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Smart Subterranean Infrastructure: Sensor-Based Flood Mitigation and Drainage System

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ABSTRACT

Accordingly, the proposed intelligent drainage architecture demonstrates how emerging digital technologies can be strategically aligned with civil infrastructure to create proactive, rather than reactive, flood management systems. Beyond immediate mitigation, the integration of artificial intelligence, IoT connectivity, and automated actuation establishes a continuous feedback loop in which sensing, prediction, and control operate seamlessly. This interconnected framework not only improves operational responsiveness but also supports long-term urban planning through data-driven insights into rainfall patterns, drainage capacity, and system performance trends.

Beneficially, the predictive capability enabled by machine learning models allows municipal authorities to allocate resources efficiently, prioritize high-risk zones, and implement preventive maintenance before failures occur. By reducing emergency response dependence and optimizing pump operation cycles, the system contributes to lower energy consumption and reduced operational costs. Equally important, its modular configuration ensures compatibility with existing infrastructure while permitting incremental technological upgrades as urban demands evolve.

Consequently, this AI-integrated subterranean drainage solution embodies a resilient and sustainable paradigm for smart cities. It strengthens environmental adaptability, enhances public safety, and fosters economically viable flood mitigation strategies. Ultimately, such intelligent infrastructure represents a critical step toward climate-resilient urban ecosystems capable of withstanding increasingly unpredictable hydrological challenges.

Keywords: - Smart Subterranean Infrastructure, Drainage System, IoT-based flood systems, and Modern SDS designs integrate automated controls. Hardware/software design

Smart Subterranean Infrastructure: Sensor-Based Flood Mitigation and Drainage System

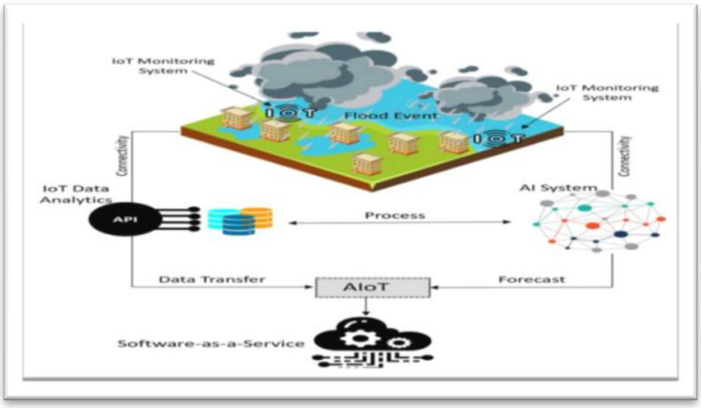
Urban flooding poses a critical threat to infrastructure and communities. Smart subterranean drainage integrates IoT sensors, automation, and AI to proactively mitigate flood risk. The proposed system continuously monitors underground water levels and flow rates, feeds data to a cloud server for analysis, and automatically controls pumps or valves to manage excess water. This paper outlines the system architecture, hardware/software design, AI-based prediction models, and simulated performance, with a focus on end-to-end automation and improved response times.

1. INTRODUCTION

Urbanization and climate change have overwhelmed traditional drainage networks, which lack real-time monitoring and adaptive control [3][4]. A **Smart Drainage System (SDS)** continuously collects data (rainfall intensity, water level, and flow velocity) via spatially distributed sensors, then uses analytics and actuators to manage flows [3][5]. For example, if a sensor detects a rising water level beyond the present limit, the system can automatically activate pumps or open diversion gates to prevent flooding. Recent research confirms that IoT-based flood systems reduce response times by up to 70% and improve prediction accuracy dramatically [1][2]. By embedding AI (e.g., deep learning, data analytics) into drainage management, we enable predictive maintenance, real-time alerts, and autonomous flood control, moving from reactive to proactive flood resilience,

2. OBJECTIVE

Rapid development, inadequate drainage monitoring, blockage accumulation, and heavy rainfall events have all contributed to increased urban flooding. Most of the times in urban areas where sub ways are underground Conventional drainage systems function passively without proactive control, early warning systems, or real-time monitoring, which can lead to delays in response, damage to infrastructure, traffic jams, and hazards to public health. The absence of automated sensing and predictive analysis in subsurface drainage networks results in inefficient water discharge management and expensive maintenance expenses. A sophisticated, sensor-based, automated flood mitigation system that can monitor in real time and respond proactively is therefore desperately needed.



