Application of big data classification effects based on neural network in video English course and relevant optimization suggestions

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Abstract

Due to the improvement of Internet technology and information technology, more and more students hope to learn and consolidate knowledge through video in the classroom. Teachers are more accustomed to using video in the classroom to improve and improve their teaching quality. In the current English class, teachers and students are more accustomed to using video English for teaching. English teaching videos are informative, intuitive and efficient. Through video teaching, we can make the classroom atmosphere more interesting, thus simplifying complex problems. In this context, this paper analyzes how neural networks can improve the application effect of English video courses in the context of big data, optimizes the pdcno algorithm by using the neural network principle, and then discusses the impact of the optimized pdcno algorithm on classification and system performance. This improves the accuracy of English video, reduces the execution time of the algorithm and reduces the memory occupation. Compared with ordinary video, the training time required under the same training parameters is shorter, and the convergence speed of the model itself will be faster. From the students' attitude towards video teaching, we can see that students prefer video English teaching, which also reflects the effectiveness of neural network big data in English video teaching. This paper introduces the neural network and big data technology into the video English course to improve the teaching effectiveness.

1. Introduction

Due to the continuous development and improvement of Internet technology and information technology,video products are widely welcomed. Video has become a part of people's daily life. Especially during the period of COVID-19, all primary and middle schools across the country have organized online video live teaching, and video and teaching are inseparable [1]. In the actual classroom, video courseware is often used. In the regular high school English class, everyone more or less uses video to learn in the teaching, so as to increase the fun of learning, simplify the complexity of problems, or the learning process itself involves the form of video [2]. Video English is loved by many teachers and students for its rich information, high efficiency and flexibility, and has become an important part of English teaching. The current era is the information age. The outline of China's basic curriculum education reform also emphasizes that information technology the teaching process itself should be integrated with the course content[3]. Students live in the information age, many traditional education methods are no longer applicable to today's students, and cannot stimulate their learning motivation and interest [4]. However, the introduction of information education into daily teaching can attract students' interest and stimulate their enthusiasm for learning, in this way, the teaching quality and effect can be improved[5]. If video teaching is used for teaching, we can find that there are many advantages in the form of video teaching: through video teaching, we can turn the originally boring teaching content into a video with pictures, text and sound, so as to attract students' interest and facilitate their understanding [6]. Compared with many other teaching methods, video teaching can save classroom time and increase classroom content, thus improving teaching efficiency and curriculum effectiveness, and saving time for teachers and students [7].

2. Relevant Work

This paper introduces a new optimization algorithm of deep convolution neural network, i.e. parallel pdcno algorithm. The algorithm can pre train the network, which is implemented by introducing feature-based pruning strategy, so as to realize the compression of the network to adjust the parameters, reduce the complexity and the overall training time [8]. The conjugate gradient secant line correction is designed in the literature, which can fully reduce the convergence time of the network, make the global classification effect of the system more rapid and accurate, and complete the adjustment of the target data through the parallel system acceleration [9–10]. The literature introduces firefly optimization algorithm to search and share information, initializes parameters based on IFAS algorithm and realizes parallel training for DCNN to improve the optimization ability of the network [11]. And then obtain the global training results based on parallel computing, effectively cluster the data, reduce the time-consuming of this process and improve the cluster efficiency. The simulation results show that this algorithm can effectively reduce the training cost of DCNN and improve the performance of parallel system to a certain extent [12]. The literature proposes an RNN model, which can predict based on time series, called time step residual recurrent neural network or tsr-rnn for short. The model identifies the remaining connections between hidden states at different time steps, which can effectively slow down the gradient loss phenomenon during network training, and can obtain the increase and decrease information of patterns between time steps, thus making the model more predictable and explanatory [13]. Compared with common RNN variants such as LSTM and Gru, tsr-rnn is more efficient in training and prediction without introducing redundant parameters, but the prediction accuracy is still close to the former two [14]. The literature has designed a deep convolution computing model, which can solve some problems of existing deep learning models, such as difficult to solve complex fusion relations [15].

3. Neural Network Algorithm

3.1 Big data characteristics

Big data is a microcosm of various things in real life. As the carrier of various information, it has rich knowledge and great value [16]. At present, big data has penetrated into society, economy, scientific research and other aspects, providing important support for people to understand the essential laws of social development in a data-driven manner, and has become an important topic for academic research of various industries and governments [17].

