Hindawi
Security and Communication Networks
Volume 2023, Article ID 9805373, 1 page
https://doi.org/10.1155/2023/9805373

*Retraction*

# Retracted: Research on the Effect of IOT Wireless Network Technology on the Educational Management of China's Universities

**Security and Communication Networks**

Received 5 December 2023; Accepted 5 December 2023; Published 6 December 2023



This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] M. Zhao, "Research on the Effect of IOT Wireless Network Technology on the Educational Management of China's Universities," *Security and Communication Networks*, vol. 2022, Article ID 9405897, 9 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 9405897, 9 pages
https://doi.org/10.1155/2022/9405897



*Research Article*

# Research on the Effect of IOT Wireless Network Technology on the Educational Management of China's Universities

**Minxiao Zhao**

*Jinhua Polytechnic, Jinhua, Zhejiang 321000, China*

Correspondence should be addressed to Minxiao Zhao; 20050165@jhc.edu.cn

Received 22 March 2022; Revised 24 April 2022; Accepted 3 May 2022; Published 6 June 2022

Academic Editor: Muhammad Arif



The Internet of Things (IoT) wireless network technology is gradually making its way into campus life in today's information-driven modern world, bringing convenience to students' daily lives and studies while also placing new demands on the quality of teaching and management effectiveness of universities. In order to make colleges and universities have a more rational approach to talent training, relevant workers need to grasp the characteristics of the data era, keep up with excellent educational examples, innovate educational and teaching methods, and guide students' learning and growth in the data era. To that end, this paper begins by examining the practicality and importance of IoT for teaching and management in colleges and universities by examining the current state of teaching in colleges and universities, the application of IoT in colleges and universities, and the shortcomings of IoT, as well as the use of network technology on campus. Furthermore, it proposes the IoT education management platform combined with machine learning technology. Finally, we offer an IoT education management platform that combines machine learning technologies, which we believe will be useful to relevant practitioners.

## 1. Introduction

IoT, or the "Internet of Things," is an interconnected network that collects information about objects through various sensors and connects objects with things and things with people using networks to achieve control, intervention, and adjustment of the environment and manufacturing processes [1]. The IoT is a kind of Internet, but it contains more objects than the Internet. It is a network that can be extended and expanded wirelessly to connect various information-acquiring devices to the network so that people, machines, and things can exist together in a huge network, thereby enabling real-time data transmission and control [2]. There are two outstanding features of the IoT:

(1) Its data transmission still relies on the Internet, which is the basis and core of the realization of the IoT.
(2) Users who use the IoT can control the items within the IoT and monitor information exchange and communication. With the Internet and communication technology with megabit speed, IoT is no longer a pipe dream; it has been applied in display life, such as a smart home system that monitors teachers at home in real time for us, a smart car that can provide us with route and navigation, and smart traffic that can remind us of traffic jams there [3]. And most of these applications rely on wireless network technology.

IoT needs to collect various information from objects and connect them for real-time interaction. The collected information includes, among others, temperature, humidity, voltage, form, and location of objects, and the collected information is sent out through communication devices to facilitate data analysis and application. Therefore, it is unlikely to realize the transmission of various information by only relying on wired network technology and wireless network technology, which can realize data transmission without fixed lines [4]. The most important feature of wireless networks is the interconnection of communication devices without the need to lay fixed lines. Depending on the application, wireless networks can be expanded and contracted as appropriate. In practical applications, wireless network technology can realize both a global range of voice and data transmission, as well as infrared and RF data acquisition within a certain range. There are many different wireless network technologies, which can be classified according to coverage, application, and architecture. Local area networks (LAN) are the most common wireless networks we use, and our devices must be within a specified range to connect to the network [5]. Wireless network has the following characteristics:

(1) Good mobile characteristics, no space and time restrictions. Relying on transmitting radio waves, wireless networks can transmit network signals without a fixed line, but this transmission method often has a range limitation and the network transmission speed decreases with distance.

(2) The network can be expanded flexibly. Wireless networks, unlike wired networks, do not require fixed lines, and people can connect their devices to the network as long as they are within the signal coverage area, which has advantages that wired networks do not have, such as easier network configuration and expansion, and more efficient and convenient network access and information [6]. Wireless networks not only get rid of the trouble of laying lines but also make it easier and cheaper to build a local area network.

(3) Wireless network architecture is simple, easy to set up and maintain, and the hardware is inexpensive. Obviously, compared to the complex and tedious wiring methods required for wired networks, wireless networks first save the cost of wiring and eliminate the hassle of designing wiring. The realization of the wireless network only needs a wireless transmitting device, and no network cable connection between objects is needed [7]. For large networks, this undoubtedly reduces the cost of later network maintenance and facilitates the analysis of network faults by staff. Because there is often only one transmitting device for wireless networks, it is only necessary to debug and replace it in later maintenance. From the above comparison, it can be seen that wireless networks have lower line requirements, and only one network source is needed to achieve coverage of a certain range of networks, eliminating the limitations of wired networks and making them freer and more convenient for people to use the network. At the same time, it also brings cost reductions for operators. Wireless network equipment architecture is simple, easy to maintain and has a long service life, which is conducive to cost recovery and profit output for network operators. Relying on the popularity of wireless network technology, the realization of the IoT has also become possible. While helping people to get smarter production and life, IoT has also come into the campus, used to help students learn more efficiently and help teachers to manage their classes better [8]. The role of the Internet-based, IoT big data platform in the impact on the management of education in China's universities is to have researchers carry out research.