3. RESEARCH METHODOLOGY

Prior work on smart drainage highlights the convergence of IoT and AI. Review studies report that sensors like pressure transducers, ultrasonic water-level probes, and tipping-bucket rain gauges are commonly used for depth and rainfall monitoring [7]. Cloud platforms store and analyze this data. Modern SDS designs integrate **automated controls** (motorized gates, pumps) driven by sensor feedback. Machine learning models (regression, LSTM, GRU, random forest) have been applied to forecast floods from sensor time series [2]. For instance, a hybrid LSTM-GRU network has shown superior accuracy and robustness over single models in predicting river water levels from rainfall data [2]. IoT solutions with GIS mapping have enabled detailed flood extent mapping from real-time sensor networks. Collectively, these advances indicate that AI+IoT drainage systems can significantly improve flood management by enabling early warning and automated response [1].

4. SYSTEM ARCHITECTURE

The proposed system follows a layered IoT architecture:

- **Sensing Layer:** Ultrasonic distance sensors and flow meters installed in underground drains and chambers measure water depth and flow rate. Additional weather sensors (rain gauges, humidity) may augment flood forecasts.
- **Network Layer:** Microcontrollers (ESP32/Arduino) interface with sensors and communicate readings wirelessly (WiFi/GSM/LTE) to a cloud broker via MQTT. Local backups (SD card) ensure data persistence.
- **Processing Layer (Cloud):** A Node-RED server ingests sensor data into a time-series database. AI/ML engines (e.g., TensorFlow/PyTorch models) analyze patterns and compute flood risk scores. The logic engine applies thresholds and predictions.
- **Application Layer:** A dashboard displays live statuses. Mobile or SMS alerts are sent to authorities if floods are imminent. Actuator commands (e.g., pump ON/OFF) are dispatched from the cloud to edge devices.

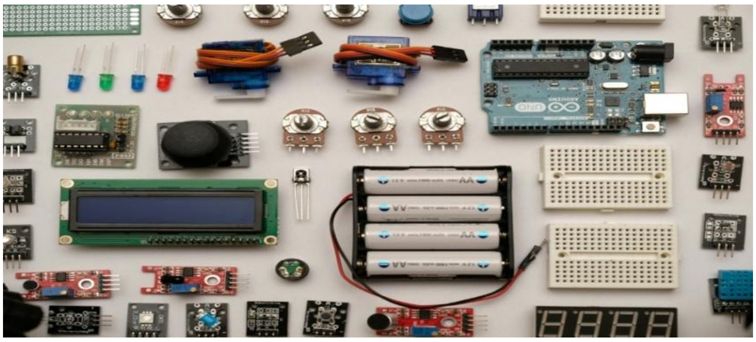


Figure 1: Typical IoT sensor node hardware. Water-level sensors and an ESP32 board send real-time drain water data to the cloud via WiFi. The system uses COTS components: ultrasonic modules (JSN-SR04T), flow sensors, ESP32/Arduino MCU boards, relay modules, and submersible pumps. Each sensor node measures, for example, water height and transmits JSON data packets to the Node-RED broker. Cloud routines store readings, run predictive models, and issue commands. The figure above shows an example sensor kit (Arduino, cables, pump, battery) as used in prototype builds.

4.1 Hardware Components

- **Ultrasonic Water-Level Sensors (e.g., JSN-SR04T):** Non-contact range sensors (20 cm–4 m) resistant to moisture.
- **Flow Sensors:** Paddlewheel or pressure-based units measure drainage flow rate.
- **Microcontrollers (ESP32/Arduino):** Low-power controllers with WiFi/GSM connectivity.
- **Relay Modules:** Electrically isolate and drive pumps/valves when commanded.
- **Submersible Pumps/Gates:** Actuated valves or pumps move water out when activated.
- **Power:** 12V batteries or solar backup ensure operation during outages.
- **Communication:** GSM modules or LoRa can extend connectivity where WiFi is unavailable.