3.2 Data model

The feature calculation process of each layer input is as follows:

$$y_l = f\left(\sum_{r \in I} w_r^l * x_r^{(l-1)} + b^l\right)$$

1

Suppose there is a sample in total, and adjust the weight by comparing the expected output and predicted output of the network. Define the final goal function of the network as:

$$E\left(w\right)=\min\sum_{i=1}^{M}L\left(p_r\right)+\lambda\left(w\right)$$

2

Among them, L (pr) is the loss function, which can reduce the classification error through iterative form. pr is the final output value in the formula (1), λ (W) is a regularization function, and W is the power value of the network. Using the output of the SoftMax function to minimize the cross -entropy loss function, then:

$$L\left(p_r\right)=-\log\sigma_r\left(p\right)$$

3

Among them, r is a normalized probability function, which is defined as:

$$\sigma_r\left(p\right)=\frac{\exp\left(p_r\right)}{\sum_{v=1}^{I}\exp\left(p_v\right)},r=1,\ldots,I$$

4

Definition 1

Standard Castle Gradiental Method Define the following iteration formulas to generate rights sequence {Wi}:

$$w_{i+1}=w_i+\eta_i d_i, i=0,1,\ldots,N$$

5

Definition 2

search direction is the downward direction of the target value when the optimal solution of the Gradiental Method. It is defined as:

$$d_u=\begin{cases}-g_0, & i=0\\ -g_i+\beta_i d_{i-1}, & \text{otherwise}\end{cases}$$

6

Among them, the parameter βi is:

$$\beta_i^{HS}=\frac{g_i^T y_{i-1}}{y_{i-1}^T d_{i-1}},\beta_i^{FR}=\frac{\left\|g_i\right\|^2}{\left\|g_{i-1}\right\|^2}$$

7

Definition 3

standard positive formula is the approximation matrix expression of the Hazi matrix, which is defined as:

$$B_i s_{i-1}=y_{i-1}$$

8

Definition 4

The curvature accuracy of the cord formula to improve the co -ladder method is defined as:

$$\mathrm{B_{i-1}s_{i-1}} = \bar{\mathrm{y}}_{\mathrm{i-1}}, \bar{\mathrm{y}}_{\mathrm{i-1}} = \mathrm{y_{i-1}} + \frac{\theta_{\mathrm{i-1}}}{\mathrm{s_{i-1}^{T}k}}\mathrm{k}$$

9

Fireflies optimization algorithm is an optimization algorithm that simulates fireflies information exchange. The main steps are as follows:

Update fluorescein according to equivalent (10):

$$\mathrm{l_i}\left(\mathrm{t}\right) = \mathrm{l_i}(1-\rho)(\mathrm{t}-1) + \gamma \mathrm{f}\left(\mathrm{x_i}\left(\mathrm{t}\right)\right)$$

10

Calculate the probability of moving, select the fluorescence highlights that are higher than your own fireflies in the vision set in the neighboring domain, and calculate the probability of moving from i to j according to the formula (11):

$$\mathrm{p}\left(\mathrm{t}\right) = \frac{\mathrm{l_j}\left(\mathrm{t}\right) - \mathrm{l_i}\left(\mathrm{t}\right)}{\sum_{\mathrm{k}\in \mathrm{N}}\left(\mathrm{l_j}\left(\mathrm{t}\right) - \mathrm{l_i}\left(\mathrm{t}\right)\right)}$$

11

Update the position of fireflies to iterate, and finally find the best solution to the problem by continuously moving the fireflies into a better individual within the detection range.

Parallel calculation entropy:

$$\mathrm{E} = \sum_{\mathrm{k}=1}^{\mathrm{n}}\left(\mathrm{q_k}\mathrm{lb}\frac{1}{\mathrm{q_k}}\right)$$

12

3.3 Algorithm optimization

LA formula:

$$\overline{\mathrm{La_i}} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{M}}\left\|\mathrm{F_{i,j}}\right\|_{\mathrm{a}}}{\mathrm{M}}, \mathrm{a} = \left\{\begin{array}{c} 1,\ \text{low layer} \\ \infty,\ \text{deep layer} \end{array}\right\}$$

