DOI: 10.53469/jtpes.2024.04(01).14

Applying Machine Learning Algorithm to Optimize Personalized Education Recommendation System

Wangmei Chen[1,*], Zepeng Shen[2], Yiming Pan[3], Kai Tan[4], Cankun Wang[5]

[1] Computer Science(Software Technology), The National University of Malaysia,Malaysia
[2]Network Engineering, Shaanxi University of Technology, Shaanxi 723001, China
[3]Computer Science, Individual Contributor, Austin, TX, USA
[4]Electrical & Computer Engineering ,University of Washington, Seattle, WA, USA
[5]Biomedical Informatics, The Ohio State University, Columbus,USA
**Correspondence Author, chancandy898@gmail.com*

Abstract: ***In recent years, with the continuous progress and development of science and technology, especially the continuous development of artificial intelligence, machine algorithm and other technologies, the education system has also begun to carry out more personalized content from traditional functions. Traditional education systems often adopt a one-size-fits-all approach to teaching that does not take into account the unique needs and learning styles of each student. An education system personalized and optimized by machine learning algorithms can provide customized learning materials and recommendations based on each student's learning history, interests and abilities to improve learning outcomes, and machine learning algorithms can provide real-time feedback on student performance and adjust learning plans based on feedback. This makes the learning process more dynamic and personalized. It can therefore be applied to all types of education, including language learning, mathematics, science, etc. However, improving the efficiency of machine learning algorithms depends more on the improvement of numerical optimization algorithms, so it is necessary to summarize the optimization algorithms in large-scale machine learning. This paper tries to make a detailed overview of the existing machine learning algorithms in optimizing personalized education recommendation system, and introduces the algorithm optimization process.***

Keywords: Machine learning; Optimization algorithm; Intelligent recommendation; Education system Logistics Automation.

1. INTRODUCTION

The smart revolution is sweeping the world. At the beginning of 2017, the mysterious chess player Master won the New Year's Go war between many world-class players from China, Japan and South Korea came to an end, and then Master was confirmed to be the AlphaGo that defeated Lee Sedol in March 2016. This is an absolute "historical event" in the history of artificial Intelligence. AI is also impacting People's Daily lives.

The educational reform brought by new technology is in the ascendant, and artificial intelligence and smart education lead the innovation of education and teaching, which has become an inevitable trend in the development of education informatization[1-3]. With the rise of big data in education, how to analyze a large amount of data to support accurate prediction is a new topic facing the era of artificial intelligence. Machine learning, as an important branch of artificial intelligence, can meet the needs of educational big data analysis and prediction. Therefore, through the analysis of the object, process, specific methods and stakeholders of machine learning, the appropriateness of machine learning and intelligent education is discussed. By combing and summarizing the results of foreign case studies on the application of machine learning in education based on real data in recent years, it is found that the current application of machine learning in education mainly focuses on six aspects, such as student modeling, student behavior modeling, predicting learning behavior, warning of dropout risk, learning support and evaluation, and resource recommendation. From the three levels of cross-border, technology and teaching, the framework based on intelligent education puts forward relevant suggestions for the educational application and innovation of machine learning.

2. RELATED WORK

Although the current artificial intelligence has gradually developed, it is still in the initial stage in the integration process with education and teaching practice, and has not yet developed to a mature period. In view of the cases and research results of the combination of education system and artificial intelligence at home and abroad in recent years, the research on technology development and application has reached a high degree of attention. Among them, the four major applications of artificial intelligence in education, namely "intelligent learning guide system, automated assessment system, educational games and educational robots", have attracted particular attention from scholars[3-4]. It is also the main direction used by teachers in the field of basic education. Among them, the intelligent learning guide system is the most popular intelligent product nowadays, which can customize personalized learning programs according to the learning style, personality characteristics, knowledge structure and emotional state of learners, and meet the requirements of "individualized teaching".

