Application of Deep Learning Video Signal Processing Technology in University Management

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The rapid growth of deep learning and edge computing technologies presents the possibility to completely transform university administration systems, which have been more ineffective owing to their incapacity to adjust to complex, dynamic learning settings. Scalability, real-time data processing, and integration across several operating platforms are challenges traditional systems face. To overcome these limitations, this work investigates the development of an advanced video signal processing system utilising edge computing and cyber-physical systems (CPS). Our research approach combines CPS with advanced video information processing technology to provide a scalable and effective university network management and monitoring system. To improve the real-time processing of video data and enable better security and surveillance, we employed deep convolutional neural networks (CNNs). Because of the system's modular architecture, cloud agents installed on edge devices may be integrated, and improvements can be made gradually. The results show significant gains in system operability and real-time stability. The management system demonstrated improved capacity for coding, transmitting, and capturing video data, which improved operational effectiveness and decreased management expenses. In addition to meeting the current demands of campus security, implementing this system offers a scalable approach that can keep up with future technological developments.

Keywords: deep learning; video signal processing; university management; edge computing; cyber-physical fusion system

1. INTRODUCTION

Video surveillance systems have been widely constructed in public safety management and have played an indispensable role. The application of video surveillance systems in teaching is mainly reflected in internal examinations. Many schools install video surveillance systems for campus safety management [1]. Video surveillance systems are essential in Chinese universities as they enhance security by providing real-time monitoring, recording incidents, acting as visible deterrents, and implementing preventive measures. These systems prevent crime, tackle security weaknesses, and facilitate quick emergency assistance through instant alerts and collaboration with police forces. Incorporating access control systems guarantees that only approved individuals can enter restricted areas. Sophisticated features such as visitor tracking, behaviour analysis, predictive security measures, and resource optimization improve campus safety by monitoring movements, detecting potentially dangerous behaviour, forecasting security problems, and effectively deploying security staff. Video surveillance plays a significant role in enhancing technical security measures and promoting a safer campus environment. There are different voices on whether surveillance cameras should enter the classroom. Even if monitoring equipment is installed in the school, it is only used for examinations and classroom management, not daily monitoring of teaching processes. Colleges and universities need to solve the problems plaguing teaching quality improvement, such as poor monitoring of the whole teaching process and inadequate handling of the issues in the teaching process. How can the video surveillance system play a more significant role in the field of teaching, especially how to use the system to monitor and provide feedback on the teaching process, diagnose and improve the teaching status, promote the construction of teaching style and learning style of teachers and students, and enhance the quality of teaching is an essential topic in the field of current teaching management [2].

Computer video signals are high-speed. Display circuits are complex. The amount of data stored is substantial, and the update speed is breakneck. This complicates the circuit structure of the traditional single-chip microcomputer-based driver board, and the video output effect is unsatisfactory. If the control logic of the driver board adopts integrated circuit technology, the structure of the circuit is greatly simplified, and the quality of the dynamic image will be improved. However, under the existing conditions of the school, it is unrealistic to make the drive control part an application-specific integrated circuit [3]. In intelligent video surveillance signal processing, the amount of video data and calculation is considerable, and the structure of various algorithms is very complex. Therefore, digital signal processing chips with solid communication capabilities, fast computing speed, and convenient addressing were born. Deep Learning (DL) has not only achieved success in image and video recognition but also made significant progress in traditional image and video processing. Improvements in deep learning techniques like convolutional neural networks (CNNs) have boosted the performance of tasks related to recognizing pictures and videos. CNNs employ convolutional layers to acquire features in visual data, enhancing the detection of patterns and objects. Innovations such as residual connections, attention mechanisms, and recurrent neural networks (RNNs) have increased model performance by capturing spatial and temporal

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dependencies. Significant annotated datasets such as ImageNet and Kinetics have also influenced training models, leading to better accuracy and generalization. These advancements have greatly improved the capabilities of recognizing images and videos [4].

In recent years, the application of DL in computer vision has made significant progress. Computers can complete image processing tasks with low, medium, and high semantics using deep Convolutional Neural Networks (CNNs). CNN can fully use image features to complete different image recognition tasks using machine learning techniques for training on a huge image database. A critical neural network design is the convolutional neural network (CNN) to process video data in university administration systems. Activation, pooling, output, feature extraction, classification, and standardized video frame layers are all included. For faster processing, improved security, and administration in university settings, preprocessing procedures such as noise reduction, data augmentation, normalization, and selective frame analysis are crucial. Transfer learning involves adjusting a pre-trained model from a broad dataset onto a smaller dataset for improved results on a similar task. In CNN training for image recognition, transfer learning extracts high-level features from images using a pre-trained model, reducing computational needs and labelled datasets. It boosts efficiency by utilizing previous model training to more accurately classify new images. DL-based video surveillance systems can efficiently use data compared to traditional video surveillance technology. This is undoubtedly a huge advantage in today's significant data era. Meanwhile, as an essential means of artificial intelligence technology, video surveillance systems based on DL are also more intelligent. It can be more effective in preventing campus safety accidents [5].

First, this paper uses mature video information processing technology based on the above problems. It adopts a Cyber-Physical System (CPS) to construct a management architecture to develop and implement a university network monitoring and management system. Incorporating CPS in schools enhances safety and security with real-time monitoring, fast response times, and advanced analytics. CPS merges computational and physical elements to proactively address safety concerns. Enhanced monitoring systems with immediate data analysis identify potential threats, while environmental sensors detect dangers like fires. Biometric authentication and automated access control limit access to approved individuals. Integrated systems activate alarms, ensure secure evacuations, and detect security issues early. Anticipatory maintenance prevents breakdowns, while unified security platforms offer a comprehensive safety perspective, revolutionizing campus security. Second, the overall scheme design of the management system is carried out. The overall requirements of the management system are analyzed. Efficient and accurate identification of unmanned platforms in neural network models requires a workflow that includes data acquisition, preprocessing, feature extraction, data augmentation, and validation processes. Different and inclusive samples in different situations must be collected, along with preprocessing techniques such as normalizing images and reducing noise. Utilize feature extraction methods for unmanned platforms and incorporate data augmentation to ensure model generalization. Assessing workflow performance through validation processes is essential before deploying neural network models. The unmanned platform identification system based on a neural network is designed in the network environment according to each functional module and workflow. Developing an identification system for unmanned platforms entails a meticulous process involving data collection, preprocessing, model selection, training, integration, and real-time monitoring within a network setting.

