BASIC DIRECTION AND REALIZATION PATH OF PE TEACHING INNOVATION IN PSS BASED ON DEEP LEARNING MODEL

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ABSTRACT

At present, the traditional model of PE in PSS (PSS)has seriously affected the quality of PE teaching in PSS and the perception of PE among primary and secondary school students. Because of the urgent need for innovation in PE in PSS, this study proposes the LSTM model to achieve an accurate prediction of the innovation direction of PE in PSS. Based on the LSTM model, the user behavior is classified by extracting the important features of the innovation direction. Expression to achieve accurate prediction of the future development direction of PE. Using the data confusion matrix to estimate the prediction accuracy of the LSTM model, the four evaluation indicators of Accuracy, Precision, F1, and AUC are 0.0532~0.2323 higher than the baseline model. The prediction results of PE teaching innovation in PSS from three aspects of teaching thought, teaching content, teaching objectives and essence are output, which has obvious guiding significance for the overall optimization of PE classrooms in PSS. This result shows that the LSTM prediction model has important practical value.

KEYWORDS

PE; Artificial intelligence; LSTM network; Model analysis; Innovate

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PAPER INDEX

1. INTRODUCTION

Ball games, track and field, and some sports have converted the governments of PE in PSS. Methods such as explanation and demonstration have greatly affected teachers' teaching quality and students' cognition of PE[1]. Such as demonstration and explanation, teaching students to start, long jump, and pull up. Make students directly participate in imitation, resulting in a poor experience and poor effect[2-3]. Therefore, PE teachers need to enrich their teaching methods, improve their teaching ability, make teaching innovations, and flexibly use their innovative methods to teach students, so that students can enjoy high-quality PE courses[4]. Therefore, the reform of PE in schools is domineering.

At present, a considerable part of the exploration of sports innovative education focuses on the innovation of teaching methods[5]. However, if we only innovate in teaching methods all the time, it is difficult for PE to have a leap-forward development. Therefore, the overall reform of PE teaching is highly praised by researchers[6]. To cultivate students' comprehensive sports ability and innovative sports consciousness, researchers propose that PE should become a kind of lifelong education, and the teaching model at this stage must be reformed[7]. According to the characteristics and differences between modern sports and traditional sports, some researchers have made a comparison from the aspects of innovative teaching environment, inducing students' original interest, teachers' innovative teaching technology, teaching evaluation, and extracurricular activities[8-9]. This paper expounds on the design of an innovative education model in PE from four aspects. In addition, some scholars pointed out that in the long-term PE teaching, it is necessary to reform the "systematic learning" mode (traditional teaching mode). Only by combining organically in PE teaching can we innovate. Some researchers also believe that cultivating students' innovative spirit, improving the interest of monks, and resonating through students' innovation, to build a set of general and innovative PE innovation modes in the new era with innovative function and positive thinking[10].

Based on the development of the deep learning model[11], relevant grounds have developed explosively[12-13], and these developments have promoted the innovative development of other industries and other fields. Among them, LSTM is mainly used for the processing of time series. It can accurately predict the most suitable behavior mode for users according to the characteristic data with obvious time input by model users. If the user selects other options, it can make a selection based on the current prediction[14-15]. However, when choosing an innovation direction, it is often related to the existing direction, that is, there is a certain opportunity. According to this characteristic, this study applies the LSTM network to predict the innovation direction of PE teaching in schools of primary and secondary and determines the implementation content and path according to the prediction direction.

2. RELATED WORKS

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2.1. RECOMMENDATION ALGORITHM BASED ON DEEP LEARNING AND ITS APPLICATION

Deep learning technology models can accurately capture attributes or features and promote them to a higher level of representation[16]. Early such technologies were limited by the Boltzmann machine (RBM)[17-18]. Hinton et al. Used the Boltzmann machine for modeling according to the data and optimized the fitting efficiency of the Boltzmann machine by using the contrast divergence algorithm[19]. The results showed that the optimized method can be well applied to Netflix. Song et al. proposed to use the NNM of DNN to extract Netflix user information, which is based on a recommendation model[20-21].

