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Research Article

A Classification Method for National Culture Propagation Using Deep Learning

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This paper combines the artificial intelligence (AI) and deep leaning technologies to classify the spread of national culture. First, we use the Python language to build a crawler technology in order to obtain the sample data of national culture from authoritative websites. Then, we use the natural language processing (NLP) expertise to analyze and preprocess the text of national diversity. In this way, we realize vectorization and the feature word extraction of the text related to national cultural resources based on the doc2vec technology. The vectorized texts of national cultural resources are clustered based on the K-means clustering technique. Moreover, the elbow rule process is implemented to determine the optimal number of clustering clusters. Finally, the text association relationship of the national cultural resources is obtained. Moreover, this paper adopts the unsupervised training method, which can reveal the semantic information contained in the text of national cultural resources. This can also help us during the identification process of the category connection amongst the texts of national cultural resources and provide us with methodological support for the gathering, storing, and other smart services of enormous national cultural resources. The outcomes demonstrate that the correctness rate of the suggested algorithm is greater than the accuracy of the linear regression and can reach up to 80%.

1. Introduction

With the increasing modernization and internationalization of social development, the protection, defense, and inheritance of ethnic minority traditional culture are facing a crisis. Using information technology (IT) to comprehend the digitization, sharing, and dissemination of minority culture has become an important means for the fortification, inheritance, development, and exploitation of minority culture. At present, the digitization of minority culture and the main means of communication are various minority culture websites. Due to the characteristics of diversity, dispersion, group closure, and so many other factors, the content of ethnic culture resources of similar ethnic culture websites is relatively scattered, with unstructured characteristics, which is difficult to be found, applied, and integrated. At the same time, different websites and platforms have inconsistent descriptions and understandings of minority cultures, resulting in ambiguity or differences in people's understanding and understanding of minority cultures, which is not conducive to the dissemination and protection of national cultures. By means of distributed web crawler, data mining, natural language processing (NLP), and machine learning techniques to collect, examine, process, and cluster the text of national cultural resources will help automatically collect, recognize, and share massive national cultural resources, better understanding the deep semantics of national cultural resources text. Furthermore, this may also help in offering technical support for the intelligent and smart services of national cultural resources.

The multiplicity of human beings and their accomplishments regulates the productivity and variety of social culture. There are differences in the cultures of different regions and nations, and there is no completely unified development model. The same cultural phenomenon can be interpreted differently in different cultures and obtain different cultural meanings. Any social group is constrained by the culture that has continued from history, and it is under the action of the same culture that the members of this social group show the consistency of mutual recognition in their way of thinking, values, behavior patterns, and customs. For other cultures, this consistency becomes the difference or particularity that distinguishes them. In modern civilization, if any two cultures are compared together, differences are reflected in all aspects. The formation of cultural diversity has gone through a long historical process. At the beginning of the formation of human beings on the Earth, culture is relatively single. Even if they live in different regions of the world and face different natural environments, overall, culture still reflects more similarities, and differences are not that obvious.

The evolution of culture has its own laws. The cultures designed in dissimilar areas will change bestowing to the laws and regulations of their specific growth, but, in fact, this development is by no means synchronous. For thousands of years, the rapid progress of human technology in transforming nature has not only brought Earth shaking changes to human society, but also constantly endowed a culture with various characteristics different from other cultures [1, 2]. Although the similarities of primitive cultures can also be seen from those ancient cultures, however, the speed of progress of different civilizations has been gradually replaced by cultural differences. The differences of world cultures formed in the long-term historical development process are gradually fixed as the basic characteristics of a culture [3]. The technical problem to be solved in this paper is to provide a technique of clustering analysis for the ethnic cultural communication diversity that is constructed on the deep neural network (DNN) models. Similarly, based on the cultural diversity text data, the suggested method can improve the recognizability and understandability of substantial cultural resources and assist the smart sharing and recommendation of immense cultural resources. The following are the major contributions of our research.