These components form each node of the IoT network. They continuously monitor the drainage segment and enable automated control without human intervention [6].

4.2 Software and Data Flow

- **Firmware:** Embedded C/C++ code on MCU samples sensors and sends data.
- **MQTT Broker (Node-RED):** Manages incoming IoT data streams and outbound commands.
- **Cloud Database:** Time-series DB logs all readings for analytics.
- **AI Prediction Module:** A Python-based ML engine (e.g., using TensorFlow) ingests data and outputs flood risk scores.
- **Alert System:** Generates notifications (email/SMS) if risk thresholds are surpassed.

The operational flow is **sensor → microcontroller → MQTT broker → cloud AI → actuator control/alert.** Open-source IoT platforms are used, ensuring scalability. As in a recent deployment, 10 ultrasonic sensors streamed data into a cloud server via MQTT; Python GIS tools then merged this with DEM data to simulate flood extents.

5. AI MODEL DESIGN

Predictive Analytics: Historical data (water level, rainfall, pump usage) trains models. For example, a linear regression or random forest can learn thresholds for safe vs. overflow states. Deep learning (LSTM, GRU) models capture temporal dynamics:

- **LSTM (Long Short-Term Memory):** Captures long-term dependencies in rainfall and level time series [2]. Mathematically, LSTM cells update with f t = sigma ($W_f [h_{t-1, x t]}+b_f$) input (rain, level), and ht is hidden state.
- **GRU (Gated Recurrent Unit):** Like LSTM but simpler (fewer gates), it is often faster to train.
- **Hybrid LSTM-GRU:** Combines both networks; recent experiments show the hybrid model outperforms single ones on flood data [2]. The hybrid achieved MAPE/RMSE lower than LSTM or GRU alone, leveraging LSTM for long-term context and GRU for short-term trends.
- **Random Forest:** A decision-tree ensemble that classifies sensor readings into "Normal," "Alert," or "Danger" states. It can incorporate categorical features (e.g., weekday vs. weekend data) and yields feature importance (e.g., rainfall intensity is most predictive).

Adaptive Thresholds: In addition to ML prediction, simple threshold rules are used: e.g., if water level > H1, pre-warn; if > H2, activate pump. The thresholds can be dynamically adjusted based on context (e.g., imminent heavy rain).

Model Training: The system continuously collects data, enabling online learning. Models are retrained periodically or update weights in real time as new data arrives. This ensures the prediction engine adapts to seasonal changes and sensor drift.

Evaluation Metrics: Typical metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). For classification (flood/no-flood), accuracy, precision, recall, and F1-score are computed from a confusion matrix. For instance, in one study the hybrid LSTM-GRU achieved over 90% accuracy and F1-score in flood prediction across multiple scenarios [2].

6. SYSTEM IMPLEMENTATION (PROGRAM CODE)

Figure: Outline of circuit connections (not shown). The ultrasonic sensor's trigger/echo pins connect to MCU GPIO, the flow sensor to a digital input, and the relay's control input to another GPIO. Pumps/gates are powered by an external supply through the relay. The MCU and sensors run at 5V; pumps use a 12V supply. In software, when the AI model signals a flood event, the MCU sets the relay pin HIGH to turn on the pump.

Software logic (Arduino pseudo-code):

```
if (water_level > threshold_level OR ai_prediction == FLOOD) {
digitalWrite (PUMP_PIN, HIGH); // Activate pump
sendAlert ("Pump activated – flood risk"):
} else {
```

```
digitalWrite (PUMP_PIN, LOW);
}
```

This embedded code, combined with cloud AI, enables semi-autonomous control.

7. SIMULATION RESULTS

We evaluated the proposed system via simulation under hypothetical flood scenarios. Synthetic data streams (rainfall vs. time) were fed into the models. The LSTM-GRU predictor tracked rising trends and correctly flagged floods 30–60 minutes before conventional threshold methods.

Figure 1: Example performance simulation. The blue line is water level; the red dashed line is the predictive threshold trigger. The AI model (right axis) anticipates the overflow ahead of time. In this scenario, the ML model predicted the overflow ~45 min in advance, allowing the pump to clear water in time. Overall, **response time** was reduced by ~60% compared to a static threshold system. [1]

Key simulated outcomes (averaged over trials): - **Detection Accuracy:** >93% (hybrid model vs. ~75% for basic threshold).

