

# Enhancing Computer Digital Signal Processing through the Utilization of RNN Sequence Algorithms

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## ABSTRACT

With the increase in computing power and the availability of large amounts of data, deep learning techniques, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have become important tools for processing complex signals. These methods show excellent performance in speech recognition, image processing, natural language processing and so on. In this paper, we explore the application of recurrent neural network (RNN) sequence algorithms in the field of computer digital signal processing, highlighting current artificial intelligence techniques and their capabilities in solving complex signal processing problems. First, the paper reviews the basic principles and development of deep learning and RNN sequence algorithms, highlighting the advances these advanced technologies have made in simulating the way the human brain processes information. The practical application and effect of RNN sequence algorithm in computer digital signal processing are demonstrated through experimental data. By comparing with traditional algorithms, we demonstrate the efficiency and accuracy of RNN in processing complex signals, such as speech recognition in noisy environments and real-time video data processing. The experimental data not only demonstrate the effectiveness of RNNs in this field, but also highlight the unique advantages of deep learning methods when dealing with large and high-dimensional data. Through these empirical studies, this paper aims to provide researchers and engineers with an in-depth understanding of the potential of RNNs in digital signal processing applications, and looks forward to the future development direction of artificial intelligence technology in this field.

## KEYWORDS

Deep learning; RNN sequence algorithm; Signal processing; Computer vision.

## 1. INTRODUCTION

The development status of deep learning in the field of computer digital signal processing shows significant growth and wide application. With the increase in computing power and the availability of large amounts of data, deep learning techniques, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have become important tools for processing complex signals. These methods show excellent performance in speech recognition, image processing, natural language processing and so on[1]. At the same time, deep learning research continues to deepen, including the innovation of network architecture, optimization algorithm improvement, and the

exploration of network interpretation, which has promoted the continuous development and technological breakthroughs in the field.

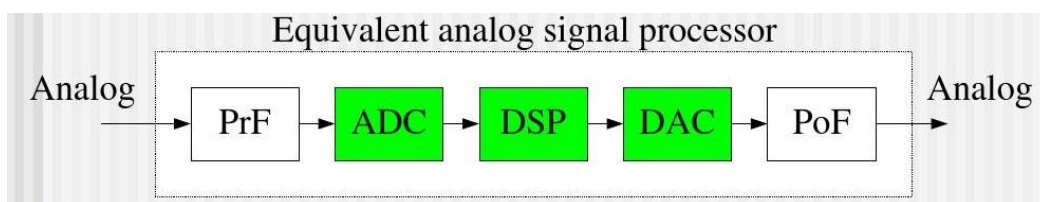
Compared with traditional digital signal processing algorithms, deep learning methods perform better in dealing with high dimensional and nonlinear problems. Traditional algorithms often rely on hand-extracted features and predefined processing rules, which may not be efficient or accurate enough when processing signals with complex or unknown patterns[2-3]. In contrast, deep learning is able to extract complex features and patterns from large amounts of data through automatic feature learning and end-to-end learning patterns. This gives deep learning greater accuracy and flexibility when processing complex real-world signals, such as recognizing speech from noisy environments or detecting disease from medical images. However, deep learning models often require large amounts of data and computational resources, and their inner workings are relatively opaque, which are challenges to consider in their applications.

## 2. RELATED WORK

### 2.1. Digital signal processing

Digital signal processing (DSP) refers to the process of using digital methods and techniques to analyze, modify, or extract information. It involves converting analog signals into digital form (by sampling and quantization) and then using algorithms to process these digital signals. Digital signal processing has a wide range of applications covering many fields, including communications (such as data and voice transmission), image processing (such as applications in medical imaging and photography), audio processing, radar systems, satellite navigation, biological signal processing, etc. In these areas, DSP is used to improve the quality of signals, filter noise, compress data, and extract valuable information.