The data era has come and impacted the traditional education methods and management methods in China's universities, among which the most concerned is how to better guide students' learning in the data era. At present, there are a large number of information-based teaching platforms in China, which make the teaching methods change, and students have more communication platforms when they communicate with each other. The most important feature of the information era is that information is more fluid, and some traditional ways of recording information have gradually shown the possibility of being eliminated, and the information era also makes the application of computers and the Internet more popular. The computer and the Internet have made some current education methods into more multimedia-oriented education methods. Some colleges and universities have also become more intelligent in the way they manage talent files, and some resource models for managing talent files have even used AI intelligent technology [9]. This has increased the efficiency and speed of planning for file management, and the probability of making mistakes in information planning has been greatly reduced. It can be said that the management of university education has become more convenient and easier in the era of big data. But at the same time, such an era also poses many new challenges to the management of universities; for example, a lot of information will be lost unconsciously when saved, and students will be easily scammed by the Internet so that their learning atmosphere is affected to a certain extent [10]. Based on this, based on IoT wireless network data and combined with machine learning technology, this paper makes further research on the impact of IoT wireless network technology on education management in China's universities.

The following is a summary of the research: Section 1 contains the introduction and literature review. Section 2 reviews some concepts of the related works. Section 3 describes the algorithm description as well as experimental results. Finally, the paper ends with the conclusion in Section 4.

## 2. Related Works

*2.1. IoT-Related Technologies.* The exchange of information between objects and between people and objects is fundamental to the IoT. The IoT is characterized by the holistic perception of objects, reliable transmission of information, and intelligent processing of processes. Among them, sensing can be achieved by devices, such as RF technology, QR code identification, and global positioning. Combined with the Internet and wireless network transmission technology, a reliable data transmission network can be formed to realize real-time and accurate collection and transmission of object information and to achieve the ubiquitous connection between information objects. Intelligent process processing can use AI technology to make production processes more intelligent, which is still based on the transmission and analysis of sensory data and information [11]. Based on the IoT characteristics and combined with the information science perspective, intelligent processes around information flow can be constructed, the IoT information processing process can be summarized as shown in Figure 1, including original data collection, data filtering, data storage, and data analysis.

Talking about IoT, we have to mention the key technologies for IoT implementation, RFID technology, MEMS, and M2M. M2M system framework and cloud computing, which is the realization of the IoT, are the environmental technologies that enable the IoT.

The application field of IoT covers all aspects. The IoT is silently changing our lives, and it has penetrated into every aspect of our lives. In the process of daily life, work and study, we always enjoy the convenience brought by the IoT [12]. The popularity of IoT effectively promotes the intelligent control of our processes so that we can produce and live more efficiently. In work and study, daily entertainment, financial investment and purchase, and other areas closely related to life, it is also not difficult to find the IoT everywhere [13]. These applications have greatly improved the quantity and quality of information available to people and improved the quality of their lives. In addition, the IoT is also used in defense and military fields, although it is not as common as in daily life, the changes it can bring are still worth looking forward to.

A smart house, which is physically realized as a residential platform, is a typical IoT application in people's daily lives. The temperature, humidity, lighting, security, audio, and video in the residence are combined into a comprehensive platform for people to alter in order to improve their quality of life in this residential platform, which uses wireless network technology. In order to get a safer and more comfortable home life and to cause as little pollution to the environment as possible, the IoT-based smart home provides a good choice and it is gradually integrating into people's lives [14]. Smart home devices, as shown in Figure 2, touch all aspects of family life and are the most basic IoT applications in the house.

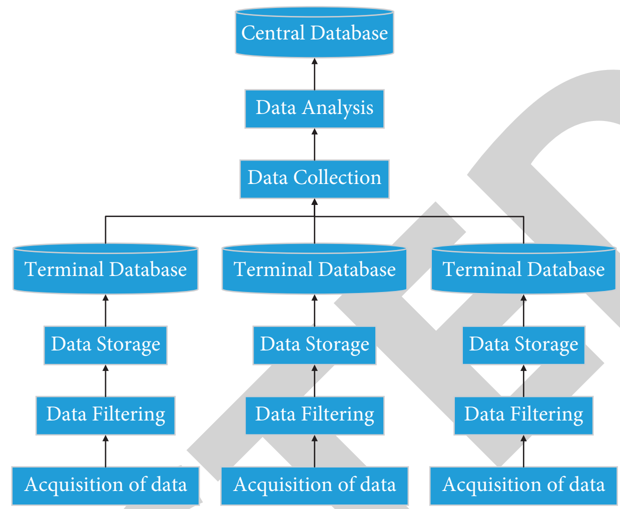


FIGURE 1: IoT data processing flow chart.

