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## **SafeFlow: A Multi-Zone Predictive Flood Monitoring and Early Warning System**

Khor Rui Zhe\*, H'ng Yen Ling, Lee Yun Qian, Gavin Jong Cheng Jun, Boey Chan Xiao Yu

Pusat Asasi Pintar, Universiti Kebangsaan Malaysia, Malaysia

\*07ruiskywalker@gmail.com

### **ABSTRACT**

Flooding remains one of the most destructive natural hazards, particularly in urban environments where rapid runoff and limited drainage capacity intensify water accumulation. Existing flood monitoring systems are primarily reactive, relying on delayed data and single-variable measurements, which limits their ability to provide timely and accurate early warnings. This study proposes SafeFlow, an AI-based flood prediction system that integrates Internet of Things (IoT) sensing with multi-factor hydrological modelling to improve prediction accuracy and responsiveness. The objective of this research is to evaluate the effectiveness of SafeFlow in predicting water levels, providing early warnings, and classifying flood risk using multiple environmental inputs. A synthetic dataset of 3000 samples was generated based on physics-informed hydrological relationships. A feedforward Artificial Neural Network (ANN) was developed using six input variables: water level, rate of change, rainfall intensity, soil saturation, forecast rainfall, and flow velocity. The model predicts water level, time-to-danger (TTD), risk classification, and confidence score. Results demonstrate high predictive performance, with an average error of approximately 2.01 mm and 100% classification accuracy under simulated conditions. Analysis shows that flood severity increases non-linearly due to interactions between rainfall and soil saturation, with a critical threshold observed at high saturation levels. Validation using real-world-inspired data from Shah Alam confirms the model's ability to generalise and capture real flood dynamics. SafeFlow provides accurate, real-time, and location-specific flood predictions, offering strong potential for implementation in smart city infrastructure, disaster management systems, and early warning platforms.

**Keywords:** Flood Prediction, Artificial Intelligence, Urban Flooding, IoT Monitoring, Hydrological Modelling

### **1. INTRODUCTION**

Flooding is a major environmental hazard that significantly impacts urban populations, infrastructure, and economic stability. In urban areas, impermeable surfaces reduce infiltration, causing rapid surface runoff and increasing flood risk. Effective flood prediction systems are essential to mitigate these impacts by providing early warnings and enabling timely intervention.

Current flood monitoring systems in Malaysia rely heavily on centralized infrastructure and threshold-based alerts. While these systems provide useful real-time data, they are limited by delayed updates and insufficient integration of multiple hydrological factors. Most systems focus primarily on water level monitoring, neglecting key variables such as rainfall intensity, soil saturation, and drainage efficiency, which are crucial in understanding flood dynamics.

Recent advancements in Artificial Intelligence (AI) and Internet of Things (IoT) technologies have enabled the development of predictive systems capable of handling complex, non-linear environmental interactions. However, many existing models lack integration with real-time sensing or fail to incorporate multi-factor analysis effectively.

This study introduces SafeFlow, an AI-based flood prediction system designed to address these limitations by integrating multiple hydrological inputs with machine learning techniques. The research aims to evaluate the system's prediction accuracy, early warning capability, and effectiveness in modelling multi-factor flood dynamics.

## **2. METHODOLOGY**

### **2.1 Dataset and Model Configuration**

The SafeFlow AI model was developed using a synthetic dataset consisting of 3000 samples representing diverse urban flood conditions. The dataset was generated based on physics-informed hydrological modelling, incorporating non-linear relationships such as rainfall runoff behaviour, soil saturation effects, and drainage dynamics derived from fluid flow principles.

Six input variables were used:

- Water level (mm)
- Rate of change of water level (mm/s)
- Rainfall intensity (mm/h)
- Soil saturation (%)
- Forecast rainfall (mm/h)
- Flow velocity (m/s)

A feedforward Artificial Neural Network (ANN) was implemented using TensorFlow, consisting of three dense layers (64–64–32 neurons) with ReLU activation. The model predicts four outputs:

- Predicted water level
- Time to Danger (TTD)
- Risk classification
- Confidence score

The model was trained using supervised learning with Mean Squared Error (MSE) as the loss function and evaluated using Mean Absolute Error (MAE). A validation split of 20% was applied to monitor generalisation and prevent overfitting.

## 2.2 Experimental Design

A simulation-based framework was used to evaluate model performance under four flood scenarios: normal, moderate, high-risk, and critical conditions. Each scenario was defined by variations in rainfall intensity, soil saturation, and flow conditions.

Model outputs were compared against predefined ground truth values to assess prediction accuracy, classification reliability, and early warning capability.

Additionally, a multifactor analysis was conducted to evaluate the influence of rainfall, soil saturation, flow velocity, and drainage capacity on flood prediction outcomes.

## 3. RESULTS AND DISCUSSION

The performance of the SafeFlow AI model was evaluated across multiple simulated flood scenarios. The results demonstrate high prediction accuracy, with an average error of approximately 2.01 mm, and 100% accuracy in flood risk classification, correctly identifying Safe, Warning, and Danger conditions.