Choosing the appropriate neural network structure for object detection and classification is crucial, followed by iterative training to achieve accurate detection while avoiding overfitting. Careful planning of deployment, interfaces, and security is necessary for successful integration with the network environment, enabling live analysis and adaptive learning for enhanced awareness and security against unmanned platform threats. Finally, Edge Computing (EC) establishes a shallow edge agent with a neural network. Cloud agents in the deep part of the neural network are deployed on edge devices. Multi-agent is built in the edge-cloud collaborative manner to automatically collect, process, and classify information in multiple aspects of universities. The study examines how edge and cloud work together in academic settings, emphasizing how edge computing and cloud infrastructure are better connected. This alliance enhances data collection, processing, and analysis by combining local edge devices with central cloud resources. By optimizing resource usage and decreasing network congestion, this technique lowers latency and improves scalability, flexibility, and real-time decision-making.

The paper will follow an introduction with a literature review to provide an overview of existing research on network monitoring and management platforms for universities and video signal processing technology based on deep neural networks. The materials and methods section will outline the approach to constructing the network monitoring and management platform and implementing video signal processing technology. The results and discussion section will present the study's findings, specifically focusing on the results and subsequent analysis and interpretation. Finally, the paper will conclude with a comprehensive conclusion summarizing the key findings, their implications, and potential areas for future research and development.

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2. LITERATURE REVIEW

With the rise of deep CNNs, most current object detection algorithms use algorithms based on DL. The purpose is to identify a specific object in the image, locate the position of the object's centre point, predict the size of its encirclement, and determine the target category. Sreenu proposed using a selective search algorithm to generate candidate image regions. Then, the candidate region was clipped to the network to learn the in-depth features, the extracted features were classified, and the candidate region was finely corrected. Compared with other target detection algorithms at that time, the accuracy of this algorithm had been significantly improved, but it also had the disadvantage of a relatively redundant algorithm [6]. Sung treated the image as a uniform grid. If the object's centre fell into a grid, the prediction target in the grid belonged to the confidence level of the foreground and background, the size, and the category of the bounding box. There is no need to suggest the extraction of the region. This enables fast target detection at 60 frames per second [7].

The hardware of the teaching video surveillance system is mainly composed of high-definition video camera equipment, a central monitoring room, and a computer monitoring software system installed in the teaching place. Purwto took the operation practice of the college teaching video surveillance system as an example to illustrate the promotion role of the system in improving the quality of classroom teaching and considered the improvement and function of the system [8]. University management systems have difficulties because of their complexity, scalability, and changing technology requirements. Scalability is a challenge for traditional approaches, and outmoded systems have challenges with improved functionalities, security, data-driven decision-making, integration, regulatory compliance, and integrating edge computing, AI, and IoT. Hew installed video surveillance in university classrooms. The original belief and assumption were that video surveillance could improve university teachers' teaching enthusiasm and enhance college students' learning participation. Improving the teaching quality of university teachers also promotes the cultivation of the core literacy of college students [9]. The purpose is to increase college students' engagement in learning by installing video monitoring systems in classrooms. These tools offer real-time data to track instructional strategies and behaviours, increasing student involvement and instructor zeal. Better results and greater student participation in learning activities are produced by this method, which establishes an interactive, adaptable learning environment. Zhang believed that the digital video surveillance system could meet multiple video inputs. The various video signals were stored, analyzed, encoded, and denoised on a single computer suitable for long-distance digital signal transmission. The digital video system was easy to maintain. It was resistant to interference and had a high level of integration [10]. Zhang and Lakshmana Kumar et al. (2024) described students' academic success as greatly affected by the quick growth of technology and information. A multimedia-assisted ideological and political education system employing deep learning techniques (MIPE-DLT) is presented to improve the quality of instruction. To attain greater accuracy and processing rates, a high-order performance ratio, and a low delay rate, this model evaluates students' skills to obtain information and use multimedia approaches [11].

In summary, with extensive attention and in-depth research on surveillance video signal processing technology domestically and internationally, the performance of digital video processors is also constantly improving, and intelligent video surveillance systems are developing rapidly. Based on the concept of DL, this paper integrates CPS and edge cloud computing technology and designs a video signal recognition system based on the neural network under DL according to each functional module and workflow to realize the acquisition of video data and the mutual conversion between formats. The system's real-time stability is improved to reduce the school's management cost and efficiency by optimizing university monitoring and management's video collection, encoding, and transmission. Overall, the traditional management education in colleges and universities has become inadequate due to the rapid development of deep learning and edge technology and the emergence of new systems to reform these institutions. There is a need to enhance the video surveillance system to play a more significant role in the field of teaching, especially in monitoring and providing feedback on the teaching process, diagnosing and improving the teaching status, promoting the construction of teaching style and learning style of teachers and students, and enhancing the quality of teaching. Additionally, the existing conditions of the school make it unrealistic to make the drive control part an application-specific integrated circuit in the field of intelligent video surveillance signal processing.

3. MATERIALS AND METHODS

3.1 Construction of network monitoring and management platform for universities

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With the development of China's education system, the scale of schools has expanded, the area of colleges and universities has increased, the layout has been scattered, and the flow of students has increased. Educators can use various methods to track students' progress in class beyond monitoring devices. Formative assessments such as quizzes and writing tasks provide insights into comprehension and engagement. Encouraging active participation and dialogue enables observation of verbal and group interactions. Teacher observations and self-assessments offer valuable information on behaviour and learning patterns. Hands-on experiences and project-based learning activities also help evaluate student improvement. Integrating these methods with standard monitoring tools provides a comprehensive view of student learning and participation.

All these have brought significant challenges to the traditional security management model. Traditional security management models in Chinese higher education institutions struggle due to increasing campus size and student mobility. The vast and complex nature of modern university campuses presents challenges in effectively monitoring and securing all areas. As schools expand, the need for robust surveillance systems and staff grows to ensure complete monitoring, especially in buildings, amenities, and outdoor spaces. The rise in student numbers and visitors leads to overcrowding and congestion, escalating security risks like unauthorized entry, theft, and violence. Adapting to evolving threats such as cybersecurity risks, protests, and health emergencies is difficult for outdated security frameworks. Inadequate resources and communication among security departments exacerbate these challenges, underscoring the need for innovative security management approaches in Chinese higher education institutions. Scientific and efficient modern information management mode is gradually applied to the security management of colleges and universities. Among them, the video surveillance system has shown significant efficacy in the security management of various universities. The surveillance system combines network, video processing technology, and computer processing power. It is essential to strengthen the construction of technical prevention facilities in colleges and universities. Colleges and universities are facing safety challenges related to the mental health of students, faculty, and staff. The campus community is seeing increased levels of stress, anxiety, and depression, exacerbated by academic pressure, social isolation, and financial difficulties. Addressing these issues requires prevention, early intervention, and access to mental health resources. Educational institutions must adapt to changing mental health trends by implementing awareness campaigns, peer support programs, counselling services, and crisis intervention protocols to safeguard campus safety. It is also indispensable for colleges and universities to do an excellent job in safety precautions and management and ensure campus safety and stability in the new situation [12].