13

Balanced positive extension:

$$B_{i-1}s_{i-1}=\bar{y}_{i-1},\bar{y}_{i-1}=y_{i-1}+\sigma_{i-1}\frac{\max\{\theta_{i-1},0\}}{s_{i-1}^{T}k}k$$

14
Set the search parameter βi and set its direction as the direction of the optimal solution. Based on this, a convergent solution is obtained. Based on the global convergence principle of the common gradient method, βi is defined as:

$$\beta_i^{IHS}=\max\left\{\frac{g_i^T y_{i-1}}{\underset{=}{}},0\atop y_{i-1}d_{i-1}^T\right\}$$

15
Because the direction of the decline cannot be guaranteed, sometimes the algorithm is required to restart the convergence in the actual calculation process. Based on the FR law, the search direction is determined:

$$d_i=-\left(1+\beta_i^{IHS}\frac{g_i^T d_{i-1}}{\|g_i\|}\right)g_i+\beta_i^{IHS}d_{i-1}$$

16
The server contains n nodes, its inherent load capacity is ci, and the current load is Li. When the parallel system reaches the load balance:

$$P_i=\frac{L_i}{C_i}=\frac{L_j}{C_j}$$

17
When the server reaches the load balancing, the load rate of each node shall be equal to the average load rate, that is,

$$\overline{P_i}=P_1=P_2=\cdots=P_n$$

18
The comprehensive load rate of the node is:

$$Load_i=P_i\left(D[i]+G[i]+M[i]+W[i]+N[i]\right)$$

19
In actual applications, when the server reaches a load balancing, there are:

$$\overline{Load}=Load_1=Load_2=\cdots=Load_n$$

20
T1, T2, and T3 are determined as compression of network compression, some categories of obtaining bureaus, and the global classification value, which can express the time complexity of the PDCNO

algorithm.

To set a network contains a voltage layer of D convde layers, the number of CL is the number of cores of the voltage layer. M and K respectively represent the edge length of the feature diagram and convolution kernel.

$$T_s = O(mlogm)$$

21

In addition, the pruning time cutting below the preset threshold is:

$$T_a = O\left(m\right)$$

22

Therefore, the time complexity of the use of PFM strategy for network compression is:

$$T_1 = O(mlogm) + O\left(m\right)$$

23

3.4 Simulation analysis

The experimental results are shown in Table 1.

Table 1
Classification results of different algorithms comparison

Dataset	Algorithm	FI	Accuracy	Floating -point operation times per second
SVHN	PDCNNO	93.84%	98.83%	1.49E + 08
	DCNN-PABC	62.95%	83.50%	0.98E + 08
	CNN-MR	80.05%	91.72%	0.74E + 08
Emnist_Digits	PDCNNO	88.51%	94.08%	1.16E + 08
	DCNN-PABC	62.75%	74.40%	0.80E + 08
	CNN-MR	74.71%	82.04%	0.65E + 08
ISLVRC2012	PDCNNO	80.05%	72.22%	97.9E + 08
	DCNN-PABC	58.32%	53.11%	52.5E + 08
	CNN-MR	60.05%	56.57%	67.6E + 08

The execution time and memory occupation of PDCNNO and MR-DCNN and PDCNN algorithms are shown in Fig. 1.

Figure 1 Execution results of the three algorithms: (a) algorithm execution time (b) algorithm memory occupation

The results of the operation time are shown in Fig. 2.

It can be found that the training efficiency of tsr-rnn is similar to that of conventional RNN, because tsr-rnn only introduces residual identity mapping connection and does not introduce any redundant parameters. It can also be seen from Fig. 2 that no matter how the residual depth is set, the result does not change much. The training time of LSTM and Gru is about three times that of tsr-rnn. This is because the access unit parameters of LSTM and Gru need to participate in gradient descent for training, so the training time is longer than that of general RNN.

The change of loss function in the experiment is shown in Fig. 3.

It can be seen that the convergence speed of tsr-rnn is very fast, and it is close to the final value at the early stage of training. The reason for this phenomenon is that the tsr-rnn network uses residual connections on time steps, which forces the model to learn information about the differences between hidden layer states rather than directly learning the hidden layer itself. Therefore, it can be assumed that the difficulty of training the network will be correspondingly reduced and the convergence speed of the model will be faster.