2.1 Intelligent Recommendation System

Intelligent recommendation system is a personalized recommendation service based on user historical data and machine learning algorithm. With the popularization of the Internet and the accumulation of massive data, intelligent recommendation system has attracted more and more attention and gradually become one of the hot research directions in the field of artificial intelligence[5].

At present, the research of intelligent recommendation system mainly includes four aspects: recommendation algorithm, user behavior modeling recommendation effect evaluation and recommendation system application. Recommendation algorithm is the core of intelligent recommendation system. Researchers mainly start from collaborative filtering, deep learning, image recommendation, sequence recommendation and other aspects, and constantly improve and optimize the algorithm to improve the accuracy and efficiency of recommendation. And the application scenarios of intelligent recommendation systems are also constantly expanding and deepening, such as e-commerce, social networks, art and other fields. However, there are not many applications of intelligent recommendation system in the field of education at present, especially the intelligent recommendation system of application tools has not been developed and perfected[6-8]. Combined with the above analysis of the research status of artificial intelligence in the field of basic education, this study is mainly to design and develop a kind of recommendation system of intelligent application tools to solve the current problems. And gradually update and improve the relevant functions in the later stage.

2.2 Machine Learning and Intelligent Recommendation

The intelligent recommendation system based on machine learning is mainly composed of data preprocessing feature engineering, collaborative filtering algorithm and recommendation system management module. The data preprocessing part is mainly responsible for cleaning the original data and extracting features to get the feature vector; In feature engineering, the user's behavior characteristics are extracted by analyzing the user's historical behavior.In practical application, The core problem of recommendation system is to recommend products with high similarity of interest to users. At this point, a function f(x) is needed to calculate the similarity between the candidate product and the user, and recommend the product with high similarity to the user[9]. In order to predict the function f(x), the historical data can be used mainly: the historical behavior data of the user, the information of other users related to the user, the similarity between the goods, and the description of the text.
Suppose that set C represents all users and set S represents all items that need to be recommended. Function f represents the utility function of the availability between item x and user c:

$$f: C \times S \rightarrow R \tag{1}$$

Where R is a total sorted set, for every user $c \in C$, want to select from the set of goods, that is, $s \in S$, in order to maximize the value of the application function f.

2.3 Collaborative Filtering

Collaborative filtering is a classic and commonly used recommendation algorithm, which is completely dependent on the behavioral relationship between users and items. From its name "collaborative filtering", we can also peek at the principle behind it, that is, "cooperate with everyone's feedback, evaluation and opinions, filter massive information together, and screen out the information that users may be interested in[10]." Collaborative filtering algorithms are mainly divided into two categories:

1) Item-based collaborative filtering algorithm: recommend items to the user that are similar to the items he previously liked.
2) User-based collaborative filtering algorithm: recommend items to users who are similar to their interests.

For example, the whole process of a certain e-commerce recommendation system from obtaining the original data to generating the final recommendation score can be summarized into 6 steps, as shown in the following figure:

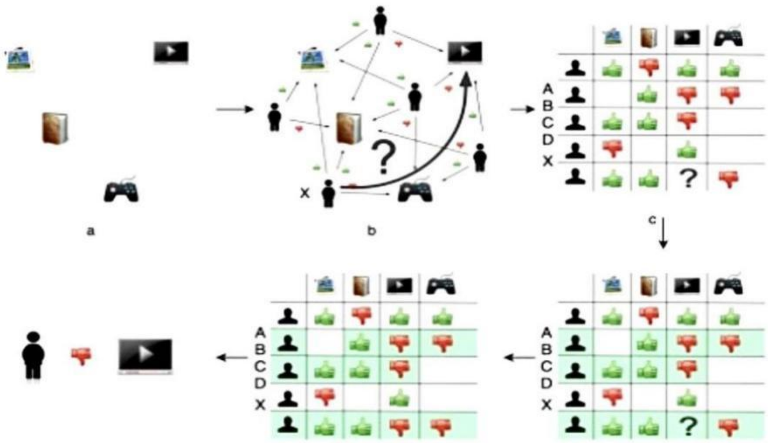

Figure 1: Cooperative filtering intelligent recommendation principle

In the above e-commerce website recommendation system, the use of co-occurrence matrix can effectively predict the user's preference for goods. This process first converts the user's positive (like) and negative (step) comments into a number in the co-occurrence matrix, which is 1 and -1, respectively, and 0 if there is no data. Then, by analyzing the similarity of evaluation among users, the system finds out the users whose interests are closest to the target users.