The video surveillance system directly views the situation of the monitored place through the remote-control camera and its auxiliary equipment. Cameras and additional equipment that are controlled remotely are essential components in video surveillance systems within Chinese higher education institutions. They offer extensive coverage, adjustable viewing angles, and real-time monitoring of entry points, common areas, and sensitive locations. Integration with analytics and AI enables the automatic identification of dubious actions and prompt reaction to security risks. The system's ability to scale ensures it can adjust to changing security requirements. This integration improves how efficiently operations are carried out and boosts safety on campus. The images and sounds of the monitored place are simultaneously transmitted to the monitoring centre so that the situation is displayed, which is convenient for the timely detection, recording, and disposal of abnormal conditions. The monitoring system can record all or part of the images and sounds of the monitoring place, providing a convenient backup and an essential basis for processing certain events in the future [13]. Video surveillance systems in Chinese universities offer benefits like providing backup footage and analyzing events. The footage aids in investigations, identifying perpetrators, and improving campus safety. However, concerns arise about privacy violations, resource allocation for data handling, and potential misuse of stored footage. Balancing privacy, security, and resource utilization is crucial to ensure responsible implementation and minimize drawbacks. The wiring direction of the monitoring system is shown in Figure 1.

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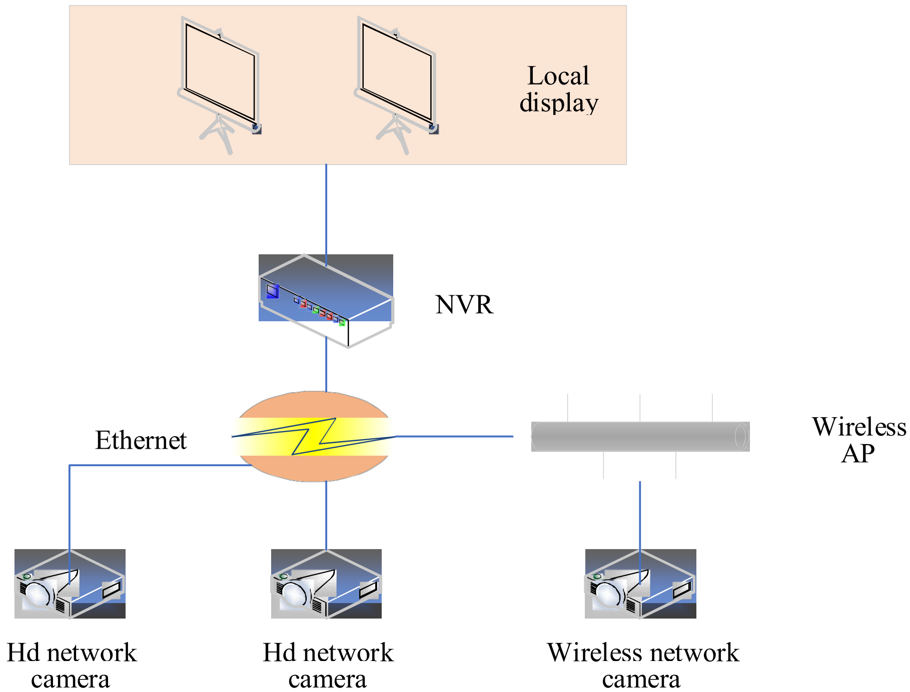

Figure 1: Campus monitoring system

The general video surveillance system comprises three parts: a front-end system, a transmission system, and a terminal system. Table 1 demonstrates the composition of each component and the main tasks.

Table 1: Video surveillance system components

Each component system	Ancillary facilities	Main tasks
Front-end system	Voice control system	Get monitoring information
	Alarm probe	
Transmission facilities	Transmission control devices	Control the transfer of information
	Transmission line	
Terminal facilities	Signal processing,	Issue control instructions
	recording device,	
	listening devices,	
	communication equipment	

Colleges and universities have the characteristics of open management, dense personnel, large campus areas, weak security forces, and many expensive teaching instruments and equipment, and safety management is complex. As campuses grow, meeting more students' needs is a challenge. Overcrowded classes and limited resources are common issues, with infrastructure often falling short. Budget and space constraints hinder the expansion of academic buildings, housing, and dining facilities. Increased students also require more teachers, administrators, and support services to maintain education quality. Planning and investment are crucial to ensure campuses can support growth and provide a conducive learning environment. Therefore, the issue of campus safety precautions is becoming increasingly important. Campus safety is upheld by the essential presence of campus security staff, emergency response teams, and external agencies. Security staff conduct patrols, monitor surveillance systems and ensure adherence to campus policies to maintain a safe environment. Emergency response teams are prepared to manage emergencies such as medical and natural disasters by practising drills and responding quickly to events.

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External organizations, like local law enforcement and fire departments, assist during significant events, working with campus officials to improve safety. Through collaborating in joint training exercises and sharing information, these entities establish a thorough safety network that safeguards the campus community and fosters a safe learning environment.

In addition, the security prevention work of colleges and universities needs to use various means to collect, collate, and process the required information. Information is expressed in multiple ways, including text, data, sound, and images. Sound and image information can most accurately illustrate and reflect the situation more fully [14]. The essential characteristics of video surveillance precisely meet the needs of university security work and become a necessary part of university security prevention. University video surveillance systems play an important role in campus security by preventing crime, monitoring busy areas in real-time, and assisting with investigations. They balance security needs and privacy concerns by strategically planning coverage areas and avoiding monitoring private spaces. Incorporating other security measures boosts security overall by offering a comprehensive strategy for identifying and responding to threats. These systems are essential for ensuring a secure environment on campus, balancing privacy issues, and improving overall efficiency. Its functions mainly include the following aspects (Figure 2).

