive capture of the key information in the film. The output layer dimension is set to $\mathrm{m} = 32$, which is based on the diversity of the cultural features and the model's ability to recognize different categories or labels. The 32 output dimensions effectively represent the cultural information of the film, supporting subsequent classification and recognition tasks.

The batch size is 100, which is determined through comparative testing of different batch sizes during the experimentation process. Smaller batch sizes help improve training stability, prevent gradient vanishing, and enhance the model's sensitivity to input data. After testing, a batch size of 100 can provide an ideal balance between training time and accuracy. The model is trained for 80 iterations. Based on observations during the training process, 80 iterations are found to ensure convergence of the BPNN model on the training set while avoiding overfitting due to excessive iterations. After each iteration, the model's performance is evaluated on the validation set. Training is stopped when the model's performance stabilizes.

The Adam optimizer (Adaptive Moment Estimation) is chosen to optimize the loss function and improve training efficiency. Adam combines momentum and adaptive learning rate techniques, allowing it to adjust the learning rate based on the historical gradients of each parameter. This avoids the instability learning rate issues associated with standard gradient descent. Here, the Adam optimizer demonstrates good training convergence speed and stability. The initial learning rate is 0.001, indicating that a smaller learning rate at the beginning of training helps avoid large fluctuations in the loss function. The learning rate adjustment is conducted through experiments and cross-validation, and it is adapted during training based on the model's feedback to ensure stable convergence.

Dropout technology is used in the network's hidden layers to prevent the model from overfitting. Dropout is a regularization technique that reduces model complexity by randomly dropping a portion of neurons during each training iteration, preventing the model from relying too heavily on the output of certain neurons. Here, the dropout probability is set to 0.3, effectively reducing overfitting while maintaining the model's generalization ability. The BPNN network has a total of 286 weights and 19 thresholds. Through learning from the training data, the weights and thresholds in the network are continuously adjusted to optimize the model's performance on the input data. These weights and thresholds are updated during each iteration through the BPNN algorithm to minimize the loss function.

During the training of the BPNN model, cross-validation and Grid Search methods are used to find the most appropriate hyperparameter combination. Cross-validation effectively evaluates the model's generalization ability under different hyperparameter configurations, helping to select the optimal configuration. Additionally, Grid Search helps identify the best parameters by searching through a set of predefined hyperparameter combinations, improving the model's accuracy and stability. Cross-validation tests the impact of different learning rates (such as 0.001, 0.005, and 0.01) on model performance. The results show that when the learning rate is set to 0.001, the model exhibits an ideal convergence speed and performance on the training and validation sets, so this value is selected. Testing different batch sizes (such as 50, 100, and 200) reveals that a batch size of 100 yields the best training effect, effectively speeding up the training process while ensuring model stability. The impact of different Dropout values (such as 0.2, 0.3, and 0.5) is also tested, implying that a Dropout value of 0.3 effectively alleviates overfitting while maintaining a fast training speed. All hyperparameter adjustments are validated through cross-validation. During each validation step, the model's training and testing accuracy are recorded to help assess its generalization ability. This approach ensures that the BPNN model performs consistently on the training and testing sets, avoiding overfitting or underfitting.

After hyperparameter optimization, an optimally tuned BPNN model is obtained, effectively identifying and classifying the cultural features in Chinese mythology-themed animated films. With a low loss value and high accuracy, the optimized model shows significant improvement in performance on the testing set, proving its practical application potential in cultural communication.

Performance evaluation

To evaluate the performance of the model constructed, a comparison is made with BPNN, ResNet[31], BiLSTM[32], and Tzirakis et al. (2023) in recognition of effectiveness for loss and accuracy. Additionally, various models are assessed based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) indicators.

The model algorithm, along with BPNN, ResNet, BiLSTM, and Tzirakis et al. (2023), is analyzed from the perspective of loss values. Figure 4 presents the results.

Figure 4 demonstrates the superiority of the proposed cultural feature recognition model based on the fusion of BPNN and BiLSTM algorithms in loss value. First, it can be observed that the model exhibits significant convergence during the training process, with the loss value reaching a relatively stable state after approximately 30 iterations, stabilizing at around 0.60. This is much lower than the final loss values of other models. In contrast, the traditional BPNN and ResNet models maintain relatively high loss values, exceeding 0.84, indicating that they struggle with complex cultural feature recognition tasks. While the BiLSTM model shows some improvement during iterations, its final loss value remains around 0.85, failing to achieve the optimization results of the model

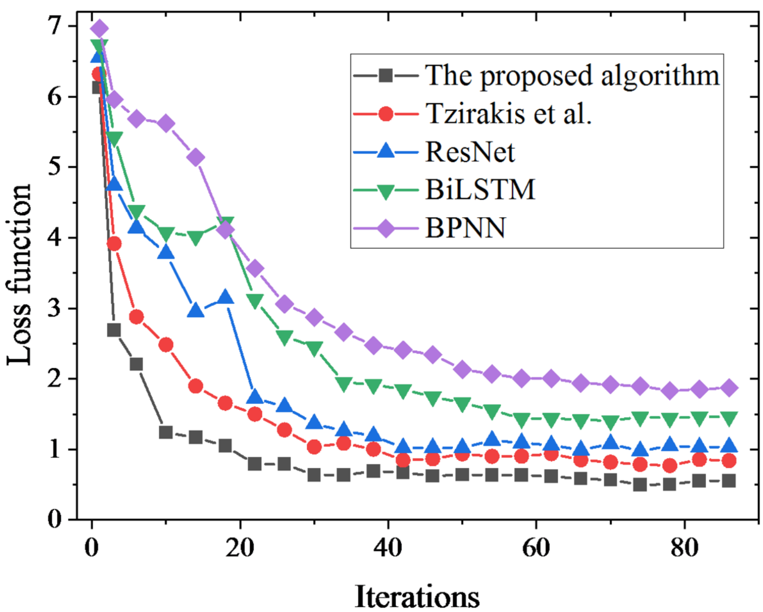

Fig. 4. Loss value result.

proposed. The model by Tzirakis et al. (2023), which addresses a similar task, shows a loss value performance similar to that of BiLSTM, highlighting the limitations of this algorithm.

