STM JOURNALS

Journal of
Microcontroller Engineering and Applications

ISSN: 2455-197X
Volume 12, Issue 1, 2025
January–April
DOI (Journal): 10.37591/JoMEA

https://journals.stmjournals.com/jomea

Review JoMEA

Integrated Dam Automation: Real-Time Monitoring and Controlling Using IoT

Umar Farooq Babulal Mokashi[1,*], Manikanta G.[2], Pavan Kumar B.[1], Rahul K.[1], Adarsh Gowda S.P.[1]

Abstract

Dam automation is a critical area in water resource management, especially given the rising demand for sustainable and safe water control systems. An integrated approach to dam automation involves implementing advanced sensors and monitoring systems to improve structural safety, water quality, and resource management. This paper presents a comprehensive automation model that combines crack detection, convolutional neural networks (CNNs), water level monitoring, turbidity sensing, and rainfall data to ensure real-time safety, structural integrity, and environmental responsiveness in dam operations. The role of CNNs in predictive crack detection involves the automated analysis of images to identify structural cracks in dams. Initially, high-resolution images of the dam surface are captured using cameras or drones. CNNs then process these images by extracting features such as crack shapes, textures, and patterns, allowing them to automatically identify cracks without the need for manual feature identification. The network is trained on a large dataset of labeled images, learning to differentiate between cracks and other surface anomalies internet of things (IoT)-enabled real-time monitoring and flood control use interconnected sensors to continuously gather data from a dam's environment, such as water levels, rainfall, and structural health. This data is transmitted in real time to a centralized system for constant monitoring. By analyzing water levels and rainfall data, the system can predict flood risks and automatically adjust operations, like controlling water release through gates, to prevent overflow. Additionally, IoT systems can trigger alerts when critical conditions are met, enabling operators to respond quickly.

Keywords: Convolutional neural networks (CNNs), turbidity sensor, rainfall sensors, LiteC3 module, actuators, communication technologies

***Author for Correspondence**
Umar Farooq Babulal Mokashi
E mail: umarfarooqmokashi84@gmail.com

[1]Student, Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India
[2]Assistant Professor, Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India

Received Date: January 16, 2025
Accepted Date: January 22, 2025
Published Date: January 28, 2025

Citation: Umar Farooq Babulal Mokashi, Manikanta G., Pavan Kumar B., Rahul K., Adarsh Gowda S.P. Integrated Dam Automation: Real-Time Monitoring and Controlling Using IoT. Journal of Microcontroller Engineering and Applications. 2025; 12(1): 31–38p.

INTRODUCTION

The main goal of an automated system is to maintain the structural integrity and functionality of the dam. This is achieved through advanced sensors and machine learning techniques. A key aspect of safety monitoring in dams is crack detection. These cracks can be early indicators of potential structural failure or collapse; if not managed properly, they could lead to catastrophic dam failures. This system allows for the quick identification and classification of potential hazards by utilizing convolutional neural networks (CNNs), which analyze images to spot crack formations, enabling prompt intervention and maintenance. The significance of integrated dam automation lies in its capacity to improve the safety, reliability, and efficiency of dam operations.

Dams are vital infrastructures that serve essential purposes such as water supply, irrigation, flood control, and hydropower generation. However, failures or shortcomings in dam operations can result in severe economic, environmental, and social consequences, including loss of life, habitat destruction, and damage to communities downstream. The following sections outline the importance of each component in an integrated dam automation system [1].

Structural Health and Crack Detection

Cracks in a dam's structure are often the first signs of potential collapses that, if not detected and addressed promptly, can lead to disastrous outcomes. Crack detection systems, particularly those based on CNN technology, facilitate the early identification and analysis of structural anomalies. By enabling predictive maintenance, they help prevent significant failures, reduce repair costs, and extend the operational lifespan of the dam [2].

Monitoring Water Levels as a Protective Measure and Management Tool

Maintaining optimal water levels is crucial for balancing resource availability and flood control. Automated sensors for water level monitoring provide immediate insights and facilitate timely adjustments.

