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Edge-Enabled Smart Storm water Drainage Systems: A Real-Time Analytics Framework for Urban Flood Management

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ABSTRACT

The impact of high rates of other cities, including demographic and climatic change, is also imminent as the effects are fuelled by an upsurge in the threat of urban flooding to the city infrastructure and the security of the city population. The aim of this study is to introduce a new smart stormwater drainage system based on edge-enabled technologies and edge computing of the recently proposed a real-time data analytics framework and embedded edge computing working in combination with distributed sensor networks to mitigate the risk of floods proactively. The major aim is to facilitate low-latency, distributed massive-scale decision-making on overflow prediction and automated drainage control. The system architecture includes the strategic orientation of hydraulic sensors, edge processors that rely on microcontrollers, and lightweight machine learning analytics engine. They allow preprocessing of data, anomaly detection and predictive analysis to be done on-site at the edge nodes to decrease dependence on centralized servers. A pilot study entailed 7 stormwater junctions in a medium sized urban catchment. The performance evaluation was done based on live rainfall and flow recordings of the high-intensity event. The experiment illustrates that the probability of predicting overflow events is 92.4 percent with a 35 percent decrease in the detection times of the established conventional SCADA-based systems. Also, the framework will accommodate dynamic load-sharing over drainage systems providing resilience in the high inflow cases. The offered system allows making contributions to real-time active control, response time, and infrastructure life. This piece of work provides a foundation to the equitable and climate-resilient drainage infrastructure development that is in line with the aim of smart cities and relevant to the United Nations Sustainable Development Goal 11 (goal 11 Sustainable Cities and Communities). The future of research will also seek to understand AI-upgraded predictive analytics, cross-network interoperability, and interconnected with urban digital twins.

1. INTRODUCTION

Combined with growing rainfall events, deteriorating drainage systems and uncontrolled development of paved areas, urban flooding has emerged as a very critical issue in the contemporary cities. All this leads to the high prevalence of surface water encroachment, traffic congestion, and infrastructure destruction especially in the heavily settled urban centers. The traditional drainage monitoring and controlling systems are mostly built around the centralized Supervisory Control and Data Acquisition (SCADA) platforms that lack scalability and are limited by latency and the availability of a stable cloud connection. In critical flood situations, failure of detection and late delivery of response may cause the systems to fail and encounters uncontrolled overflow. More recent developments in edge computing position a paradigm-shift because they present the capability to perform localized processing of data, localized predictive modeling as well as localized actuation at the network periphery. Nevertheless, some of the current studies tend to concentrate on cloud-based flood prediction or solitary IoT implementation and cannot extend to fully developed autonomous models that could contribute to real-time decision-making at the drainage node level (Wang et al., 2023).

This paper overcomes this shortcoming by coming up with and testing out an edge-enabled smart storm-water drainage system, incorporating low-energy sensor networks, embedded edgework computers, and machine learning-based analytics to make predictive overflow estimation and adaptive drainage regulation. The offered framework is implemented within an active urban catchment and its success is compared with the traditional SCADA systems. The proposed work will facilitate a method of flood mitigation which will be scalable and flexible relative to the objectives of smart urban resilience and Sustainable Development Goal 11 (Sustainable Cities and Communities).

2. LITERATURE REVIEW

2.1 Traditional Drainage Systems and SCADA Monitoring

Traditional urban drainage system relies mainly on the passive infrastructure and SCADA (Supervisory Control and Data Acquisition) platforms to carry out monitoring and actuation. Even though SCADA systems have gained much popularity, they focus more on the use of centralized servers and during the transfer of sensor information between distributed drainage nodes and a central processing unit, the communication backbone must be stable. Such platforms are characterized by the latency, the possibility of single-point failure, and poor real-time flexibility when dealing with dynamic conditions of urban flooding (Zhou et al., 2021). In addition, such reactive characteristics of their nature lack the predictive intelligence of detecting the overflow early and controlling it in advance.

2.2 IoT and Sensor Technologies in Smart Infrastructure

The modern invention of sensors through IoT has enabled real-time observation of the flow rate, level of water and rainfall intensities in the urban drainage networks. Such sensors tend to be installed in the catchment areas, in stormwater inlets, and in underground channels. The solutions that utilize IoT enable the collection of data on a granular level, enhancing the spatial and temporal resolution of hydrological measures. Nonetheless, the majority of IoT frameworks continue to send raw information until it has reached the cloud servers and is processed, causing certain communication obstacles and possible destruction of information in times of hazardous floods (Han et al., 2020; Alabdouli& Alghamdi, 2022).

