



DATA COLLECTION AND ANALYSIS BASED ON SENSOR TECHNOLOGY IN SPORTS TRAINING

XIANBIN SHI* AND HUAGANG ZOU†

Abstract. In order to realize the automatic monitoring of physical fitness index in athletic training, a new method of automatic monitoring and identification is put forward in this paper. In this paper, a network structure model is designed to automatically monitor the physical fitness index in sports training based on IOT and WSN. The collected a number of physical parameters in sports training, including heart rate, maximal oxygen absorption, respiration entropy, and load parameters. Then, by monitoring heart and lung function data, Cooper's method was used to measure the maximal oxygen intake, and EQO₂ was used as the training index. Then, the dynamic parameters of physical fitness index were extracted, and the change of gas metabolism and critical threshold were analyzed. This paper builds a system structure model to monitor the physical fitness index of physical training, and realizes the modular design of the system. The experiment results indicate that the system is not very different from the real one, and it can be used to automatically monitor the physical performance index in sports training. Practice has proved that the system has good stability and reliability, and is suitable for physical monitoring in the process of sports training.

Key words: Sensors, Sports training, Physical fitness indicators, automatic monitoring

1. Introduction. With the continuous progress of technology, the application of sensor technology in sports training is becoming increasingly common. Sensors, as an advanced technological tool, can collect and analyze athlete data, provide precise motion details and real-time feedback, thereby helping coaches and athletes improve training methods and technical levels. The development of sensor technology has brought tremendous changes and innovations to sports training [1]. The application range of sensor technology is very wide, which can be applied to various sports, including football, basketball, athletics, swimming, etc. Sensors can be embedded into the equipment of athletes, such as shoes, jerseys, protective gear, etc., or directly fixed on the sports field. Through real-time monitoring and data collection of sensors, coaches and athletes can obtain a large amount of information about the athlete's body posture, strength output, speed, acceleration, heart rate, and other aspects. These data can be used to analyze whether the athlete's technical movements are correct, whether the training intensity is appropriate, and whether their physical condition is good.

The application of sensor technology has revolutionized traditional observation and recording methods. Sensors can provide more objective and accurate data, reducing subjective interference. Sensors can monitor the movements of athletes in real-time, transmit data to computers or smart devices, analyze and process them through software, and generate visual results and reports [2]. Coaches can use this data to accurately analyze and evaluate athletes, develop targeted training plans, help athletes improve their technical skills, reduce injury risks, and optimize training outcomes. The application of sensor technology can also provide real-time feedback, helping athletes adjust their movements and postures in a timely manner. Sensors can transmit information to athletes through sound, light, vibration, and other means, guiding them to perform correct actions [3]. For example, in football training, sensors can remind athletes of the appropriate kicking force through vibration, indicate the correct angle when passing the ball through sound, and display the accuracy of the athlete's movement through light. This real-time feedback can help athletes correct mistakes faster, improve the accuracy and efficiency of technical movements.

The application of sensor technology can also promote communication and confrontation between athletes. Sensors can compare and analyze data from multiple athletes, helping coaches understand the differences and advantages among different athletes and develop corresponding training plans. At the same time, sensors can

*Anhui Business College, Wuhu, Anhui, 241002, China (Corresponding author's e-mail: shixianbin2021@abc.edu.cn)

†School of Physical Education, Anhui Normal University, Wuhu, Anhui, 241002, China

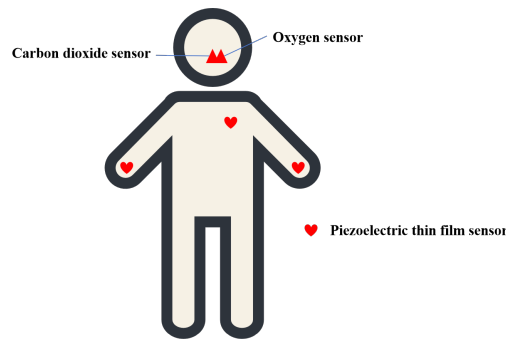


Fig. 2.1: Sensor Layout

also share data, allowing athletes to engage in real-time confrontation and competition [4].