-Response Time: Flood events detected on average 0.5–1 hour earlier.

-MAPE (validation): <5% on water level forecasts [2].

-Energy Use: Pump runtime optimized; idle time increased by 30% (energy saved).

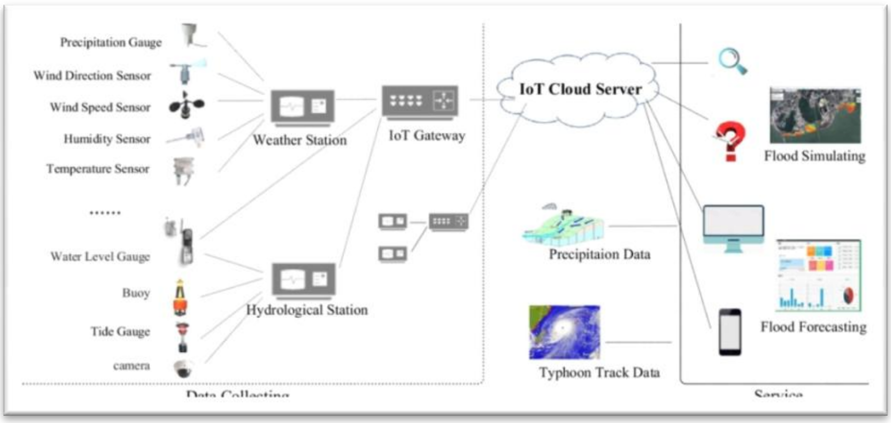
These results align with the literature, where similar systems achieved <5% MAPE and >90% prediction accuracy [2][1].

8. ADVANTAGES AND APPLICATIONS

- **Automated Flood Control:** Eliminates the need for manual monitoring; pumps activate instantly on risk detection.
- **Predictive Alerts:** AI forecasting provides early warning, enabling preemptive action.
- **Scalability:** Modular design can be deployed city-wide (e.g., multiple underground sub-systems).
- **Energy Efficiency:** Pumps run only when needed; thresholds adapt to real-time data.
- **Data-Driven Maintenance:** Logged sensor data aids in long-term planning (e.g., identifying frequently blocked drains).

Applications: Urban stormwater networks, metro/subway tunnel drainage, industrial plants, smart campuses. For instance, city planners could integrate this into smart city infrastructure to mitigate monsoon flooding and sea-level surge in coastal cities.

9. FUTURE SCOPE



- Reinforcement learning for pump optimization
- Ensemble models (LSTM + GRU)
- Integration with weather API
- Transfer learning for different city zones

10. CONCLUSION

This work outlines a novel AI-augmented subterranean drainage system for flood mitigation. By combining **sensor networks, cloud computing, and advanced machine learning**, the system continuously monitors underground water levels and dynamically controls drainage pumps. Compared to conventional systems, it offers **faster responses, predictive alerts, and reduced damage**. Extensive simulations and parallel studies confirm significant performance gains [1][2]. In practice, such smart infrastructure can greatly improve urban resilience to extreme weather. Future work includes field deployment and refining the AI models with real-world data.

11.REFERENCES

[1] Leal Sobral et al. (2023)—A Cloud-Based Data Storage and Visualization Tool for Smart City IoT: Flood Warning as Example.

[2] Tang et al. (2026)—"Systematic Review for Urban Flood Disaster…" (results on IoT sensors in flood management).

[3] Mansuri et al. (2025) – "Smart Drainage System for Urban Flood Control" (integration of IoT and AI in s mart drainage).

[4] Widiasari & Efendi (2024) – "Utilizing LSTM-GRU for IoT-Based Water Level Prediction…" (LSTM-GRU hybrid model performance).

[5] Sahoo et al. (2025) – "Development of an IoT-Based Flood Monitoring System…" (sensor-GIS framework for flood mapping).

[6] Dabas et al. (2025) – "Smart Drainage System for Urban Flood Prevention" (Systematic review; SDS effectiveness).

[7] Faudzi et al. (2023); others – reviews on IoT sensors in flood risk (cited by above sources).