(i) To classify the spread of national culture, we use Python to build a crawler technology to obtain the sample data of national culture from authoritative websites;

(ii) We use the natural language processing (NLP) expertise to analyze and preprocess the text of national diversity and realize the vectorization and the feature word extraction of the text of national cultural resources based on doc2vec technology;

(iii) The obtained data is clustered based on K-means clustering procedure, along with the elbow rule technique, which is used to determine the optimal number of clustering clusters;

(iv) Finally, the text association relationship of national cultural resources is obtained.

The remainder of this paper is structured in the following manner. We deliver an overview of the state-of-the-art works in Section 2. Application of in-depth learning in the dissemination and classification of ethnic documents is illustrated in Section 3. An empirical study on the influence of national cultural communication on audiences is provided in Section 4. In Section 5, the obtained results in terms of prediction error and precision are deliberated. Finally, Section 6 summarizes this study and provides some future research directions.

2. Related Work

How to use multimedia to spread history and culture? How can the spread of history and culture promote the development of local economy and various undertakings? This is a major topic for scholars and journalists of news communication theory and business research. Many researchers are concerned about this and are discussing it carefully. In foreign countries, researchers have conducted various aspects of research on cultural inheritance and dissemination. The authors in [1] have discussed popular culture, the collection and editing of cultural information, influential media celebrities, and the dissemination of local culture. Furthermore, the research conducted in [2] demonstrates that social media, online consumer behavior, and cross-cultural trends are conducive to the emergence of new channels for the global dissemination of culture, which will change the face of the cultural industry. Population changes and mixing, trade, and long-distance dissemination of cultural characteristics will clue towards fluctuations in cultural symbols used by human beings. The authors in [3] introduced the thoughts and experience of new media that combines art, technology, exhibition, communication, and service tools to realize cultural inheritance, protection, development, and innovation. Pinto et al. studied the problem of cultural communication in different situations and how the mass media can attract more potential users by establishing a feedback mechanism. Rigaud et al. [4] used personal decorations as a carrier to record the changes of cultural geography to study the transition period from the Mesolithic Age to the Neolithic age. The cultural heritage of a city is a unique symbol of its identity. Deep excavation, effective utilization, and dissemination of urban cultural wealth are important measures to highlight the characteristics of urban culture and promote urban development based on the research on the new media display system of Pingdingshan Museum.

In addition, the research results of multimedia communication are also very rich. Anderson et al. [5] have provided clear evidence for media violence to increase the possibility of short-term and long-term environmental violations and violence through the research on violent TV programs, films, video games, and music. The research in [4] used the Parliamentary records of MKS political activities and the regularity of the MKS news as test data. The structural equation model shows that the confidence of politicians, over the media power, rises their enthusiasm and efforts in exposure of media, which will subsequently produce greater media influence and more parliamentary activities. Similarly, the authors in [6] studied and investigated the impact of media factors on the brand launch effect in the real-life environment. Based on the survey of 1195 viewers, it is found that the type of program, the attitude of program, and the information value of program show a constructive part in the response of brand layout. The category of audience behavior is partially reconciled by the perceived information value of the program. The research shows the importance of environmental factors to the brand launch effect. In [7], the authors have conducted the research on the defense of famous cultural and historical capitals, towns, and villages, in the republic of China. Furthermore, the authors proposed that the protection and development of prominent cultural and historical capitals in the process of urbanization have their own characteristics and laws, which conform to the objective laws of the defense and expansion of famous cultural and historical towns and cities.