RNN is commonly used to process sequence data. Hidari[22] uses the neural network system to take the sequence data of the user's click items in the session record as the input data of RNN. If the quantity of data is large and concentrated, the prediction effect of RNN is very accurate. According to the above research, some researchers[23-24] took the historical behavior of news users as input and used RNN for a recommendation. The research found that it has good results. Liu et al.[25-26] used nearly 15 different RNN algorithms to process user information. On this basis, they found a new deep learning algorithm, which has a two-way RNN structure.

2.2. RECOMMENDATION ALGORITHM AND APPLICATION BASED ON LSTM

LSTM network is improved based on RNN hidden layer unit and has long-term memory function. Generally speaking, the problem that RNN can solve is the problem that LSTM can handle and perform well. At present, the LSTM network is mainly used for natural language processing, speech recognition, and image understanding. Graves[27] et al. Took the lead in applying the LSTM network to word prediction. After training in English and French databases, the accuracy of word prediction is 8% higher than that of standard RNN. Li et al. [28] proposed a Twitter tag recommendation system based on the LSTM network. The system first uses the skip-gram model to generate vocabulary, then uses CNN to generate each sentence in the article into a sentence vector, and finally uses this sentence vector to train the LSTM network. The experimental consequences show that the recommendation based on LSTM achieves better results than the recommendation model of standard RNN and Gru. A large number of research results show that LSTM network is suitable for time series information flow modeling.

3. RELATED CONCEPTS

3.1. RNN NETWORK STRUCTURE

RNN is a kind of time recurrent network, which is considered to be the result of repeated and alternating on the same timeline in a neural network architecture. The

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structural characteristics of RNN determine that it is more conducive to processing time-series. RNN structure is shown in Fig.1, where a is the processing unit of the RNN hidden layer, X^T is the input value of the current time, and H^T is the output value of the current time hidden layer. As can be seen from Fig.1, H^T is determined by the current input value X^T and the output value H^{T-1} of the previous time. H^T will affect the output the next time, that is, each output difference is not only related to the current input value. It is also related to the output difference of the previous time. Theoretically, RNN can process any length of time series data. Pascanu[29] and others used detailed digital reasoning to explain the causes of these phenomena, that is, the traditional RNN mode usually changes according to the correct direction of the weight at the end of the time series in the training environment. However, the longer the input time interval, the smaller the impact on the correct change of connection weight. Therefore, the network system is more inclined to input new data and does not have the function of long-term memory.

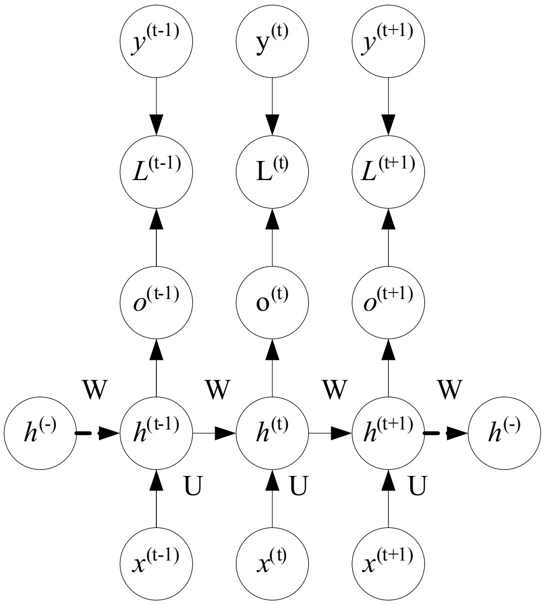

Figure 1. RNN network structure

3.2. LSTM NETWORK STRUCTURE

LSTM completes the problem of gradient disappearance and gradient explosion of the RNN model and retains information for a long time. LSTM and RNN have similar network structures, but the structure of the hidden layer is more complex, as exposed in Fig.2