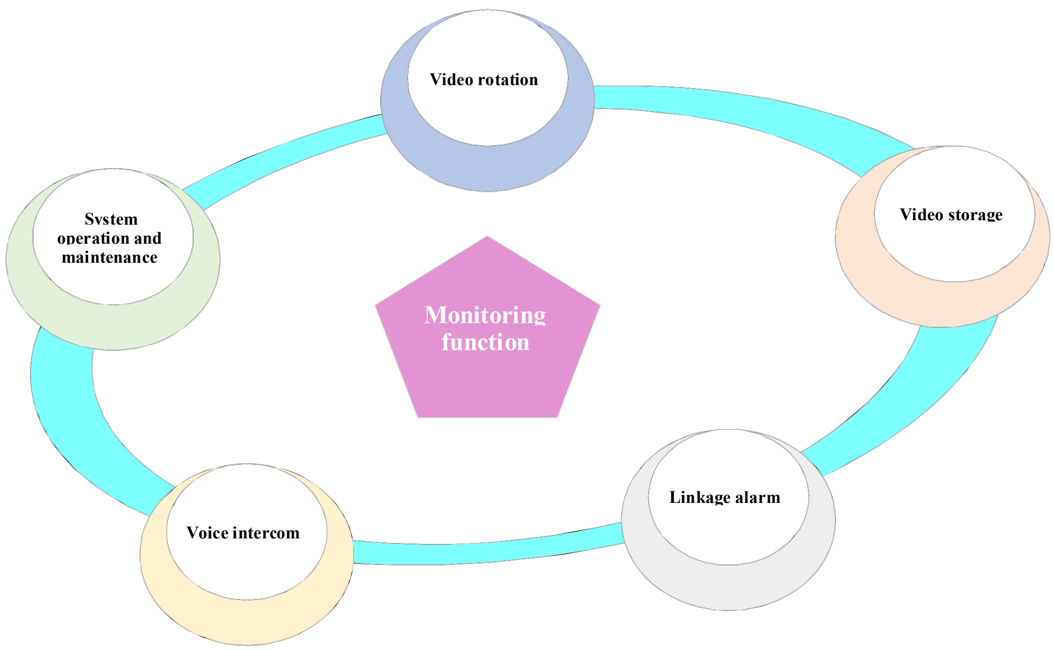

Figure 2: University video surveillance function

Currently, there are two main modes of monitoring system networking: all-digital and digital-analog combination modes. System networking applications provide flexible solutions for security and surveillance needs in digital or digital-analogue modes. Digital systems offer scalability, image quality, and advanced features, suitable for large areas like campuses or business complexes. They enable remote access, video analysis, and integration with other security systems for improved situational awareness. Digital-analogue modes combine digital and analogue technologies, allowing for a gradual transition to fully digital systems. Both modes offer customized solutions for modern security settings, delivering efficient surveillance and protection against security risks. The typical symbol of the former is network cameras and digital matrices, and the usual symbol of the latter is analogue cameras and video encoders. Through field research and comparative analysis, the total number will be more in line with the construction of this management platform [15]. The all-digital network video surveillance system is the most advanced architecture of current network video surveillance.

Integrating a fully digital network video surveillance system offers benefits over analogue cameras in scalability, image quality, and application functionality. Digital systems allow easy expansion and integration with existing network infrastructure, reducing installation costs. High-quality digital cameras provide sharper images for improved object and person recognition, which is crucial for facial and license plate recognition tasks. Advanced features like remote access, motion detection, and video analytics enhance surveillance capabilities.

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Overall, digital systems are superior to modern security needs compared to traditional analogue methods. It is the future development direction of network video surveillance. Other network monitoring modes will gradually transition to all-digital mode. The digital-only surveillance system ensures durability by quickly adapting to evolving security needs, expanding with the campus setting, and offering remote access for monitoring and maintenance. The system's scalability, flexibility, and advanced features like analytics and AI functionalities enhance its ability to detect and respond to threats, ensuring long-term sustainability on college grounds.

An all-digital network video surveillance system is the cornerstone of cost-effective high-definition video surveillance. It can quickly expand and develop new application functions. The digital network video surveillance system enables scalable growth and the simple creation of new application features. It can work with current network infrastructure, enabling smooth integration and growth without significant upgrades. Surveillance coverage can be quickly expanded by connecting more cameras to the network, allowing easy deployment and scaling. Features such as video analytics, motion detection, facial recognition, and object tracking can be quickly added using software updates. Remote access and management can also be done, allowing for monitoring from any location with internet connectivity. The system can be tailored to meet the unique requirements of organizations and effectively tackle changing security issues, making it versatile and adjustable. It is a set of sustainable and advanced network video surveillance systems in line with the law of development [16]. As the video surveillance system's image acquisition device, the quality of the image obtained by the camera will directly affect the encoded image quality, impacting the image quality presented in the monitoring centre [17]. Compared with the traditional analogue camera + video encoder method, the network camera will bring the following benefits (Table 2).

Table 2: Advantages of network cameras

Advantage comparison	Video encoder	Network Camera
Environmental adaptability	Stability can be affected in weak wells with poor environments.	Comparable to a traditional work environment
Cabling installation	Video, audio, control, power supply, and network cable required	A network cable
Clarity	400,000 pixels	Two megapixels
Data source	All-digital signal processing	Analog signal
Anti-interference	There are various types of interference.	No analogue transmission process
Average cost	Low value for money	Cost-effective

3.2 Video signal processing technology based on deep neural networks

CNNs are one of the most commonly used base models among DL models for video signal processing. It can directly use images as input for feature extraction and performs well. CNNs utilize three unique treatments to

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reduce the parameter scale of the model to make model training easier: (1) The first is local perception. The size of each convolution kernel is generally tiny. It does not perceive the global image but the part of the image to extract the features of a specific local area of the image or feature map. (2) The second is weight sharing. Local features of the image may appear in other areas. Therefore, convolution kernels with the same weight parameters can be used for different regional areas of the image, significantly reducing the number of parameters. (3) The third is downsampling. After the convolutional layer's operation, the large output still contains noise. Therefore, the feature map is introduced into pooling to reduce the dimension of the feature map [18]. The classical CNN structure consists of convolutional, pooling, fully connected, and output layers. Its structure is displayed in Figure 3.

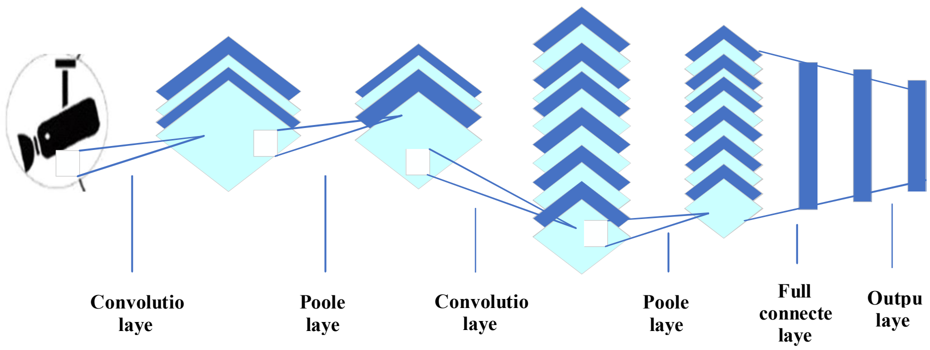

Figure 3: CNN structure

The convolution operation only performs a linear input calculation, and the description of image features cannot be expressed linearly alone. A nonlinear activation function needs to be introduced to increase the expressive power of the entire network. Nonlinear activation functions in neural networks enhance expressive capabilities and efficiency by adding complexity and nonlinearity to calculations, enabling understanding of intricate patterns in data. Utilizing functions like ReLU, Sigmoid, or Tanh improves classification, regression, and deep network training performance, addressing vanishing gradient issues. Overall, nonlinear activation functions enhance network efficiency and the ability to handle complex tasks in image recognition, natural language processing, and pattern recognition. In convolutional layers, the convolution operation's result obtains the convolutional layer's accurate output through a nonlinear activation function. If the lth layer is a convolutional layer, the function expression for that convolutional layer is:

$$x_j^l = f\left(\sum_{i-1}^{N^l-1} G_{i,j}^l (k_{i,j}^l \otimes x_i^{l-1}) + b_j^l\right) \quad (1)$$