Taking user X and TV set as an example, by comparing the similarity of user X's evaluation mode with other users, the system selects user B and user C whose interests are most similar to user X's. Since these two similar users rated the TV negatively, the recommendation system predicted that user X's attitude toward the TV would also be negative. Therefore, the intelligent recommendation system based on the collaborative filtering algorithm decides not to recommend the TV set to user X in order to optimize the user experience and recommendation effect[11-15].

To sum up, collaborative filtering algorithms play a key role in the intelligent recommendation of education systems, with the advantage of providing personalized learning content and resource recommendations by analyzing and matching the behavior and preferences of users (such as students and teachers). The algorithm uses the mutual evaluation and feedback among users to identify similar user groups, and then recommends those educational resources or courses favored by similar users. Based on this principle, this paper analyzes the application status of collaborative filtering in modern innovative education through the collaborative filtering intelligent recommendation optimization combined with machine learning. And by providing a customized learning experience, it helps to improve learning efficiency and motivation, thereby optimizing the overall educational experience.

3. METHODOLOGY

Genetic algorithm and K-means clustering algorithm are used to optimize the collaborative filtering algorithm, and a personalized recommendation model of collaborative filtering is constructed[16][17]. The questionnaire survey shows that 98% of the students think the personalized course resource recommendation system is effective, and only 2% think it is ineffective. The above results indicate that the collaborative filtering personalized recommendation model can well recommend course resources for students and improve their learning interest and efficiency.

3.1 Model Architecture

In this experiment, the personalized recommendation model of association rules in the teaching intelligent system requires a large amount of data to be analyzed, and the generation of association rules is difficult and the accuracy is low, so it cannot be truly personalized recommendation[18-21]. Therefore, it is necessary to build a recommendation system according to the collaborative filtering personalized recommendation model to achieve the purpose of personalized recommendation of course resources for students. Therefore, in the process of establishing the model, it is first necessary to give different score values to the course resources according to the degree of interest of the student users, and the score values are expressed by integer numbers 0 ~ 5. The higher the score, the greater the interest of student users in this course resource, and the greater the expectation of student users for similar courses of this course; The lower the score, the less the student user's interest in the course, and the lower the student user's expectation; When the score value is 0, it means that the student user has not scored the course resource. The student-course grading matrix is shown as the formula:

$$R(m,n)=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & & \end{bmatrix}。 \tag{2}$$

In the student-course scoring matrix of the above formula, m represents the number of users, n represents the number of courses, and Rmn represents the scoring value of the m student user for the n courses. To facilitate data collection and calculation, a binary variable (0,1) is used to express the score attribute in the matrix. 0 in the binary variable means that the student user does not like the course[22], and 1 means that the student user likes the course. The set of neighbors of the target student user can be found according to the student-course rating matrix. The similarity between the student user and the neighbor set is the key to the accuracy of the recommended course, so the similarity between the users needs to be calculated

3.2 Optimization of collaborative Filtering Recommendation Model by GA-K-means Algorithm

Collaborative filtering recommendation model can realize personalized course recommendation for students, but the model has the problems of cold start and data sparsity. The cold start problem is divided into new student user problem and new course resource problem. The problem of new student user is that a newly registered student has not evaluated and scored course resources, nor has corresponding browsing history. The collaborative filtering recommendation model cannot predict the interested course resources of this student user. It will not be possible to recommend course resources that students may be interested in.