Digital signal processing power spectrum estimation methods are divided into classical power spectrum estimation and modern power spectrum estimation. The modern power spectrum estimation is represented by the parametric power spectrum estimation. The parametric power spectrum model is as follows:



**Figure 1.** DSP digital signal processing model

$$u(n) \longrightarrow H(z) \longrightarrow x(n)$$

The basic idea of the parameter model is:

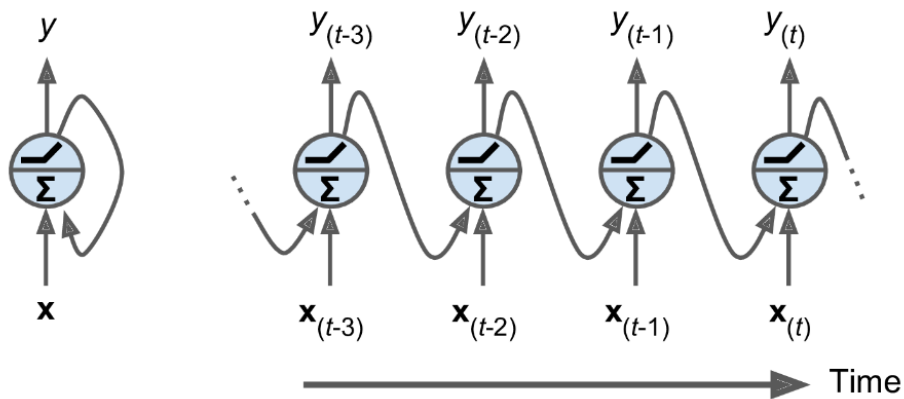
The parametric model assumes that the study process is an input sequence  $u(n)$  that excites the output of a linear system  $H(z)$ . - Estimate the parameters of  $H(z)$  from the output  $x(n)$  of the assumed parameter model or its autocorrelation function - Estimate the power spectrum of  $x(n)$  from the parameters of  $H(z)$

Therefore, there are two steps to solve the power spectrum of the parametric model[4]:

- (1) Parameter estimation of  $H(z)$  model.
- (2) The power spectrum was obtained according to the model parameters.

## 2.2. Recurrent neural network (RNN) sequence

Recurrent neural network (RNN) sequence algorithm is closely related to digital signal processing, because RNN is particularly suitable for processing sequence data, which is one of the core requirements of digital signal processing. In digital signal processing, data often comes in the form of time series, such as audio waveforms or video frame sequences, and RNNs are able to process this data efficiently because they are able to remember the output of the previous state and use this information for processing of the current input[5-6]. This makes RNNs excellent for digital signal processing tasks such as speech recognition, predicting future signal trends, and natural language processing. By taking advantage of these features of RNNs, digital signal processing can analyze and predict data patterns more accurately, providing greater efficiency and functionality in various application fields.



**Figure 2.** A circulating neuron (left) unfolds over time (right)

Where activation flows in only one direction, from the input layer to the output layer (some exceptions are discussed in Appendix E). A recurrent neural network looks a lot like a feedforward neural network, except that it also has backward-pointing connections[7]. Let's look at the simplest RNN, where one neuron receives input, produces output, and sends output back to itself, as shown in Figure 15-1 (left). At each time step  $t$  (also called a frame), this circulating neuron receives the input  $x(t)$  as well as its own output from the previous time step,  $y(t-1)$ . Since there is no previous output in the first time step, it is generally set to 0. We can represent this tiny network against a timeline, as shown in Figure 2. This is called a time-spread network (it is the same circulating neurons represented once per time step).

## 2.3. Digital signal processing sequence classification

(1) discrete time signal (time series), specifically, the digital signal processing process is: analog signal input - analog signal conditioning - sampling - storage - processing/calculation - output sampling results; The advantages of doing so are: 1. Flexible, each link can process the signal; 2. Compared with direct storage of analog signals, the cost of digital signal processing is lower; The steps required to move from analog to digital: 1. sampling (sampling) 2. quantization (sampling) : to change a signal from a continuous function of time to a discrete function of  $n$  (Integer), also called a sequence, which can be used:

$$\{x(n)\}, n \in \mathbb{Z} \quad (1)$$

Strictly speaking,  $x[n]$  represents the specific  $N$ th term in the sequence, but for ease of expression, we also use  $x(n)/x[n]$  to represent the entire sequence.

(2) Discrete convolution formula:

You can see that  $tmp(0)$  is the multiplication of  $g(0)$  with each value in the first sequence.

tmp(1) is the multiplication of g(1) and the first sequence by one unit to the right of each of its elements.

tmp(2) is the multiplication of g(2) and the first sequence by two units to the right after each of its elements.