The significance of this result lies in the fact that a lower loss value indicates higher precision and lower error rates in the cultural feature recognition process. This suggests that the proposed BPNN-BiLSTM model is more effective at capturing and processing cultural features in Chinese mythology-themed animated films. Meanwhile, this model demonstrates superior learning ability when dealing with complex nonlinear relationships and long-term dependencies. Additionally, the speed of loss convergence is also a pivotal performance indicator. In Fig. 4, the model proposed quickly reduces the loss value in the early iterations and maintains stability in the later stages. This indicates that the proposed model can achieve high recognition accuracy while having an advantage in training efficiency.

The accuracy results of the model proposed and other algorithms on the training and testing sets are further analyzed. The analysis results are depicted in Figs. 5 and 6.

In Fig. 5, as the number of training iterations increases, the accuracy of all models generally shows a gradual upward trend, eventually stabilizing. Specifically, the proposed cultural feature recognition model based on the fusion of BPNN and BiLSTM algorithms achieves an accuracy of 93.97% on the training set, outperforming all other comparison models. The BPNN model exhibits a slower accuracy growth, stabilizing in the later stages of training, but its final accuracy is much lower than that of the proposed model. The ResNet and BiLSTM model shows a rapid accuracy increase in the early stages, but ultimately fail to reach the accuracy of the proposed model, settling around 90%. The algorithm proposed by Tzirakis et al. (2023), although showing similar performance in certain iteration epochs, does not surpass the proposed model overall. These observations suggest that the proposed model can achieve high accuracy within a shorter training period, reflecting its stronger learning ability and superior feature extraction capabilities.

Figure 6 shows that similar to the training set performance, the accuracy of all algorithms on the test set gradually increases with the number of iterations and eventually stabilizes. On the test set, the BPNN-BiLSTM fusion model attains an accuracy of 94.39%, at least 4.72% higher than the other algorithms. This result demonstrates the model's generalization ability on external data, indicating that it can efficiently fit the training data and accurately recognize unseen test samples. The proposed model exceeds all other models on the test set, especially in terms of performance after accuracy stabilizes. The model proposed by Tzirakis et al. (2023) is relatively close to the proposed model in the early stages. However, its final accuracy stabilizes around 89%, significantly lower than the 94.39% accuracy of the proposed model. The BPNN, ResNet, and BiLSTM models show relatively weak performance on the test set, failing to exceed 90% accuracy, reflecting their limitations in complex cultural feature recognition tasks.

The results reveal that the proposed model's accuracy outperforms all other comparison models on the training and test sets. This indicates that it possesses strong training capabilities and effectively improves the accuracy of recognizing unseen data. Compared to other algorithms, the proposed model maintains a high level of accuracy after stabilization, demonstrating strong stability and good generalization ability. In comparison to the BPNN, ResNet, BiLSTM, and Tzirakis et al. (2023) models, the proposed BPNN-BiLSTM fusion algorithm exhibits remarkable advantages in cultural feature recognition tasks, particularly in terms of high precision, stability, and generalization performance.

To evaluate the proposed model's recognition error performance, the model algorithm is assessed against BPNN, ResNet, BiLSTM, and Tzirakis et al. (2023) based on MAE, RMSE, and MAPE indicators, as depicted in Figs. 7, 8 and 9.

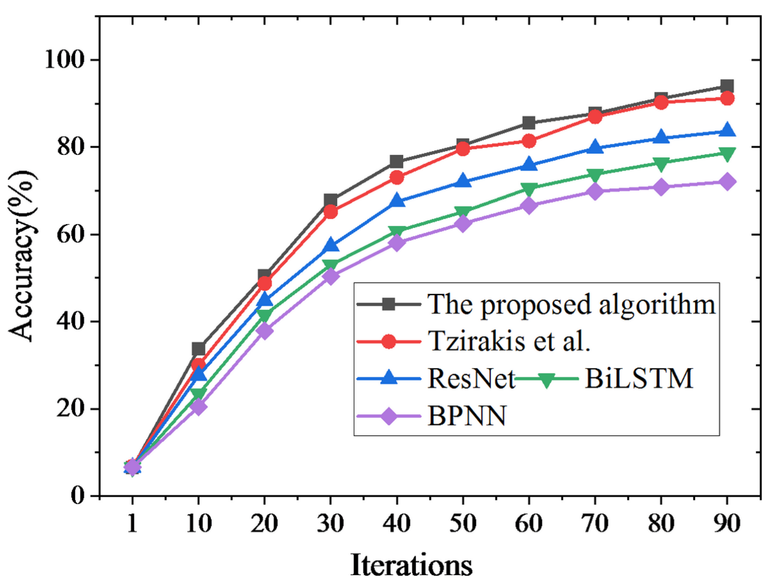

Fig. 5. Changes in recognition accuracy of various algorithms in the training set with increasing iterations.