4. Research And Application Of The Effectiveness Of Video English Course

4.1 Basic concepts

(1) The principle of video teaching

Nowadays, students can use computers, TVs, mobile phones and tablet devices at any time, and these devices play an important role in video broadcasting. When connected to the Internet, they can watch many different videos. The study found that students prefer to watch videos rather than read books, and they will find the videos more interesting. However, judging through the pictures in the books or multiple-choice questions will not arouse students' interest. What more interesting content and materials are there in the traditional classroom. Although the introductory materials and exercises in the book are very useful and are often used by all, the students do not seem to be more motivated or motivated to learn. However, if we use video for classroom teaching in another way, will students' attitudes be completely different and will they be attracted by video.

(2) Definition of video teaching

As a part of the classroom, video teaching takes about 3–5 minutes in the classroom and plays an important role in teaching activities. Video teaching can be divided into "video" and "teaching", and "video" is based on educational content. Teachers use some relevant videos to focus students' attention, stimulate their learning desire and guide them to prepare for learning. "Teaching" means to let students understand the internal relationship of what they have learned, guide them to establish their own internal perspective, so that students can better understand the learning objectives. Using video teaching can effectively guide students' learning behavior, which is one of the important technologies in the field of teaching. Therefore, good teaching determines whether teachers can achieve their teaching objectives and is also a bridge between teachers and students.

(3) The role of video teaching

The tasks of video teaching include attracting attention, stimulating learning motivation, setting teaching goals, explaining learning tasks and creating exercises. Video is a part of classroom teaching, providing clear information and contact for teachers and students. Video teaching is the key to classroom success. Poor quality videos will affect students, make it difficult for students to stimulate their initiative in the next course, and distract students' attention. However, good videos are like bridges between teachers and students. A good video can become a bridge between teaching and learning, new knowledge and old knowledge. Help students review what they have learned, stimulate their enthusiasm for the new course, and strongly stimulate their thirst for knowledge. The following four points are the four functions of video teaching.

4.2 Study design

Research object:

The subjects of this questionnaire are students from 8 classes in a school, and the subjects of classroom observation are 4 English teachers.

Research questions:

The problems studied in this paper are: what is video teaching, what types of video based on format, what teaching effects can be achieved by using different video formats in the main courses of high school English (listening, reading, grammar and writing), and how to make more effective use of video to improve the English Teaching level in high school English classes.

Research tools:

This paper adopts two research methods: questionnaire survey and classroom observation. The teaching video questionnaire is divided into two versions: teacher version and student version. 10 questionnaires were distributed to teachers, and 10 were recovered, with an effective rate of 100%. From class 1 to 9, 360 questionnaires were distributed and 315 questionnaires were recovered, with a recovery rate of 87.5%. The effective questionnaire score was 280, and the effective rate was 88.9%. Through the questionnaire, we can see everyone's attitude towards the video teaching method in class, and summarize which video teaching method should be used in different types of classes.

The classroom observation and interview are divided into two parts. One part is conducted by four teachers of the Department and eight classes they teach. Each teacher has an average of eight classes, totaling 64 hours. The other part is conducted by six teachers who teach six classes at the same time. The two parts have a total of 70 hours. During classroom observation and interview, each teacher sits at the back of the classroom to listen to the class, records the contents of the teacher's class and the students' reactions to the class, and records the video recording type, which belongs to the video type in this category. The course type (such as reading, grammar, vocabulary, writing) and content, as well as the student activities recorded in the video teaching part (such as the number of discussions, the number of viewers, etc.).

The teacher's attitude towards the video is shown in Table 2:

Table 2
Teachers' attitudes towards videos

Do you like video teaching			**Can video teaching attract students' attention?**			**When teaching with video, can you stimulate students' interest in learning?**		
Option	Number	Ratio	Option	Number	Ratio	Option	Number	Ratio
do not like	0	0%	Never	0	0%	Never	0	0%
generally	1	10%	Occasionally	1	10%	Occasionally	1	10%
like	4	40%	often	4	40%	often	4	40%
Very much like	5	50%	always	5	50%	always	5	50%

It can be seen from Table 2 that no one does not like video teaching. 10%is occasionally liked, 40%likes, and 50%like it very much. Therefore, the video is still very popular with the teacher: there is no teacher who thinks that the video does not attract students' attention or does not attract their learning interest. Generally speaking Interest, 60%of teachers believe that videos can always attract and stimulate students' interest. It seems that teachers believe that video is an effective teaching method that can attract students 'attention and stimulate students' interest.