Beside the above works, the authors in [5] put forward the principles of the protection and development of famous historical and cultural cities through the investigation and research of prominent historical and cultural capitals in Yunnan. Taking Jinan as an example [8], the authors discussed the safety and rational utilization of Jinan's renowned historical and cultural municipalities by explaining the noncontradictory relationship between the defense of renowned and well-known historical and cultural municipalities. Moreover, they deliberated the economic development of Jinan, drawing on the defense examples of prominent historical and cultural municipalities at home and abroad and using the frontier theories, principles, and scientific protection methods of domestic historical and cultural heritage protection. Furthermore, the authors in [9] profoundly elaborated on the defense of prominent historical and cultural municipalities, townships, and rural community and proposed to further strengthen the theoretical research, adopt positive response ideas, strategies, and public policies, promote protection and development to complement each other, achieve harmony and win-win results, and strive to get out of the misunderstanding of large-scale demolition and reconstruction. Apart from the above discussion and research, the researchers in [10] analyzed the importance of cultural protection, the protection process from international to domestic the current situation, and working methods of historical and cultural heritage protection in China. Beskow et al. [11] reviewed the development of urbanization and the fortification of historical and cultural municipalities in the republic of China after the founding of new China and pointed out that the protection situation of cultural and historical cities in China is still severe, and the phenomenon of constructive destruction has not been effectively curbed.

From the perspective of regional economics, historical geography, management, and other disciplines, it is not only limited to the "cultural" connotation of the ancient city, but also from the perspective of advertising and brand in the strategic and strategic aspects of historical and cultural cities, especially with the rise of cultural and creative industries. From "creativity" to "brand," the idea of constructing the ancient city culture communication is to find a practical path. For example, [12] focuses on Hunan, analyzes the problems existing in the media selection, communication mode, media strategy, comprehensive benefits, and other aspects of the main body of Hunan food culture communication, adopts CIS Theory, constructs the Hunan food culture communication system, and puts forward the communication strategy of multiple media linkage communication mechanism. Based on the analysis of the main problems faced by Xi'an in the dissemination of history and culture, similarly, [13] made a SWOT analysis of how to promote the dissemination of Xi'an history and culture with the help of the animation industry, so as to summarize the strategies of the animation industry to promote the dissemination of Xi'an history and culture [11].

The authors of [14] also looked at how national cultures effect initial public offerings' underpricing abroad (IPOs). In short, Lee and David [15] established a framework based on Hofstede's concepts of the cultural context of accounting and accounting and culture to explain how national culture impacts national accounting systems. The study emphasizes that social preferences based on culture regarding the avoidance of uncertainty contribute to the understanding of cross-national differences in the current financial system configuration, building on research that examines why some financial systems are based on banks and others on markets. According to a theory put forth by researchers in [16], political institutions constrain this relationship. The research done in [17] presents collaborating skills that guarantee the integration of educational contents that are absolutely intended for encouraging the ethnic, national, and religious tolerance. Furthermore, with respect to dissimilar culture's values, the authors have engrossed on various aspects of cross-cultural communication, enculturation, and also the socialization factors of the individual.

The analysis of the influences of formal institutions and national culture on corporate risk-taking is one of [18]'s contributions. The core objective of authors in [19] is to lay out a dominant pattern of the state-supported Islamization process. Similar to [20], which examines the fusion of national culture Furthermore, by shedding light on the cultural roots of cross-functional coopetition, [12] brings cross-functional coopetition to the international management literature. The objective of authors in [21], consequently, is twofold. Other influential works that have focused on the BP neural network and other deep learning techniques include [12, 13, 22].

3. Application of In-Depth Learning in the Dissemination and Classification of Ethnic Documents

3.1. The BP Neural Network and Its Basic Working Mechanism. The BP neural networks are also recognized as error backpropagation neural networks. It is a typical error correction method. Theoretically, it has the ability to approximate nonlinear continuity functions and has simple structural signs. It is easy to be programmed and processed by computer. Its application fields are very wide. The topology of BP neural network in the form of single hidden layer feedforward network is shown in Figure 1. In practical applications, three-layer network structure is usually selected, namely, input layer, hidden layer, and output layer. Its characteristic is that there can be no connection between

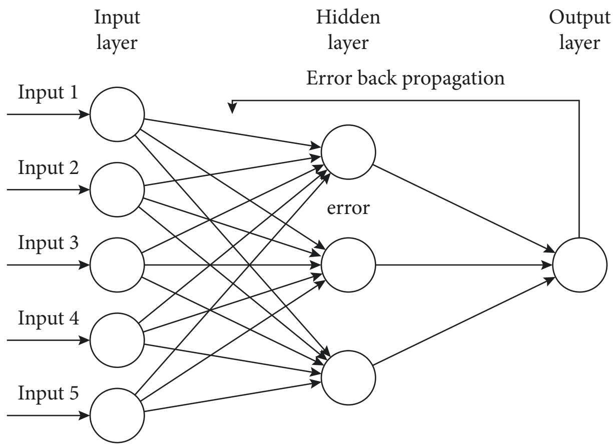

Figure 1: The BP neural network structure.