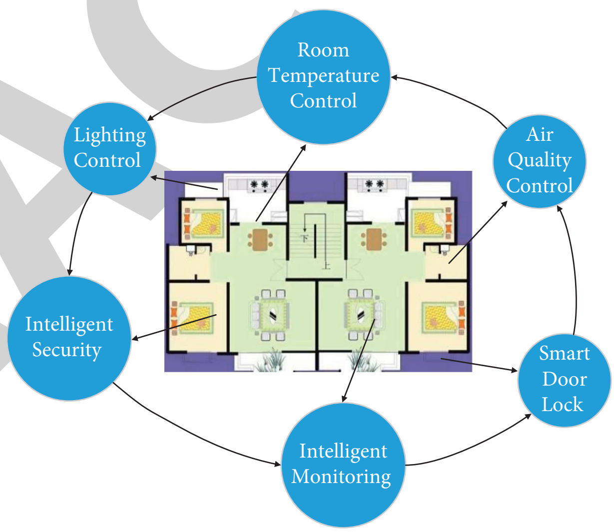


FIGURE 2: Smart home system diagram.

*2.2. Application of IoT in Universities.* Many universities have started to try to use IoT for more efficient teaching and management work in recent years, thanks to the popularity of the on-campus wireless network, and many researchers have made attempts in this area, including IoT-based classroom management platforms, IoT-based archive management platforms, and IoT-based intelligent library, which will be briefly introduced below.

China has a total of 2956 colleges and universities, according to data from the Ministry of Education. Colleges and universities have a lot of electricity-consuming devices and use a lot of them every year. Most of the colleges and universities have the phenomenon of electricity waste, mainly concentrated in teaching buildings, libraries, and other occasions; because the management of colleges and universities is relatively lax, the phenomenon of classroom unoccupied lights always on and air conditioners working is often seen, which wastes a lot of electric power resources. The literature [15] proposes a classroom energy-saving management platform based on the wireless network of IoT, which uses a wireless network to transmit control signals to control and manage the electricity-using equipment in classrooms. The management platform goes from the logistics management center to the electricity-using equipment in classrooms, realizing a large classroom energy-saving management system based on a combination of wireless network and school wired LAN. The management platform includes a logistics management center, teaching building console, floor control nodes, classroom relay nodes, and classroom electrical nodes. The management adopts distributed control mode. The teaching system, logistics management center, teaching building console, and floor control nodes use the school's cable LAN to send signals, while the floor control nodes and classroom internal control nodes use a wireless ZigBee network to send signals. There will be a range of conditions in the actual operation process, such as the necessity for temporary meetings or the temporary transfer of some classes; thus, each classroom equipment should have a variety of control modes. The system provides three control modes:

(1) Automatic control mode:

After the system is running, the logistics management center will uniformly manage the electrical equipment of each classroom according to the scheduling data of the teaching system.

(2) Independent control mode:

In the automatic control mode, after each teacher enters data through the logistics system, they can verify their fingerprints and set their classrooms as independent control mode, and teachers have the authority to control the electrical equipment in the classrooms through the man-machine touch screen and switch control in each classroom.

(3) Intelligent control mode:

Under the premise of automatic control mode, you can switch to intelligent control mode, and in the case of system preset value parameters, you can decide whether to turn on the fluorescent lights or air conditioning and other equipment in the classroom depending on the suitability of the room. The intelligent classroom management system based on the wireless network can save the trouble of wiring, installation, and arrange conveniently and quickly, and through the management control of the teaching system and logistics system, it can effectively control the electrical equipment in each classroom, save more electricity resources, and make the electricity resources serve the university management and teaching more efficiently.

Literature [16] suggested an intelligent management system design for university archives based on IoT, based on the basic hierarchical architecture of IoT and the needs of university archives management. The framework is composed of three layers, the lowest of which is the perception layer, which primarily completes the identification, sensing, and recognition of archives as well as the information sensing and processing of the environment in which the archives are placed. Above the perception layer is the network layer, which mainly realizes the access to the underlying perception devices and the transmission, processing, and fusion of perception information. At the top is the application layer, which mainly provides archive management and intelligent services. For the identification and management of archives, an RFID system is used. An RFID system consists of three parts: electronic label, reader (read-write), and application software system, which realize the functions of electronic label generation, destruction, inquiry, positioning, and so on. The electronic label hardware system consists of an electronic label, read-write, PC terminal, and system platform base network, through sensor nodes and wireless radio frequency equipment to obtain the relevant data and information of the electronic label to realize the automatic recognition of the archives and the automatic recognition of the storage position. The RFID-based archive management operation process can be described as follows: Firstly, the RFID read-write writes the archive-related information based on the EPC encoding mechanism to the electronic label and attaches it to the archive. It uses the fixed RFID read-write and the handhold mobile RFID read-write to combine RFID label information carried on reading and processing. The fixed RFID reader is configured on the wall of the archive room, and the handheld reader is carried by the archive management personnel in order to facilitate the acquisition of archive-related news by reading the tag information anytime and anywhere. For the monitoring of the archive room environment, the temperature, humidity, and smoke-type sensors are used to obtain environmental information, and at the same time, video sensors are added to routinely monitor the archives. The management system uses RFID and wireless sensor network technology to realize remote and networked management of archive identification, recognition, incoming, outgoing and query functions, as well as intelligent monitoring and management of the archive environment, which provides a reference method for intelligent management of university archives.