For example, in swimming competitions, sensors can monitor the speed and posture of athletes in real-time, display data on screens next to the swimming pool, and allow the audience and coaches to clearly see the performance of each athlete, and compare and evaluate them. However, the application of sensor technology also faces some challenges and limitations. Firstly, the cost of sensors is relatively high, which may be difficult for some economically disadvantaged sports and athletes to afford. Secondly, the reliability and accuracy of sensors also need to be continuously improved and enhanced [5]. In the complex environment of sports fields, sensors may be subject to interference, resulting in inaccurate data. In addition, for some special sports such as gymnastics, judo, etc., the application of sensors may face technical difficulties. Due to the complex and varied actions of these projects, sensors may not be able to accurately capture and analyze relevant data.

Overall, the application of sensor technology in sports training has brought about significant changes and innovations. Sensors can collect and analyze athlete data, provide precise motion details and real-time feedback, thereby helping coaches and athletes improve training methods and technical levels. However, the application of sensor technology still faces some challenges and limitations, which require continuous improvement and refinement. With the further development of technology, it is believed that sensor technology will play a more important role in sports training, providing better support and guidance for the growth and progress of athletes [6]. The purpose of this study is to explore the application of sensor based data collection and analysis in sports training. By collecting sports data of athletes, such as posture, speed, strength, and other indicators, combined with real-time feedback provided by sensor technology, we can understand the performance of athletes and conduct scientific analysis. By collecting and analyzing data, more comprehensive and accurate training evaluations and guidance can be provided for coaches and athletes, thereby improving training effectiveness and competitive performance.

2. Overall System Architecture. In order to realize the automatic monitoring of the fitness index in the multi-sensor sports training, the overall structure of the system is based on the combination of the heart rate, the maximal oxygen absorption, the breathing entropy, and the collecting and analyzing of the load parameters. The ZigBee Network Sensor Monitoring System is used to build an auto-extracting model of Physical Fitness Indicator Parameters in Physical Training [7]. Combining with Physiology Parameter Recognition and Information Monitoring, a Hardware Device System for Monitoring and Detecting Physical Fitness Index in Sports Training with Wearable Device, Establishes Information Exchange Model and Command Transmission Control Model for Sports Training in XML and Web Middleware.

Wearable sensors such as oxygen, carbon dioxide and piezoelectric thin film sensors are used to collect heart rate, maximum oxygen uptake, respiratory entropy and load parameters, and video sensors are used to collect video data on exercise training as shown in Figure 2.1.

The maximum amount of oxygen is achieved by running or cycling with a mask on, depending on the difference between the data from the oxygen sensor and the CO₂ sensor; Calculate respiratory entropy based on the ratio of carbon dioxide production and oxygen consumption at the same time; When hemodynamic changes

occur, light enters the human body and undergoes predictable scattering. Using this principle, piezoelectric thin film sensors generate PPG waveforms for measuring heart rate and use heart rate data as basic biological characteristic values to ensure the accuracy of heart rate, load parameters, and other physiological parameter measurement results [8]. Arrange video sensors in the athlete training venue to collect athlete training video data, laying a solid data foundation for automatic monitoring of physical fitness indicators in subsequent sports training.

Among them, VO_2 , CO_2 emission (VCO_2), HR, etc., are the most important parameters in the automatic monitoring of ECG. The monitored the physical performance index of the sports training, which is divided into the primary and the secondary. Based on the change of gas metabolism and critical threshold, it can be used to automatically monitor the performance index in different sports programs and situations. Based on the general structure of the Physical Fitness Index Automatic Monitoring System in Sports Training, the SOA Framework Protocol is used. The automatic monitoring system of physical fitness index in physical training is composed of the main circuit control module, the data processing terminal module, the human-machine interaction module, and the bus output control module. Using JMS and HTTP protocols, we set up a system of service structure to monitor the performance index of sports training [9]. This article introduces an automatic monitoring system based on XML and Web middleware, which can monitor physical fitness index based on the M flag in the RTP header during exercise training. In sports training, we established an evaluation index called PE index and constructed a control model on the web service client to manage the components of PE index in sports training. In order to implement this system, we adopted a three-layer architecture design, which is the network layer, information fusion layer, and data output layer. Below, we will provide a detailed introduction to the functions and roles of these three levels.