The end result is to add them all up, and the length of the final sequence is the sum of the lengths of the two sequences minus 1

$$h(n) = f(n) * g(n) = \sum_{k=0}^n f(n-k)g(k) \quad (2)$$

From the extrapolated result, we can know that the representation of the function is actually the convolution of the original function and an impulse function. As can be seen from the previous discrete convolution, since the second function only has a value at one place, the convolution only computes the value at one place. So you can see a signal convolved with a shock signal, and you get itself[8]. If a signal is convolved with a shift of an impulse function, then according to the analogy of discrete convolution, the starting point of the function needs to be moved to the starting point of the second sequence, and then multiplied and added, corresponding to continuous functions, is the process of integrating. So the end result is a shifted signal relative to the original signal.

## 2.4. Technical characteristics of digital signal processing

This technology is characterized by its ability to efficiently process and analyze signals while maintaining high accuracy and speed. With the continuous progress of computing technology, especially the integration of artificial intelligence (AI) technology, the application field of digital signal processing has been greatly expanded and deepened. At present, the combination of digital signal processing and artificial intelligence is mainly reflected in the application of machine learning algorithms, so that signal processing is not limited to traditional filtering and noise cancellation, but also includes more complex tasks such as feature recognition and pattern analysis. For example, in the medical field, digital signal processing technology combined with artificial intelligence can be used to analyze biomedical signals such as electrocardiograms (ECG) and electroencephalograms (EEG) [9] to diagnose and monitor diseases. In self-driving cars, it can process signals from sensors such as radar and cameras to enable environmental perception and decision making. These applications show the great potential and application space of digital signal processing combined with artificial intelligence.

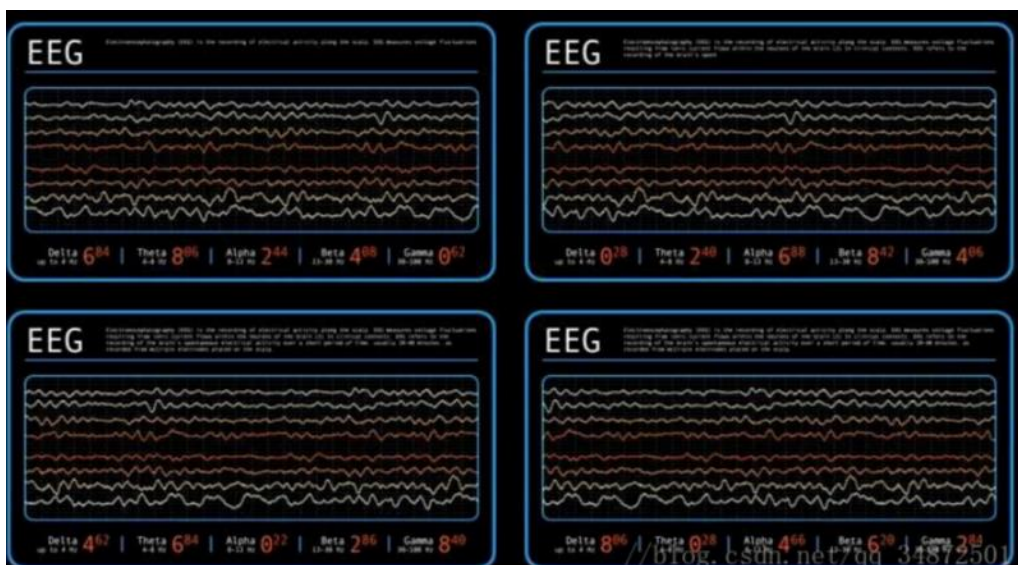


Figure 3: EEG digital signal processing diagram

The differences in the EEG system in Figure 3 above are usually due to the number of electrodes, the quality of digitization, the quality of the amplifier, and the number of snapshots the device can take per second (which is a sampling rate in Hz). Electroencephalography (EEG) is a physiological method for recording the electrical activity generated by the brain through electrodes placed on the surface of the scalp. For faster application, electrodes are mounted in an elastic cap similar to a shower cap to ensure that data can be collected from the same scalp location for all subjects[10]. Therefore, in the processing of EEG digital signals, algorithms will be applied through deep learning and RNN sequences, and EEG usually has a high sampling rate, which is one of the fastest applied imaging technologies.