LITERATURE REVIEW

Detecting cracks in underwater dams is crucial for maintaining structural integrity and ensuring safety. Currently, this process relies on underwater robotic systems equipped with cameras for the automatic identification of cracks in submerged structures. However, many existing methods for crack detection depend on semantic segmentation, which struggles to identify multiple crack types in a single image. To tackle these challenges, the development of instance segmentation technology has been proposed. Unfortunately, recent instance segmentation techniques often fall short in terms of detection speed and performance in aquatic environments. In response, we introduce a new framework for underwater crack instance segmentation [3].

First, we present the CSPLiteNet feature extraction network, designed to enhance the backbone architecture and enable the network to extract features at various scales. We are currently exploring the LiteC3 module, which features an innovative design that integrates information from different branches, resulting in more comprehensive and richer feature representations. This approach enhances the model's robustness while simultaneously reducing computational demands [4]. Lastly, we introduce spatial feature scaling pyramid pooling (SFSPP), a reconfiguration module for the atrous pyramid that expands the receptive field within the network. Our proposed method demonstrates significant effectiveness in underwater crack and object detection, achieving AP50 scores of 51.4% and 55.3%, respectively. A dam is an artificial structure designed to retain and control water flow in lakes or rivers. However, poor dam management or extreme weather can lead to both human-made and natural disasters. Therefore, it is essential to implement effective monitoring systems to maintain safe water levels in dams [5].

GAPS INDENTIFIED

The structural integrity of dams faces increasing challenges due to aging infrastructure and the impacts of climate change, making the identification of cracks more crucial than ever. Although there have been advancements in automated systems and real-time monitoring that improve surveillance capabilities, significant gaps remain in the integration of various sensor technologies, the use of artificial intelligence for immediate crack detection, and the development of predictive maintenance frameworks. Often, the system does not provide a comprehensive view of real-time data from multiple sensors. This paper aims to tackle these well-documented shortcomings by proposing a framework that combines real-time monitoring, artificial intelligence (AI)-driven analysis, and predictive maintenance to enhance dam safety and prevent failures [6].

There is a lack of comprehensive integration of multiple sensors into a single platform for real-time monitoring and automated decision-making. Various sensors, including internet of things (IoT) devices, drones, and advanced sensors, can be unified into a single system for crack detection and structural health monitoring, providing a more complete perspective on dam safety.

Progress in real-time automation of crack detection systems driven by artificial intelligence is lacking, despite significant advancements in image analysis for detecting structural cracks, particularly through the use of deep learning architectures. Additionally, there is a pressing need for systems that not only predict detection times but also forecast the potential growth or consequences of a crack over time [7].

The World Commission on Dams has reported that there are over 58,000 large dams worldwide, with many countries depending on these structures for water supply, power generation, and flood control. Despite the progress made in dam engineering, the risks associated with deteriorating infrastructure remain a significant concern.

METHODOLOGY

The Integrated Dam Automation System combines sensors, actuators, communication technologies, and advanced software algorithms to automate dam operations, ensure the safety of water resources, and conduct real-time assessments of structural integrity. The following section outlines how all components of the system interact to guarantee safe and effective dam management.

Environmental and Structural Monitoring

The system gathers real-time data from a network of sensors distributed throughout the dam, allowing for the collection of essential environmental and structural parameters [8].

Rain Sensor

The rain gauge tracks the amount of precipitation in its vicinity. When rainfall increases significantly, the system assumes that the water level in the dam rises correspondingly and adjusts its operations to prevent flooding. It can also enhance monitoring frequency or trigger additional alarms for a quicker response.

Water Level Sensor

This sensor measures the current water level within the dam's structure. The data it collects is sent to either an Arduino controller or an ESP32 controller, allowing for the categorization of water levels into three states:

- *Low water level:* The gates are closed to minimize water wastage.
- *Medium water level:* The system partially opens the gates to control water outflow.
- *High water level:* The gates close completely, and the temperature sensors monitor the temperature of the water. Any unusual changes in water temperature may prompt someone to investigate potential environmental issues or the presence of contaminants that are typically not found in normal water conditions [9].