Firstly, the network layer is responsible for handling communication between the system and external devices. In our system, motion training data is obtained through the M flag in the RTP header and transmitted to the information fusion layer for processing. The network layer is also responsible for communicating with web service clients, receiving and sending relevant data. Next is the information fusion layer, which is the core part of the system. In this layer, we use XML to encode and decode motion training data, and determine the type of motion based on the M flag. By analyzing and calculating exercise data, we can obtain the evaluation results of physical fitness index [10]. At the same time, the information fusion layer is also responsible for transmitting these evaluation results to the data output layer for users to view and analyze. Finally, there is the data output layer, which presents the evaluation results of physical fitness index to users in a visual form. Through the web service client, users can easily view and monitor changes in their physical fitness index. In addition, we can also control and adjust the composition of the PE index according to user needs to achieve better training results.

Through a three-layer architecture design, we have achieved effective communication and data processing between the network layer, information fusion layer, and data output layer. This system provides a scientific, convenient, and visual monitoring method for sports training, which helps to improve training effectiveness and the physical fitness level of athletes. Figure 2.2 shows a three-layer structural system [11].

On the basis of the three layers structure of the system, the dynamic parameters of the physical fitness index are extracted. Based on the change of gas metabolism and critical threshold, this paper establishes the structural model for the monitoring of the physical fitness index. Based on the data collection of HRMS and the physical function analysis, the data is synthesized in the sensor. In the application layer, the exchange of data is carried out, and in the network layer, the information exchange, the data fusion, and the characteristic output of the physical fitness index are realized [12]. The system's functional module architecture is illustrated in Figure 2.3.

The physical fitness index is one of the important indicators for measuring a person's energy level. By extracting and monitoring the dynamic parameters of physical fitness index, it is possible to better understand and evaluate an individual's physical and health status. To achieve this goal, this article proposes a physical fitness index monitoring system based on a three-layer system structure [13].

Firstly, at the bottom of the system, we construct a structural model of the stereoenergy index by analyzing gas metabolism and changes in critical thresholds. Gas metabolism is an important indicator of energy metabolism during human movement. By monitoring and analyzing gas metabolism, the individual's physical

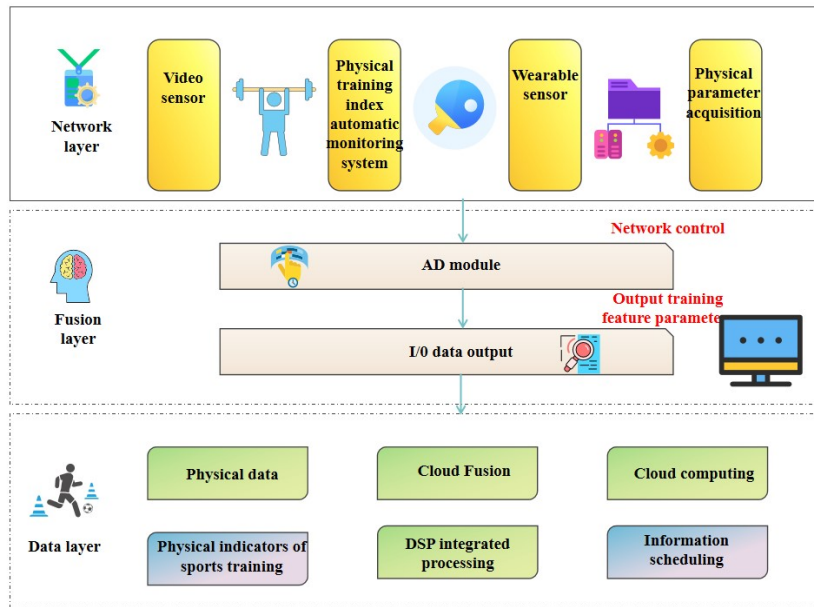


Fig. 2.2: The three-layer structural system of the system

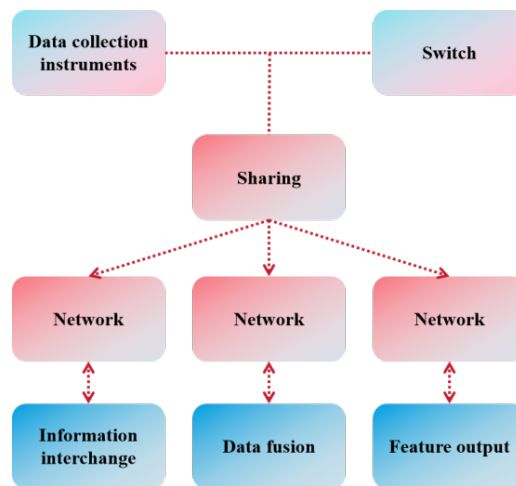


Fig. 2.3: System Function Module Structure

adaptability and ability level can be inferred. The critical threshold refers to the critical value of physical fitness index at a specific exercise intensity, exceeding which may lead to physical fatigue and overtraining. By comprehensively analyzing gas metabolism and critical thresholds, we can obtain an accurate physical fitness index model for monitoring an individual's physical condition [14].

