Title of the Paper

An alternative for predicting real-time water levels of urban drainage systems

Main Objective
To develop an AI-based model for real-time prediction of water levels in both sewer systems and street networks during rainstorms by leveraging a dynamic neural network trained on numerical simulation data from a real urban area.

Dataset Used

- Real-world water stage records from manholes (nodes) in the sewer drainage network of **Lugang Township, Changhua County, Taiwan**.
- Data collected from **water level gauges installed at multiple manhole locations**, providing time-series measurements every 10 minutes.
- **12 rainfall events** used for calibrating the SWMM, with observed water stages from four specific node locations.
- **120 rainfall events** (1960–2020) used for training and testing the AI model, covering a range of rainfall intensities (10–110 mm/h).

Technique or Model Used

- **Long Short-Term Memory (LSTM)** neural network for time-series prediction.
- **Two-stage training procedure**: Stage 1 predicts sewer water levels; Stage 2 predicts street inundation depths.
- **Data preprocessing** using DBSCAN clustering to group nodes by flooding risk.
- Integration with **SWMM (Storm Water Management Model)** for generating labeled training data.

Limitations

- Dependency on **SWMM-simulated data** as labels for training, which may inherit model inaccuracies.
- Limited to **one urban township** (Lugang), raising questions about generalizability to other regions.
- Requires **extensive calibration** of SWMM parameters using observed data.
- No mention of **real-time deployment or live municipal integration** during the study.

Outcomes Achieved

- High prediction accuracy: **MRE ≤ 1.542%**, **R^2 ≥ 0.932**, **PC ≥ 0.955** compared to SWMM simulations.
- Improved map similarity: **98.5% for sewer networks** and **96.6% for street networks** compared to numerical benchmarks.
- **9.1× faster computation** than SWMM, enabling near-real-time forecasting.
- Validated with **observed water stage data** from real manholes, confirming model reliability.

Title of the Paper

Machine Learning and Urban Drainage Systems: State-of-the-Art Review

Main Objective
To provide a comprehensive review of recent machine learning applications in Urban Drainage Systems (UDS), focusing on operation, management, and maintenance.

Dataset Used

- The paper is a **review article** and does not use a primary dataset itself.
- However, it **cites and summarizes multiple studies** that used real-world data, including:
    - **CCTV inspection videos** from sewer systems in Canadian cities (Regina and Calgary).
    - **Sensor-based measurements** (e.g., rainfall, inflow, water level) from real urban drainage networks.
    - **United States Geological Survey (USGS)** discharge data.
    - **Satellite and drone imagery** for flood inundation mapping.

Technique or Model Used

- **Deep Learning**: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Deep Q-Networks (DQN)
- **Traditional ML**: Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Random Forest
- **Reinforcement Learning** for real-time control of pumps and gates
- **Hybrid Models**: e.g., Wavelet-ANN, Physics-ML fusion models

Limitations

- Many studies rely on **limited sensor coverage** or **small-scale data**.
- **Lack of large-scale, multi-source data integration** (e.g., combining CCTV, sensor, and satellite data).
- **Generalizability issues**—models trained in one city may not perform well in another.
- **Dependence on simulation data** in some studies for validation where real data is scarce.
- **Computational demands** for complex deep learning models.

Outcomes Achieved

- **High accuracy in defect detection**: e.g., CNNs achieved >75% precision in detecting sewer pipe defects from CCTV images.
- **Improved flood prediction**: LSTM and CNN models showed high performance in predicting flood depth and duration with low RMSE.
- **Real-time control**: Reinforcement learning models successfully automated pump/gate operations, reducing flooding and CSO events.

- **Real-world validation**: Some models were tested during actual flood events or validated with municipal inspection data.

Title of the Paper
Smart Drainage System for Urban Flood Prevention

Main Objective
To develop and propose a Smart Drainage System that uses IoT, AI, and real-time monitoring to dynamically control water flow and provide early flood warnings.

Dataset Used

- **Indian Meteorological Department (IMD) APIs:** Real-time and forecast government weather data.
- **Municipal GIS Maps:** Real-world city geospatial data for mapping drainage networks and flood-prone areas.

Technique or Model Used

- **Hybrid AI-IoT Framework:** Integration of IoT sensors (water level, debris) with a central AI-based control hub.
- **AI-Driven Predictive Analytics:** Machine learning models for flood prediction and blockage detection.
- **GIS-based Analysis:** For spatial mapping and integration with urban infrastructure.

Limitations

- The paper proposes a system architecture but does not provide performance metrics from a live, city-scale deployment.
- The practical integration and scalability of the proposed system across diverse urban landscapes remain to be fully validated.
- Relies on the successful integration of multiple external data sources (IMD, GIS), which can be a challenge in practice.

Outcomes Achieved

- Proposed a comprehensive framework for **proactive flood management** and **early warning**.
- Designed for dynamic drainage flow control and real-time monitoring via a **municipal dashboard** for decision support.
- The system is conceptualized to offer **offline operation** and **manual override** for uninterrupted functioning during emergencies.