In Eq. (1), $k_{i,i}^l$ Represents the convolution kernel parameters of that convolutional layer. b_i^lRepresents the bias parameters of this convolutional layer. The operator sign ⊗ indicates a convolution operation.
The window sliding method in the pooling operation is the same as the sliding method of the convolution kernel window in the convolution operation. Using sliding techniques in pooling operations is essential for maximizing neural network efficiency. These techniques determine how the pooling window moves across feature maps, impacting the spatial layout of features. Factors like computational efficiency and feature preservation are vital in evaluating performance. Traditional methods may cause information loss, while modern approaches use overlapping areas or adjust sizes to combat this. Understanding sliding techniques helps optimize neural network performance for tasks like image recognition and object identification, with operations like max-pooling aiding in reducing dimensionality and maintaining essential information. Still, the pixels that the pooling layer slides through two consecutive steps do not overlap. If layer l+1 is pooled, the layer can be calculated according to Eq. (2).

$$x_j^l = p(x_j^{l-1}) \quad (2)$$

In Eq. (2), $p(x)$ represents the pooling operation. The pooled kernel size is typically set to 2×2.

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The output of the fully connected layer is passed to the output layer, which usually uses the SoftMax function. If the lth layer is fully connected, and the previous layer is also fully connected, the layer can be calculated according to Eq. (3).

$$x^l = f(\omega^l x^{l-1} + b^l) \tag{3}$$

In Eq. (3), ω^l represents the weight parameter for that layer. b^l represents the bias parameters for that layer. The function $f(x)$ denotes the nonlinear activation function used by the layer.

CPS is a multi-dimensional complex system for comprehensive computing, network, and physical environments for manufacturing. Cyber-physical systems are complex systems that blend digital processes with tangible components, creating intricate relationships and behaviour. They integrate digital information processing with physical processes, resulting in complex feedback loops. Components like sensors, actuators, networks, and control systems interact across multiple levels. In manufacturing, CPS coordinates robots, machines, sensors, and humans, managing uncertainties and failures. Holistic approaches are crucial for designing and controlling dynamic systems. Recognizing CPS as a multi-dimensional complex system helps address challenges in digital and physical realms. It realizes real-time perception, dynamic control, and information services of large-scale engineering systems through the organic integration and in-depth collaboration of communication, computer, and control technology. CPS realizes the integrated design of computing, communication, and physical systems. It makes systems more reliable, efficient, and collaborative in real-time. It has crucial and broad application prospects. Through the organic integration, in-depth collaboration, and feedback optimization of the computing and physical processes, CPS realizes the whole process monitoring, intelligent optimization, and collaboration in video signal processing, thereby reducing the management cost of the school and improving the management efficiency [19].

The overall structure of this system is composed of three parts: multimedia video card, driver board, and display board. Multimedia video cards are commercially available moulded products. This design approach requires all signal distribution and conversion processes in the driver board. It also puts forward higher requirements for the workload of signal processing and the circuit's operating frequency, which is quite challenging to design. The multimedia system requires the multimedia video card, driver board, and display board as essential components. The GPU in the video card enhances system performance by managing complex tasks to render images and videos using graphics data. The driver board facilitates communication between the video card and the operating system by translating commands effectively. The display board processes video signals and manages display settings to ensure clear visuals. These components collaborate to seamlessly provide top-notch multimedia experiences, such as gaming and graphic design [20]. The overall structure of the system is shown in Figure 4.

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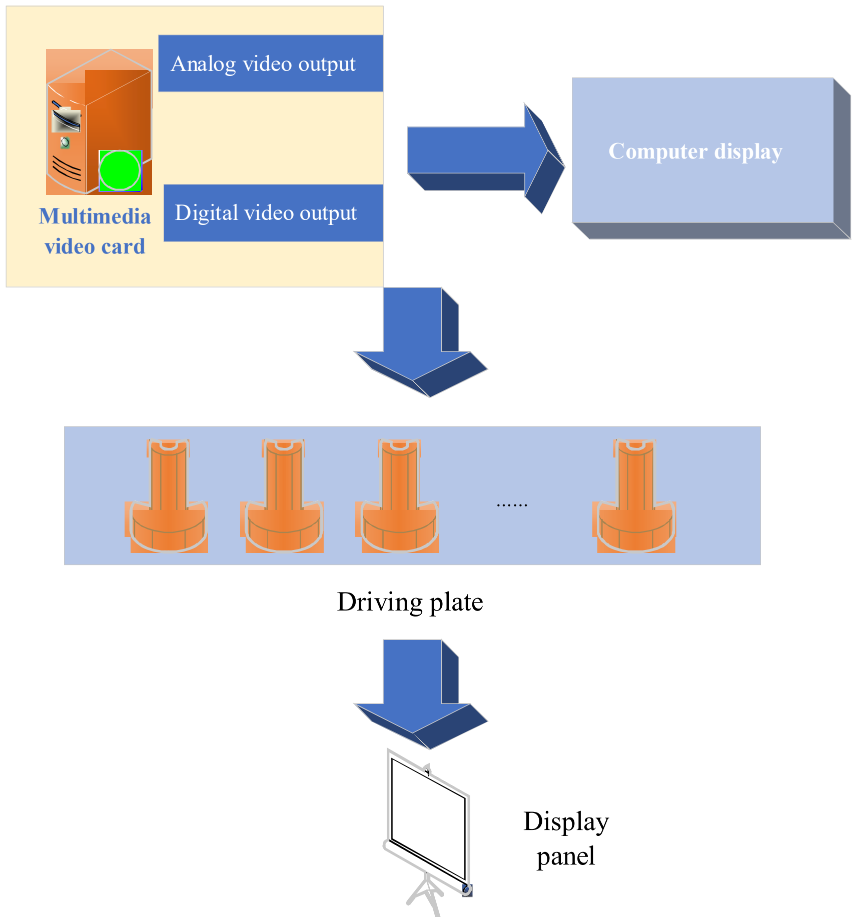

Figure 4: Video signal processing system structure

The video signal is output from the digital video interface of the computer multimedia video card and sent to the driver board for area recognition, data caching, block reading, and pulse width modulation. Finally, it is sent to the display board to scan the image. All signal processing is done on the driver board. Signal data updates are fast, and the amount of data is enormous. The whole processing process has the characteristics of high speed, real-time, and high synchronization [21].