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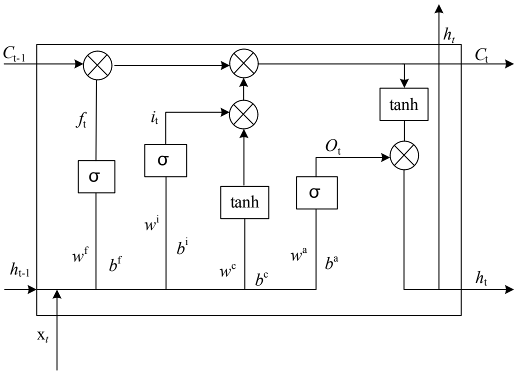

Figure 2. LSTM Structure neurons

There are three control doors inside the LTSM, which are input gate i_t, output gate o_t and forgetting gate f_t. The input x_t at each moment and the output H_{t-1} at the previous moment jointly determine that the state value of each gate unit at the current time has been the intermediate unit C_t. At time t, the update formula of each door is as follows [30].

$$f_t = \sigma\left(w^f \cdot [h_{t-1}, x_t] + b^f\right) \tag{1}$$

$$i_t = \sigma\left(w^i \cdot [h_{t-1}, x_t] + b^i\right) \tag{2}$$

$$\tilde{C}_i = tanh(w^c \cdot [h_{t-1}, x_t] + \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

$$o_t = \sigma\left(w^o \cdot [h_{t-1}, x_t] + b^o\right) \tag{5}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{6}$$

3.3. PREDICTION RESULT OUTPUT LAYER

The output layer of the prediction results is a two-layer full connection layer: each node of the first layer is connected to all the data features output by the LSTM unit to realize the integration of local features; Each node of the second layer is connected to the second layer, and each node is fully connected. The integration feature is calculated and the predicted value is output. The calculation is shown in formula (7).

$$y_t = w_t \times h_t \tag{7}$$

4. INNOVATION DIRECTION MODEL BASED ON LSTM MODEL

The recommendation mode can be divided into input part, processing part, and output part according to function. The input part converts the user's original education

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method into the numerical form required for calculation through the LSTM network, and the education vector representation used by each user is shown in Fig.3. The processing part processes the input data through the LSTM network to obtain the output result. The structure of the LSTM network needs to be determined, including the number of network layers, time step, and connection settings between layers. We used the educational method as the number of eigenvalues, defines the dimensions of input and output data, and determines the structure of the whole LSTM network model. The softmax layer maps the value of the output vector of the LSTM processing layer to the (0,1) region. The output part takes the last dimension of the processing results of the softmax layer to get the final development direction.

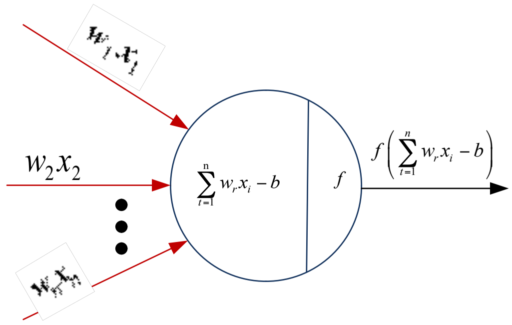

Figure 3. Output model

This study constructs an LSTM classification model. It can be used to identify the index categories of three main sports innovation methods and provide information for the construction of sports innovation development direction. In this paper, the LSTM model adopts a three-tier structure. The number of the intermediate network are 70, 50, and 25 respectively. The "CNN" algorithm is used for gradient training and optimization of network functions. Maxepochs is 70, minibacksize is 30, and the learning rate is 0.001. For each type of sports innovation direction, 70% of data are randomly selected as the data of the training set and 30% as data for testing. An LSTM model is constructed on the MATLAB software platform, and the model is established and trained by using the deep learning function package. The NVI 7732 processor and NVI 7790 processor equipped with Intel are one set of experiment environments.