Secondly, in order to collect and analyze data, we introduced HRMS (Exercise Physiology Monitoring System) as a data collection tool. HRMS can monitor individual physiological parameters such as heart rate, blood pressure, and body temperature in real-time, and transmit these data to the system's sensors. By analyzing and processing these data, we can obtain information on individual movement status and physical fitness. At the application layer of the system, we conducted data exchange and processing [15]. Through data

Table 3.1: Prior parameters of VO_{2max} monitoring distribution

Pilot projects	gender	VO_{2max}
laboratory experiment	male	0. 43
	female	0. 45
Outdoor experiment	male	0. 87
	female	0. 73

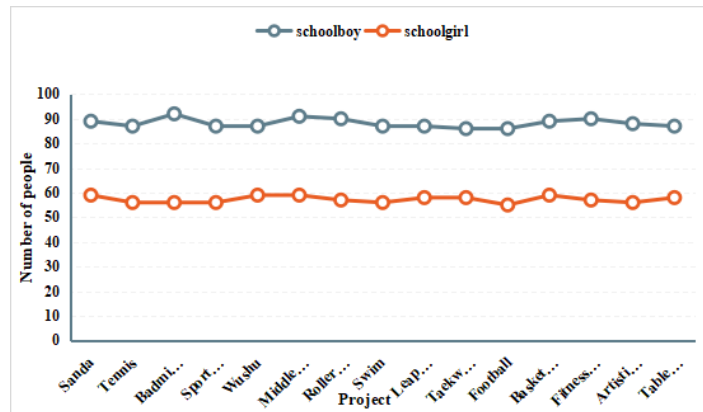


Fig. 3.1: Experimental Test Objects

transmission with HRMS, we can obtain real-time physiological parameter data of individuals and transmit it to the network layer for processing. At this level, we obtained the physical fitness index of individuals through data fusion and feature extraction. The physical fitness index is an evaluation index that takes into account individual physiological parameters, exercise ability, and physical condition, and can objectively reflect an individual's physical fitness level and health status.

Finally, at the network layer of the system, we achieved feature output for information exchange, data fusion, and physical fitness index. The network layer serves as a bridge for data transmission and processing, integrating and analyzing data from sensors, and outputting the final evaluation results. Through the operation of the network layer, we can achieve real-time monitoring and evaluation of individual physical fitness index [16].

3. System data analysis and experimental testing.

3.1. Experimental Method and Object. In the data analysis, the maximal oxygen uptake was measured by Cooper's method, and EQO_2 was used as the training target. In this paper, the distribution of physical fitness index was established, and the differences of the maximal oxygen uptake VO_{2max} , O_2 Pmax and $METS_{max}$ were analyzed. Physical fitness index monitoring was performed, and the original VO_{2MAX} monitoring profile of each group was given, as shown in Table 3.1.

Sports such as Sanda, tennis, badminton, sports dance, martial arts, and roller skating were selected as the test subjects, and the distribution of test participants is shown in Figure 3.1.

Based on the distribution of test subjects in Figure 3.1, this paper presents a method to monitor the performance of physical fitness index in the design of the automatic monitoring system. The participants were classified into two categories: technology, combat, long and short distance running, and ball. Figure 3.2 illustrates the distribution of monitoring information density for sensor sampling for various projects [17].