Students' attitude towards video is shown in Table 3:

Table 3
Students' attitude towards video

Do you like video teaching			Can video teaching attract students' attention?			When teaching with video, can you stimulate students' interest in learning?		
Option	Number	Ratio	Option	Number	Ratio	Option	Number	Ratio
do not like	18	5.7%	Never	17	5.4%	Never	20	6.3%
generally	14	4.4%	Occasionally	58	18.4%	Occasionally	66	20.9%
like	72	22.8%	often	188	59.6%	often	205	65.1%
Very much like	211	67.1%	always	52	16.6%	always	24	7.7%

4.3 Experimental results

After the experiment, the author conducted a questionnaire survey of 49 students in the experimental class. Submit 49 questionnaires and return 49 copies, including 49 valid questionnaires. Taking the students of the experimental group as an example, the general data of the four dimensions of the questionnaire is descriptive statistics. The result Table 4:

Table 4
Video English Teaching in English Classroom Questionnaire Data Description Statistics

Questionnaire	Number of cases	Min	Max	Mean	SD
Student learning interest	49	2.5	5	4.2956	0.72220
Self -learning ability	49	2.1	5	4.0936	0.82340
Classroom teaching efficiency	49	2.1	5	4.2461	0.79259
Student learning environment	49	1.6	5	4.2461	0.85352

4.4 Improve the effectiveness of video English courses

Teachers must continue to strengthen their ability to adapt. In the process of making videos, teachers need to consciously use different methods to express the content of English subjects. You can try to break through the limits of the video with different methods, stimulate and guide students' visual and intuitive feelings; second, simplify video production technology as much as possible so that the production difficulty is as close as possible. Teachers are the main team of video development. They must assume different responsibilities in teaching activities and ask them to become a computer proficient in computer technology. Therefore, it is very important to simplify the technology of making video as possible to reduce the cost of recording videos.

In addition, schools can also provide teachers with guidance and technical assistance through forming a technical group, and provide appropriate help when teachers encounter difficulties in making videos. On the contrary, teachers can get rid of technical issues and focus on design content; in the end, the video itself should reduce the requirements of the equipment to avoid unnecessary burden on students, teachers or learning. Teachers and parents should also create a good video learning environment for students when using videos to ensure that they can learn video teaching content smoothly.

5. Conclusion

Students are the absolute subject in the teaching process, while teachers are mainly responsible for guiding students, supervising students in teaching, and are the main organizers of teaching activities. In the traditional teaching process, teachers often only let students accept knowledge passively, and rarely or not interact with students, thus reducing students' initiative in learning, resulting in poor English performance. Therefore, the author has changed and optimized the traditional classroom teaching method and adopted the big data video based on neural network to carry out English teaching, thus realizing effective classroom language teaching, thus improving students' learning achievements and promoting their learning initiative. The combination of modern neural network technology and English video class has fully improved the effect of English video class and created a clear and interesting English video teaching class.

Declarations

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interests

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Data Availability

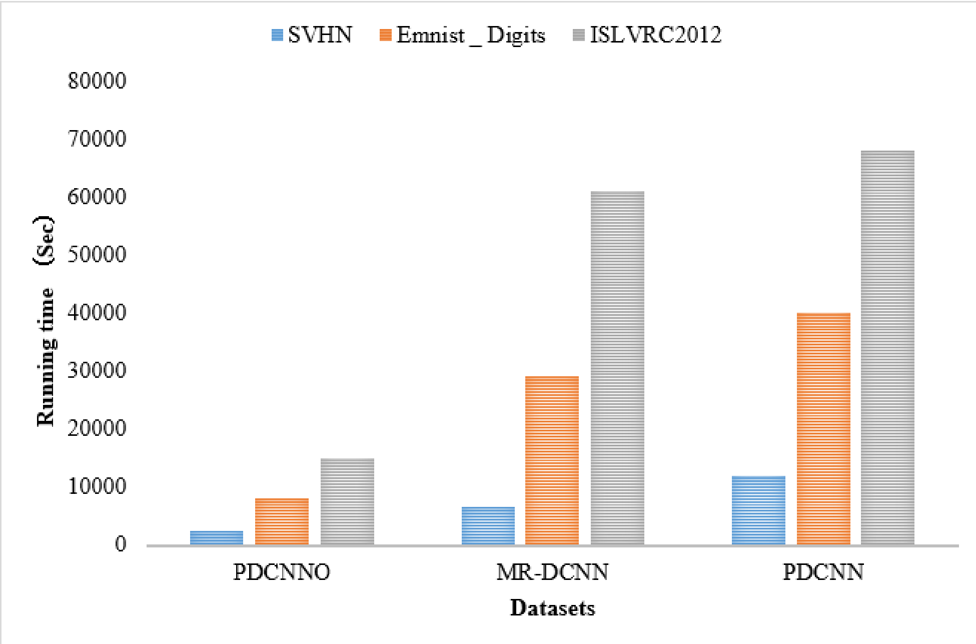
Data will be made available on request.