The EC model integrates the hardware unit with computing power into the original video surveillance system software and hardware platform to realize a new system with EC capability. In EC models, computing usually occurs near the data source. Video data processing is carried out at the edge of video data collection. Universities utilize deep learning algorithms to analyze video data and identify.

Significant patterns to identify security issues. These algorithms, frequently found in neural networks, automate the analysis of surveillance footage to detect anomalies, unauthorized activities, and potential threats. Through extensive training with large video datasets labelled, algorithms are taught to identify particular security-related actions, objects, or incidents such as trespassing, theft, or aggression. They oversee campus environments in real time by utilizing object detection, motion tracking, and anomaly detection, highlighting potentially suspicious activities for necessary action. Continual research advances algorithm precision and productivity, enhancing safety on campus.

On the one hand, the preprocessing function module based on an intelligent algorithm performs the fuzzy calculation. The preprocessing function module utilizes an intelligent algorithm to execute fuzzy computations using fuzzy logic principles to manage imprecise or uncertain inputs. Fuzzy logic involves assigning membership degrees to categories to represent uncertain concepts. This unit converts unprocessed data into fuzzy sets with membership values assigned to linguistic terms. This allows for transforming numerical information into fuzzy representations to grasp uncertainty. Fuzzy inference rules can be utilized to make decisions based on the data,

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enhancing system adaptability. It performs part or all of the computing tasks on the real-time collected video data, which can provide timely response services for application requests with high real-time requirements. On the other hand, designing a scalable, elastic storage function module and using intelligent algorithms to sense and monitor behaviour changes in the monitoring scene is necessary to achieve high spatial storage efficiency [22]. The block diagram of the video surveillance system based on EC is presented in Figure 5.

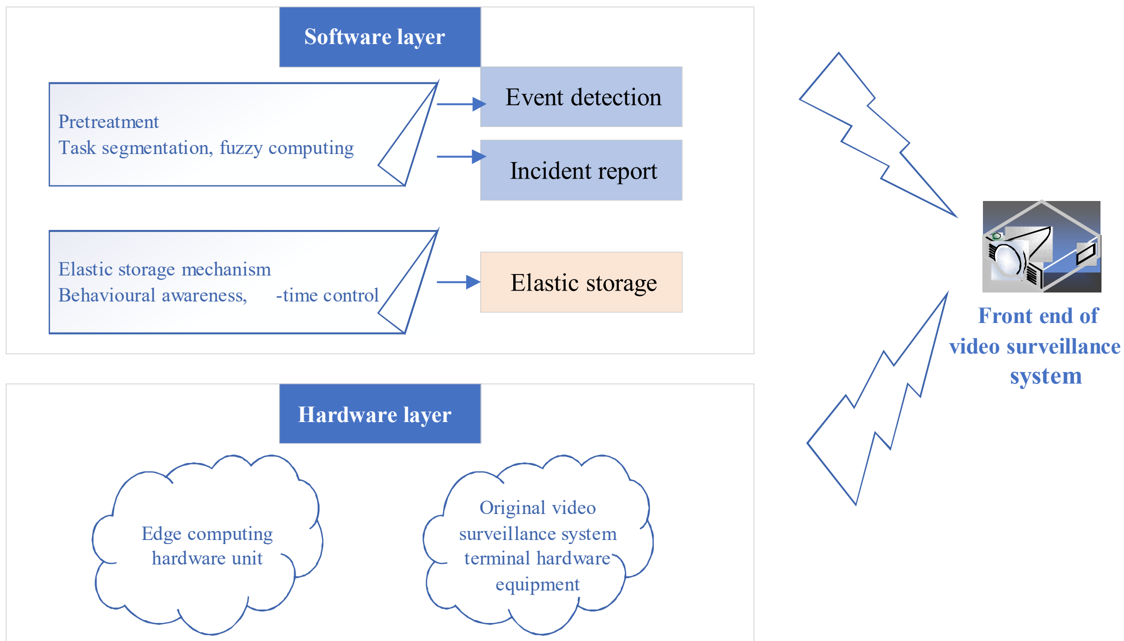

Figure 5: Block diagram of a video surveillance system based on EC gateway

Based on the technical advantages and characteristics of EC from the current industrial development, it will be applied in scenarios with high requirements for latency, bandwidth, cost, and other indicators, such as smart cities, smart transportation, smart homes, and intelligent energy. The current cloud computing and Internet of Things technologies combined with EC will significantly improve the support capacity for the above high-demand scenarios. For example, through the video EC gateway, the behaviour analysis functions such as face recognition and cross-boundary alarm are moved from the system master station computing and processing to the scene, which can effectively reduce the network bandwidth requirements and communication costs of the video surveillance system [23].
This project installs cameras in student dormitories, teachers' offices, campus gates, campus supermarkets, and observation decks to monitor campus security and precautions. This provides the relevant basis for investigation and evidence collection within the campus and higher regulatory authorities. When setting up a surveillance system, various factors must be considered to ensure optimal coverage, visibility, and compliance with data integrity and privacy laws. Cameras should be strategically placed to cover high-risk areas without blind spots, with adjustments to fields of view, resolution, and angle for high-quality footage. Lighting and obstructions must be evaluated, secure data storage solutions implemented, and privacy regulations followed. Balancing these factors creates a system that enhances security while respecting privacy and data integrity. Table 3 shows the distribution of front-end monitoring points in this project.

Table 3: Distribution of monitoring points on campus

Location	Installation location	Camera type	Installation method	Quantity
School gates	West gate	License plate camera	Pole type	Three
	South gate	Infrared camera	Pole type	Two
Classroom	South building	High-speed net smart ball	Wall-mounted	Five
	North Building	High-speed net smart ball	Wall-mounted	Five

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Student dormitory	Building 1-12, Nanshan	Infrared camera	Wall-mounted	Twelve
	Building 1-10, Zige	Infrared camera	Wall-mounted	Ten

As the spire of the entire system, the centralized monitoring centre carries out comprehensive management of the system's resources. It has a remote monitoring and control function, alarm function, configuration function, security management function, report function, communication management function, display function, and printing function. The centralized monitoring centre can also realize the monitoring of field devices through the monitoring sub-centre computers distributed in various areas of the campus, with a remote access function. The data server is the storage centre of files and databases. The network's core is also responsible for processing the monitoring system's data, authority management, fault classification, and other definitions.

The analogue video signal consists of video analogue data and video synchronization data used by the monitor to display the image correctly. The details of the image depend on the video standard or format applied. Here, video signal processing technology based on DL and EC uses a luminance signal and two chromatic aberration signals that are compatible with black-and-white TVs as transmission signals. The main parameters of this video format are presented in Table 4.