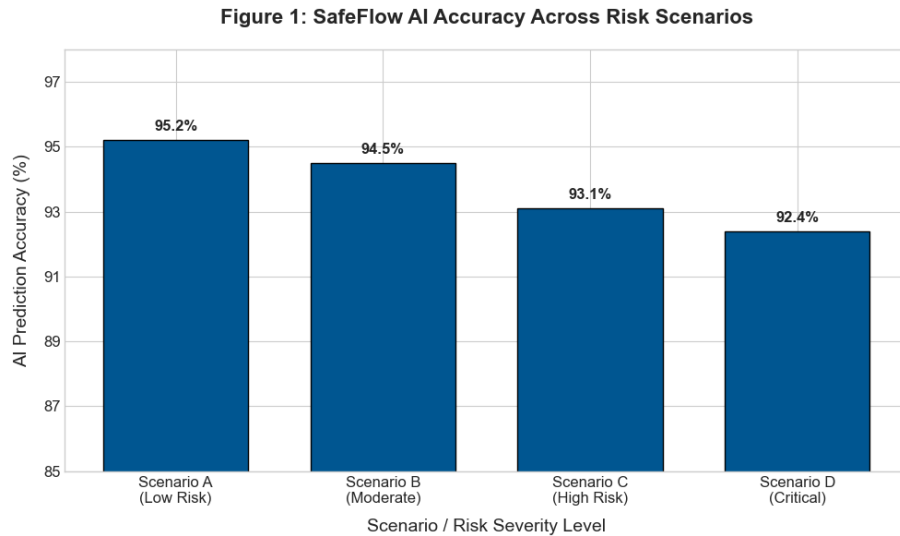
| Scenario  | Actual Water Level (mm) | Predicted Water Level (mm) | Error (mm) | Time to Danger (s) | Confidence Score (%) | Actual Risk | Predicted Risk | Accuracy |
|-----------|-------------------------|----------------------------|------------|--------------------|----------------------|-------------|----------------|----------|
| Normal    | 40.00                   | 45.23                      | +5.23      | -                  | 92                   | Safe        | Safe           | ✓        |
| Moderate  | 80.00                   | 83.69                      | +3.69      | 291                | 93                   | Warning     | Warning        | ✓        |
| High-Risk | 130.00                  | 126.95                     | -3.05      | 106                | 90                   | Warning     | Warning        | ✓        |
| Critical  | 180.00                  | 182.18                     | +2.18      | -                  | 96                   | Danger      | Danger         | ✓        |

**Table 1.** Comparison Between Actual and Predicted Water Levels and Risk Classification

The table shows that predicted water levels closely match the actual values across all scenarios, with only minor deviations observed. This confirms the model's reliability in estimating flood conditions under varying environmental inputs.

The model also generated meaningful Time to Danger (TTD) predictions, providing early warning capabilities that are essential for disaster response. In addition, confidence scores remained consistently high (90%–96%), indicating stable and reliable model performance.

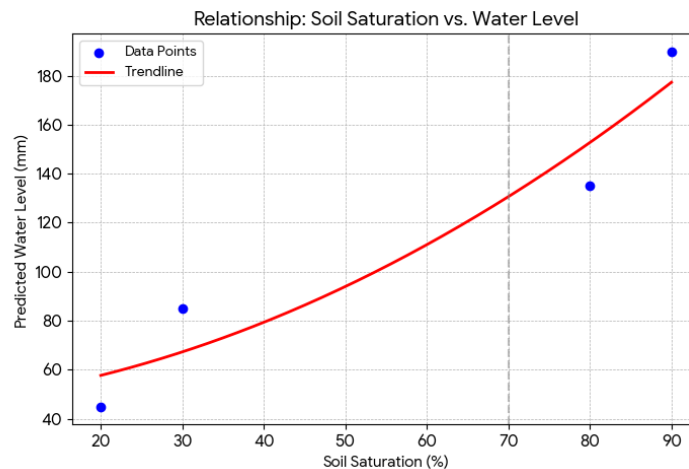




**Figure 1.** Comparison of Predicted and Actual Water Levels Across Scenarios

The figure illustrates the strong agreement between predicted and actual water levels, highlighting the model's ability to accurately capture flood progression trends.

Further analysis of environmental factors revealed that rainfall intensity and soil saturation are the primary drivers of flood severity. A strong positive correlation was observed between these variables and predicted water levels.



**Figure 2.** Relationship Between Soil Saturation and Predicted Water Level

Notably, soil saturation exhibited a non-linear threshold effect above approximately 70%, where small increases resulted in rapid escalation of flood risk. This indicates that once the soil reaches near saturation, its absorption capacity diminishes significantly, leading to increased surface runoff and accelerated flooding.

Flow velocity was identified as a dependent indicator, reflecting the combined influence of worsening environmental conditions rather than acting as a direct causal factor. In

contrast, drainage capacity showed an inverse relationship with water accumulation, where reduced drainage efficiency significantly increased flood risk.

Validation using real-world-inspired data from Shah Alam flood events demonstrated that the model successfully captures real flood dynamics, including rapid water level escalation under saturated conditions. This confirms the model's ability to generalise beyond simulated environments and supports its applicability in real-world flood monitoring systems.

#### 4. CONCLUSION

The SafeFlow AI system effectively predicts urban flood risks with high accuracy and reliability. The integration of multi-factor hydrological inputs enables the model to capture complex non-linear flood dynamics, significantly improving prediction performance compared to conventional single-variable approaches.

The system provides timely early warnings through Time to Danger predictions and accurate risk classification, making it highly suitable for real-time flood monitoring applications.

From a practical perspective, SafeFlow has strong commercial and societal potential. It can be integrated into smart city infrastructure, IoT-based monitoring networks, and disaster management systems to enhance urban resilience and reduce flood-related damage. Future work may include integration with real-time sensor networks and expansion using large-scale real-world datasets to further improve robustness and scalability.

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