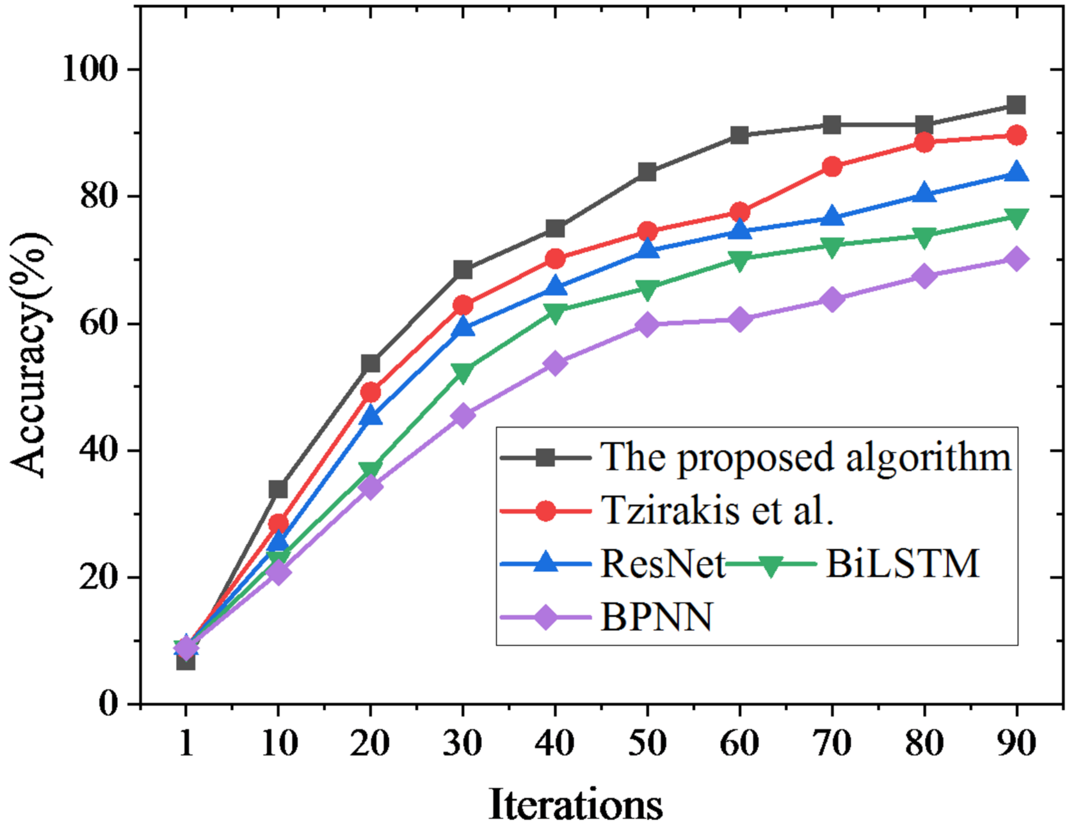

Fig. 6. Changes in recognition accuracy of various algorithms in the testing set with increasing iterations.

Figure 7 demonstrates that the proposed BPNN-BiLSTM model shows significantly lower RMSE values than other comparative algorithms. Specifically, the final RMSE of the proposed model is 4.62, which outperforms other models. Notably, compared to the BPNN and ResNet models, the proposed model exhibits smaller errors, indicating that it provides more accurate predictions in handling cultural feature recognition tasks. This result further validates the advantages of the BPNN and BiLSTM fusion algorithm in processing complex data and capturing cultural features. They can effectively reduce the model's prediction error and enhance the model's overall accuracy and stability.

Figure 8 suggests that the proposed model maintains significantly lower MAE values throughout the training process compared to other algorithms. Particularly in the later stages of iteration, the proposed model's MAE value steadily remains around 5.23, much lower than that of the BPNN, ResNet, and BiLSTM algorithms. This indicates that the proposed model maintains high prediction accuracy in cultural features while effectively controlling errors when handling complex cultural information. It avoids common issues such as overfitting or error accumulation in traditional algorithms.

Figure 9 illustrates the changes in the MAPE with different algorithms during the training process. MAPE measures the relative size of prediction errors and is a vital indicator for evaluating the model's relative error; the smaller the value is, the smaller the deviation between predicted results and actual values is. In Fig. 9, the proposed model achieves a MAPE value of 7.40, which is noticeably lower than that of other comparison models, especially the BPNN and ResNet algorithms, whose MAPE values exceed 10. This result confirms the precision and reliability of the proposed model in cultural feature recognition. Particularly in the context of the "Belt and Road" initiative, it can accurately assess the international communication value of Chinese mythology-themed animated films, ensuring the effective transmission and expression of cultural information.

Thus, the proposed BPNN-BiLSTM model excels across all three evaluation indicators—RMSE, MAE, and MAPE—demonstrating significantly lower error values than other comparative models. This indicates that the model is highly effective in reducing errors and providing more precise predictions in cultural feature recognition tasks. The low error values suggest that the proposed model is better at capturing cultural features in Chinese mythology-themed animated films and accurately identifying them. This has significant practical implications for enhancing the influence of Chinese culture in international communication, particularly within the framework of the "Belt and Road" initiative.