$$\hat{r}_{ui}=\frac{\sum_{v\in N_i^k(u)} sim(u,v)\cdot r_{vi}}{\sum_{v\in N_i^k(u)} sim(u,v)} \tag{3}$$

K-means clustering algorithm (K-means clustering algorithm) is a common partitioning clustering method. Its principle is to take a random K objects in a data set as the clustering center, and other data objects in the data set will be determined according to the distance from the K data objects[23]. Automatically grouped into a class with the nearest cluster center; These classes are then iterated so that the data objects are moved in the class and the average value is calculated based on the update of the data in the class, and the data objects are redistributed, thus improving the class until the maximum number of iterations is reached or no new clusters are generated.

In the personalized recommendation process, the User-Embedding_K matrix and Embedding_k-item matrix (Em bedding K is a hyperparameter, set by yourself), the multiplication of the two matrices can just get the User-Item matrix.

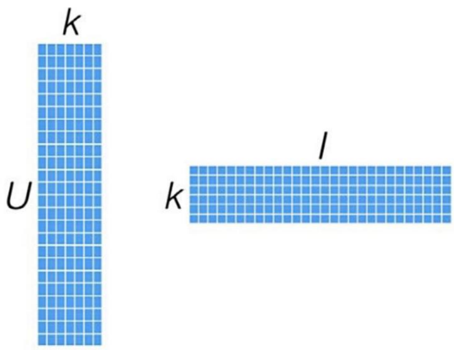

Figure 2: User-Embedding，Embedding-Item

3.3 Performance analysis of Collaborative Filtering Personalized Recommendation Model

Recommendation accuracy is an important index to evaluate the performance of personalized recommendation model. Only when the recommendation accuracy is high enough, the personalized recommendation model can truly achieve the purpose of personalized recommendation of course resources for students. The smaller the MAE difference, the higher the prediction accuracy of the model, and the better the personalized recommendation effect of the model. The unoptimized collaborative filtering recommendation model and the collaborative filtering recommendation model optimized by genetic K-means algorithm were constructed respectively, and tested with the same student data. The nearest neighbors were taken from 5 to 30, and the neighbor number interval was 5. The test results were shown in the figure.

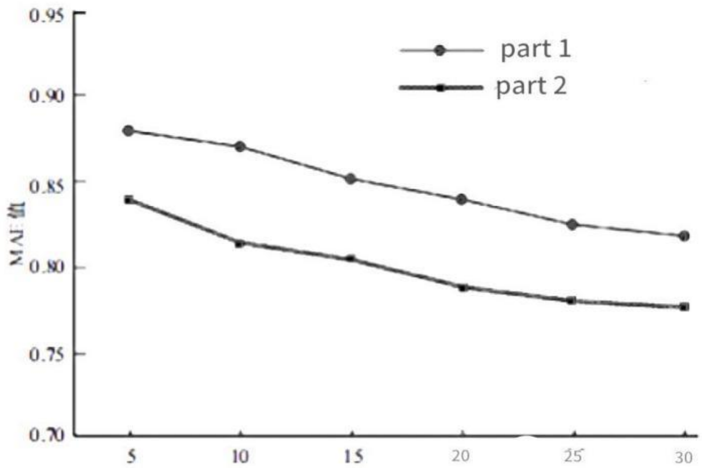

Figure 3: Accuracy analysis results

As can be seen from the figure, the MAE value of both models gradually decreases with the increase of the number of nearest neighbors, indicating that the more the number of nearest neighbors, the closer the predicted student score of the model is to that of the real student score, and the better the recommendation effect of the model.