5. MODEL EVALUATION

Compare the predicted classification results of the LSTM model with the actual labeling results[31] to estimate the presence of the LSTM model. For the model, the binary classification confusion matrix is calculated[32]. The category recognition model uses a one-to-many method to define the confusion matrix[33]. Table 1 lists the "one to many" method of binary classification based on the classical matrix.

Table 1. Confusion matrix of training data set

Class I	On class I
Correct prediction as a positive example (TP_I)	Incorrectly predicted as a counterexample (FN_I)
Incorrectly predicted as positive (FP_I)	Correctly predicted as a counterexample (TN_I)

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TP_I is the class I positive sample correctly classified by the model; FN_I is the first type of positive sample of model misclassification; FP_I is another class i samples of model misclassification; TN_I is the class i other samples correctly classified by the model. The average accuracy, average accuracy, average recall, average Kappa coefficient, F_1, and area AUC are calculated to appraise the classification performance of the two BILSTM models[34], as follows:

$$AA = \left(\sum_{i=1}^{k} \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \right) / \mathrm{k} \tag{8}$$

$$AP = \left(\sum_{i=1}^{k} \frac{TP_i}{TP_i + FP_i} \right) / \mathrm{k} \tag{9}$$

$$AR = \left(\sum_{i=1}^{k} \frac{TP_i}{TP_i + FN_i} \right) / \mathrm{k} \tag{10}$$

$$F_1 \text{ score } = \frac{2AP \cdot AR}{AP + AR} \tag{11}$$

$$AUC = \frac{1}{2}\left(\sum_{i=1}^{k} \frac{TP_i}{TP_i + FN_i} / \mathrm{k} + \sum_{i=1}^{k} \frac{TN_i}{TN_i + FP_i} / \mathrm{k} \right) \tag{12}$$

$$\text{Kappa } = \left(\sum_{i=1}^{k} \frac{p0_i - pe_i}{1 - pe_i} \right) / \mathrm{k} \tag{13}$$

Where $p0_i$ is the accuracy and N is the total number of records.

The individual leveling rate index is not very accurate. F_1 score represents the effectiveness of classifier recognition positive classification[35]. Kappa coefficient is an index for conformance testing[36-37].

$$macro - P = \frac{1}{n} \sum_{i=1}^{n} P_i \tag{14}$$

$$macro - R = \frac{1}{n} \sum_{i=1}^{n} R_i \tag{15}$$

$$macro - F_1 = \frac{2 \times macro - P \times marco - I}{macro - P + marco - R} \tag{16}$$

$$E_{\text{accuracy}} = \frac{N_T}{N} \tag{17}$$

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$$E_{\text{RMSE}} = \sqrt{\frac{\sum_{i=1}^{N} (g_i - p_i)^2}{N}} \tag{18}$$

Where N_T is the number of environments, N is the total index, g_i is the classification result, and p_i is the classification result predicted by the model[38-39].

6. RESULT ANALYSIS

6.1. BASELINE MODEL PARAMETER SETTING

To prove the efficiency of the projected model, we choose some machine learning methods based on artificial feature engineering to extract features. These methods are often used in decision prediction, Including DT, NB, LDA, LR, SVM, GBDT, and RF. In addition, we also selected two prediction models based on deep learning CNN and CNN RNN as comparison methods. The settings of some baseline model parameters are shown in Table 2, and the other model parameters without initial values are the default values.

Table 2. Setting of baseline model parameters

Baseline method	Baseline parameters	Value
SVM	C, y	C=1,y=1/210
DT	criterion	gini'
GBDT	n_estimator	500
RF	n_estimator	500

We could see from Table 3 that the model proposed in this study is 0.0532 ~ 0.2323 higher than the baseline model in terms of accuracy, precision, F_1, and AUC, and 0.0422 higher than the most competitive CNN-RNN on average. Among the traditional machine learning algorithms, GBDT and RF have the best average performance on the five evaluation indexes, because GBDT and RF are classifiers based on the idea of decision tree integration, and the final result is determined by multiple trees. Better prediction. In the application model of deep learning, CNN-RNN has better performance than CNN, because the CNN-RNN model can not only obtain the locally relevant information between learning behaviors but also capture the time relationship between learning behaviors. To a great extent, it captures potentially important information and improves prediction accuracy. Compared with the deep learning models CNN-RNN and CNN, our CLNN model performs better in the prediction of sports innovation direction. This is mainly because the LSTM model can effectively solve long-standing problems. The simple recurrent neural network (RNN) can make the error transfer through the time and layer gate mechanism when the level is more constant, allowing the periodic network to learn multiple time steps, establish the long-term cause-effect relationship, and expand the prediction presentation of the model.