In addition to the applications mentioned above, literature [17] proposes an intelligent monitoring and control design scheme for the library environment, which combines wireless sensor network technology, temperature and humidity sensors, and microcontroller control technology to realize environmental parameter monitoring and regulation of automatic equipment operation based on the current state of the library preservation environment. Wireless sensor network subsystem, monitoring and management platform, and wireless device control module are the three components of the system. First, the wireless sensor nodes are configured to each monitoring domain to realize the gridded monitoring of the book library, and the monitoring management platform is used to process and store the monitoring data and visually display the gridded book library and monitoring domain in a view. At the same time, a flexible editing alarm strategy defines the correspondence between the monitoring domain and wireless sensor nodes, binding all controlled devices in the monitoring domain. Finally, according to the set alarm policy and the source address information of the wireless sensor in the packet conforming to the alarm policy, the monitoring domain where the wireless sensor is located is identified on the view in the form of a flashing color change. After the alarm message appears again, the management platform will start the corresponding device in the monitoring domain where the alarm message appears and eliminate the alarm in time. The practical application proves that the system requires no wiring, is easy to deploy, can carry out all-round real-time and precise monitoring of the library antiquarian book library, and can accurately and effectively control the air conditioner, dehumidifier, and other equipment to take intelligent processing measures to ensure the good degree of the antiquarian book library environment.

The above application of IoT in colleges and universities mainly involves the reasonable deployment of resources on campus and involves less research on education management. In this paper, we design a kind of intelligent management platform based on wireless network technology of IoT to improve the teaching quality and safety of university experimental classes in order to address the problems of low teaching quality and danger arising from students' easy disoperation in traditional experimental classes.

## 3. Algorithm Description

In this chapter, we define the abnormal behavior detection module, laboratory abnormality detection methods, and experimental results in detail.

*3.1. Abnormal Behavior Detection Module.* The educational management platform designed in this paper includes video surveillance, which can be analyzed to detect abnormal behaviors of students in the laboratory so that teachers can make timely treatment. To improve the accuracy of abnormal behavior detection, a network branch with a 3D self-encoder as the main body is used to codify the video's time-domain information, while a time-domain branch with an optical flow fusion strategy is used to provide additional time-domain information [18]. The flow of the whole model is shown in Figure 3. There are two branches: the network branch and the time-domain branch. The network branch uses a 3D self-encoder to extract the spatio-temporal domain features of consecutive video frames and reconstruct the input. Since the self-encoder is trained using only normal samples, it theoretically has a higher reconstruction error for anomalous regions, and the time-domain branch obtains optical flow results with the background. By combining the findings of the two branches, computing the final reconstruction error, and detecting whether anomalous behavior occurs, the model's final output is achieved.

It is worth noting that when the background is fused, the background of the optical stream is black. When calculating the reconstruction error from such optical flow frames to the original video frames, additional bias is introduced, which negatively affects the results. Therefore, before fusing the optical stream and the network reconstruction results, the optical stream frames are fused with the background, which is calculated by (1), to obtain the optical stream frames with background (OFB).

Let $I_t$ be a frame $t$ in the video sequence and $I_{t+1}$ be a frame $t+1$ in the video sequence, and by their calculation, the optical flow frame is $d$, corresponding to $I_t$; then,

$$\mathrm{OFB}_t^{xy} = \begin{cases} d_t^{xy}, & d_t^{xy} \leq n, \\ I_t^{xy}, & d_t^{xy} > n, \end{cases} \tag{1}$$

where $x$, $y$ denote the horizontal and vertical coordinates of the pixel points in the two-dimensional optical flow and $n$ is the set threshold. $\mathrm{OFB}_t$ is the $t$ optical flow frame with background fusion performed at the time is a two-dimensional matrix.

In the training of the model, the input of the network branch is a video block formed by stacking 16 consecutive frames in a backward stacking manner. The last frame of the video sequence is used to replace the frames that exceed the maximum frame number during the stacking process. The network is trained in the direction of minimizing the reconstruction error, and the batch size is set to 8. The time-domain branch only requires the input optical flow results, and no additional training is required.

*3.2. Laboratory Abnormality Detection Methods.* This section contains 3 parts: the first part is used to define the possible anomaly problems in the laboratory; the second part introduces the self-encoder-based anomaly detection method; and the third part trains and tests the proposed method.

*3.2.1. Exception Problem Definition.* For monitoring systems built in laboratories, anomalous problems are mainly sensor data in the laboratory that may cause safety problems. Usually, when students work in the laboratory, various sensor data in the laboratory should be within a reasonable range, such as the temperature in the experiment, the voltage in the experimental equipment, and the behavior of students in the laboratory. Abnormal problems, that is, data that do not conform to the rules in the laboratory, such as smoke concentration exceeding the standard in the laboratory, require the monitoring system to detect the abnormalities and notify the teacher in time so that the teacher can deal with the problems in the laboratory in time to ensure the teaching and the safety of students. There are various reasons for abnormal data in the laboratory, such as students playing in the monitoring area, equipment overload in the laboratory, low sensor power, and interference in the wireless communication process. For the actual situation in the lab, we defined five types of abnormal problems, including abnormal student behavior, abnormal room temperature, abnormal room smoke, abnormal room equipment voltage, and no abnormal causes found.