Table 4: Main parameters of video formats

Main parameters	Luminance bandwidth (MHz)	Chroma bandwidth (MHz)	Lines per frame (lines)
Value	5.6	1.2(U), 1.2(V)	600
Main parameters	Frequency (Hz)	Subcarrier (MHz)	Sound carrier (MHz)
Value	28	4.38	6.3

4. RESULTS AND DISCUSSION

4.1 Results

The platform's latency and bandwidth are tested to verify the application's adequate support. The end-to-end latency and bandwidth of remote cloud platforms at the network's edge and under different access modes are compared. Various techniques are used to compare the latency and bandwidth of remote cloud platforms through different access modes. Real-world application testing assesses performance metrics under different network configurations. Data analysis and modelling examine performance across wired, Wi-Fi, and mobile networks, considering factors like network congestion, distance to cloud data centres, and quality of service mechanisms. Integration of these techniques allows for comprehensive evaluation and comparison of cloud platform efficiency. Besides, the network services that provide stability, low latency, and high bandwidth are compared. Essential factors in assessing network services include latency, bandwidth, stability, reliability, QoS, scalability, and user experience. Latency is measured using RTT and Jitter, while bandwidth is assessed through Throughput and Bandwidth Utilization. Stability and reliability are evaluated using Packet Loss Rate, Uptime, Availability, and Error Rates. QoS is determined by traffic prioritization and SLAs. Scalability is tested for load handling and elasticity. User experience is analyzed through Application Performance and Feedback. The comparison of video test accuracy is given in Table 5.

Table 5: Video test accuracy comparison

Video test comparison	Camera acquisition	Mobile phone acquisition
Average accuracy (%)	93.58	81.17
Average false detection rate (%)	1.76	3.58
Average missed detection rate (%)	3.34	12.65

The performance of the two platform servers is close and almost at the same level regarding the average accuracy of statistical video detection and the processing time under the same bit rate. Surveillance camera acquisition has excellent advantages over mobile phone terminal processing. The algorithm analysis speed of the system designed here is tested with multiple video inputs. The results can be revealed in Table 6.

Table 6: DL model speed with different numbers of video channels

Number of video channels	1	2	3
Model processing time	23 ms	28 ms	34 ms
Post-processing time	6 ms	8 ms	12 ms
Processing speed	45FPS	22FPS	24FPS

According to the data in Table 6, the system can still achieve the speed of real-time analysis (22FPS) with two input video streams. When three video streams are input, the system cannot achieve real-time processing speeds

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but can still achieve relatively fast processing speeds (24FPS). The post-processing time in Table 6 includes the processing time using maximum pooling as the non-maximum suppression algorithm and the image expansion algorithm. Effective post-processing is crucial in image processing projects, particularly object detection and recognition tasks. Non-maximum suppression (NMS) and image dilation are critical algorithms used in post-processing. NMS reduces overlapping detections by selecting the most significant ones, improving outcome accuracy. Image dilation expands identified areas for better object localization and spatial understanding. Implementing these algorithms enhances image processing systems, increasing result quality and usability in various applications like computer vision and autonomous systems.

4.2 Discussion

In his research, Blinder introduced concepts related to video signal processing and the challenges faced by video signal processing technology. The complexity of algorithms for intelligent video surveillance arises from processing large amounts of real-time data. Features extraction, object detection, and motion tracking are computationally demanding. The ever-changing nature of video data complicates tasks like motion estimation and scene comprehension. Real-time processing requires efficient optimizations and hardware accelerations. Advanced algorithmic methods and parallel processing are crucial for developing scalable surveillance systems. Then, video coding technology, interactive three-dimensional video technology, and intelligent video processing technology in multimedia applications were introduced, compared, and analyzed. Video coding technology, interactive three-dimensional video technology, and intelligent video processing technology were compared in multimedia applications. Video coding emphasizes effective compression and delivery but lacks interactive features. 3D video provides immersive experiences but demands computational resources. Intelligent video processing allows for object detection and recognition; however, it raises privacy concerns. The analysis highlights these technologies' range of abilities and compromises, offering guidance on incorporating them into multimedia applications according to particular needs and goals. Finally, he introduced some typical application cases of video processing technology using intelligent video surveillance, video servers, and video phones as examples [24]. Cao proposed using DL to solve the problem of low recognition accuracy caused by human occlusion and body misalignment in the recognition task in the surveillance video. Two algorithms were proposed: (1) a deep network combining classification and multi-scale matching models was designed, and high-level feature maps were obtained using the classification model. Based on this, the multi-scale matching model was used to convolve the feature map at different scales to capture the semantic association of different pedestrian images and overcome the influence of body misalignment. (2) Second-order pooling was used to realize attention pooling to effectively extract the characteristics of the human body area, overcome the interference of external factors such as background, and improve the accuracy of video behaviour recognition [25]. This paper uses the CPS to construct the management architecture and develop and implement the university network monitoring and management system. It designs the management system's overall scheme, analyzes its requirements, and designs an unmanned platform identification system based on a neural network in the network environment according to each functional module and workflow. Finally, EC establishes a shallow edge agent of the neural network. The cloud agent of the deep part of the neural network is deployed on the edge device. The multi-agent is built through edge-cloud collaboration to automatically collect, process, and classify the university's multi-directional information. The advantages of using deep learning and edge computing technologies in an advanced video surveillance system for university administration are covered in this study. This system improves campus security by offering real-time monitoring, facilitating quick threat identification and response, and enhancing decision-making, resource allocation, and emergency response. It lowers operating expenses as well. Universities must evaluate their infrastructure, include stakeholders, run experimental programs, train employees, and take ethical and privacy concerns seriously. It takes frequent user input, upgrades, and monitoring to keep up with emerging technologies and new issues.

5. CONCLUSION

The application of video surveillance systems in public safety is receiving more and more attention. New video surveillance systems based on EC add higher computing power, lower transmission delay, and more accurate processing power to video signal processing. With the development of EC system architecture and improved customized functions, EC can better promote the application of new video surveillance systems in public safety. Overall, the proposal of mobile EC can effectively solve the problems of increasing user traffic and low latency services in the existing network. Video analytics tracking and detection services can improve performance based

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on the mobile EC platform, enhance the system's scalability, and efficiently use network computing and storage resources.

Additionally, the network openness capability of mobile EC can better promote the development and prosperity of the innovative mobile application market. EC has broad application prospects. There is still broad development potential in video analysis, video acceleration, and intensive computing assistance. Due to concerns about data privacy, the system's complexity and scalability, and the possibility of significant setup, maintenance, and operating expenses, this cutting-edge system—which uses edge computing and deep learning—might not be practical for institutions with limited infrastructure. To further improve the security and accessibility of these systems, future research should concentrate on strengthening data privacy safeguards, investigating affordable alternatives, optimizing algorithm performance, and growing cross-institutional studies. This will increase the system's applicability and reveal particular challenges in various contexts.