the units of the same layer, and the activation signal can only be output from the units of each layer to the units of the high layer [23]. Changing the weight coefficient of any layer can change the performance of the whole multilayer neural network. In terms of determining the number of neurons in each layer, the number of neurons in the input layer and the output layer can be set according to the specific classification problems encountered, while there is no universally applicable criterion for determining the number of neurons in the hidden layer.

The internal mechanism of the BP neural network is as follows: the external input information is input into the network through the neurons of the input layer and then transmitted to the intermediate layer for information transformation and information processing. The processed information continues to be propagated and processed to the output layer, and finally, the information processing outcomes are fed to the freestanding layer through the output layer [24]. In fact, the BP neural network is a particular category of the multilayer feedforward neural networks with one-way propagation, which can solve the learning problem of neural connection weight hidden in multilayer networks. In short, the BP neural network take account of two processes: (i) forward propagation of information; and (ii) backpropagation of error. It is a highly nonlinear mapping from input to output. The signal of BP neural network is transmitted forward, and it has no feedback and interlink structure within the layer. The output of each layer of neuron node only affects the input of the next layer of neuron node.

Through the error backpropagation process, the network can modify the connection weight of the network and adjust the parameters to make the network output ideally close to the expected output under the condition of minimum mean square error. If the output result of the output layer is significantly different from the expected output, the input backpropagation process needs to be carried out, and the error between the actual output and the expected output needs to be transmitted back layer by layer through the output layer, the hidden layer, and the input layer. The process of BP neural network is repeated, and cyclic correction is the process of BP neural network learning and training, which continues until the final error reaches an acceptable range or reaches the preset learning times.

For a mathematical model of the three-layer BP neural network, let $X = (x_1, x_2, \ldots x_i, \ldots x_n)^T$ be the input vector of the model; $Y = (y_{1,}, y_{2,}, \ldots y_j, \ldots y_n)^T$ is the output vector of the hidden layer of the model; $O = (o_1, o_2, \ldots o_k, \ldots o_l)^T$ is the output vector of the model output layer; $d = (d_1, d_2, \ldots d_k, \ldots d_l)^T$ is the expected output vector of the model. $V = (V_1, V, V_J, V_m)$ represents the weight matrix from the input layer to the hidden layer, in which the subvector V_j is the weight vector corresponding to the jth neuron of the hidden layer; $W = (W_{1,}, W_{2,}, \ldots W_k, \ldots W_l)$ represents the weight matrix from the hidden layer to the output layer; and the subvector W_k in it is the weight vector, which is essentially consistent with the k^{th} neuron of the output layer [25].

It should be noted that, for the output layer, there exist the following formulas:

$$o_k = f(\text{net}_k), \quad k = 1, 2, \ldots, l, \tag{1}$$

$$n_k t_k = \sum_{j=0}^{m} w_{jk} y_j, \tag{2}$$

where f is the function that defines the BP network model and k denoted the layer. For the hidden layer, there exist the following formulas:

$$y_j = f\left(\text{net}_j\right), \quad j = 1, 2, m, \tag{3}$$

$$\text{net}_j = \sum_{i=0}^{n} v_{ij} x_i, \quad j = 1, 2, \ldots, m. \tag{4}$$

Using equation (5), we set the transformation functions $f(x)$ to be unipolar sigmoid functions:

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{5}$$

Derivation can be obtained using the following equation:

$$f'(x) = f(x)[1 - f(x)]. \tag{6}$$

We define the output error, characterized by E, as given by the following equation:

$$E = \frac{1}{2}(d - O)^2 = \frac{1}{2}\sum_{k=1}^{l} (d_k - o_k)^2. \tag{7}$$

After this, we extend the error definition to the hidden layer, and then, the error is given by the following equation:

$$E = \frac{1}{2}\sum_{k=1}^{l} [d_k - f(\text{net}_k)]^2 = \frac{1}{2}\sum_{k=1}^{l}\left[d_k - f\left(\sum_{j=0}^{m} w_{jk} y_j\right)\right]^2. \tag{8}$$

Finally, we have the input layer as illustrated in the following equation:

$$E = \frac{1}{2}\left\{\sum_{k=1}^{l} d_k - f\left[\sum_{j=0}^{m} w_{jk} f\left(\text{net}_j\right)\right]\right\}^2 = \frac{1}{2}\sum_{k=1}^{l}\left\{d_k - f\left[\sum_{j=0}^{m} w_{jk} f\left(\sum_{i=0}^{n} v_{ij} x_i\right)\right]\right\}^2. \tag{9}$$

3.2. Experimental Steps of Deep Learning in the Classification of National Cultural Propagate. We use the elbow rule technique to decide the optimal amount of clusters and finally obtain the text association of national cultural resources [26]. The clustering analysis technique of the national cultural resources is founded on the deep neural network (DNN) model according to the previous statement, which is characterized in that; and the specific steps are given as follows:

(i) Step 1: text data crawling of ethnic cultural resources: obtain the text data of ethnic cultural resources from ethnic culture related websites and databases through distributed web crawler technology.

(ii) Step 2: pretreatment of ethnic cultural resources: the following substeps are performed.

  (i) Step 2.1: preprocess the data of national cultural resources obtained in step 1, including detagging, deleting the content of head and other irrelevant areas, and label escape, so as to extract the body content of the text and obtain the text of national cultural resources.

  (ii) Step 2.2: yes, step 2.1. Remove the stop words from the national cultural resource text obtained in step 1, and retain the entity words. The stop words include prepositions, adjectives, and adverbs, and the entity words include verbs and nouns.

  (iii) Step 2.3: Chinese word segmentation of the text of national cultural resources processed in step 2.2.

(iii) Step 3: vectorization of national cultural resources: the following substeps are performed.

  (i) Step 3.1: based on the deep neural network model doc2vec, build the distributed bag of words model, and carry out model training and feature extraction for the text of national cultural resources.

  (ii) Step 3.2: according to Step 3.1, express the text of national cultural resources as a text vector with ID.

  (iii) Step 3.3: set Step 3. The output result of Step 2, that is, the text feature vector of national cultural resources, is normalized to the [0, 1] interval.

  (iv) Step 3.4: execute Step 3 n times 1-Step 3. Step 3: get the vector matrix of national cultural resources. Moreover, N is the number of texts inside the national cultural resources. After vectorization, we get the following matrix of national cultural resources:

$$\phi_i = \left[\phi_{i(1)}, \phi_{i(2)}, \ldots \phi_{i(n)}\right], \tag{10}$$

  where $\varphi_i \in \mathrm{R}^{n\times m}$, and m characterizes the total amount of characteristic words inside the text of national cultural resources.

(iv) Step 4: clustering of national cultural resources: after carrying out the text vectorization process of national cultural resources, through Step 3, the corresponding feature vector of each text can be acquired. This is due to the fact that the topic resemblance amongst the texts can be quantified through the clustering procedure [27]. Furthermore, so as to realize the association and distinction between the national cultural resources texts, in order to acquire the paramount clustering outcome, the elbow rule can be used to select the best cluster number K. In fact, we set the initial value of the number of clusters K to 1 and cycle through Step 4.1 to Step 4.2 m times. The specific steps are illustrated as follows:

  (i) Step 4.1: obtain the K value of the number of clustering clusters, and increase the K value by 1 every cycle. Call the K-means clustering procedure to make clusters of the text vector matrix for national cultural resources.