*3.2.2. Self-Encoder.* A self-encoder is a simple neural network that can be used for feature extraction and recognition [19]. Typically, a self-encoder packs an input layer, several hidden layers, and an output layer. Figure 4 shows the structure of a self-encoder with one hidden layer. Self-coding differs from neural networks in that its output is a reduction of the input; that is, the data is first encoded and then decoded [20]. The decoder is located between the input and hidden layers, and the decoder is located between the hidden layer and the output layer, and its mathematical expression is shown in equation (2).

$$y = f\left(W g x + b_f\right), \tag{2}$$

where $x$ is an $n$-dimensional input layer, $y$ is a $k$-dimensional hidden layer, and $W_{[k\times n]}$ and $b_{f[k\times 1]}$ are the weighting matrix and deviation vector of the encoder, respectively. $f(g)$ is the nonlinear mapping function of the encoder, and the Sigmoid function is often used as the mapping function

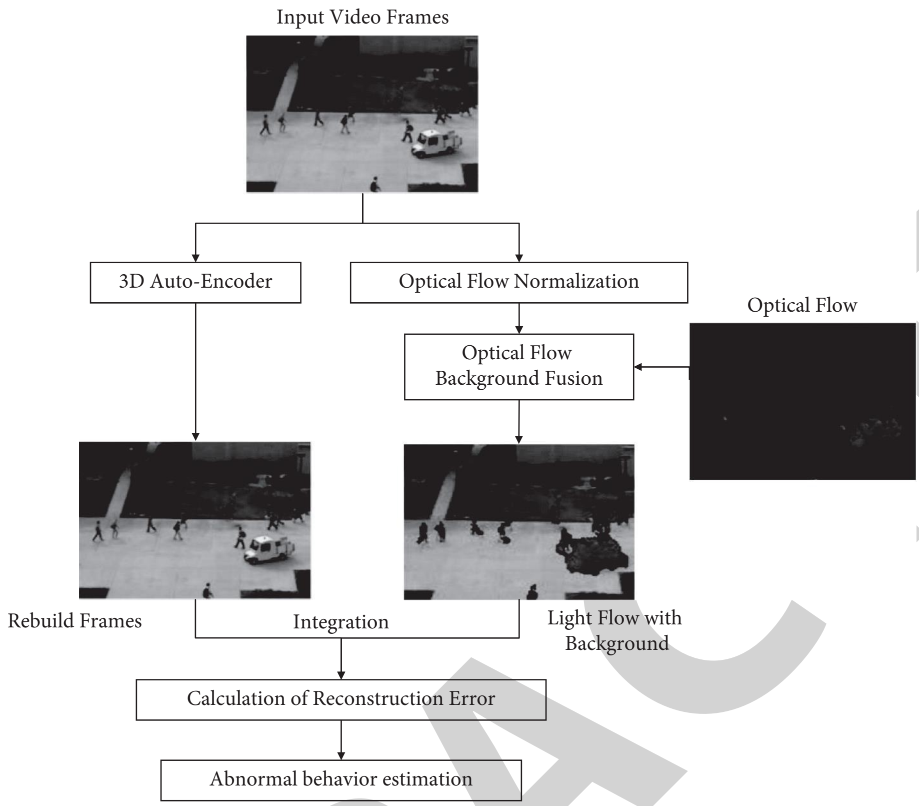


FIGURE 3: Flowchart of the abnormal behavior detection model.

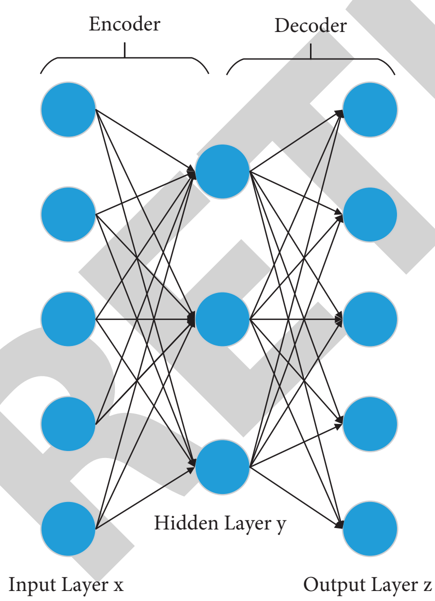


FIGURE 4: Structure of single hidden layer self-coding neural network.

of the encoder. The mathematical expression of the decoder is shown as follows.

$$z = g\left(\mathrm{V}gy + b_g\right), \tag{3}$$

where $y$ is the hidden layer vector, $z$ is the $n$ output layer vector, and $V_{[n\times k]}$ and $b_{g[n\times 1]}$ are the weighting matrix and deviation vector of the encoder, respectively. $g(g)$ is the nonlinear mapping function of the decoder, and the commonly used decoder mapping functions are the Sigmoid function and constant function.

Since anomalous data are to be detected from encoding to decoding error fluctuations, the objective function is defined as the squared error before and after data vector reduction, as follows.

$$\begin{aligned} J_{\theta,\theta'} &= \frac{1}{m}\sum_{i=1}^{m}\left\| z^{(i)} - x^{(i)}\right\|_2^2 \\ &= \frac{1}{m}\sum_{i=1}^{m}\left\| g_{\theta'}\left(f_\theta\left(x^{(i)}\right) - x^{(i)}\right)\right\|_2^2, \end{aligned} \tag{4}$$

where $m$ is the amount of data used for training. The optimized model parameters are obtained by minimizing the objective function $\theta = \{W, b_f\}$ and $\theta' = \{V, b_g\}$. A gradient descent algorithm combined with small batch computation is used for error calculation and tuning the model parameters for the purpose of training the model.