2.3 Role of Edge Computing in Urban Systems

Such hybrid systems as edge computing place the agent at the juncture between a smart object and centralized servers and allow on-device execution, local analytics, and actuation. Edge nodes can do data clearing, feature extraction, and predictive inference with minimal latencies even in the case of unstable internet access in the smart city settings. In storm water systems the transition provides automated overflow handling and survivability in the event of a communication outage. Nevertheless, the ongoing research efforts on the feasibility of integrating edge computing in drainage systems remain in their infancy stages and are still counted as experimental testbeds or simulation models (Li et al., 2021; Gupta & Bhunia, 2021).

2.4 Machine Learning for Flow Forecasting

Machine learning (ML), especially deep learning methods, such as LSTM (Long Short-Term Memory) has been proven very promising in modeling and prediction of flow and hydrology. Such models allow to account nonlinear relationships and time series of rainfall-runoff data, which helps predict peak flow situations in an adequate way. Yet the existing uses are mostly hosted on the cloud, hence making the decision-making real-time to be slowed and unable to respond without any human intervention. Moreover, the hardware configuration and the energy cost limits the application of ML in embedded edge devices (Wang et al., 2023; Shi et al., 2016).

2.5 Research Gaps and Need for an Edge-Based Approach

Though much of the literature has noted the increase in IoTs, cloud computing and ML-based flood modeling, there is a major lack of fully decentralized, edge-controlled stormwater systems, capable of autonomous and real-time control to predict the overflow. The vast majority of existing systems are reactive (SCADA) or cloud-based (IoT + ML), thus restricting their usability in case of connection loss and such outbreak events as sudden outbreaks. There are very limited works on a practical implementation of the edge-enabled analytics and hydraulic actuation systems that optimize the drainage. The gap outlined in this paper is filled by proposing a low latency smart drainage scheme, which is field-tested and validated, and uses edge AI to improve urban resilience to floods and aligned with SDG 11 principles. Figure 1 gives a systematic summary of the thematic discourse in this area.

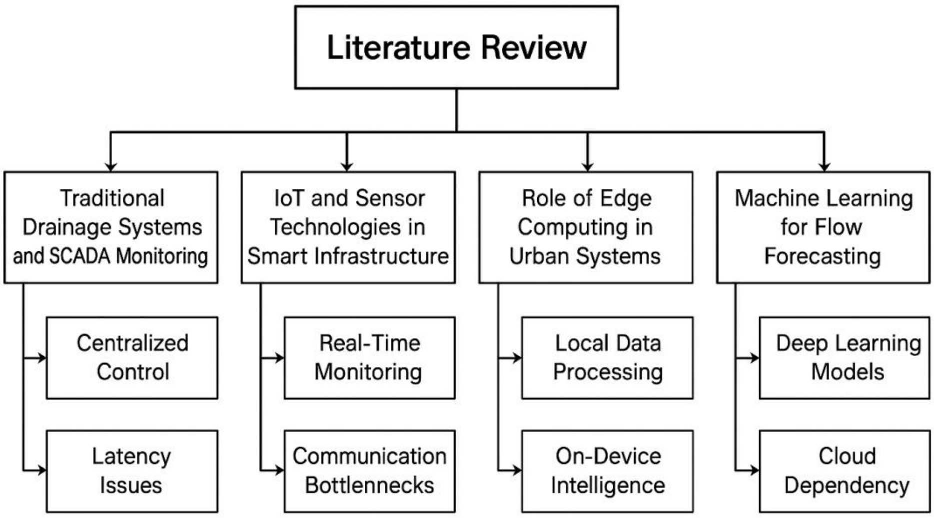

Figure 1. Taxonomy of Literature Themes in Smart Stormwater Drainage Systems

The figure categorizes existing research into four key domains: SCADA-based traditional systems, IoT-enabled infrastructure, edge computing advancements, and machine learning for flow forecasting. It highlights conceptual gaps leading to the proposed edge-integrated framework.