  (ii) Step 4.2: determine the sum of squares of errors, denoted by SSE. Moreover, calculate and record the sum of squares of errors SSE value of each clustering process. The sum of squares of errors (SSE) of text data of national cultural resources is premeditated by the following equation:

$$\text{SSE} = \sum_{i=1}^{k}\sum_{p\in C_i}\left|p - m_i\right|^2. \tag{11}$$

  where C_i characterizes the i^{th} cluster, m_i is the average rate of all samples that belong to C_i cluster, and p is the sample point in C_i cluster. Note that the SSE metric, in fact, represents the error in clustering of all samples and characterizes the advantages and disadvantages of clustering influence.

(iii) Step 4.3: execute Step 4 after M cycles 1-Step 4. After 2 steps, m k values and SSE values are obtained, so as to draw the relationship graph between K values and SSE values, and the K value corresponding to the elbow in the graph is selected as the number of nearest clustering clusters.

(v) Step 5: outputs: finally, the clustering results of national cultural resources based on topic similarity are obtained.

4. An Empirical Study on the Influence of National Cultural Communication on Audiences

This paper deals with and analyzes the data collected through the interview survey of different audiences, establishes multiple regression models and the BP neural network model to study the current situation of multimedia on national culture communication, and finds out the strength and differences of the influencing factors of multimedia national culture on different audiences. Furthermore, the paper also studies the strategies and regulations that multimedia should adopt for national culture communication according to the questionnaire [28].

The construction of multiple regression model and the BP neural network model is usually realized established on SPSS software and MATLAB software, respectively. In view of this, the general workflow of this paper is as follows:

(i) Step 1: according to the characteristics of the two models, we preprocess the collected audience data, so that redundant data can be avoided, and we divide the samples into the training group and testing group.

(ii) Step 2: we use the training group data and SPSS software to realize the modeling process of multiple regression model; then, with the help of MATLAB software and the BP neural network toolbox, the modeling process of the BP neural network is realized through independent programming.

(iii) Step 3: finally, we use the test group data to realize the prediction function of the two models and use the comparison between the model output values and the actual values to reflect the prediction accuracy.

The accuracy of the prediction results can be measured using the well-known mean average percentage error (MAPE) and root mean square error (RMSE) evaluation metrics as given by the following equations:

$$\mathrm{MAPE} = \frac{1}{z}\sum_{i=1}^{z}\frac{\left|\widehat{x}_t - x_t\right|}{x_t},$$
$$\mathrm{RMSE} = \sqrt{\frac{1}{z}\sum_{i=1}^{z}\left(\widehat{x}_t - x_t\right)^2}. \tag{12}$$

In the above equations, $`x_i$ and x_i denote the predicted value and the real value, respectively. Furthermore, z characterizes the total number of samples that were used for validation purposes. The lower the values, the more accurate the prediction, and vice versa.

5. Results and Discussion

Table 1 gives the descriptive statistics of the total 212 samples. The average score of each item is in descending order: overall broadcast media score, overall paper media score, overall TV media score, overall network media score, overall mobile media score, and overall score. This is consistent with the situation of real life. With the development of Internet technology, traditional radio and paper media are declining, and their influence is becoming smaller and smaller. Compared with radio and paper media, TV media have a stronger influence on the dissemination of national culture. Internet media and mobile media have the strongest impact on cultural communication, and their average scores are roughly the same. It can be comprehended that the Internet has changed the traditional mode of communication of national culture.

When constructing the communication strategy of national culture, we should consider the influence of modern technology as much as possible, especially the influence of the Internet, which will make the communication strategy more efficient. This can also be comprehended from the results reported in Table 1 that the average value of the overall score is the highest, indicating the positive evaluation given by the respondents to the effect of the overall dissemination of national culture. This can be perceived from the standard deviation statistics that the standard deviation of the overall score is the smallest, followed by the standard deviation of the overall online media score. Overall, the standard deviation is a little larger than the average score, which shows that the respondents' score value for the spread of national culture fluctuates greatly, and they have different attitudes.