References

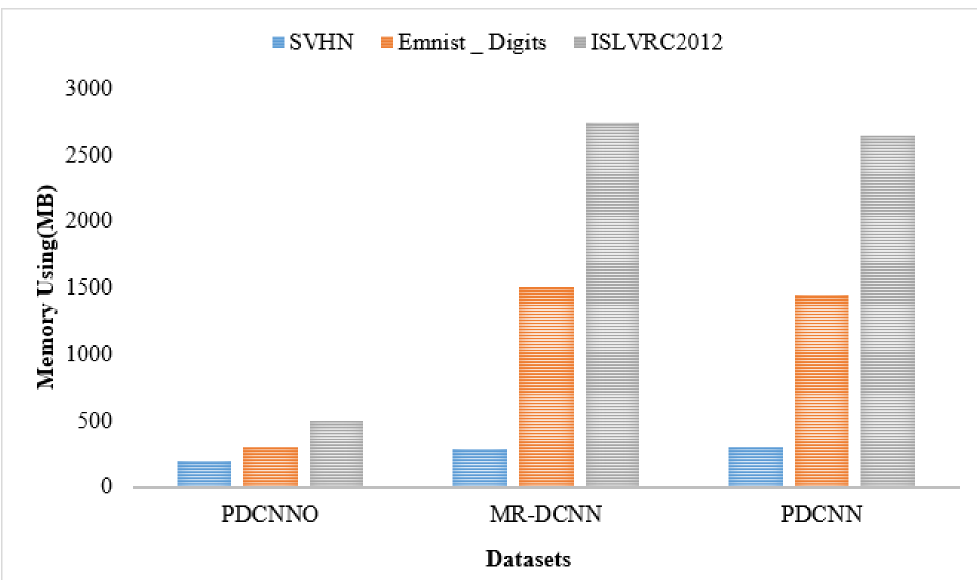
1. J. A. DeCesare, “The expanding role of online video in teaching, learning, and research,” Library Technology Reports, vol. 50, no. 2, pp. 5-11, 2014.
2. Y. H. Ying, W. E. W. Siang, & M. Mohamad, “The challenges of learning English skills and the integration of social media and video conferencing tools to help ESL learners coping with the challenges during COVID-19 pandemic: A literature review,” Creative Education, vol. 12, no. 7, pp. 1503-1516, 2021.
3. B. Muniandy, & S. Veloo, “Managing and utilizing online video clips for teaching English language: Views of TESOL pre service teachers,” In 2nd International Conference on Education and Management Technology, IPEDR, Vol. 13, No. 2011, pp. 173-178, 2011.