Automated Dam Operations

This system analyzes data collected from environmental sensors and automatically adjusts dam operations to improve flow management and reduce the risk of flooding while ensuring safety standards are met.

Servo Motors for Gate Control

Servo motors manage the opening and closing of the dam gates. Using data from the water level sensor, these motors adjust the gates to regulate the appropriate amount of water flow. During periods of high-water levels, the gates are fully opened to release excess water and prevent dam overflow. Conversely, when water levels are normal or low, the gates are closed to conserve water [10].

Relay-Controlled Water Pump

A relay controls the water pump's operation. The pump's on or off status is determined by the current water levels. If the water level rises too high, indicating a risk of flooding, the pump activates to remove excess water, preventing overflow until levels return to a safe range.

Structural Health Monitoring

This system employs a camera and computer vision algorithms to detect cracks or damage in the dam's structure, ensuring its integrity. The system activates pumping to reduce water levels. These features enhance the system's ability to make dynamic decisions.

Water Quality Monitor

Turbidity Sensor

This sensor assesses water clarity. High turbidity levels may indicate the presence of suspended impurities or particulate matter, which could require additional treatment or notification procedures.

Detection of Cracks with Laptop Camera

A camera mounted on a laptop scans critical areas of the dam at regular intervals to capture images. These images are processed by a crack detection model using OpenCV, which analyzes them for signs of cracks or stress that may indicate structural issues. If any cracks are detected, an alert is sent to the relevant authorities. The crack detection model facilitates image analysis, providing timely evaluations [11]. Training a CNN involves several key steps, including data preprocessing, designing the architecture, optimizing the model, and evaluating its performance. CNNs are particularly effective for image-related tasks such as classification, object detection, and segmentation because they can learn hierarchical features directly from raw data. A solid understanding of datasets, performance metrics, and potential challenges is crucial for achieving the best results [12].

Data Preparation

The foundation of effective CNN training lies in selecting and preparing the right datasets. ImageNet, for instance, is a large dataset containing over a million labeled images. Smaller-scale experiments often utilize CIFAR-10 and CIFAR-100, while handwritten digit classification is typically performed on the MNIST dataset. In many specialized cases, custom datasets are created and annotated for specific applications, such as medical imaging or autonomous vehicles [13]. Preprocessing methods include resizing images to a consistent dimension, normalizing pixel values to maintain stability, and applying data augmentation techniques like random cropping, flipping, rotation, and brightness adjustments. These augmentation techniques enhance the model's generalization ability by increasing the diversity of the training dataset. To ensure accurate model evaluation, the dataset is divided into three distinct subsets: training, validation, and testing [14].

Model Development and Training

The architecture of a CNN features convolutional layers that focus on extracting important features, pooling layers that help reduce spatial dimensions, and fully connected layers that are used for tasks like classification or regression. Some well-known architectures include ResNet, VGGNet, and EfficientNet, which are recognized for their solid design principles and often serve as benchmarks in the field. For optimizing models, loss functions such as cross-entropy are typically employed for classification tasks, while mean squared error is used for regression tasks to evaluate the difference between predicted and actual results. Common optimization algorithms include SGD (stochastic gradient descent) with momentum and adaptive methods like Adam, which adjust learning rates throughout the training process. Additionally, scheduling techniques such as step decay and cosine annealing are utilized to fine-tune the learning rate during training. Key hyperparameters include batch size, total epochs, and dropout rates, which are adjusted to strike a balance between computational efficiency and overall performance [15].