3.4 Realize the Effect Pattern Example

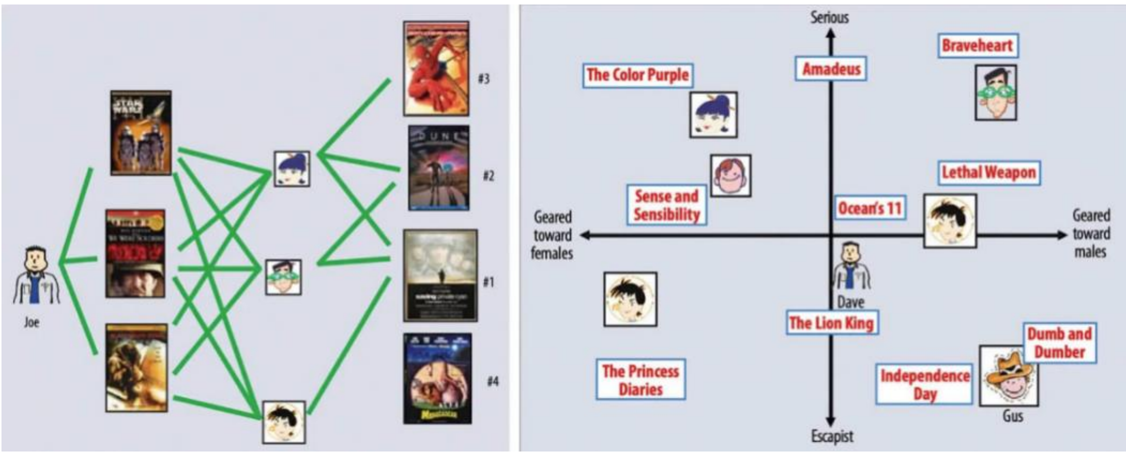

Figure 3: Collaborative process decomposition renderings

As shown in the figure on the left, the collaborative filtering algorithm finds personalized courses that users are likely to like in an intuitive way. It uses the user's history courses as a basis to find similar users who have watched the same courses as the target user Joe, and then finds other videos that these similar users like to watch most and recommends them to the target user.

Collaborative filtering is a recommendation algorithm that filters a large amount of information and screens out the information of interest to users by cooperating with everyone's feedback, evaluation and opinions[23-25]. Its implementation process mainly consists of three steps: first, create a co-occurrence matrix according to the user behavior history, then find similar users according to the co-occurrence matrix, and then recommend the personalized part that the target users like according to the content that similar users like.

However, the ability of collaborative filtering to deal with sparse matrix is relatively poor, so a matrix decomposition algorithm is proposed, which generates user vector matrix and item vector matrix by decomposing co-occurrence matrix, and then obtains user hidden vector and item hidden vector. You can treat the final result entirely as a user Embedding and item Embedding.

4. CONCLUSION

The experimental results show that using genetic algorithm and K-means clustering algorithm to optimize the collaborative filtering recommendation model can significantly improve the personalization and accuracy of course resource recommendation in the education system. Through the collaborative filtering personalized recommendation model, 98% of students believe that the personalized course resource recommendation system is effective, which not only improves students' learning interest and efficiency, but also reflects the effectiveness of the model in predicting students' preferences and providing personalized learning resources. In addition, the model shows strong adaptability and solving ability to deal with the cold start problem of new users and new course resources and the problem of data sparsity, which further strengthens the robustness and practicability of the recommendation system.

In the future, there is great potential for the application of machine learning in educational recommendation systems. With the continuous progress of algorithms and the enhancement of data processing capabilities, personalized recommendation systems will understand and predict students' needs and preferences more accurately, thus providing more suitable and efficient learning resources. This not only optimizes the learning path, but also motivates students to learn, providing each student with a unique, customized learning experience. At the same time, with the development of artificial intelligence technology, these systems are expected to become more intelligent and able to respond to students' learning progress and feedback in real time, further driving the education industry to a more efficient and personalized direction.

ACKNOWLEDGEMENT

The research results of this paper have been inspired and helped by many aspects. in particular, I would like to express my heartfelt thanks to Kai Tan's "Imaging and parameter estimating for fast moving targets in airborne SAR" for his profound insight and theoretical support. This paper plays an indispensable role in this research, and provides an important reference and guidance for the theoretical basis and practical direction of the application of intelligent recommendation algorithm in education system optimization. Kai Tan's research not only enriches the academic depth of this paper, but also points out the direction for the progress of this research. Here, I would like to express my sincere thanks to Kai Tan for his outstanding contribution and selfless sharing.