To validate the impact of data optimization methods (data augmentation and random sampling) on model accuracy and generalization ability, a series of tests are conducted under different experimental setups. The experiments evaluate the effect of each optimization method on model training performance by comparing the results of the original dataset with those of the dataset after applying the optimization strategies. The results are exhibited in Table 1:

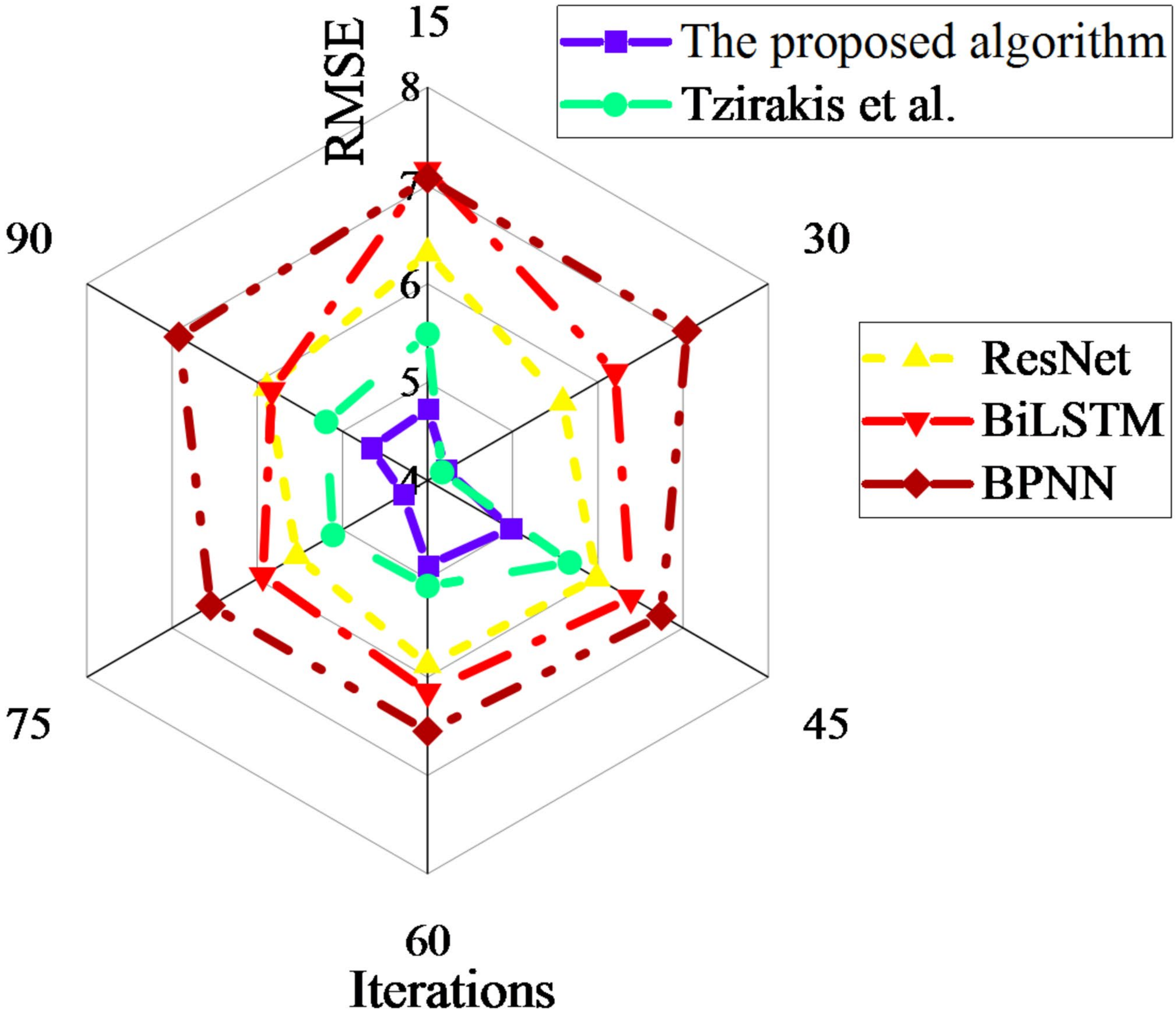

Fig. 7. Changes in RMSE for various algorithms with increasing iterations.

In Table 1, when no data optimization is applied and the model is trained on the original dataset, the model's accuracy is 88.12%, with a loss value of 0.72. This result reflects some imbalance in the dataset, with certain cultural symbol categories (such as mythological characters and complex cultural backgrounds) being underrepresented, leading to lower recognition accuracy for these categories. By applying data augmentation to both the text and image data, the diversity of the dataset is effectively increased, particularly in the recognition of text descriptions and visual symbols. The augmented dataset incorporates diverse cultural feature samples, enabling the model to learn more cultural information from different perspectives, thus improving the accuracy of cultural symbol recognition. As a result, the model's accuracy increases to 93.62%, and the loss value decreases to 0.65. This demonstrates that data augmentation significantly enhances the model's accuracy in recognizing cultural symbols, especially for complex and diverse cultural symbols (such as mythological character images and traditional cultural scenes).

To further increase the sample size of minority categories and improve the model's adaptability to these categories, a weighted random sampling technique is applied during training. The study employs data augmentation techniques to expand minority category samples, including rare mythological characters and cultural backgrounds. This balancing process mitigates model bias that would otherwise result from underrepresented categories. With the random sampling optimization, the model's accuracy increases to 91.54%, with a loss value of 0.70. The accuracy improvement, though observable, remains relatively modest compared to data augmentation results. This suggests random sampling effectively mitigates data imbalance while demonstrating a somewhat limited impact on complex symbol recognition tasks.