Performance Measures

The performance of a CNN can be evaluated using metrics that are specific to the task at hand. For classification tasks, metrics like precision, recall, F1-score, and accuracy are particularly important, especially when dealing with datasets that have class imbalances. In object detection tasks, common metrics include intersection over union (IoU) and mean average precision (mAP), which assess how

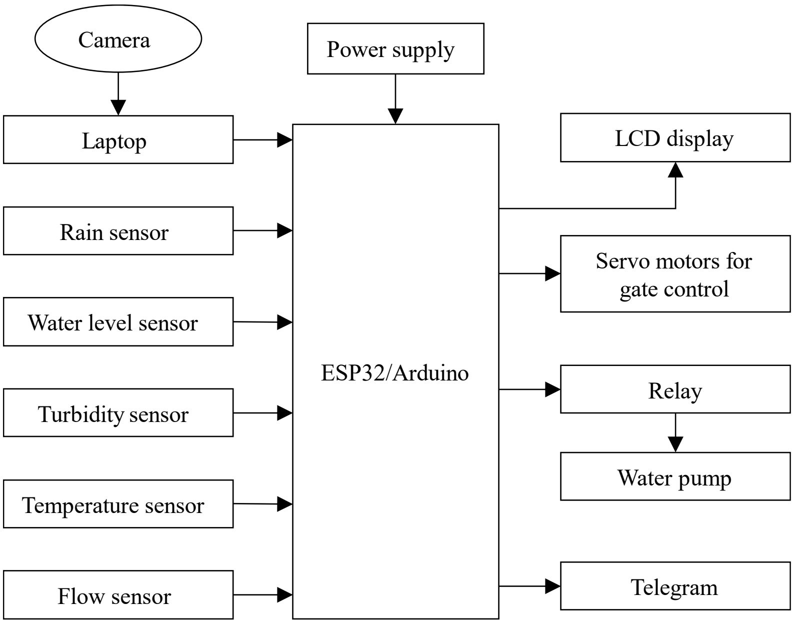

Figure 1. Block diagram of integrated dam automation.

well the predicted bounding boxes align with the actual objects. For segmentation tasks, pixel accuracy and the Dice coefficient are used to evaluate how well the predicted masks overlap with the ground truth masks [16]. Monitoring these metrics on the validation set throughout the training process is crucial for identifying issues like overfitting and underfitting.

Training CNNs comes with several challenges. One of the primary concerns is overfitting, which tends to be exacerbated with smaller training datasets. This can be mitigated through regularization techniques such as dropout, L2 weight decay, and data augmentation. Class imbalance can lead to biased predictions, which can be addressed by oversampling the minority classes or implementing a weighted loss function. Deep networks often face issues with vanishing or exploding gradients, which can be managed through techniques like batch normalization or architectures that utilize skip connections, such as ResNet. Additionally, the high computational demands of deep learning can be alleviated by using lightweight models like MobileNet or by applying model pruning and quantization methods [17].

Detecting and reporting anomalies in real-time systems is crucial when it comes to timing. A trained CNN model can analyze a 512 × 512 image in about 0.05 seconds, translating to 20 frames per second, provided there is support from modern GPUs (graphics processing units). In contrast, traditional methods, such as the Hough transform, usually take around 0.5 to 1 second per image due to their iterative nature. A block diagram of integrated dam automation is shown in Figure 1. This efficiency makes CNNs particularly well-suited for real-time monitoring applications, like assessing the condition of structural components in bridges or pavements.

Quantitative results indicate that CNNs, including UNet, have achieved an IoU of 0.91 in crack segmentation tasks, while traditional machine learning algorithms like SVM (support vector machine), which rely on handcrafted features, only reach an IoU of 0.68. Additionally, the recall rate for CNN-based systems surpasses 92%, significantly outpacing traditional methods that struggle with incomplete or noisy data [18].

CNNs are employed for crack detection by utilizing convolutional layers to extract features, pooling layers to decrease data dimensionality, and fully connected layers for classification purposes. Notable architectures like UNet and DeepCrack have been implemented, with DeepCrack achieving an impressive 95.6% accuracy in pixel-level crack detection. In contrast, traditional edge detection techniques, such as Sobel and Canny filters, only reach 70% to 80% accuracy and struggle with more intricate textures and noise [19].

Optimization processes generally involve loss functions like binary cross-entropy for classification tasks or Dice loss for segmentation. The model work is shown in Figure 2. Adaptive optimizers, such as Adam, are often initialized with a learning rate of 10^{-3}, and methods like cosine annealing help ensure effective convergence. Training on a dataset comprising 5000 images at a resolution of 512 × 512 using an NVIDIA RTX 3090 GPU typically requires around 8 to 10 hours for 100 epochs with a batch size of 16 [20].