From the side, the dissemination of national culture did not allow all respondents to achieve a better unified understanding, and there is still room for improvement in the dissemination of national culture. In the next demonstration, the last 32 samples of the total 212 samples are used as the prediction group, and the others are used as the test group to identify and predict the model. Next, we carry out prediction and analysis. For the prediction of multiple linear regression model, the value of specific independent variables is substituted into the following regression equation:

$$y = 18.644 - 0.172x_1 + 0.201x_2 + 0.339x_3 - 0.229x_4 + 0.657x_5. \tag{13}$$

After comparing with the actual filling value of the questionnaire, it is concluded that, among the 15 prediction samples, 3 are misjudged, and the accuracy rate is 80%. Figure 2 shows the BP neural network training and test results.

From Figure 2 and the model output results, we can know that the training process of the BP neural network

Table 1: The overall descriptive statistics.

	Average values	Standard deviation	Number of cases
Overall score	82.934	9.4621	212
Overall paper media score	60.495	20.3226	212
Overall broadcast media rating	59.726	18.6977	212
Overall TV media rating	77.858	13.5359	212
Overall online media rating	82.524	11.5609	212
Overall mobile media score	82.868	12.4395	212

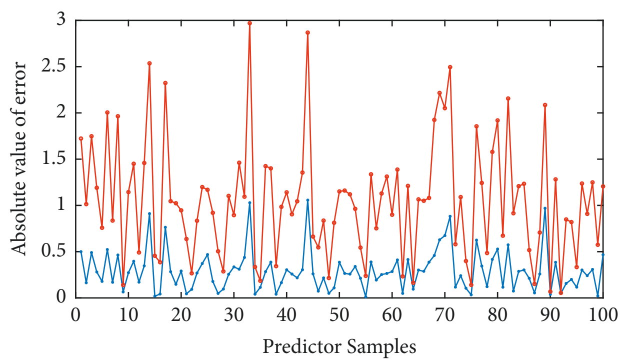

Figure 2: The predictor values.

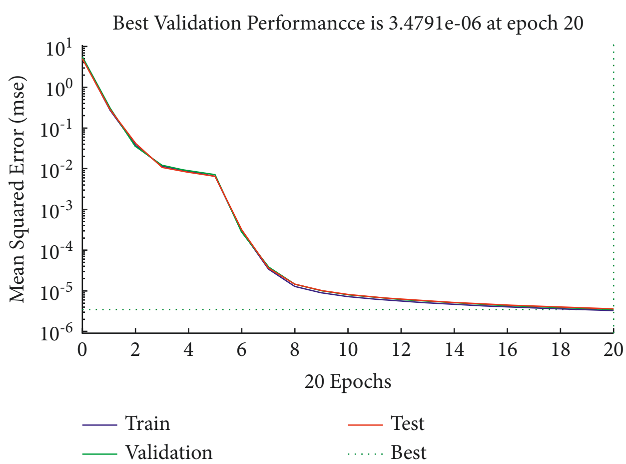

Figure 3: The best validation performance.

performs well; nevertheless, in the prediction process, only 9 samples are predicted correctly, and the others are predicted incorrectly.

The best validation performance is shown in Figures 3 and 4. From the outcome's values reported in Figures 3 and 4, we know that the best validation performance reaches up to 10^{-5} with the 20 epochs. Figure 5 demonstrates the prediction accuracy, in terms of MAPE and RMSE, for linear regression (LR) and the backpropagation neural network (BFNN) model. The higher the values, the more accurate the prediction, and vice versa. The proposed BP neural network is more accurate than the classical linear regression technique. The accuracy of the proposed method can reach up to 80.11% along with higher values for the MAPE and improved RMSE.

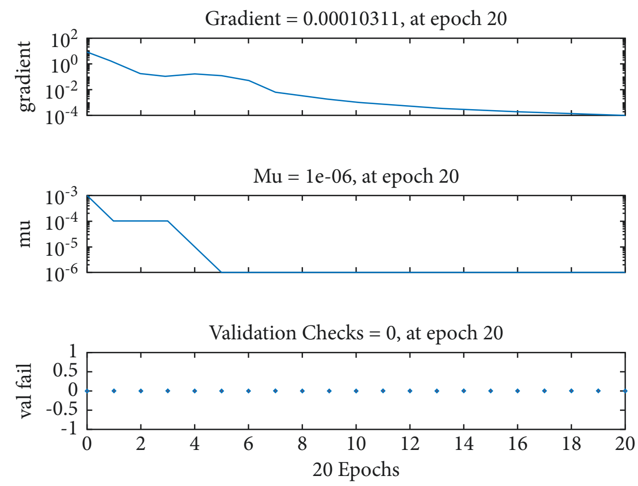

Figure 4: The Gradient calculation.