Finally, a comprehensive optimized dataset is constructed by combining data augmentation and random sampling. The combined application of both methods simultaneously improves sample diversity and maintains balanced representation across cultural feature categories. This dual approach enables more comprehensive

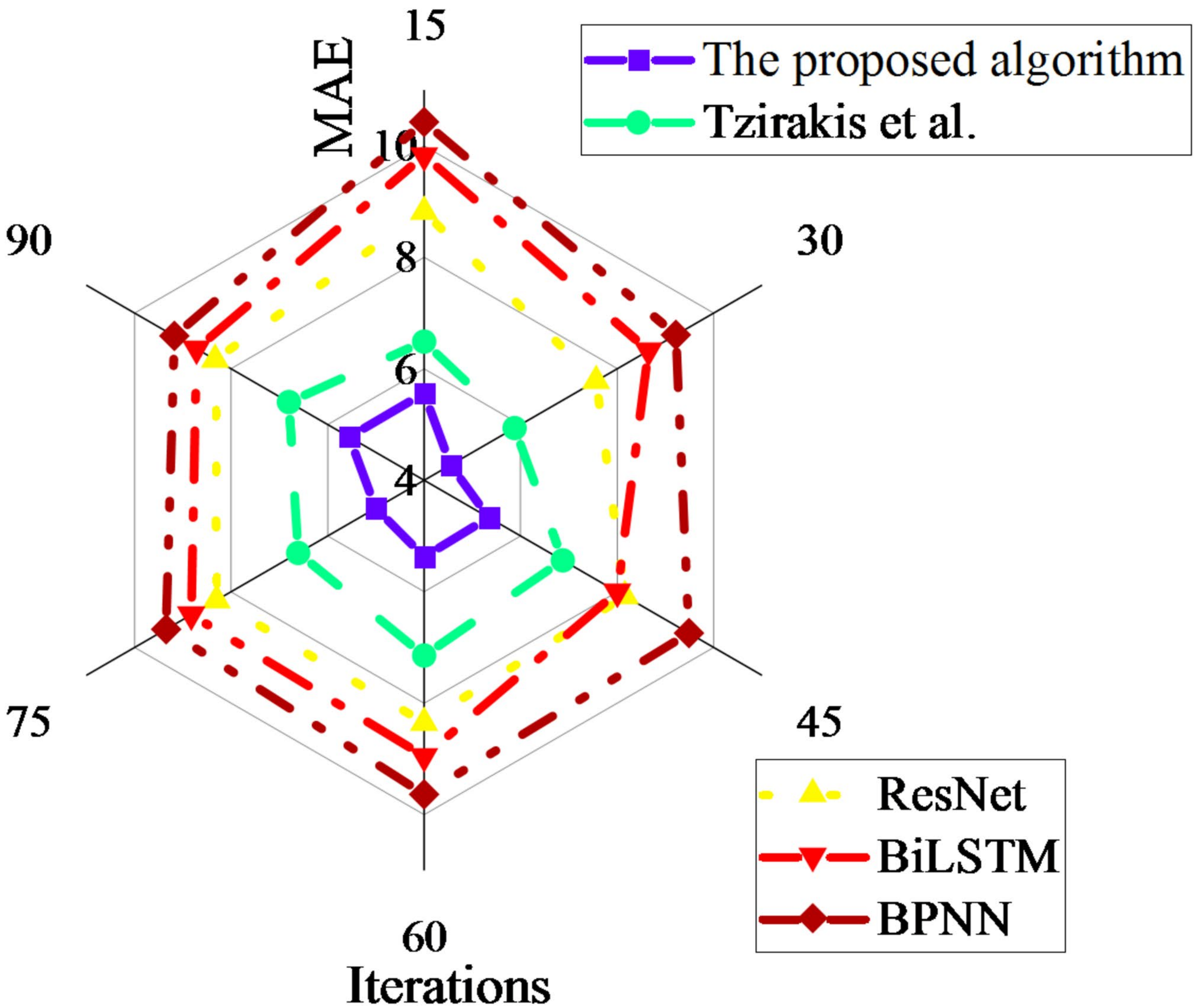

Fig. 8. Changes in MAE for various algorithms with increasing iterations.

learning of category-specific characteristics, with particular effectiveness in processing nuanced cultural symbols. After optimization, the model's accuracy increases to 94.39%, with a loss value of 0.60. This result indicates that integrating data augmentation and random sampling enhances the model's accuracy. Also, the model significantly improves adaptability and stability in recognizing various cultural symbols in cross-cultural communication. The model demonstrates more precise performance, especially when handling challenging cultural backgrounds and complex mythological symbols.

Discussion

This study conducts a comparative evaluation of cultural feature recognition models for Chinese mythology-themed animated films. The proposed BPNN-BiLSTM fusion model is benchmarked against baseline models including standalone BPNN, ResNet, BiLSTM, and Tzirakis et al.'s (2023) approach. The findings reveal a significant advantage in loss values, accuracy, and recognition error performance. Specifically, the proposed model achieves the lowest loss values, attains an outstanding accuracy of 94.39% on the testing set, and exhibits lower RMSE, MAE, and MAPE values in terms of recognition errors. Therefore, the proposed model based on the BPNN fused with the BiLSTM algorithm demonstrates superior performance and accuracy. This consistency with the viewpoints of Kaimaris (2024)[33] and Bai et al. (2024)[34] provides robust support and guidance for further research and applications in this field.

The proposed model's advantages reflect its algorithmic performance and practical application in cultural communication.