RESULTS

This integrated dam automation system, designed and developed in this project, proves that the concept of IoT is truly going to make a difference in changing dam safety and operational efficiency. Real-time monitoring of the operation of the dam is made possible by integrating a network of water level, quality, and environmental sensors along with the gate automation control. Crack detection thus represents an integral safety layer by preventing structural issues from reaching serious levels. The accuracy of different image processing techniques is shown in Figure 3.

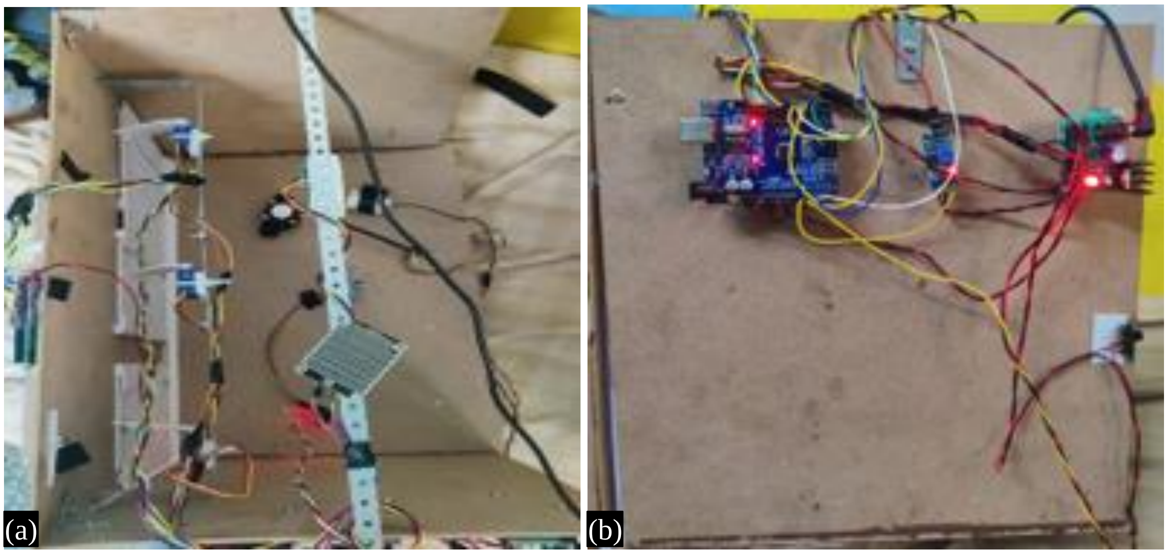

Figure 2. Model work.