*3.2.3. Abnormality Detection Process.* Figure 5 illustrates the flow of the anomaly data detection method, as shown in Figure 5, which consists of three main phases for the initialization, training, and anomaly detection tasks, respectively.

Before training starts, it is important to ensure smooth data collection and transmission. During the initialization phase, nodes collect and transmit data in the form of wireless

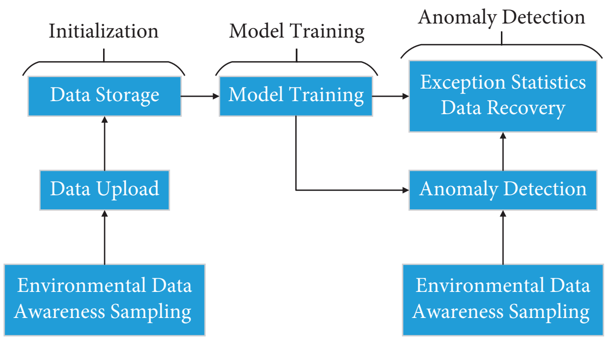


FIGURE 5: Flowchart of abnormal data detection method.

network broadcasts and thus self-organize to form a network covering the laboratory. After confirming that the network is successfully connected, the nodes collect and transmit data periodically

$$x_i^{(t)} = \left[x_{i,1}^{(t)}, x_{i,2}^{(t)}, \ldots, x_{i,p}^{(t)}\right]^T, \tag{5}$$

where $p$ is the number of physical variables detected by node $i$. The collected data are transmitted to the cloud platform using the proximity principle through the wireless network that is closest to the node and capable of communication, and the subsequent operations are performed on the cloud platform. In this phase, the nodes only play a transitional role and are responsible for transferring data without computational functions, and they are responsible for uploading the collected raw data to the cloud [21]. For the part responsible for the output computational volume, it is mainly done on the head, including the training of the model, the decoding and reduction of the data, where the complexity of obtaining the optimal neural network parameters and the type of data collected in the laboratory are mainly considered. This phase of the continuation of the processing of the stored historical data, and the transmission node $i$ stored in time $T$ is

$$X_i = \left[x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(T)}\right]. \tag{6}$$

The data are normalized to eliminate the effects of different scales on the data.

$$\overline{x}_{i,j}^{(t)} = \frac{x_{i,j}^{(t)} - \min\left(x_{i,j}\right)}{\max\left(x_{i,j}\right) - \min\left(x_{i,j}\right)}, \tag{7}$$

where $x_{i,j} = [x_{i,j}^{(1)}, x_{i,j}^{(2)}, \ldots, x_{i,j}^{(T)}]$ is the amount of historical data stored at time $T$ for the physical variables $j$ monitored by node $i$ and $\min(x_{i,j})$ and $\max(x_{i,j})$ are the minimum and maximum values of $x_{i,j}$.

Abnormal data detection is achieved through the calculation of node data. Using nodes to calculate whether the data is abnormal can reduce the bandwidth pressure on the backbone links connected to the cloud platform, which is helpful to achieve real-time detection. The self-encoder can realize the reduction of the data, but a certain error will still be generated during the reduction process [22]. And the error generated by anomalous data in the reduction process is much larger than that of normal data. Relying on the relatively large fluctuation of the anomalous data, our method can detect the anomalous data. At the time, the squared error between the original sampled data and the restored value is defined as follows.

$$\varepsilon = \left\| g_{\theta'}\left(f_\theta\left(\overline{x}^{(t)}\right) - \overline{x}^{(t)}\right)\right\|_2^2, \tag{8}$$

where $\overline{x}^{(t)}$ is the data after normalization at moment $t$ and $g_{\theta'}(f_\theta(\overline{x}^{(t)}))$ is the data after restoration. The flow of anomalous data detection algorithm is as follows. The first step to be performed is to normalize the data as a way to eliminate the differences between the data collected by different sensors. Then, the squared error of the collected data is calculated using the self-encoder [23]. When the squared error value of the collected data is greater than the threshold, it proves that there is an abnormal situation in the lab, and the original data and abnormal warnings need to be uploaded to the cloud platform and sent to the mobile platform to facilitate the teacher to handle the situation accordingly. In addition, in order to speed up the detection, when the squared error of data is below the threshold, then the encoded data is directly uploaded to the cloud platform, and the data is subsequently processed on the cloud platform.

*3.3. Experimental Results.* The self-encoder-based anomaly detection approach is trained using virtual anomaly data to improve model anomaly detection accuracy and assure laboratory safety. Laboratory anomaly problems are randomly picked during the training phase, and laboratory data gathered at 10-minute intervals is used for relevant anomaly detection analysis. The selected 5 virtual anomaly problems are divided into a cluster, where 10 sensor data are collected for each anomaly problem, so that a data vector containing 50 variables from this cluster can be collected at each sampling moment. The data are collected every 10 min during the selected sampling time, and a total of 1800 sampled data are received within 6-hour days; the data collected above are used for training. Considering the characteristics of the data in the laboratory, a self-coding with a hidden layer is sufficient. In addition, the Sigmoid function is configured for the encoder and the ReLU function for the decoder. The model is trained using a small batch gradient descent algorithm to adjust the model parameters; after the training is completed, the squared error generated by continuing to sample 100 data reductions is shown in Figure 6. Statistically, there are data abnormalities in 23 variables out of the 100 acquisition data samples. When a sufficient threshold (red line in Figure 6) can be selected for discovering anomalous data, the presence of anomalous data will result in a higher squared error of normal data.