REFERENCES

[1] Bao, W., Che, H., & Zhang, J. (2020, December). Will_Go at SemEval-2020 Task 3: An Accurate Model for Predicting the (Graded) Effect of Context in Word Similarity Based on BERT. In A. Herbelot, X. Zhu, A. Palmer, N. Schneider, J. May, & E. Shutova (Eds.), Proceedings of the Fourteenth Workshop on Semantic Evaluation (pp. 301–306). doi:10.18653/v1/2020.semeval-1.

[2] Du, Shuqian, et al. “Application of HPV-16 in Liquid-Based Thin Layer Cytology of Host Genetic Lesions Based on AI Diagnostic Technology Presentation of Liquid”. Journal of Theory and Practice of Engineering Science, vol. 3, no. 12, Dec. 2023, pp. 1-6, doi:10.53469/jtpes.2023.03(12).01.

[3] Pan, Yiming, et al. “Application of Three-Dimensional Coding Network in Screening and Diagnosis of Cervical Precancerous Lesions”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 61-64, https://doi.org/10.54097/mi3VM0yB.

[4] Song, Tianbo, et al. “Development of Machine Learning and Artificial Intelligence in Toxic Pathology”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 137-41, https://doi.org/10.54097/Be1ExjZa.

[5] Qian, Jili, et al. “Analysis and Diagnosis of Hemolytic Specimens by AU5800 Biochemical Analyzer Combined With AI Technology”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 100-3, https://doi.org/10.54097/qoseeQ5N.
[6] Zheng, Jiajian, et al. “The Credit Card Anti-Fraud Detection Model in the Context of Dynamic Integration Selection Algorithm”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 119-22, https://doi.org/10.54097/a5jafgdv.
[7] Zhao, Xinyu, et al. “Effective Combination of 3D-DenseNet’s Artificial Intelligence Technology and Gallbladder Cancer Diagnosis Model”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 81-84, https://doi.org/10.54097/iMKyFavE.
[8] Li, Shulin, et al. “Application Analysis of AI Technology Combined With Spiral CT Scanning in Early Lung Cancer Screening”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 52-55, https://doi.org/10.54097/LAwfJzEA.
[9] Liu, Bo, et al. “Detection of Esophageal Cancer Lesions Based on CBAM Faster R-CNN”. Journal of Theory and Practice of Engineering Science, vol. 3, no. 12, Dec. 2023, pp. 36-42, doi:10.53469/jtpes.2023.03(12).06.
[10] Yu, Liqiang, et al. “Research on Machine Learning With Algorithms and Development”. Journal of Theory and Practice of Engineering Science, vol. 3, no. 12, Dec. 2023, pp. 7-14, doi:10.53469/jtpes.2023.03(12).02.
[11] Xin, Q., He, Y., Pan, Y., Wang, Y., & Du, S.. The implementation of an AI-driven advertising push system based on a NLP algorithm. International Journal of Computer Science and Information Technology, 2023,1(1): 30-37.0
[12] Implementation of an AI-based MRD Evaluation and Prediction Model for Multiple Myeloma. Frontiers in Computing and Intelligent Systems, 2024,6(3): 127-131. https://doi.org/10.54097/zJ4MnbWW.
[13] Zhang, Q., Cai, G., Cai, M., Qian, J., & Song, T.. Deep Learning Model Aids Breast Cancer Detection. Frontiers in Computing and Intelligent Systems, 2023,6(1): 99-102.3
[14] Xu, J., Pan, L., Zeng, Q., Sun, W., & Wan, W.. Based on TPUGRAPHS Predicting Model Runtimes Using Graph Neural Networks. Frontiers in Computing and Intelligent Systems,2023, 6(1): 66-69.7
[15] Wan,Weixiang, et al. "Development and Evaluation of Intelligent Medical Decision Support Systems." Academic Journal of Science and Technology ,2023,8(2): 22-25.