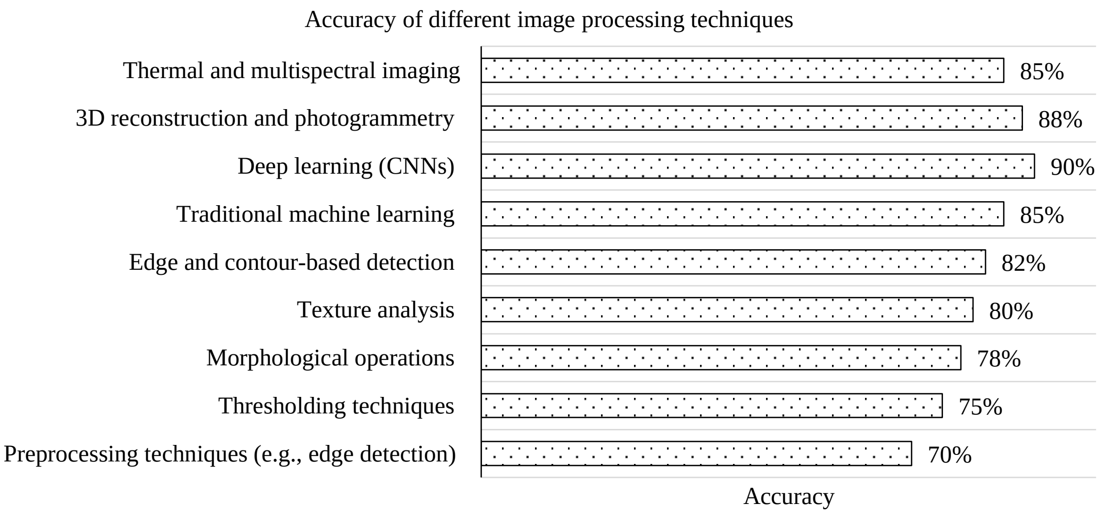

Figure 3. Accuracy of different image processing techniques.

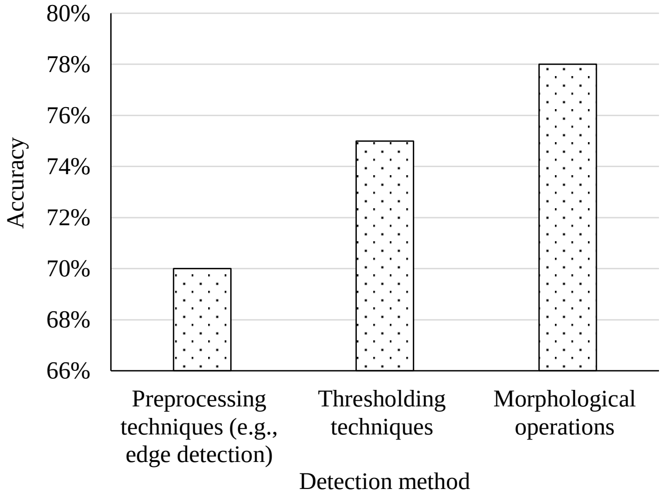

Figure 4. Crack detection accuracy.

The ESP32 microcontroller acts as the heart of the system. All data from sensors are processed and used to initiate automated responses, while the Telegram notification system sends alerts for critical conditions such as high-water levels or structural cracks to the people concerned in real time. The crack detection accuracy is shown in Figure 4. This ensures that response and mitigation measures are implemented right away, minimizing the potential risks downstream to communities and the environment.

Accuracy in Crack Detection

- Minimum of 90% accuracy of crack detection and marking on dam surfaces in case high-resolution images are employed.

Visual Output

- *Annotated images:* Highlighted cracks in various colors according to the severity such as minor cracks in yellow and major cracks in red.
- *Binary mask:* Only the detected cracks are represented by a binary image mask which can be further used for processing.

Quantitative Metrics

- *Crack count:* Total number of cracks found on the dam surface.
- *Severity breakdown:* Percentage of cracks that are minor, moderate, or severe.
- *Crack dimension statistics:* Average length and width of cracks, along with a list of the largest cracks found.

A crack position map with severity on dam surface (scatter plot) shows the spatial distribution of detected cracks on a simulated dam surface, with colors indicating crack severity (1 = minor, 3 = severe).

CONCLUSION

The entire automation system for dams focuses on crack detection, CNN analysis, water-level monitoring, turbidity, and rainfall data collection. These tools are essential for a comprehensive approach to enhancing dam safety and optimizing management practices. This system not only provides valuable insights but also offers predictive capabilities that promote proactive maintenance and improve flood management. It addresses critical concerns regarding structural integrity by detecting cracks early, allowing for timely interventions before failures occur. By utilizing a multi-sensor approach, the need for human intervention and related maintenance costs will be minimized, ensuring that dams operate sustainably and reliably. Implementing such a system represents a significant advancement in the modern, intelligent management of dams, aligning with both safety and environmental goals.