Declarations

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Conflict of interest

There is no conflict of interest among the authors.

Data Availability

All data generated or analyzed during this study are included in the manuscript.

Code Availability

Not applicable.

Author's contributions

All Authors contributed to the design and methodology of this study, the assessment of the outcomes, and the writing of the manuscript.

REFERENCES

[1] L. A. Alea, M. F. Fabrea, R. D. A. Roldan and A. Z. Farooqi, "Teachers' Covid-19 awareness, distance learning education experiences and perceptions towards institutional readiness and challenges," *International Journal of Learning, Teaching and Educational Research*, vol. 19, no. 6, pp. 127-144, 2020.

[2] Q. Fang, H. Li, X. Luo, et al., "Detecting non-hardhat-use by a deep learning method from far-field surveillance videos," *Autom. Constr.*, vol. 85, pp. 1-9, 2018.

[3] I. Ahmed and G. Jeon, "A real-time person tracking system based on SiamMask network for intelligent video surveillance," *J. Real-Time Image Process.*, vol. 18, no. 5, pp. 1803-1814, 2021.

[4] A. Prati, C. Shan and K. I. Wang, "Sensors, vision, and networks: From video surveillance to activity recognition and health monitoring," *J. Ambient Intell. Smart Environ.*, vol. 11, no. 1, pp. 5-22, 2019.

[5] L. Qin, N. Yu, and D. Zhao, "Applying the convolutional neural network deep learning technology to behavioural recognition in intelligent video," *Tehnički vjesnik*, vol. 25, no. 2, pp. 528-535, 2018.

[6] G. Sreenu and S. Durai, "Intelligent video surveillance: a review through deep learning techniques for crowd analysis," *J. Big Data*, vol. 6, no. 1, pp. 1-27, 2019.

[7] C. Sung and J. Y. Park, "Design of an intelligent video surveillance system for crime prevention: applying deep learning technology," *Multimed. Tools Appl.*, vol. 80, no. 26, pp. 34297-34309, 2021.

[8] A. Purwanto, M. Asbari, M. Fahlevi, et al., "Impact of work from home (WFH) on Indonesian teachers' performance during the Covid-19 pandemic: An exploratory study," *International Journal of Advanced Science and Technology*, vol. 29, no. 5, pp. 6235-6244, 2020.

+ Corresponding author: Zhuanhua Lu, Teacher Education Department, Shangqiu Normal University, Shangqiu 476000, Henan, China.
Email: luzhhsq@126.com, zhuan_lu69@outlook.com

[9] K. F. Hew, C. Jia, D. E. Gonda, and S. Bai, "Transitioning to the "new normal" of learning in unpredictable times: pedagogical practices and learning performance in fully online flipped classrooms," *Int. J. Educ. Technol. High. Educ.*, vol. 17, no. 1, pp. 1-22, 2020.

[10] D. Zhang, X. Han, and C. Deng, "Review on the research and practice of deep learning and reinforcement learning in smart grids," *Csee J. Power Energy Syst.*, vol. 4, no. 3, pp. 362-370, 2018.

[11] Y. Zhang, Y. Yan, R. L. Kumar and S. Juneja, "Improving college ideological and political education based on deep learning," *International Journal of Information and Communication Technology*, vol. 24, no. 4, pp. 431-447.

[12] J. C. Cheng, W. Chen, K. Chen, and Q. Wang, "Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms," *Autom. Constr.*, vol. 112, pp. 103087, 2020.

[13] M. A. Hannan, M. Faisal, P. J. Ker, et al., "A review of internet of energy-based building energy management systems: Issues and recommendations," *Ieee Access*, vol. 6, pp. 38997-39014, 2018.

[14] P. A. Harris, R. Taylor, B. L. Minor, et al., "The REDCap consortium: Building an international community of software platform partners," *J. Biomed. Inform.*, vol. 95, pp. 103208, 2019.

[15] Q. Lu, A. K. Parlikad, P. Woodall, et al., "Developing a digital twin at building and city levels: Case study of West Cambridge campus," *J. Manage. Eng.*, vol. 36, no. 3, pp. 5020004, 2020.

[16] S. Tang, D. R. Shelden, C. M. Eastman, P. Pishdad-Bozorgi and X. Gao, "A review of building information modelling (BIM) and the internet of things (IoT) devices integration: Present status and future trends," *Autom. Constr.*, vol. 101, pp. 127-139, 2019.

[17] Z. Wang, T. Wang, H. Hu, J. Gong, X. Ren, and Q. Xiao, "Blockchain-based framework for improving supply chain traceability and information sharing in precast construction," *Autom. Constr.*, vol. 111, pp. 103063, 2020.

[18] S. M. S. Abdullah and A. M. Abdulazeez, "Facial expression recognition based on deep learning convolution neural network: A review," *Journal of Soft Computing and Data Mining*, vol. 2, no. 1, pp. 53-65, 2021.

[19] L. Chen and W. Wang, "Analysis of technical features in basketball video based on the deep learning algorithm," *Signal Processing: Image Communication*, vol. 83, pp. 115786, 2020.

[20] Y. Gao, X. Kang, and Y. Chen, "A robust video zero-watermarking based on deep convolutional neural network and self-organizing map in the polar complex exponential transform domain," *Multimed. Tools Appl.*, vol. 80, no. 4, pp. 6019-6039, 2021.

[21] X. Jiang, J. Sun, C. Li and H. Ding, "Video image defogging recognition based on recurrent neural network," *Ieee Trans. Ind. Inform.*, vol. 14, no. 7, pp. 3281-3288, 2018.

[22] Y. Lu and H. Li, "Automatic lip-reading system based on deep convolutional neural network and attention-based long short-term memory," *Applied Sciences*, vol. 9, no. 8, pp. 1599, 2019.

[23] T. X. Tran and D. Pompili, "Adaptive bitrate video caching and processing in mobile-edge computing networks," *Ieee. Trans. Mob. Comput.*, vol. 18, no. 9, pp. 1965-1978, 2018.

[24] D. Blinder, A. Ahar, S. Bettens, et al., "Signal processing challenges for digital holographic video display systems," *Signal Processing: Image Communication*, vol. 70, pp. 114-130, 2019.

[25] D. Cao, R. Liu, H. Li, S. Wang, W. Jiang, and C. X. Lu, "Cross vision-rf gait re-identification with low-cost RGB-d cameras and mm-wave radars," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 6, no. 3, pp. 1-25, 2022.

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