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Table 3. Performance of different models on different evaluation indicators

Method	Accuracy	Precision	Recall	F1	AUC
DT	0.8394	0.8506	0.9666	0.9049	0.6636
NB	0.8388	0.8800	0.9217	0.9004	0.7241
GBDT	0.8792	0.8887	0.9615	0.9237	0.7694
LR	0.8542	0.8583	0.9768	0.9137	0.6848
RF	0.8622	0.8727	0.9668	0.9172	0.7174
SVM	0.8620	0.8977	0.9422	0.9194	0.7689
CNN	0.8724	0.8717	0.9678	0.9224	0.7156
CNN-RNN	0.8562	0.8932	0.9528	0.9241	0.7601
CLNN	0.9363	0.8862	0.9624	0.9602	0.8870

6.2. INNOVATIVE DEVELOPMENT DIRECTION OF PE

Through the performance of different models on different evaluation indicators, it is found that CNN has better accuracy than other models, but its decision-making accuracy is low. Therefore, CNN-LSTM used in this study is the CLNN model. CNN-RNN is optimized to improve the accuracy of prediction and decision-making. This study selects five systems, including the teaching thought system, teaching process nature, and main goal system, teaching content system, teaching evaluation system, and sports text introduction system. According to the parameter comparison of model evaluation indicators in Section 6.1, CNN-LSTM is selected for prediction, and finally, three innovative development directions are determined: innovative teaching concept, innovative nature and main objectives of PE teaching process, and innovative teaching content system.

6.2.1. INNOVATION OF TEACHING IDEAS

Establish the educational thought of "seeking knowledge and innovation" and "health first" facing the future. The thought of "health first" emphasizes the content and methodology of the combination of PE and health education, closely combines the thought of "health first" with the construction of PE discipline and expands the benefits of maintaining and promoting health. In the field of lifelong PE, we should clarify the special role of PE in quality service education and give new directions to the teaching content. PE in PSS should comprehensively promote quality education, and establish the guiding ideology of PE teaching of "seeking knowledge and innovation" and "health first" so that students can master basic physical skills and form a good habit of adhering to physical exercise. physical exercise. PE reform has also changed our thinking set of taking PE as the educational carrier and education as the goal, re-understand the goal, function, content, means, and methods of PE, and building a new PE teaching system for PSS in the 21st century.

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6.2.2. ESSENCE OF PE TEACHING PROCESS AND INNOVATION OF MAIN OBJECTIVES

PE is not equal to physical exercise. PE is not fitness. PE alone cannot solve the problem of strengthening the physique. At present, we should combine imparting knowledge and skills with cultivating consciousness, skills, and habits, and pay attention to cultivating students' self-learning and self-habit consciousness, to make students make achievements in PE and lay the foundation of lifelong PE. At the same time, PE should recognize the transformation from "the main purpose of PE is to improve physique" to "health first", and establish the main objectives of PE in PSS: (1) make students have a basic understanding and positive attitude towards PE, understand the original intention of physical exercise, and establish a healthy concept of physical exercise; (2) Master knowledge and correct methods of fitness, and be able to exercise regularly by using a variety of basic sports skills and fitness methods; (3) Exercise independence and the habit of peaceful coexistence.

6.2.3. INNOVATION OF TEACHING CONTENT SYSTEM

Establish the educational content and curriculum system of PSS in China in the 21st century, and strive to form a diversified and comprehensive PE content system. It includes: (1) the combination of PE thought education and physical exercise education; (2) The innovation of primary and secondary school teachers in the teaching methods and contents of PE and the innovation of the PE system; (3) The innovative evaluation system of primary and secondary school sports is constantly changing with the development of the times.