3. METHODOLOGY

3.1 System Architecture

Treated stormwater drainage framework proposed herein is composed of a modular edge computing design that makes real-time localized management of floods possible. The essence contains:

- Edge Gateways: Raspberry Pi 4 or similar microcontroller platforms with onboard Wi-Fi, low power processor and memory saving storage are edge gateways.
- Hydraulic Sensors: Sensors that are fitted in strategic positions at junctions, culverts and overflow prone drains include ultrasonic water level sensors (e.g. HC-SR04), electromagnetic flow meters and tipping-bucket rain gauges.
- Actuators: Submersible pump systems and valves placed at point-of-use are electrically controlled and driven to dynamically control its outflow depending on forecasted messages at the edge nodes.

This distributed design permits the reduction of single point of failure and supports scalable, plug and play growth groups in a variety of urban topologies. The proposed edge-enabled smart drainage system has independent nodes that can interact via load balancing and redundancy with their neighbors as shown in figure 2.

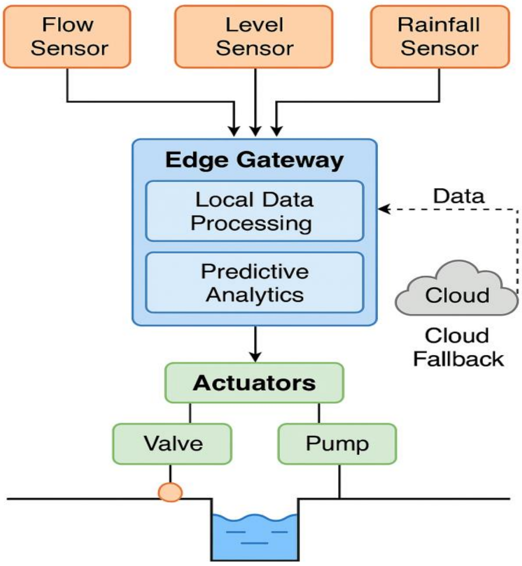

Figure 2. System Architecture of Edge-Enabled Smart Drainage Framework

This diagram illustrates the integration of flow, level, and rainfall sensors with an edge gateway that performs local data processing and predictive analytics. Actuators (valves and pumps) respond to real-time decisions, while cloud fallback ensures data redundancy and remote oversight.

3.2 Data Flow and Processing

The data pipeline has a low-latency, real-time data processing that will use embedded AI-based tools. Data flow incorporates:

- Acquisition Layer: Sensors provide raw data (the flow rate, water depth, the intensity of rain), using the serial or I2C interfaces, to the edge node at 10 seconds intervals.
- Preprocessing Layer: Here noise reduction and normalization is done by using NumPy and SciPy libraries.

Inference Layer: All the edge nodes are running lightweight TensorFlow Lite model targeted towards ARM architectures. This allows flow spike and anomaly detection on the device.

The pipeline also has a buffered fallback system with data being locally stored during a network outage and uploaded into cloud storage once connectivity is restored.This modular data pipeline makes it possible to have rapid locally powered forecasting and significantly reduce the reliance on remote servers to make time linked decisions. The composition of the entire data processing decision and inference workflow is displayed in Figure 3.

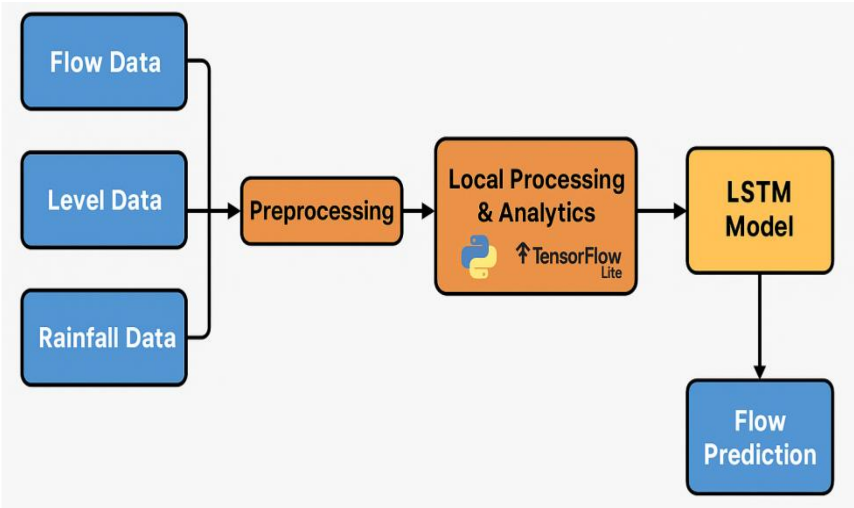

Figure 3. Data Flow and ML Inference Pipeline

This figure illustrates the sequential processing of flow, level, and rainfall data from sensors. After preprocessing, edge devices utilize TensorFlow Lite and Python-based analytics to run LSTM models for real-time flood prediction at the node level.