(1) First, Chinese mythology-themed animated films, as a critical part of Chinese culture, showcase the charm and uniqueness of traditional Chinese culture through expressive storytelling and visual effects. Compared to traditional methods of cultural transmission, the model presented can more accurately capture and con-

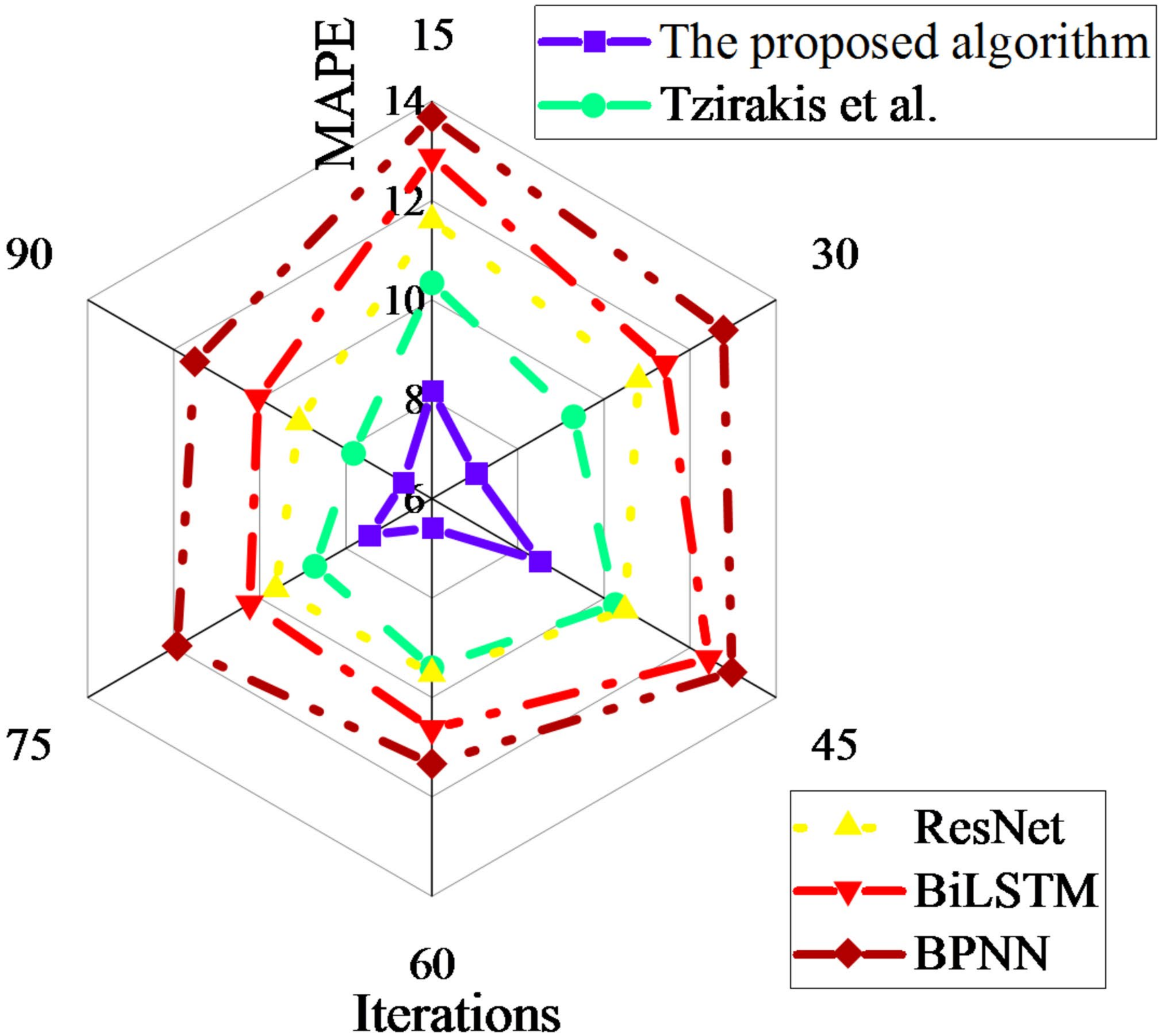

Fig. 9. Changes in MAPE for various algorithms with increasing iterations.

Method	Accuracy (%)	Model loss	Description
Raw dataset	88.12	0.72	No optimization has been made, the data is unbalanced, and a few samples are insufficient
Data augmentation (text + image)	93.62	0.65	Sample diversity is enhanced by using synonym replacement, image rotation, and other enhancement methods.
Random sampling (Weighted)	91.54	0.70	Weighted random sampling technology are used to optimize sample distribution and reduce deviation.
Data augmentation + random sampling (Comprehensive optimization)	94.39	0.60	Data augmentation and random sampling are combined to comprehensively optimize sample balance and diversity.

Table 1. Comparison of data optimization effect.

vey the cultural connotations within the films. This ensures the precise transmission of these cultural features in international markets. This offers filmmakers a powerful technological tool to enhance their films' cultural expression and align them with international audiences' aesthetic and cognitive preferences. Such optimization significantly improves cross-cultural communication effectiveness through more culturally resonant cinematic works.

(2) As cultural products, Chinese mythology-themed animated films assist in spreading traditional Chinese culture and possess strong cross-cultural communication potential. These films, through distinct cultural symbols and unique storylines, establish connections with audiences from various cultural backgrounds,

stimulating their interest in and identification with Chinese culture. The cultural feature recognition model proposed enables a more precise identification of these cultural elements, ensuring their effective expression in the international dissemination of the films. This model enhances the recognition of Chinese mythology-themed animated films in international markets while enriching their cultural content, making them more globally appealing.

(3) By accurately identifying and expressing the characteristics of traditional Chinese culture, this work contributes to enhancing the influence of Chinese culture on the global stage, further promoting cultural diversity and mutual understanding between cultures worldwide. Particularly under the framework of the "Belt and Road" initiative, the dissemination of cultural products plays a vital role in fostering cultural cooperation and exchange between countries. Through the cultural feature recognition model, Chinese film production companies can more effectively convey the cultural essence of Chinese mythology-themed films to overseas audiences. It can increase the market competitiveness of cultural products and promote cultural exchange and cooperation between the countries along the Belt and Road.