The following tests the self-encoder-based anomaly detection method for different classes of laboratory anomaly problems. Five sets of data are collected, each containing 100 sampled data. The performance of the detection method is evaluated using the average of the 5 sets of data. The results obtained from the experiments are collected in Table 1. Table 1 illustrates that for sensor-based anomalies including

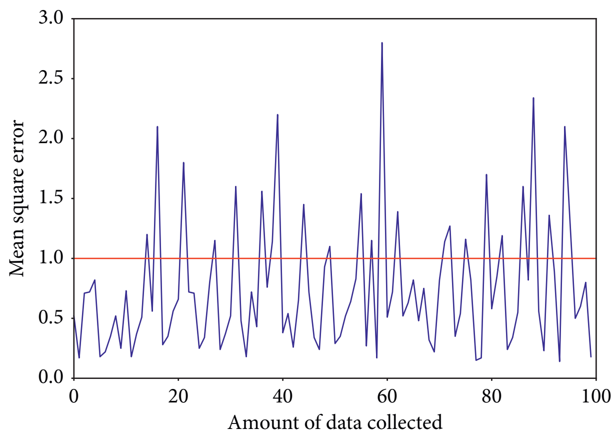


Figure 6: Sampling data/error graphs.

Table 1: Accuracy rate of detecting different categories of anomalous problems.

| Exception problem type | Accuracy rate (%) |
|---|---|
| Abnormal behavior | 78.30 |
| Abnormal temperature | 99.10 |
| Abnormal smoke | 99.40 |
| Abnormal device voltage | 100.0 |
| Abnormal cause found | 95.20 |

temperature, smoke, and device voltage, the self-encoder-based anomaly detection approach can successfully detect their abnormalities, with a near-100 percent accuracy rate. The detection of students' anomalous actions is poor, with only about 80% of them being detected, which we believe is due to insufficient training of the behaviour detection system, which we will investigate more in future studies.

To investigate the problem of inaccurate detection of anomalous behavior by the self-encoder-based anomaly detection method, we conducted an in-depth study of the anomalous behavior detection module based on the dual-stream structure in Section 3.1. We trained the anomalous behavior detection module using 5 K, 1 M, 1.5 M, and 2 M data volumes, respectively, and the experimental results are shown in Table 2. From the data in Table 2, it can be seen that at the beginning of the training, the accuracy of detecting students' abnormal behaviors is relatively low due to the insufficient amount of data. As the amount of data increased, the accuracy rate increased and then decreased again when it reached the overfitting state. To sum up, we will use 1 M data volume to train the abnormal behavior detection module to ensure that it provides accurate data for the overall method.

Finally, we applied the self-encoder-based anomaly detection method to the laboratory, and Table 3 shows the detection of anomalous problems by the method within one week. From Table 3, we can see that the self-encoder-based anomaly detection method can accurately detect abnormalities in temperature, smoke, and voltage, which have dangerous possibilities, and facilitate teachers to deal with them in time to maintain the normal operation of the laboratory and guarantee students' safety. Furthermore, the

Table 2: Training data volume and behavior detection results.

| Data volume | Accuracy rate (%) |
|---|---|
| 5 K | 82.70 |
| 1 M | 95.40 |
| 1.5 M | 96.10 |
| 2 M | 93.50 |

Table 3: Application of anomaly detection methods.

| Exception problem type | Number of predicted occurrences | Number of actual occurrences |
|---|---|---|
| Abnormal behavior | 6 | 5 |
| Abnormal temperature | 3 | 3 |
| Abnormal smoke | 5 | 5 |
| Abnormal device voltage | 17 | 17 |
| Abnormal cause found | 8 | 7 |

method has a high level of accuracy for detecting deviant behavior, which can help teachers fulfil their teaching and administration tasks more efficiently.

## 4. Conclusions

This research offers an intelligent education management method based on wireless network technology of IoT, using the university laboratory as the application occasion, in response to the problem of single and poor usefulness of education management methods in universities. To begin, the things in the laboratory are connected to one another via wireless network technology to generate a collection of the experiment's overall data. Then, the abnormality detection method is constructed based on self-encoder to monitor student behavior, temperature, smoke, and voltage inside the equipment in the laboratory to realize the overall monitoring of the laboratory. It is verified that the self-encoder-based anomaly detection method can effectively detect anomalies in the laboratory, especially temperature, smoke, and voltage anomalies that may cause safety hazards, and the detection readiness for such anomalies is close to 100%. The method may be used to monitor the situation inside the experiment during the actual exam, which helps the teacher's teaching work and also assures the safety of students in the laboratory, giving a new paradigm for educational management innovation in universities.

## Data Availability

The datasets used during the current study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The author declares that he has no conflicts of interest regarding the publication of this paper.

## References


[1] M. K. Afzal, Y. B. Zikria, S. Mumtaz, A. Rayes, A. Al-Dulaimi, and M. Guizani, "Unlocking 5G Spectrum Potential for intelligent IoT: Opportunities, challenges, and Solutions," *IEEE Communications Magazine*, vol. 56, no. 10, pp. 92-93, 2018.