4. L. Bayram, “Use of online video cases in teacher training,” Procedia-Social and Behavioral Sciences, vol. 47, pp. 1007-1011, 2012.
5. Z. Wang, “An analysis on the use of video materials in college English teaching in China,” International Journal of English Language Teaching, vol. 2, no. 1, pp. 23-28, 2015.
6. T. W. Chasanatun, & S. Lestari, “The use of camtasia video, youtube, and whatsapp in online teaching during pandemic situation,” English Teaching Journal: A Journal of English Literature, Language and Education, vol. 9, no. 1, pp. 34-39, 2021.
7. M. M. Juzwik, M. B. Sherry, S. Caughlan, A. Heintz, & C. Borsheim-Black, “Supporting dialogically organized instruction in an English teacher preparation program: A video-based, Web 2.0-mediated response and revision pedagogy,” Teachers college record, vol. 114, no. 3, pp. 1-42, 2012.
8. S. R. Dubey, S. Chakraborty, S. K. Roy, S. Mukherjee, S. K. Singh, & B. B. Chaudhuri, “diffGrad: an optimization method for convolutional neural networks,” IEEE transactions on neural networks and learning systems, vol. 31, no. 11, pp. 4500-4511, 2019.
9. P. Mukilan, & W. Semunigus, “Human object detection: An enhanced black widow optimization algorithm with deep convolution neural network,” Neural Computing and Applications, vol. 33, no. 22, pp. 15831-15842, 2021.
10. Y. Zheng, Q. Liu, E. Chen, Y. Ge, & J. L. Zhao, “Time series classification using multi-channels deep convolutional neural networks,” In International conference on web-age information management, pp. 298-310, 2014.
11. K. S. Kim, & Y. S. Choi, “HyAdamC: A New Adam-Based Hybrid Optimization Algorithm for Convolution Neural Networks,” Sensors, vol. 21, no. 12, p. 4054, 2021.
12. K. Asanovic, R. Bodik, J. Demmel, T. Keaveny, K. Keutzer, J. Kubiatowicz, ... & K. Yelick, “A view of the parallel computing landscape,” Communications of the ACM, vol. 52, no. 10, pp. 56-67, 2009.
13. W. Xue, I. B. Nachum, S. Pandey, J. Warrington, S. Leung, & S. Li, “Direct estimation of regional wall thicknesses via residual recurrent neural network,” In International Conference on Information Processing in Medical Imaging, pp. 505-516, 2017.
14. W. Cao, A. Song, & J. Hu, “Stacked residual recurrent neural network with word weight for text classification,” IAENG International Journal of Computer Science, vol. 44, no. 3, pp. 277-284, 2017.
15. Y. H. Kim, J. B. Park, M. S. Chang, J. J. Ryu, W. H. Lim, & S. K. Jung, “Influence of the depth of the convolutional neural networks on an artificial intelligence model for diagnosis of orthognathic surgery,” Journal of Personalized Medicine, vol. 11, no. 5, p. 356, 2021.
16. L. Rodríguez-Mazahua, C. A. Rodríguez-Enríquez, J. L. Sánchez-Cervantes, J. Cervantes, J. L. García-Alcaraz, & G. Alor-Hernández, “A general perspective of Big Data: applications, tools, challenges and trends,” The Journal of Supercomputing, vol. 72, no. 8, pp. 3073-3113, 2016.
17. B. Logica, & R. Magdalena, “Using big data in the academic environment,” Procedia Economics and Finance, vol. 33, pp. 277-286, 2015.

Figures



(a) algorithm execution time



(b) algorithm memory occupation

Figure 1

Execution results of the three algorithms: (a) algorithm execution time (b) algorithm memory occupation