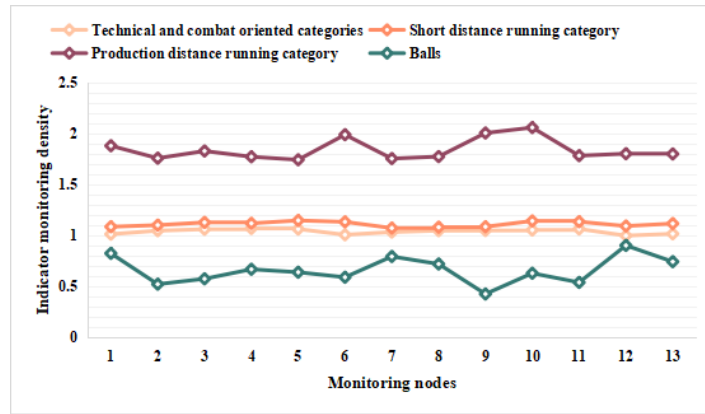


Fig. 3.2: Concentration distribution of monitoring information sampled by sensors of different projects

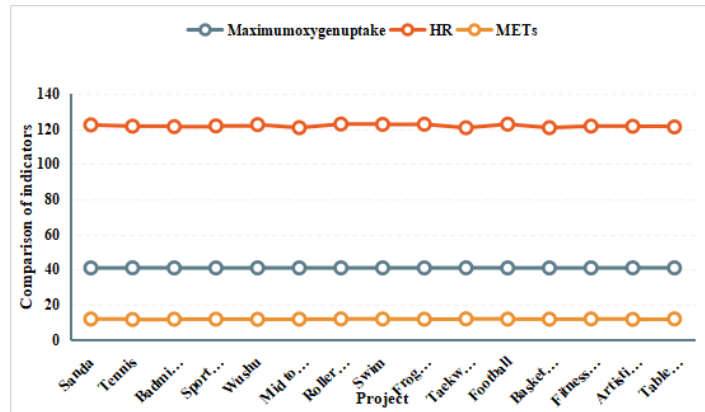


Fig. 3.3: Comparison of Various Indicators for Men’s Long Distance Running in Various Events

Table 3.2: Comparison of Various Indicators for Long Distance Running in Comprehensive Projects

	Technical and combat oriented categories	Short distance running category	Long distance running category	Balls
VO_{2max}	43.9 ± 2.54	32.4 ± 3	31.41 ± 2.23	30.3 ± 2.54
S	2032.46 ± 155.43	1852.11 ± 245.12	1546.46 ± 143.43	1653.32 ± 145.3
METs	932 ± 0.6	8.35 ± 1.6	8.12 ± 14.34	8.21 ± 0.46

According to the analysis chart, using this method for monitoring physical fitness indicators in sports training, the correlation between the feature distribution and $P < 0.05$ and $P < 0.01$. Meet the functional monitoring requirements for sports training indicators. Based on this, the comparison of various indicators for long-distance running in each project is shown in Figure 3.3. The comparison of various indicators for long-distance running in various projects is shown in Table 3.2 [18,19,20].

We test the accuracy of the training performance curve obtained as shown in Figure 3.4.

Through analyzing the above monitoring results, we can draw a conclusion that there is little difference between the monitoring of physical fitness index and the real one. The system can be used to automatically

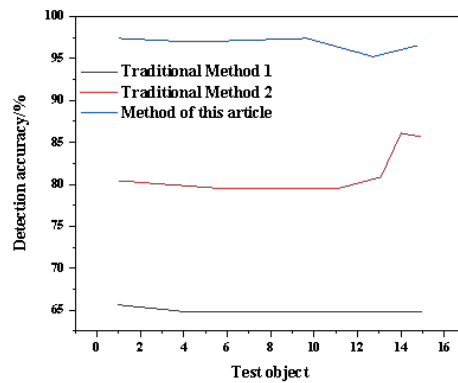


Fig. 3.4: Detection performance curve

monitor the physical performance index in physical training, and it is very adaptable to the environment and the individual.

4. Conclusion. An automatic monitoring system of physical fitness index in physical training is designed on the basis of multiple sensors. The whole structure and function modules of this system are expounded in detail. On this basis, a health index monitoring system based on wireless sensor network is proposed. Through the statistical analysis of large sample data, it is proved that the method has high credibility, can adapt to the personalized monitoring of large-scale sports activities and enhance the dynamic monitoring of BMI.