REFERENCES

1. Guidelines for Seismic Design of Earth Dams and Embankments. Indian Institute of Technology Kanpur, Gujarat State Disaster Management Authority. August 2005, Revised May 2007. [Online]. Available at https://www.iitk.ac.in/nicee/IITK-GSDMA/EQ09.pdf
2. Sadrnejad S. A multi-lined behavior simulation approach for liquefaction of earth-dam. Comput Methods Civil Eng. 2011; 2 (2): 201–218.
3. Dadgar HR, Arjomand MA, Arefnia A. Numerical analysis of cyclic loading effect on progressive failure in earth dams upon a multiline-multilaminate model. Int J Eng Technol. 2019; 11 (3): 492–504.
4. Desai CS, Siriwardane HJ. Constitutive Laws for Engineering Materials with Emphasis on Geologic Materials. Englewood Cliffs, NJ, USA: Prentice-Hall; 1984.
5. Naylor D. Stresses in nearly incompressible materials by finite elements with application to the calculation of excess pore pressures. Int J Numer Methods Eng. 1974; 8: 443–460.
6. Sheng D, Sloan S, Yu H. Aspects of finite element implementation of critical state models. Comput Mech. 2000; 26: 185–196. doi: 10.1007/s004660000166.
7. Gu C, Wang J, Cai Y, Yang Z, Gao Y. Undrained cyclic triaxial behavior of saturated clays under variable confining pressure. Soil Dynam Earthquake Eng. 2012; 40: 118–128. doi: 10.1016/j.soildyn.2012.03.011.
8. Sadrnezhad S. Constitutive model for multi-laminate induced anisotropic double hardening elastic-plasticity of sand. Int J Eng A. 2002; 15: 115–124.
9. Dadgar HR, Arjomand MA, Arefnia A. Crack detection in earth dams upon a multiline-multilaminate model. Int J Eng Technol. 2019; 11 (3): 445–455. doi: 10.21817/ijet/2019/v11i3/191103030.
10. Bažant ZP, Xiang Y, Prat PC. Microplane model for concrete. I: stress-strain boundaries and finite strain. J Eng Mech. 1996; 122 (3): 245–254. doi: 10.1061/(ASCE)0733-9399(1996)122:3(245).
11. Benmore CJ. A review of high-energy X-ray diffraction from glasses and liquids. Int Scholar Res Netw ISRN Mater Sci. 2012; 2012: 1–19.
12. Sun E, Zhang X, Li Z. The internet of things (IOT) and cloud computing (CC) based tailings dam monitoring and pre-alarm system in mines. Safety Sci. 2012; 50 (4): 811–815.
13. Raman R, Rathi T. Efficient dam water level management using cloud-based data analytics and LSTM networks. In: 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, March 14–15, 2024. pp. 1–6.
14. Negi P, Pachouri V, Pandey S, Chaudhary M, Singh R, Chhabra G. Automation intervention using the internet of things in the infrastructure of dam. In: 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, March 23–25, 2023. pp. 1185–1191.
15. Dhinakaran D, Sankar SU, Latha BC, Anns AE, Sri VK. Dam management and disaster monitoring system using IoT. In: 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, March 23–25, 2023. pp. 1197–1201.
16. Wyawahare M, Subhash A. Smart dam control: embedded systems and LSTM-based water level prediction. In: Rajagopal S, Popat K, Meva D, Bajeja S, editors. International Conference on Advancements in Smart Computing and Information Security 2023. Cham, Switzerland: Springer Nature; 2023. pp. 245–253.
17. Van de Straete HJ, Degezelle P, De Schutter J, Belmans RJ. Servo motor selection criterion for mechatronic applications. IEEE/ASME Trans Mechatron. 1998; 3 (1): 43–50.
18. Liu S, Wang X, Lu Q, Li H, Wang Y, Deng L. Dam leakage detection by borehole radar: a case-history study. Remote Sensing. 2019; 11 (8): 969.
19. Junior MM, Nunes RO, Celinski VG. Comparison of the responses of low cost electrical soil sensors, and a Arduino microcontroller platform. Iberoamer J Appl Comput. 2012; 2 (1): 29–38.
20. Rosly MA, Samad Z, Shaari MF. Feasibility studies of Arduino microcontroller usage for IPMC actuator control. In: 2014 IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2014), Penang, Malaysia, November 28–30, 2014. pp. 101–106.