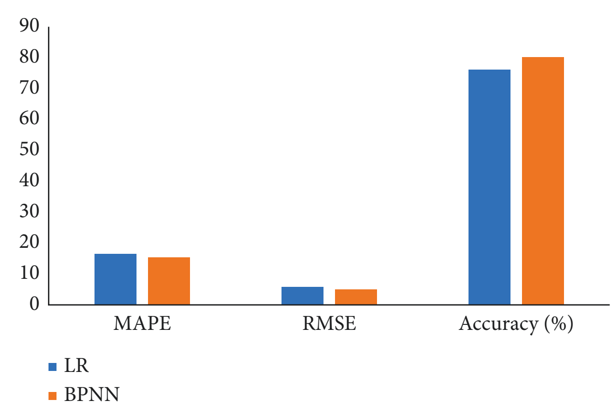

Figure 5: The prediction accuracy results for linear regression (LR) and the backpropagation neural network (BFNN) model [the lower the values for MAPE and RMSE, the more accurate the prediction].

This paper collects the data of the impact of multimedia cultural diversity on the audience through a questionnaire survey. This questionnaire survey adopts the sampling method of subregions, levels, and the nature of work units, and the respondents are selected according to the nature of population work units [29]. The questionnaire takes into account the respondents' age, position, identity, work, and other information. As of July 1st, 2020, a total of 280 questionnaires have been distributed, and 252 copies have been recovered. After preliminary data analysis, the remaining 212 copies are valid. Through the processing and analysis of the data collected from the interview surveys of different audiences, the multiple linear regression model and BP neural network model are established to study the current situation of multimedia on the dissemination of cultural diversity.

With the help of SPSS and MATLAB independent programming, the empirical research results show that students and respondents under the age of 25 do not have a deep understanding of cultural communication and have different opinions. When building cultural diversity communication strategies, we should focus on this group. Among the five kinds of media analyzed, mobile media and TV media are the most important. In the process of systematic planning and overall scheme construction of cultural diversity communication, these two kinds of media should be given priority. Through the comparison and analysis of the prediction results of multiple regression model and BP neural network model, it can be seen that the classical multiple linear regression analysis is a model worth considering when analyzing the data with strong subjectivity of evaluation and classification.

6. Conclusions and Future Work

In this paper, we established multiple linear regression models and the BP neural network model to carry out empirical research on the impact of multimedia publicity and cultural diversity on the audience. The two confirm each other and have strong persuasion. The empirical results have a certain guiding role for the construction of cultural diversity communication strategies. The relevant media leaders can formulate a systematic plan and overall plan for cultural diversity communication for audiences of different ages and identities according to the empirical results of this paper. We believe that the proposed algorithm will promote cultural diversity in an all-round way through positive public opinion and mutual cooperation. Of course, the research method of this paper is generic and can play a certain reference role for the media practitioners in the whole province and even the whole country. The empirical evaluation and experiments, using real datasets, showed the superiority of the proposed method over classical linear regression model.

In the future, we will propose other deep learning models to increase the prediction precision and improve the execution time of the training period. The dataset used in this work is small, and we will consider larger dataset to generalize our results. We will investigate further how the activation function of the neural network will affect the neurons, and therefore, the accuracy of the prediction results. Finally, we will deeply look into the convolutional networks (CNNs) and other state-of-the-art mechanism like big data and edge infrastructure, so that the training time can be significantly reduced. In the training process, if the data is large, or the deep learning method has more layers, then the training will take long time, and that needs to be optimized.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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