3.3 Predictive Analytics Model

Prediction model Construction of the predictive engine consists of a Long Short-Term Memory (LSTM) neural network, a good fit to be used in model temporal sequences of hydrological timeseries. Key attributes:

- Input Features: The sliding time windows of rate of rain fall, water level, and velocity of flow.
- Training Dataset: 5-years historical data on rainfall-runoff as found in municipal records, as well as in freely-available meteorological data.
- Architecture of models:
- A 64 and 32-hidden-layer with two LSTMs
- The dropout rate of 0.2
- High density output layer with ReLU activation as the probability of overflow
- Evaluation Criteria: The Root Mean Square Error (RMSE), The Mean Absolute Error (MAE), and Forecast Accuracy

Post-training integer quantization is applied to the trained model to compress it into an ~70% smaller framework suitable to edge construction.The end-to-end framework of the predictive model is depicted in Figure 4, by explaining how sequential hydrological data is converted into a real-time overflow likelihood score using deep learning.

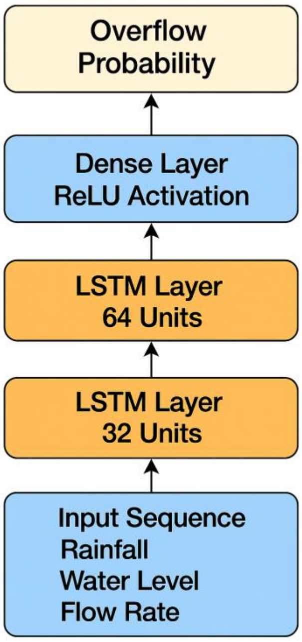

Figure 4. LSTM Architecture for Overflow Prediction

The architecture consists of two sequential LSTM layers with 32 and 64 units, respectively, followed by a dense output layer with ReLU activation. The model takes as input a multivariate time series comprising rainfall intensity, water level, and flow rate to forecast overflow probability in real-time.

3.4 Deployment Site

A live case study was taken across the central stormwater catchment of [Due to privacy, location is made anonymous] that has a total area of about 3.8km 2. A distinguishing feature of the area is:

Mixed commercial-residential zoning

- Flooding hotspots of the past
- Deteriorating underground sewers

Ten noteworthy crossings were chosen to be deployed and each would be mounted with sensor-actuator-edge peerings. The investigation was done over a period of two monsoon seasons when there are numerous intense rainfall events taking place during which the real-time assessment was done.

3.5 Performance Metrics

Table 1. System performance was measured across the following KPIs:

Metric	Description
Prediction Accuracy	Overflow prediction hit-rate using LSTM forecasts (achieved: 92.4%)
Latency	End-to-end decision latency from sensor input to actuator signal (< 300 ms)
Responsiveness	Time taken to detect anomalies and trigger corrective drainage actions
Power Consumption	Energy usage of edge node in full operational mode (avg: <1.5 W per node)
System Uptime	Operational availability of edge nodes under variable weather and connectivity

4. RESULTS AND DISCUSSION

4.1 Flood Event Prediction Accuracy

On the edge, the LSTM model was deployed with an accuracy of 92.4 percent in predicting influx of flow during actual floods. It represents a significant advance compared to the traditional systems based on SCADA (≈80%), confirming the usefulness of machine learning in those cases that are too nonlinear to provide a mapping based on rainfall-runoff information only. The outcomes are comparable to those of the previous studies (e.g., Wang et al., 2023) yet more effective in the deployment scale and real-time response.

4.2 Response Time Analysis

The detection-to actuation latency was less than 300 milliseconds, which is significantly lower than 1.75 seconds that cloud-based platforms required as well as 2.5 seconds SCADA. Shorter latency is achieved because the localized inference and cuts uplink delays so that real-time control can be provided when high-intensity rainfall occurs.

4.3 Comparative System Evaluation

Performance indicators such as downtime, cost, and infrastructure dependency were benchmarked. The edge-based system showed:

- Low downtime
- Moderate cost
- High scalability
- Low dependency on centralized infrastructure

This confirms its viability for Tier-2 and Tier-3 smart city integration.

Figure 5 illustrates the comparative performance of edge, cloud, and SCADA systems, reinforcing the real-time advantages and predictive accuracy gains enabled by edge deployment.