In many cases, ambulate EEG is set up in much the same way as a regular EEG experiment - participants place an EEG headset on their head, electrodes make contact with their skin using some kind of EEG glue, conductivity is tested, and the entire setup is checked in connected software. Although ambulatory EEG has many similarities to regular EEG, there are also differences. Mobile EEG devices need to be provided with devices that are easy to move and portable. Any participant who wears an electroencephalogram (EEG) headset for an extended period of time will need to be able to move around unimpeded and feel comfortable.

### 3. METHODOLOGY

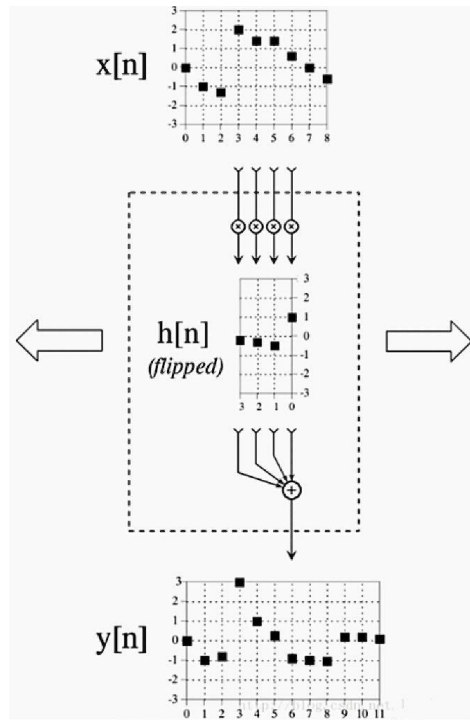
When neural networks are used in digital signal processing for sequence analysis (from time series to language), the first thing that comes to mind is recurrent neural networks. As a neural network developed specifically for sequence analysis, it can preserve underlying patterns and learn time dependencies, is a complete Turing machine and can deal with sequences of any length. But this advantage is rarely used in practice. Furthermore, we apply it to sequences that are too long (this problem occurs when we sample the convection signal at high frequencies, such as 500-100Hz). A series of problems are encountered, so in cases where multiple variables (which can be multivariate time series or word embeddings) are used for each time slice, recursive networks are more suitable for short sequences (10-100 time slices).

#### 3.1. The output signal view convolution

Each sampling point of the convolution input affects multiple samples of the output signal. In the second view, we turn the tables and look separately at which input signal sampling points are generated for each sample point of the output signal. Suppose that the most intuitive way to find the convolutional output for a given number of input signals and impulse responses is to calculate the output at each sampling point of the output signal. This requires knowing how to calculate the result of each sampling point of the output signal. Suppose for  $y(6)$  find out which inputs affect the result of  $y(6)$ . By looking at the result diagram of all 9 input sampling points passing through the system above, it can be seen that  $x(3), x(4), x(5), x(6)$  influence  $y(6)$  through the output component of the impulse response.

$$y(6) = x(3)h(3) + x(4)h(2) + x(5)h(1) + x(6)h(0)$$

The following diagram illustrates the output algorithm as a convolver, and the flowchart shows how the convolution is performed:

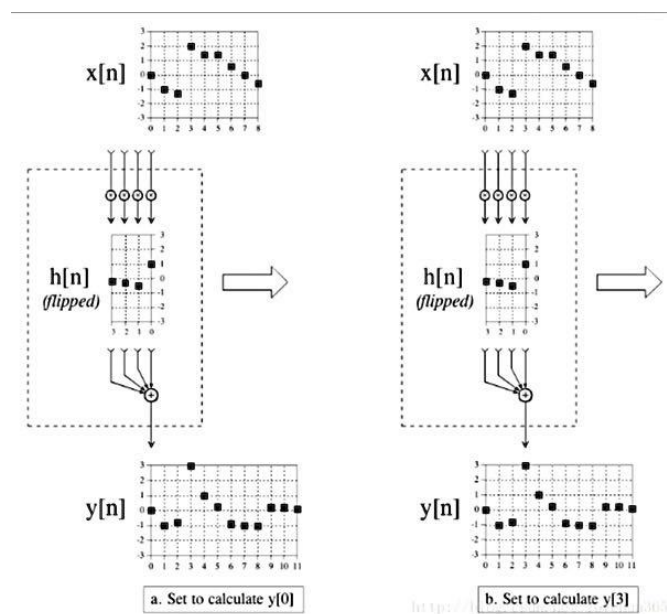


**Figure 4.** Output convolution signal processing flow

The convolver can be seen as a black box that can be moved left and right, 4 input signal sampling points enter the input, these values are multiplied by the values represented by the impulse response and the results are added. For example,  $y(6)$  is calculated from  $x(3), x(4), x(5), x(6)$ . To calculate  $y(7)$ , the convolver moves one bit to the right, and four more inputs  $x(4)-x(7)$  enter the convolver. This process is repeated for all points where the output signal needs to be calculated.

In the figure above, the impulse response in the convolver is shifted left and right, and the shift is simply convenient for mathematical calculation. The impulse response describes how each input signal point affects the output signal. The result of each point of the output signal is affected by multiplying the input signal by a flipped impulse response.

The following diagram shows the boundary processing:



**Figure 5.** Convolver boundary signal processing

The above signal is generated by the program, the frequency of this signal changes every 250ms, and it is stable in each interval. If the selected observation window is not larger than 250ms, then when the window is moved to the right from 0 along the timeline, the observed signal in the window must stabilize in some cases.

Understanding convolution from the perspective of output signals analyzes how the sampling points of each input signal affect the sampling points of many output signals. Understanding convolution from the output perspective analyzes which input signals are affected by each sampling point of the output signal[11]. This approach is useful for understanding convolution from both a mathematical and practical perspective. The formula is:  $y[n] =$  a combination of other variables. In other words, the output signal sampling point  $n$  is equal to a linear combination of many input signals and pulse responses.

The assumption we calculate the output results of the  $y[4]$  by above knowable  $y[4] = x[0]h[4] + x[1]h[3] + x[2]h[2] + x[3]h[1] + x[4]h[0]$ . That is, the output result of the current input signal point input to the linear system is a linear weighting of the pulse response of the current signal and previous signals to the current point. As stated in the formula, in order to calculate the result of  $y[4]$ , we must linearly weight the impulse response of the input  $x[0], x[1], x[2], x[3], x[4]$  acting on the position  $n = 4$ . That is to say, when  $x[0]$  enters the system, the corresponding pulse reaction at the position  $n = 4$  is  $h[4]$ , and its output is  $x[0]h[4]$ ; when  $x[1]$  enters the system, the corresponding pulse reaction at the position  $n = 4$  is  $h[3]$ , and its output result is  $x[1]h[3]$ , and so on. It can be seen that each component of the output signal is a linear combination of weights affected by the input signal, and its weight is exactly the weight value corresponding to the image flip of the pulse response[12]. This is why the convolution formula requires the input signal to be flipped in order to perform linear superposition.

Therefore, the convolution result can be obtained through the above two analyses. Looking back at the convolution machine above, consider the impulse response as a set of weight coefficients, in which view each output signal sampling point is equal to the sum of the weight inputs. Which input signal samples affect each output sampling point depends on the selection of the weight coefficient.

## 4. CONCLUSION

This paper has extensively examined the role and potential of Recurrent Neural Network (RNN) sequence algorithms in computer digital signal processing. Key highlights include the significant integration of deep learning, especially RNNs, which has transformed digital signal processing. RNNs are particularly adept at managing complex, high-dimensional data, proving to be invaluable in applications like speech recognition in noisy settings and real-time video processing. This marks a stark contrast to traditional DSP methods, which are often limited by pre-set rules and manually extracted features[13]. RNNs overcome these limitations by autonomously learning features and patterns, offering a more efficient and precise approach.