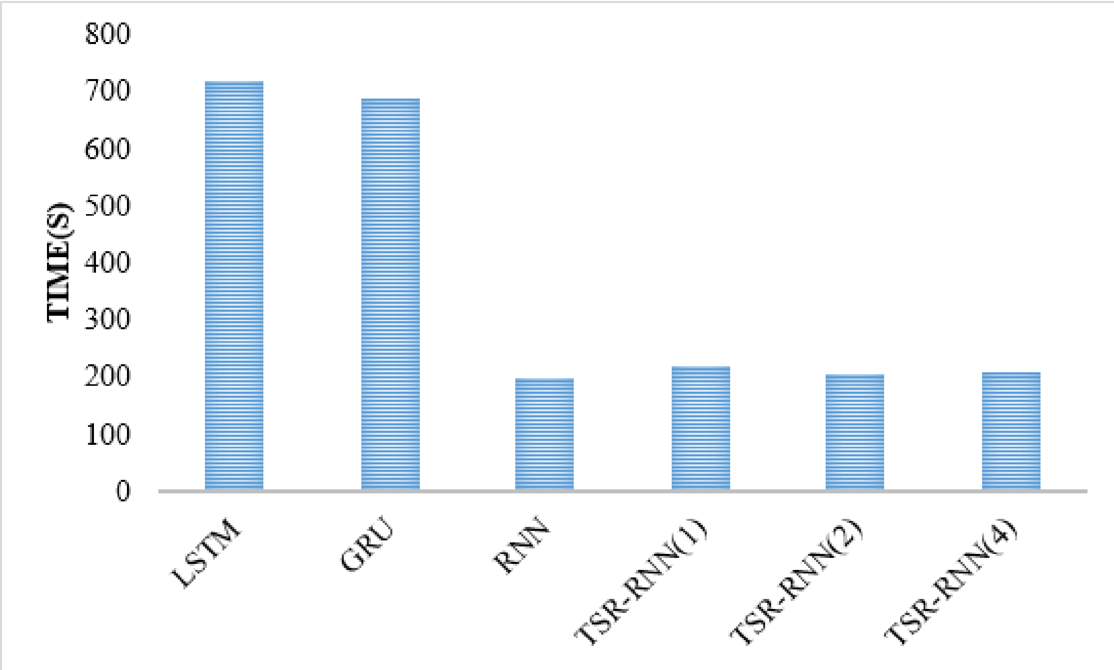


Figure 2

Comparison results of running time between tsr-rnn and other RNN models

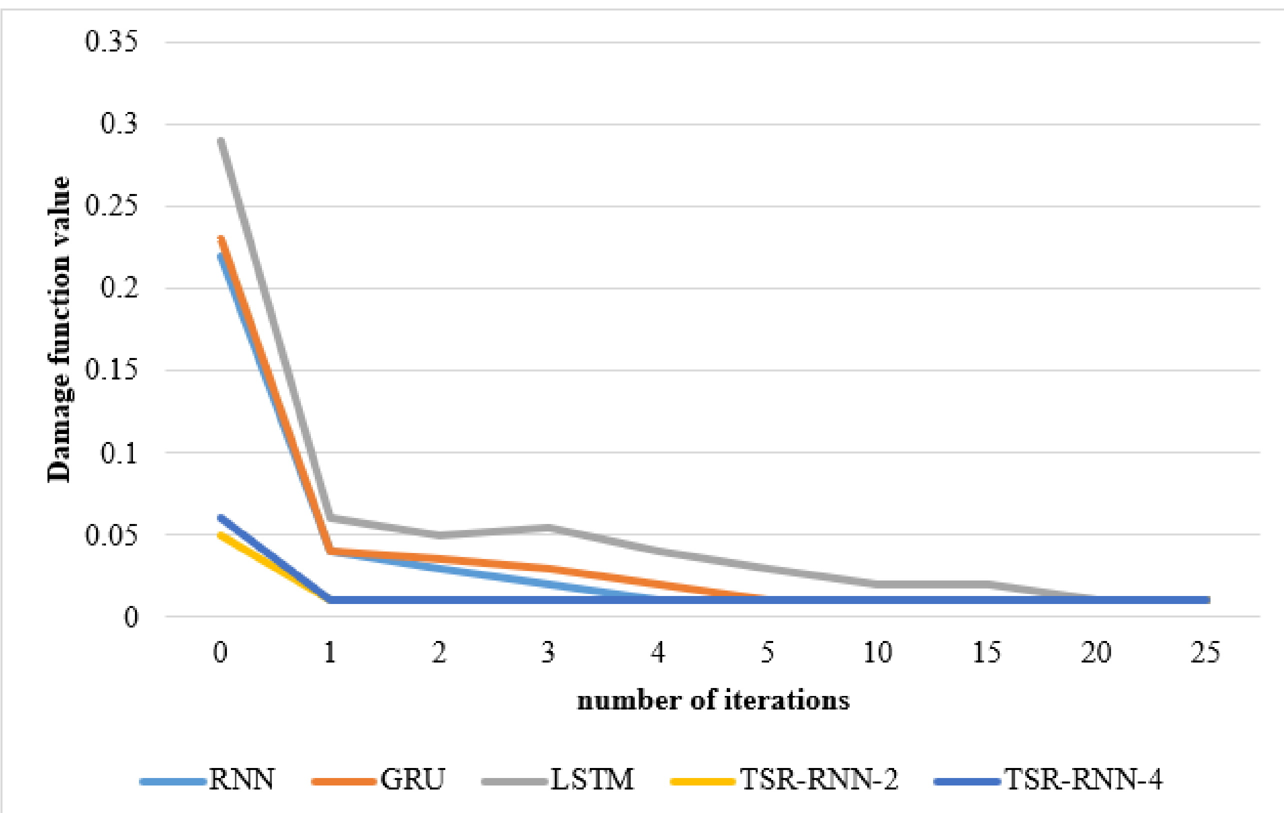


Figure 3

loss function change curve of RNN model in training stage