[2] H. W. Xu, "Research on intelligence acquisition method of Internet of Things under big data environment," *Machine Design and Manufacturing Engineering*, vol. 48, no. 4, pp. 64–67, 2019.

[3] X. H. Zhu, *Research on Aggregation and Storage Method of Cloud IOT Platform*, Xidian University, Xi'an, China, 2017.

[4] L. H. Zhou, *Development of Intelligent Gateway of IoTs and its Application*, Zhejiang University, Hangzhou, China, 2018.

[5] K. Chandra, A. S. Marcano, S. Mumtaz, R. V. Prasad, and H. L. Christiansen, "Unveiling Capacity Gains in Ultradense networks: using mm-Wave NOMA," *IEEE Vehicular Technology Magazine*, vol. 13, no. 2, pp. 75–83, 2018.

[6] J. Du, C. Jiang, Z. Han, H. Zhang, S. Mumtaz, and Y. Ren, "Contract mechanism and performance analysis for data Transaction in mobile Social networks," *IEEE Transactions on Network Science and Engineering*, vol. 6, no. 2, pp. 103–115, 2019.

[7] J. Wang, "Research on the Internet of things for wireless sensor networks," *Telecom Power Technology*, vol. 33, no. 6, pp. 152-153, 2016.

[8] F. X. Tang, Z. M. Fadlullah, B. M. Mao, and N. Kato, "An intelligent traffic Load Prediction-based Adaptive channel Assignment algorithm in SDN-IoT: a deep learning approach," *IEEE Internet of Things Journal*, vol. 5, no. 6, pp. 5141–5154, 2018.

[9] F. X. Tang, B. M. Mao, Z. M. Fadlullah, and N. Kato, "On a Novel deep-learning-based intelligent Partially Overlapping channel Assignment in SDN-IoT," *IEEE Communications Magazine*, vol. 56, no. 9, pp. 80–86, 2018.

[10] G. M. Milis, C. G. Panayiotou, and M. M. Polycarpou, "SEMIoTICS: Semantically Enhanced IoT-enabled intelligent control systems," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 1257–1266, 2019.

[11] N. Javaid, A. Sher, H. Nasir, and N. Guizani, "Intelligence in IoT-based 5G networks: Opportunities and challenges," *IEEE Communications Magazine*, vol. 56, no. 10, pp. 94–100, 2018.

[12] K. Kravari, T. Kosmanis, and A. N. Papadimopoulos, "Towards an IOT-enabled intelligent energy management system," in *Proceedings of the 2017 18th International Symposium on Electromagnetic Fields in Mechatronics, Electrical and Electronic Engineering (ISEF) Book of Abstracts*, pp. 1-2, IEEE Press, Lodz, Poland, September 2017.

[13] X. Lin, J. Wu, S. Mumtaz, S. Garg, J. Li, and M. Guizani, "Blockchain-based on-Demand computing resource trading in IoV-Assisted smart City," *IEEE Transactions on Emerging Topics in Computing*, vol. 9, no. 3, pp. 1373–1385, 2021.

[14] Z. Zou, Y. Jin, P. Nevalainen, H. Yuxiang, H. Jukka, and W. Tomi, "Edge and fog computing enabled AI for IoT-an overview," in *Proceedings of the 2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS)*, pp. 51–56, IEEE Press, Hsinchu, Taiwan, March 2019.

[15] F. C. Zhou, "The application of energy-saving monitoring platform construction in colleges and universities," *Value Engineering*, vol. 35, no. 2, pp. 106-107, 2014.

[16] C. J. Yan and Q. Chen, "Design of intelligent management system for university laboratory based on IC card," *Journal of Electrical & Electronic Education*, vol. 30, no. 1, pp. 78–80, 2008.

[17] Y. Wang and Y. Liu, "An intelligent library based on the IOT and the Robot technology," *Library Work and Study*, vol. 3, no. 7, pp. 29–32, 2012.

[18] H. Yang and L. I. Bochao, "Network abnormal behavior detection model based on adversarially learned inference," *Journal of Computer Applications*, vol. 39, no. 7, pp. 1967–1972, 2019.

[19] J. Hu, X. Zhang, and S. Maybank, "Abnormal driving detection with normalized driving behavior data: a deep learning approach," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 6943–6951, 2020.

[20] Z. J. Pan, B. Qin, and Z. Luo, "Data aggregation in WSN based on deep self-encoder," *Computer Engineering and Design*, vol. 39, no. 5, pp. 1214–1218, 2018.

[21] B. Cui, P. Shi, W. Qi, and M. Li, "Uploading multiply deferrable big data to the cloud platform using cost-effective online algorithms," *Future Generation Computer Systems*, vol. 67, pp. 276–285, 2017.

[22] X. Zhou, Z. Lin, and B. Guo, "Alternatives to the self-attention mechanism in encoder," *Modern Information Technology*, vol. 3, no. 19, pp. 64–68, 2019.

[23] S. Penaud, J. Guittard, P. Bouysse, and R. Quere, "DSP implementation of self-synchronised chaotic encoder decoder," *Electronics Letters*, vol. 36, no. 4, pp. 365-366, 2000.