Title of the Paper
Reliability Improvement of Rainwater-Drainage System Using IoT and AI

Main Objective
To improve the reliability of a rainwater-drainage system by using IoT and rain-forecast big data to initiate pump operations proactively and prevent inland flooding.

Dataset Used

- **Japan Meteorological Agency (JMA) GPV Data:** Real-world, government-provided 1-km mesh predicted rainfall data in GRIB2 format.
- **Minoshima Rainfall-Observatory Station Data:** Real rainfall measurements from a Ministry of Land, Infrastructure, Transport, and Tourism observatory for validation.
- **Real-world Pump Station Data:** Operational data (water levels, pump start/stop times) collected from the Haisenchi rainwater-drainage station in Fukuyama City.

Technique or Model Used

- **IoT-based System:** GPS receivers, wireless routers, and data loggers integrated with pump controllers.
- **Cloud Computing (AWS):** For hosting rain-cloud radar analysis and sending pump drive commands.
- **Flood Analysis Software (AFREL-SR):** Used for inland-flood analysis with real topographical and gutter data from the Geospatial Information Authority of Japan.

Limitations

- **Prediction Delays:** Experienced a 5.5-hour delay in the rain-forecast system issuing a pump command during one heavy rain event.
- **Hardware Reliability:** The external control unit based on Raspberry Pi experienced communication failures and unintentional system-offs.
- **Limited Extreme Weather Data:** The test period did not capture sufficiently heavy rain to fully validate the system's performance during extreme events.
- **Insufficient Drainage Capacity:** Analysis showed that even with forecast-based control, the existing pump capacity was insufficient to prevent flooding during extreme heavy rain.

Outcomes Achieved

- **Real-world Validation:** The system was partially tested and validated at an official drainage-pump station in Fukuyama City.
- **Proactive Operation:** Demonstrated the ability to start pump drainage based on forecast data, keeping the pump-well water level lower than conventional methods during normal rain events.
- **Identified Critical Path:** The study conclusively showed that an **advanced extreme-heavy-rain prediction system** is required, paving the way for future AI development in this area.

Title of the Paper

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

Main Objective

To develop and test a low-latency, edge computing-based smart stormwater drainage system that uses real-time sensor data and machine learning to proactively predict overflow events and automate drainage control in urban catchments.

Dataset Used

- **Real-world sensor data** from a pilot deployment at 7 stormwater junctions in a medium-sized urban catchment (3.8 km^2).
- **IoT sensors** including ultrasonic water level sensors, electromagnetic flow meters, and tipping-bucket rain gauges.
- **5 years of historical rainfall-runoff data** from municipal records and meteorological sources.

Technique or Model Used

- **Edge AI** with lightweight **TensorFlow Lite** models deployed on Raspberry Pi 4 microcontrollers.
- **LSTM Neural Network** for overflow prediction.
- **Real-time data processing** and **predictive analytics** at the edge node level.

Limitations

- Memory constraints on low-power edge nodes during large model updates.
- Data synchronization delays in non-line-of-sight or low-connectivity basins.
- Limited spatial coverage (only 7 junctions in one catchment).

Outcomes Achieved

- **92.4% accuracy** in predicting overflow events.
- **Less than 300 ms end-to-end decision latency** from sensor input to actuator signal.
- **35% faster detection times** compared to traditional SCADA systems.
- Real-world validation during **monsoon seasons** with high-intensity rainfall events.
- Enabled **proactive control** of pumps and valves, reducing flood risk and improving infrastructure responsiveness.

Title of the Paper

Intelligent Prediction Method for Waterlogging Risk Based on AI and Numerical Model

Main Objective
To develop a fast and accurate urban waterlogging prediction method by combining a numerical simulation model with a Long Short-Term Memory (LSTM) neural network.

Dataset Used

- **Real rainfall data** from 63 meteorological stations in Shenzhen from 2008–2018 (178 short-term rainstorm events)

- **Actual waterlogging measurements** from 12 ponding points in the Shenzhen River and Bay Basin during a rainstorm on 29 August 2018
- **Government and municipal data** from the Shenzhen area, including river sections, drainage networks, and urban terrain

Technique or Model Used

- **Hybrid AI-Numerical Model**: Combines a 1D/2D hydrodynamic model with an LSTM neural network
- **LSTM** used for time-series prediction of waterlogging depth based on rainfall and previous water depth data

Limitations

- Limited to 12 ponding points in one basin (spatially constrained)
- LSTM model trained on numerical simulation outputs, leading to error accumulation
- Generalizability to other cities not fully tested
- Dependency on numerical model accuracy for training data

Outcomes Achieved

- **Prediction Accuracy**: Average error of 3.05% for maximum ponding depth compared to real measurements
- **Speed Improvement**: LSTM model was **324,000 times faster** than the numerical model alone
- **Real-World Validation**: Validated against actual waterlogging data from the 2018 Shenzhen rainstorm
- **Early Warning Support**: Enables timely urban flood risk prediction and emergency response