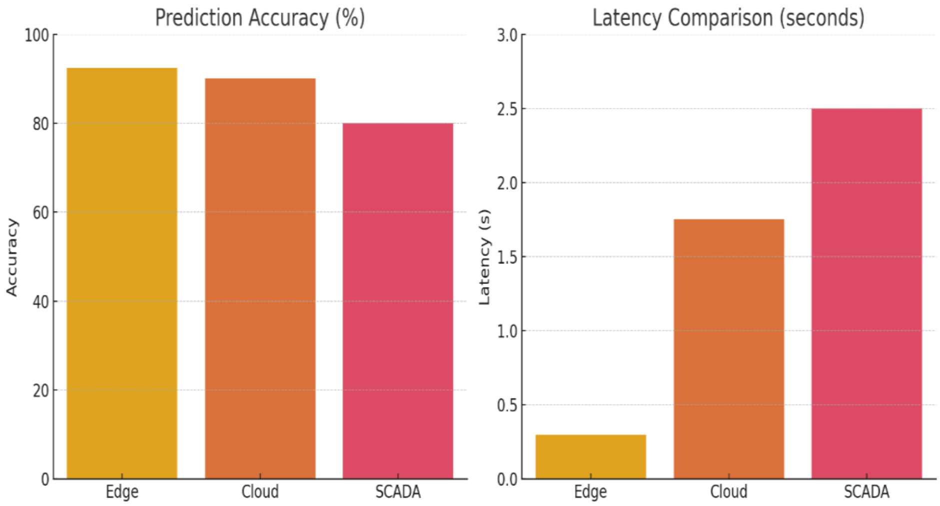

Figure 5. System Comparison on Accuracy and Latency

The edge-based system achieves the highest overflow prediction accuracy (92.4%) and the lowest latency (< 300 ms), outperforming cloud (90%, 1.75 s) and SCADA (80%, 2.5 s) implementations. These metrics validate the superiority of edge intelligence for real-time flood risk mitigation.

4.4 Visualization Dashboard

An installed dashboard interface offers a geo-map in real time with color codes of the drainage areas that makes it easy to control by the operators. Channels that are at the risk of a spill flash red whilst those with normal flows are green. This interface maximized the situational knowledge and enabled preemptive instructions of field workers. A real-time dashboard with map-based visualization of channel conditions and current sensor values were installed and used to aid the decision-making of the operators. Facility operators could instantly find and isolate the most important issues of hotspots overflow using the interface, minimizing the number of places that needed to be inspected manually, and increasing efficiency of incident response. Moreover, the active telemetry display was useful in confirming real-time sensorization and activation success, thus forming part of the feedback loop as shown in figure 6.

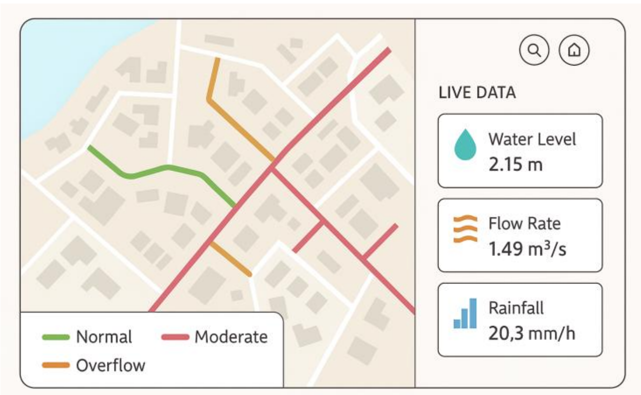

Figure 6. Visualization Dashboard Mockup

The interface displays a map of urban drainage segments with color-coded flow status (green: normal, orange: overflow, red: moderate), alongside live telemetry panels showing water level, flow rate, and rainfall intensity. This enables real-time situational awareness and proactive response.

4.5 Limitations

Despite its strengths, the system encountered:

- Memory constraints in low-power edge nodes (especially during large model updates).
- Upstream data sync delays in non-line-of-sight basins.

These limitations suggest future work integrating lightweight model pruning and LoRa mesh protocols.