(4) This work provides an innovative technical approach and practical pathway for the international dissemination of Chinese mythology-themed animated films, showcasing the enormous potential of AI technology in cultural transmission. Through this model, this work offers a technological means of cultural feature recognition for filmmakers. It also lays a theoretical foundation for future cultural communication research.

Conclusion

Research contribution

This work successfully introduces the BPNN technology from DL. Meanwhile, it proposes a cultural feature recognition model for Chinese mythology-themed animated films based on the BPNN fused with the BiLSTM algorithm. Through experimental analysis, it is found that the model achieves a recognition accuracy of over 94% and exhibits lower RMSE, MAE, and MAPE values in terms of recognition errors. This provides theoretical support and practical guidance for developing Chinese mythology-themed animated films in the context of international dissemination along the 'Belt and Road' initiative. Additionally, the model proposed for experimental analysis holds significant importance in advancing the international dissemination of Chinese mythology, especially in the context of the "Belt and Road" initiative. By accurately identifying and expressing the cultural features within films, this work provides both theoretical support and practical guidance for promoting the global distribution of Chinese mythology-themed animated films. This model helps enhance the international influence of cultural products. Also, it strengthens foreign audiences' understanding and recognition of traditional Chinese culture, further facilitating cultural exchange and cooperation.

Future works and research limitations

However, this work still presents several limitations. First, the employed dataset may contain sample bias or incompleteness, potentially affecting the model's generalization ability. Furthermore, the study scope is confined to Chinese mythology-themed animated films, requiring additional research to extend its applicability to other animation genres or cultural products. To address these limitations, future research could pursue multiple directions for expansion.

First, dataset diversification through the inclusion of varied cultural films would enhance the model's generalization ability and adaptability. Concurrently, dataset expansion would improve the model's accuracy when processing films with diverse cultural backgrounds and genres. Additionally, considering computational resource constraints and model complexity challenges, future work could explore optimized algorithm architectures or advanced DL techniques like Transformer or Generative Adversarial Networks. These approaches would improve computational efficiency, particularly for large-scale data processing, while enhancing model precision and stability.

Second, future studies could extend this cultural feature recognition model to additional domains of cultural product dissemination, including traditional music and theatrical performances. Such expansion would significantly broaden the model's applicability while offering technical infrastructure for enhanced global cultural exchange initiatives. With the ongoing development of the "Belt and Road" initiative, related cultural products are increasingly circulating globally. Subsequent research could focus on optimizing dissemination strategies across different cultural contexts to enhance the Chinese cultural products' global influence and competitiveness, thus facilitating cross-cultural communication and cultural identity integration.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author Ellen Zhu on reasonable request via e-mail el_zhu@163.com.

Received: 15 October 2024; Accepted: 5 May 2025
Published online: 08 May 2025

References

1. Liu, P. Myth, imagination and digital imaging: on the aesthetic expression of nationality in Chinese fantasy films. *Highlights Art Des.* **4** (1), 61–63 (2023).
2. Zhang, X. & Ismail, J. Animation technology to enhance communication of cultural heritage: A systematic review. *Malaysian J. Social Sci. Humanit. (MJSSH).* **8** (6), e002230–e002230 (2023).
3. Li, H. & Ito, H. Visitor's experience evaluation of applied projection mapping technology at cultural heritage and tourism sites: the case of China Tangcheng. *Herit. Sci.* **11** (1), 52 (2023).