[16] Tian, M., Shen, Z., Wu, X., Wei, K., & Liu, Y.. The Application of Artificial Intelligence in Medical Diagnostics: A New Frontier. Academic Journal of Science and Technology, 2023,8(2): 57-61.7
[17] Shen, Z., Wei, K., Zang, H., Li, L., & Wang, G.. The Application of Artificial Intelligence to The Bayesian Model Algorithm for Combining Genome Data. Academic Journal of Science and Technology,2023, 8(3): 132-135.2
[18] Zheng He, et al. “The Importance of AI Algorithm Combined With Tunable LCST Smart Polymers in Biomedical Applications”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 92-95, https://doi.org/10.54097/d30EoLHw.
[19] Prediction of Atmospheric Carbon Dioxide Radiative Transfer Model based on Machine Learning. Frontiers in Computing and Intelligent Systems, 2024,6(3): 132-136. https://doi.org/10.54097/ObMPjw5n
[20] Liu, Yuxiang, et al. “Grasp and Inspection of Mechanical Parts Based on Visual Image Recognition Technology”. Journal of Theory and Practice of Engineering Science, vol. 3, no. 12, Dec. 2023, pp. 22-28, doi:10.53469/jtpes.2023.03(12).04.
[21] Xinyu Zhao, et al. “Effective Combination of 3D-DenseNet’s Artificial Intelligence Technology and Gallbladder Cancer Diagnosis Model”. Frontiers in Computing and Intelligent Systems, vol. 6, no. 3, Jan. 2024, pp. 81-84, https://doi.org/10.54097/iMKyFavE.
[22] Liu, B.. Based on intelligent advertising recommendation and abnormal advertising monitoring system in the field of machine learning. International Journal of Computer Science and Information Technology, 2023,1(1): 17-23.
[23] Pan, Linying, et al. “Research Progress of Diabetic Disease Prediction Model in Deep Learning”. Journal of Theory and Practice of Engineering Science, vol. 3, no. 12, Dec. 2023, pp. 15-21, doi:10.53469/jtpes.2023.03(12).03.
[24] K. Tan and W. Li, "Imaging and Parameter Estimating for Fast Moving Targets in Airborne SAR," in IEEE Transactions on Computational Imaging, vol. 3, no. 1, pp. 126-140, March 2017, doi: 10.1109/TCI.2016.2634421.
[25] Zhou, H., Lou, Y., Xiong, J., Wang, Y., & Liu, Y.. Improvement of Deep Learning Model for Gastrointestinal Tract Segmentation Surgery. Frontiers in Computing and Intelligent Systems, 2023,6(1): 103-106.
[26] Liu, S., Wu, K., Jiang, C., Huang, B., & Ma, D. (2023). Financial Time-Series Forecasting: Towards Synergizing Performance And Interpretability Within a Hybrid Machine Learning Approach. arXiv preprint arXiv:2401.00534.

[27] Su, J., Nair, S., & Popokh, L. (2023, February). EdgeGym: A Reinforcement Learning Environment for Constraint-Aware NFV Resource Allocation. 2023 IEEE 2nd International Conference on AI in Cybersecurity (ICAIC), 1–7. doi:10.1109/ICAIC57335.2023.10044182
[28] Su, J., Nair, S., & Popokh, L. (2022, November). Optimal Resource Allocation in SDN/NFV-Enabled Networks via Deep Reinforcement Learning. 2022 IEEE Ninth International Conference on Communications and Networking (ComNet), 1–7. doi:10.1109/ComNet55492.2022.9998475
[29] Popokh, L., Su, J., Nair, S., & Olinick, E. (2021, September). IllumiCore: Optimization Modeling and Implementation for Efficient VNF Placement. 2021 International Conference on Software, Telecommunications and Computer Networks (SoftCOM), 1–7. doi:10.23919/SoftCOM52868.2021.9559076.