7. CONCLUSION

This deep learning technology can extract the attributes or features of the data and abstract them into higher-level representations, and use them to predict the direction of PE innovation, which has long-term guiding significance. This research predicts the direction of PE teaching in PSS based on the LSTM model. First, it analyzes and identifies the innovation direction data set, and then uses the LSTM model to extract text context features from both forward and backward directions to predict the innovation direction and implementation path of PE. Finally, the basic direction of the innovation and development of PE is determined, the research is carried out and the following conclusions are drawn: (1) The LSTM model proposed in this study is 0.0532 higher than the baseline model in the four evaluation indicators of Accuracy, Precision, F1, and AUC. ~0.2323, indicating that the LSTM model has excellent prediction accuracy and effect; (2) The PE system is first of all completely dynamic, and the development direction of PE innovation is essentially the direction jointly selected by teachers, students, and schools. PE teaching innovation in PSS should be carried out from three aspects: teaching thought, teaching content, teaching goal, and essence.

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8. CONFLICT OF INTEREST

The authors declared that there is no conflict of interest.

REFERENCES

(1) Al-Hazzaa, H. M., Abahussain, N. A., Al-Sobayel, H. I., Qahwaji, D. M., & Musaiger, A. O. (2011). **Physical activity, sedentary behaviors and dietary habits among Saudi adolescents relative to age, gender and region**. *The International Journal of Behavioral Nutrition and Physical Activity*, 8. https://doi.org/10.1186/1479-5868-8-140.

(2) A, C. W., A, X. W., Jz, A., Liang, Z. A., Xiao, B. A., Xin, N. B.,... Ehd, A. (2021). **Uncertainty Estimation for Stereo Matching Based on Evidential Deep Learning**. https://doi.org/10.1016/j.patcog.2021.108498

(3) Aubert, S. (2020). **Active Healthy Kids Global Alliance "Global Matrix" Initiative: Process, Results, Impact and Evaluation**. https://doi.org/10.20381/ruor-24426.

(4) Anthamatten, P., Brink, L., Lampe, S., Greenwood, E., Kingston, B., & Nigg, C. (2011). **An assessment of schoolyard renovation strategies to encourage children's physical activity**. *International Journal of Behavioral Nutrition & Physical Activity*, 8(1), 27. https://doi.org/10.1186/1479-5868-8-27.

(5) Aguilar-Farias, N., Cortinez-O'Ryan, A., Sadarangani, K. P., Oetinger, A. V., & Cristi-Montero, C. (2016). **Results From Chile's 2016 Report Card on Physical Activity for Children and Youth**. *Journal of Physical Activity and Health*, 13(2), S117-S123. https://doi.org/10.1123/jpah.2016-0314.

(6) Russell, R. D. (1975). **Health Education**. *Project of Joint Committee on Health Problems in Education of the National Education Association and the American Medical Association. communication quarterly*.

(7) Miao, J., Wang, Z., Ning, X., Xiao, N., Cai, W., & Liu, R. (2022). **Practical and secure multifactor authentication protocol for autonomous vehicles in 5G**. *Software: Practice and Experience*. https://doi.org//10.1002/SPE.3087

(8) Ayers, W. (2018). **The Shifting Ground of Curriculum Thought and Everyday Practice: Thinking About Schools**.

(9) Ning, X., Gong, K., Li, W., & Zhang, L. (2021). **JWSAA: joint weak saliency and attention aware for person re-identification**. *Neurocomputing*, 453, 801-811. https://doi.org/10.1016/j.neucom.2020.05.106

(10) Heyneman, S. P., & Lee, B. (2016). **International organizations and the future of education assistance**. *International Journal of Educational Development*, 48(3), 9-22. https://doi.org/10.1016/j.ijedudev.2015.11.009.