REFERENCES

- [1] Mei, Z. (2023). 3d image analysis of sports technical features and sports training methods based on artificial intelligence. *Journal of Testing and Evaluation: A Multidisciplinary Forum for Applied Sciences and Engineering*,54(7),69-72.
- [2] Wang, D., & Huang, G. (2022). Analysis of the influence of outward bound training based on data analysis in college physical training. *Computational intelligence and neuroscience*, 2022(33), 6488562.
- [3] Lee-Cultura, S., Sharma, K., & Giannakos, M. (2022). Children's play and problem-solving in motion-based learning technologies using a multi-modal mixed methods approach. *International Journal of Child-Computer Interaction*(Mar.), 31(74),23-25.
- [4] Zinnatullin, V., & Koledin, S. (2022). Visual development environment and visual programming as an effective tool for data collection and analysis. *2022 VIII International Conference on Information Technology and Nanotechnology (ITNT)*, 58(7),1-4.
- [5] Gandhi, V., Sardar, A., Wani, P., Borase, R., & Gawande, J. (2022). Iot based wireless data technology using lora and gsm. *ITM Web of Conferences*,96(4),102-105.
- [6] Zhang, Y., Liu, L., Wang, M., Wu, J., & Huang, H. (2022). An improved routing protocol for raw data collection in multihop wireless sensor networks. *Computer Communications*, 188(24), 66-80.
- [7] Hao, Y., Li, S., & Zhang, T. (2022). Multi-sensor optimal deployment based efficient and synchronous data acquisition in large three-dimensional physical similarity simulation. *Assembly Automation*,547(1), 42.
- [8] Cao, J., Li, H., & Zhang, X. (2022). Multitarget identification method for dual-plane detection based on data fusion and correlation analysis. *Microwave and Optical Technology Letters*,652(7),56-58.
- [9] Wang, D. (2022). Analysis and research on regeneration therapy of athlete tendon injury based on nanometre sensor technology. *International Journal of Nanotechnology*,63(74),54-57.
- [10] Su, Y. S., & Hu, Y. C. (2022). Applying cloud computing and internet of things technologies to develop a hydrological and subsidence monitoring platform. *Sensors and materials: An International Journal on Sensor Technology*,96(4 Pt.1), 34.
- [11] Chan, Y. K., Lai, J. C. M., Hsieh, M. Y., & Meen, T. H. (2023). Important elements of sensor technology and data management and related education. *Sensors and materials: An International Journal on Sensor Technology*,754(4 Pt.1), 35.
- [12] Zhang, R. (2022). College sports decision-making algorithm based on machine few-shot learning and health information mining technology. *Computational intelligence and neuroscience*,65(7),458-462.
- [13] Lai, S. C., Yang, M. L., Wang, R. J., Jhuang, J. Y., Ho, M. C., & Shiau, Y. C. (2022). Remote-control system for elevator with sensor technology. *Sensors and materials: An International Journal on Sensor Technology*,1784(5 Pt.1), 34.
- [14] Tahmid, K. T., Ahmed, K. R., Chowdhury, M. N., Mallik, K., Habiba, U., & Haque, H. M. Z. (2022). An integrated

- crowdsourcing application for embedded smartphone sensor data acquisition and mobility analysis. *Journal of Advances in Information Technology*, 96(5), 13.
- [15] Li, X., & Li, Y. (2022). Sports training strategies and interactive control methods based on neural network models. *Computational intelligence and neuroscience*, 2022(47), 7624578.
- [16] Chao, L. I., Tokgoz, K. K., Okumura, A., Bartels, J., Toda, K., & Matsushima, H., et al. (2022). A data augmentation method for cow behavior estimation systems using 3-axis acceleration data and neural network technology. *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, E105.A(4), 655-663.
- [17] Rajagopal, V., Velusamy, B., & Rathinasamy, S. (2023). Double q-learning-based adaptive trajectory selection for energy-efficient data collection in wireless sensor networks. *International journal of communication systems*, 652(7), 526-528.
- [18] Kulkarni, A. R., Kumar, N., & Rao, K. R. (2023). Efficacy of bluetooth-based data collection for road traffic analysis and visualization using big data analytics. *Big Data Mining and Analytics*, 6(2), 139-153.
- [19] Navarro, M., Liang, Y., & Zhong, X. (2022). Energy-efficient and balanced routing in low-power wireless sensor networks for data collection. *Ad hoc networks*(Mar.), 127(74), 63-68.
- [20] Taami, T., Azizi, S., & Yarinezhad, R. (2023). Unequal sized cells based on cross shapes for data collection in green internet of things (iot) networks. *Wireless Networks*, 29(24), 2143 - 2160.

Edited by: Hailong Li

Special issue on: Deep Learning in Healthcare

Received: Jan 19, 2024

Accepted: Feb 22, 2024