The practical application of RNNs in DSP is well-supported by experimental evidence, showcasing their superiority over traditional methods. This not only demonstrates the effectiveness of RNNs but also emphasizes the unique benefits of deep learning in handling extensive datasets. However, the use of RNNs is not without challenges. They require substantial computational resources and large data sets, and their inner workings are not entirely transparent, necessitating further research for improved understanding and optimization. Looking ahead, the future of DSP is poised for significant advancement through the continued integration of AI and machine learning technologies[14]. This evolution is expected to bring forth progress in areas like medical diagnostics and autonomous vehicles. The ongoing innovation in network architecture and algorithm optimization is set to further enhance the capabilities of DSP, blurring the lines between conventional signal processing and artificial intelligence and opening up a world of groundbreaking possibilities in the field.

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## REFERENCES

- [1] Shukla Alok, and Vedula Prakash. "A quantum approach for digital signal processing." *The European Physical Journal Plus* 138. 12 (2023):
- [2] Gao Xin. "Application of Digital Signal Processing Technology in Electronic Measuring Instruments." *Journal of Electronic Research and Application* 1. 2 (2023):
- [3] Houssam HamiciAwos Kanan ,and Khalid Al hammuri. "Optimized FIR Filter Using Genetic Algorithms: A Case Study of ECG Signals Filter Optimization." *BioMed Informatics* 3. 4 (2023):
- [4] 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>.
- [5] Shulin Li, 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>.
- [6] [1] Liu, Bo & Zhao, Xinyu & Hu, Hao & Lin, Qunwei & Huang, Jiabin. (2023). Detection of Esophageal Cancer Lesions Based on CBAM Faster R-CNN. *Journal of Theory and Practice of Engineering Science*. 3. 36-42. 10.53469/jtpes.2023.03(12).06.
- [7] 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.
- [8] Xin, Q., He, Y., Pan, Y., Wang, Y., & Du, S. (2023). The implementation of an AI-driven advertising push system based on a NLP algorithm. *International Journal of Computer Science and Information Technology*, 1(1), 30-37.0
- [9] Zhou, H., Lou, Y., Xiong, J., Wang, Y., & Liu, Y. (2023). Improvement of Deep Learning Model for Gastrointestinal Tract Segmentation Surgery. *Frontiers in Computing and Intelligent Systems*, 6(1), 103-106.6
- [10] Implementation of an AI-based MRD Evaluation and Prediction Model for Multiple Myeloma. (2024). *Frontiers in Computing and Intelligent Systems*, 6(3), 127-131. <https://doi.org/10.54097/zJ4MnbWW>.
- [11] Zhang, Q., Cai, G., Cai, M., Qian, J., & Song, T. (2023). Deep Learning Model Aids Breast Cancer Detection. *Frontiers in Computing and Intelligent Systems*, 6(1), 99-102.3
- [12] Xu, J., Pan, L., Zeng, Q., Sun, W., & Wan, W. (2023). Based on TPUGRAPHS Predicting Model Runtimes Using Graph Neural Networks. *Frontiers in Computing and Intelligent Systems*, 6(1), 66-69.7
- [13] Wan, Weixiang, et al. "Development and Evaluation of Intelligent Medical Decision Support Systems." *Academic Journal of Science and Technology* 8.2 (2023): 22-25.
- [14] Tian, M., Shen, Z., Wu, X., Wei, K., & Liu, Y. (2023). The Application of Artificial Intelligence in Medical Diagnostics: A New Frontier. *Academic Journal of Science and Technology*, 8(2), 57-61.7
- [15] Shen, Z., Wei, K., Zang, H., Li, L., & Wang, G. (2023). The Application of Artificial Intelligence to The Bayesian Model Algorithm for Combining Genome Data. *Academic Journal of Science and Technology*, 8(3), 132-135.2
- [16] 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>.
- [17] Prediction of Atmospheric Carbon Dioxide Radiative Transfer Model based on Machine Learning. (2024). *Frontiers in Computing and Intelligent Systems*, 6(3), 132-136. <https://doi.org/10.54097/ObMPjw5n>

- [18] Liu, Y., Duan, S., Shen, Z., He, Z., & Li, L. (2023). Grasp and Inspection of Mechanical Parts based on Visual Image Recognition Technology. *Journal of Theory and Practice of Engineering Science*, 3(12), 22-28.1
- [19] 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>.
- [20] Liu, B. (2023). Based on intelligent advertising recommendation and abnormal advertising monitoring system in the field of machine learning. *International Journal of Computer Science and Information Technology*, 1(1), 17-23.
- [21] 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.
- [22] 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.