(11) Hao, X., Zhang, G., & Ma, S. (2016). **Deep Learning**. *International Journal of Semantic Computing*, 10(03), 417-439. https://doi.org/10.1142/S1793351X16500045

(12) Qiu, L., Liu, Y., Hu, Q., & Liu, Y. (2018). **Student dropout prediction in massive open online courses by convolutional neural networks**. *Soft Computing*, 23. https://doi.org/10.1007/s00500-018-3581-3

(13) Yang, B., Lei, Y., Liu, J., & Li, W. (2016). **Social Collaborative Filtering by Trust**. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1-1. https://doi.org/10.1109/tpami.2016.2605085

(14) Naeen, H. M., & Jalali, M. (2019). **A decentralized trust-aware collaborative filtering recommender system based on weighted items for social tagging systems**. https://doi.org/10.48550/arXiv.1906.05143

(15) Yan, C., Pang, G., Bai, X., Liu, C., Xin, N., Gu, L., & Zhou, J. (2021). **Beyond triplet loss: person re-identification with fine-grained difference-aware pairwise loss**. I*EEE Transactions on Multimedia*. https://doi.org/10.1109/TMM.2021.3069562

(16) Khatun, A., Denman, S., Sridharan, S., & Fookes, C. (2020). **Joint identification-verification for person re-identification: A four stream deep learning approach with improved quartet loss function**. *Computer Vision and Image Understanding,* 197-198, 102989. https://doi.org/10.1016/j.cviu.2020.102989

(17) Cai, W., Zhai, B., Liu, Y., Liu, R., & Ning, X. (2021). **Quadratic polynomial guided fuzzy C-means and dual attention mechanism for medical image segmentation**. *Displays*, 70, 102106. https://doi.org/10.1016/j.displa.2021.102106

(18) Roch, S. (2011). **Phase Transition in Distance-Based Phylogeny Reconstruction**. *Computer Science*. https://doi.org/10.48550/arXiv.1108.5781

(19) RUMELHART, D. E., Hinton, G. E., & Williams, R. J. (1988). **Learning Internal Representations by Error Propagation: Readings in Cognitive ence**. https://doi.org/10.1007/978-0-387-39940-9_3246

(20) Theodoros K. Dikaliotis, Tracey Ho, Sidharth Jaggi, Svitlana Vyetrenko, Hongyi Yao, Michelle Effros, Jörg Kliewer, Elona Erez. (2010). **Multiple-access Network Information-flow and Correction Codes**. *IEEE Transactions on Information Theory*, 57(2), 1067-1079, https://doi.org/10.1109/TIT.2010.2095130.

(21) Ning, X., Duan, P., Li, W., & Zhang, S. (2020). **Real-time 3D face alignment using an encoder-decoder network with an efficient deconvolution layer**. *IEEE Signal Processing Letters*, 27, 1944-1948. https://doi.org/10.1109/LSP.2020.3032277

(22) Hidasi, B., Karatzoglou, A., Baltrunas, L., & Tikk, D. (2015). **Session-based Recommendations with Recurrent Neural Networks**. *Computer ence*. https://doi.org/10.48550/arXiv.1511.06939

(23) Haruki Okamura, Hiroko Tsutsui, Toshinori Komatsu, Masuo Yutsudo, Akira Hakura, Tadao Tanimoto, Kakuji Torigoe, Takanori Okura, Yoshiyuki Nukada, Kazuko Hattori, Kenji Akita, Motoshi Namba, Fujimi Tanabe, Kaori Konishi, Shigeharu Fukuda & Masashi Kurimoto. (1995). **Cloning of a new cytokine that induces IFN-gamma production by T cells**. *Nature*, 378(6552), 88. https://doi.org/10.1038/378088a0

(24) Shan, W. (2022). **Digital streaming media distribution and transmission process optimisation based on adaptive recurrent neural network. Connection Science**, 34(1), 1169-1180. https://doi.org/10.1080/09540091.2022.2052264