4. Liu, Y., Lei, X. & Li, L. *A Study on Exoticism and its Local Transformation Innovation in Chinese Animation Films*, 620–626 (Revista Ibérica de Sistemas e Tecnologias de Informação, 2023).
5. Li, D. Kongqi theory and the aesthetic spirit of Chinese film. *J. Chin. Film Stud.* **3** (1), 71–84 (2023).
6. Chen, D., Guo, C., Lu, W., Zhang, C. & Xiao, C. Rapid quantification of Royal jelly quality by mid-infrared spectroscopy coupled with backpropagation neural network. *Food Chem.* **418**, 135996 (2023).
7. Wu, L., Mei, J. & Zhao, S. Pipeline damage identification based on an optimized back-propagation neural network improved by Whale optimization algorithm. *Appl. Intell.* **53** (10), 12937–12954 (2023).
8. Zhang, Y. et al. Intelligent feature recognition for STEP-NC-compliant manufacturing based on artificial bee colony algorithm and back propagation neural network. *J. Manuf. Syst.* **62**, 792–799 (2022).
9. Yan, Y. et al. Backpropagation with sparsity regularization for spiking neural network learning. *Front. NeuroSci.* **16**, 760298 (2022).
10. Tang, H. & Gong, X. A study of the inherited relations between classical mythology and the making of Chinese animation films. *Adv. Appl. Sociol.* **11** (9), 415–429 (2021).
11. Zhao, Y. & Zheng, D. Traditional Chinese mythology in animation Art. *Highlights Art Des.* **3** (3), 61–63 (2023).
12. Deng, Y. Analysis of Shanhaijing elements in ancient Chinese mythological animated films. *Highlights Art Des.* **4** (2), 170–173 (2023).
13. Shafira, V. & Rui, C. Semiotics Analyisis of Representation Chinese Culture in Sony Pictures Animation Film Wish Dragon Movie. *MANDARINABLE: J. Chin. Stud.* **2**(2), 86–103 (2023).
14. Chen, H., Qu, W. & Chen, X. The innovative expression of traditional Chinese cultural archetypes in animated films: Establishing a reliable, admirable, and respectable image of China. *Contemp. Social Sci.* **9** (1), 34 (2024).
15. Qian, F. Ancient routes, new Dream: the silk roads and China's belt and road initiative. *J. Cult. Herit. Manage. Sustainable Dev.* **12** (1), 45–57 (2022).
16. Sigley, G. The great tea road and the belt and road initiative: cultural policy, mobility narratives and route heritage in contemporary China. *Int. J. Cult. Policy*. **29** (3), 314–327 (2023).
17. Ding, C. Research on the innovative path of precise communication of Chinese martial arts under the background of the one belt and one road. *Social Sci. Humanit. J. (SSHJ)*. **8** (03), 34576–34655 (2024).
18. Sattar, A., Hassan, A., Noshab Hussain, M., Sakhi, U., Hordofa, T. & T Does China's education and cultural diplomacy promote economic growth in the belt and road countries? *Chin. Econ.* **57** (1), 18–32 (2024).
19. Zhao, B. et al. Research on intelligent prediction of hydrogen pipeline leakage fire based on finite ridgelet neural network. *Int. J. Hydrog. Energy*. **47** (55), 23316–23323 (2022).
20. Zhao, B. et al. Risk assessment of refinery unit maintenance based on fuzzy second generation curvelet neural network. *Alexandria Eng. J.* **59** (3), 1823–1831 (2020).
21. Zhao, B. & Song, H. Fuzzy Shannon wavelet finite element methodology of coupled heat transfer analysis for clearance leakage flow of single screw compressor. *Eng. Comput.* **37**, 2493–2503 (2021).
22. Mantello, P., Ho, M. T., Nguyen, M. H. & Vuong, Q. H. Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward emotional AI in the workplace. *AI Soc.* **38** (1), 97–119 (2023).
23. Depounti, I., Saukko, P. & Natale, S. Ideal technologies, ideal women: AI and gender imaginaries in redditors' discussions on the Replika bot girlfriend. *Media Cult. Soc.* **45** (4), 720–736 (2023).
24. Brooks, J. A. et al. Deep learning reveals what vocal bursts express in different cultures. *Nat. Hum. Behav.* **7** (2), 240–250 (2023).
25. Wei, Z., Zhang, M. & Ming, Y. Understanding the effect of tourists' attribute-level experiences on satisfaction–a cross-cultural study leveraging deep learning. *Curr. Issues Tourism*. **26** (1), 105–121 (2023).
26. Tasneem, S., Ageeli, A. A., Alamier, W. M., Hasan, N. & Safaei, M. R. Organic catalysts for hydrogen production from noodle wastewater: machine learning and deep learning-based analysis. *Int. J. Hydrog. Energy*. **52**, 599–616 (2024).
27. Wright, L. G. et al. Deep physical neural networks trained with backpropagation. *Nature* **601** (7894), 549–555 (2022).
28. Obeso, A. M., Benois-Pineau, J., Vázquez, M. S. G. & Acosta, A. Á. R. Visual vs internal attention mechanisms in deep neural networks for image classification and object detection. *Pattern Recogn.* **123**, 108411 (2022).
29. Lyu, Z. et al. Back-propagation neural network optimized by K-fold cross-validation for prediction of torsional strength of reinforced concrete beam. *Materials* **15** (4), 1477 (2022).
30. Metlek, S. A new proposal for the prediction of an aircraft engine fuel consumption: a novel CNN-BiLSTM deep neural network model. *Aircr. Eng. Aerosp. Technol.* **95** (5), 838–848 (2023).
31. He, R., Xiao, Y., Lu, X., Zhang, S. & Liu, Y. ST-3DGMR: Spatio-temporal 3D grouped multiscale ResNet network for region-based urban traffic flow prediction. *Inf. Sci.* **624**, 68–93 (2023).
32. Singla, P., Duhan, M. & Saroha, S. An ensemble method to forecast 24-h ahead solar irradiance using wavelet decomposition and BiLSTM deep learning network. *Earth Sci. Inf.* **15** (1), 291–306 (2022).
33. Kaimaris, D. Measurement accuracy and improvement of thematic information from unmanned aerial system sensor products in cultural heritage applications. *J. Imaging* **10** (2), 34 (2024).
34. Bai, Y. et al. Residual current detection method based on improved VMD-BPNN. *Plos One* **19**(2), e0289129. (2024).

Author contributions

Nan Zhang: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, funding acquisition Ellen Zhu: writing—review and editing, visualization, supervision, project administration.

Funding

The Youth Fund Projects for Humanities and Social Sciences Research of the Ministry of Education in 2021, Innovation Research on the Construction of National Cultural Image in the Overseas Communication of Chinese Animation (2004–2020), No.21YJC760106. The key project of Beijing Social Science Fund, Research on the Construction of Beijing Cultural Identity in the New Era of Cross-media Image Practice, No.22YTA004. Scientific Research Project of Jilin Provincial Department of Education, Research on the Copyright Protection Strategy of Chinese Animation IP in the Context of New Media, No, JJKH20241460SK.

Declarations

Competing interests

The authors declare no competing interests.

Ethics statement

The studies involving human participants were reviewed and approved by Academy of Arts and Design, Tsinghua University Ethics Committee (Approval Number: 2023.654184). The participants provided their written informed consent to participate in this study. All methods were performed in accordance with relevant guidelines and regulations.

Additional information

Correspondence and requests for materials should be addressed to E.Z.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.