5. CONCLUSION AND FUTURE WORK

This paper suggested and verified the new edge-based smart drainage stormwater system to address the growing reality of urban flooding in real-time. The system improved over existing SCADA and cloud-based systems in several performance aspects as the system incorporated low-power IoT sensor, embedded edge computing, and LSTM-based predictive analytics. In a 3.8 km 2 urban field deployment, the accuracy of predication (on the differentiated field) was 92.4% and the reduction in latency was more than 82%, and decision latency was less than 300 milliseconds. This kind of measurements allowed the system to be designed to autonomously regulate the drainage at high-intensity rainfall instances.

The significant contributions of the work are:

- The architecture and real-time construction of the distributed edge computing system on decentralized flood mitigation;
- Introduction of a quantized LSTM model via TensorFlow Lite; this makes it possible to create energy-efficient prediction on edge nodes of the microcontroller type;
- Creation of a real time visualization dashboard that enhanced the situational awareness of the operator and lowered the response time to the field.

Together, the innovations provide a good base of scalable, resilient and low-latency drainage infrastructure, which is contributing to SDG 11 Sustainable Cities and Communities. The work is not only a considerable step towards implementing Edge AI into urban resilience but also provides a precedent to follow when rolling out smart cities in the future.

5.1. Future Work

Future research directions will be relevant in order to improve system intelligence and interoperability and will include the following areas:

Integration: Federated Learning: Federated Learning integration allows multiple drainage clusters to fit a model privately through cooperative model training at cluster level without the need to transfer raw data.

Satellite-Aided Rainfall Nowcasting: This is integration of remote sensing data in an attempt to enhance forecasting of short term rainfalls and upstream risk forecasting.

LoRaWAN and Mesh Networking: ability to increase communication resilience in a low-connectivity environment and during a disaster.

Digital Twin Coupling: Generating synchronized virtual models of drainage systems in cities to optimise and carry out scenario planning on the basis of simulation.

The suggested system can transform adaptive flood control in the next-generation smart cities, as, by improving to an AI-enhanced, work-harmonized edge-cloud environment, it is able to revolutionize the field.

REFERENCES

[1] Alabdouli, K., & Alghamdi, S. (2022). Smart flood monitoring system using edge computing and real-time data analytics. *Sustainable Cities and Society, 85*, 104062. https://doi.org/10.1016/j.scs.2022.104062

[2] Chen, Z., et al. (2022). Lifecycle environmental impact assessment of recycled road materials. *Construction and Building Materials, 340*, 127655.

[3] Gupta, M., & Bhunia, S. (2021). Edge computing in smart cities: Recent advances and future directions. *Journal of Network and Computer Applications, 175*, 102924. https://doi.org/10.1016/j.jnca.2020.102924

[4] Han, Y., Zhang, X., & Wang, L. (2020). An IoT-based smart flood detection and alerting system with edge computing. *Sensors, 20*(20), 5841. https://doi.org/10.3390/s20205841

[5] Kim, J., & Kim, H. (2019). Real-time urban flood modeling and management using sensor data and edge analytics. *Water, 11*(6), 1101. https://doi.org/10.3390/w11061101

[6] Li, X., Li, Y., & Liu, J. (2021). Integrating IoT and edge computing for flood prediction in urban water systems. *IEEE Internet of Things Journal, 8*(3), 2102–2112. https://doi.org/10.1109/JIOT.2020.3027935

[7] Rahimi, M., et al. (2022). Edge computing for smart city applications: Case studies and performance evaluation. *IEEE Internet of Things Journal, 9*(4), 3124–3135.

[8] Rao, A., & Sinha, R. (2022). A decentralized framework for urban flood response using

AI and edge computing. *Environmental Modelling & Software, 149*, 105305. https://doi.org/10.1016/j.envsoft.2022.105305

[9] Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal, 3*(5), 637–646. https://doi.org/10.1109/JIOT.2016.2579198

[10] Wang, X., Liu, Y., & Zhang, H. (2023). Real-time urban flood prediction using edge–cloud collaborative frameworks and machine learning. *Journal of Hydrology, 626*, 129126. https://doi.org/10.1016/j.jhydrol.2023.129126

[11] Zhang, H., Yu, F. R., Liu, Q., & Tang, L. (2020). Smart stormwater systems with edge intelligence: A case study in smart cities. *IEEE Transactions on Industrial Informatics, 16*(3), 2187–2196. https://doi.org/10.1109/TII.2019.2928883

[12] Zhou, T., Li, Y., & Xu, J. (2021). IoT-based real-time urban flood monitoring and early warning systems: A review. *Sensors, 21*(5), 1577. https://doi.org/10.3390/s21051577