(25) Szegedy, C., Liu, W., Jia, Y., Sermanet, P., & Rabinovich, A. (2014). **Going Deeper with Convolutions**. *IEEE Computer Society*. https://doi.org/10.1109/CVPR.2015.7298594

(26) Ying, L., Nan, Z. Q., Ping, W. F., Kiang, C. T., Pang, L. K., Chang, Z. H.,... Nam, L. **Adaptive weights learning in CNN feature fusion for crime scene investigation image classification**. *Connection Science*. https://doi.org/10.1080/09540091.2021.1875987

(27) Graves, A. (2012). **Long Short-Term Memory**. *Springer Berlin Heidelberg*. https://doi.org/10.1007/978-3-642-24797-2_4

(28) Li, W., & Abiad, V. (1990). **Institutions, Institutional Change and Economic Performance**. *Social Science Electronic Publishing*, 18(1), 142-144. https://doi.org/10.1017/CBO9780511808678

(29) Pascanu, R., Mikolov, T., & Bengio, Y. (2012). **On the difficulty of training Recurrent Neural Networks**. *JMLR.org*. https://doi.org/10.1007/s12088-011-0245-8

(30) Le, Q. V., & Mikolov, T. (2014). **Distributed Representations of Sentences and Documents. arXiv e-prints**.

(31) Zhou, Y., Daamen, W., Vellinga, T., & Hoogendoorn, S. P. (2019). **Ship classification based on ship behavior clustering from AIS data**. *Ocean Engineering*, 175(MAR.1), 176-187. https://doi.org/10.1016/j.oceaneng.2019.02.005.

(32) Meng, W., Wei, Y., Liu, P., Zhu, Z., & Yin, H. (2019). **Aspect Based Sentiment Analysis With Feature Enhanced Attention CNN-BiLSTM**. *IEEE Access*, 7, 167240-167249. https://doi.org/10.1109/ACCESS.2019.2952888.

(33) Yu, S., Liu, D., Zhu, W., Zhang, Y., & Zhao, S. (2020). **Attention-based LSTM, GRU and CNN for short text classification**. *Journal of Intelligent and Fuzzy Systems*, 39(1), 1-8. https://doi.org/10.3233/JIFS-191171.

(34) Ma, J., Jia, C., Yang, X., Cheng, X., & Zhang, C. (2020). **A Data-Driven Approach for Collision Risk Early Warning in Vessel Encounter Situations Using Attention-BiLSTM**. *IEEE Access*, 8, 188771-188783. https://doi.org/10.1109/ACCESS.2020.3031722.

(35) Ma, X., & Hovy, E. (2016). **End-to-end Sequence Labeling via Bi-directional LSTM-CNNs-CRF.** *Paper presented at the Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, 1*. https://doi.org/10.13140/RG.2.1.2182.5685.

(36) Chen, G., Lin, H., Hu, H., Yan, Y., Wan, Y., Xiao, T., & Peng, Y. (2022). **Research on the Measurement of Ship's Tank Capacity Based on the Monte Carlo Method**. *Chemistry and Technology of Fuels and Oils*, 58(1), 232-236. https://doi.org/10.1007/s10553-022-01371-x.

(37) Sheng, K., Liu, Z., Zhou, D., He, A., & Feng, C. (2017). **Research on Ship Classification Based on Trajectory Features**. *Journal of Navigation*, 1-17. https://doi.org/10.1017/S0373463317000546.

(38) Dewani, A., Memon, M. A., y Bhatti, S. (2021). **Development of computational linguistic resources for automated detection of textual cyberbullying threats in Roman Urdu language**. *3C TIC. Cuadernos de desarrollo aplicados a las TIC*, 10(2), 101-121. https://doi.org/10.17993/3ctic.2021.102.101-121

(39) Hong Chen,Xuefei Peng & Caiyun Chen. (2022). **Corporate social responsibility fulfilment, product-market competition and debt risk: Evidence from China**. *Applied Mathematics and Nonlinear Sciences, 7(2), 757-772*. https://doi.org/10.2478/AMNS.2021.2.00163.