FLOOD PREDICTION AND RELIEF USING DEEP LEARNING

[1]Sourav Aggarwal, [2]Suraj Uppal, [3]Varun Narang

[1,2,3]Students

Department of Computer Science and Engineering

Maharaja Agrasen Institute of Technology

Abstract

Floods, which become more severe in summer in India, pose a major challenge to disaster management and often result in human, economic and environmental losses. Traditional flood forecasting methods rely on historical data and traditional forecasting models, and their limitations indicate an urgent need for new technologies that are high-quality, accurate and timely. This study provides a new way to improve flood forecasting and forecasting using deep learning techniques. We developed a prediction model using convolutional neural networks (CNN), specifically using the ResNet-18 architecture, adapted to the complexity of monsoon-induced floods. The model was studied in the form of satellite images and aims to improve the accuracy and timeliness of flood forecasting. We have also developed a mobile application that provides instant flood warnings and facilitates community participation, data collection and usability. Preliminary results demonstrate the effectiveness of the model in predicting flood events; thus providing disaster management authorities with a promising tool to reduce the negative effects of floods. This study adds to the growing body of research advocating the integration of AI into natural disaster prediction and management and highlights the potential of deep learning for changing cultural practices around flood prediction and assistance.

1. INTRODUCTION

Floods are one of the most devastating natural disasters affecting millions of people worldwide. The monsoon season in India brings rains necessary for agriculture, but it also brings with it great dangers, affecting people's lives, businesses and the environment. The size and diversity of the country, together with the large number of people living in flood-prone areas, make it more difficult to predict and manage flood events. Traditional flood prediction methods in India are based on historical rainfall data and groundwater models. Although these methods[1] provide a source of prediction, they often fall short in accuracy and time, which are essential elements of disaster management and mitigation strategies[2].

The emergence of deep learning and artificial intelligence (AI) technology offers new opportunities to improve flood forecasting and management practices. Deep learning is a branch of machine learning that uses algorithms inspired by the structure and function of neural networks in the brain. It has demonstrated an outstanding ability to process large and complex data beyond traditional standards in terms of accuracy and efficiency in many fields, such as natural disaster forecasting[3]. This study aims to develop an advanced forecasting model for flood prediction in India using deep learning, specifically convolutional neural network (CNN). By identifying patterns in weather data, location and historical flood data, the model provides a better understanding of flood risk, making it more accurate and timely.

In addition, this study recognizes the importance of community participation and immediate dissemination of information in disaster management. Therefore, the development of a mobile application that can be used to create effective flood warnings for the public and authorities is also being investigated. The app supports instant data collection and analysis by integrating data from the crowd to improve the accuracy and reliability of flood forecasting.

This article describes methods for developing deep learning models and mobile applications, provides results and references for preliminary experiments, and discusses the implications of integrating technology into flood forecasting and relief efforts. With this approach, the research focuses on the overall goal of reducing the negative impact of floods in India and damage control by setting a precedent in the use of information in the world of technology.

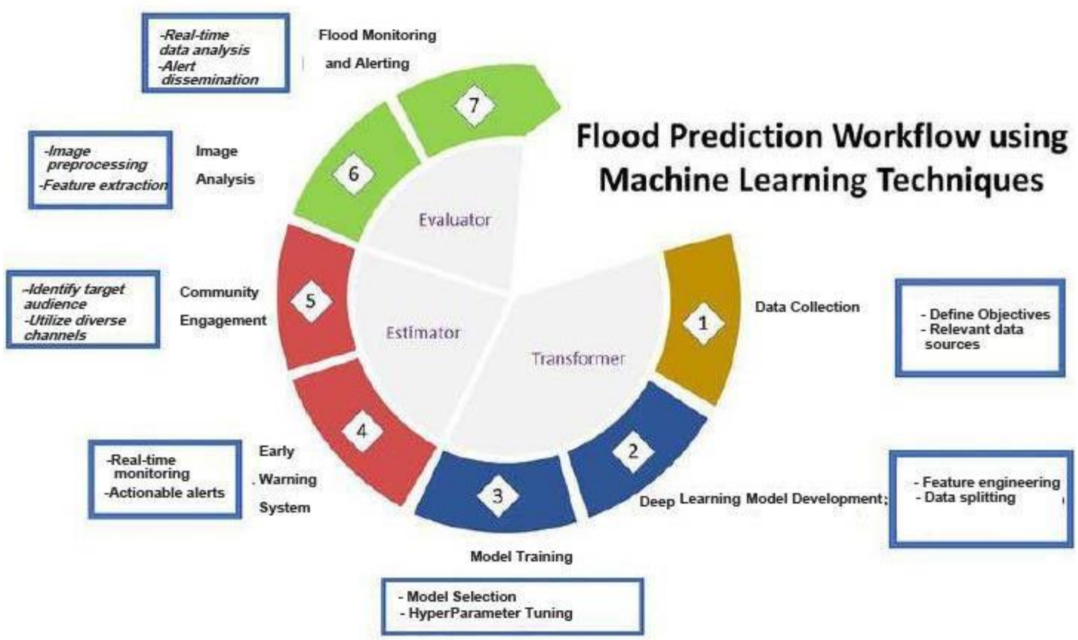

Fig.1: Flood Prediction Workflow

2. LITERATURE REVIEW

India's chronic flood problems during the monsoon season have led to a critical re-evaluation of flood management strategies, especially in the face of unreliable data disseminated on social media. In this context, the integration of advanced technologies such as smart computing models and mobile applications represents a shift towards more predictive and participatory management. This literature review explores and gathers information on the evolution of flood forecasting, the role of deep learning models, and new applications of collaborative technology in the community.

2.1. Evolution of Flood Prediction Models

Historically, flood predictions were largely based on hydrological models using flow meters and meteorological data[4]. Although useful to some extent, these models often lack the overall information and forecast accuracy required for timely and regional flood warnings. The advent of geographic information systems (GIS) and remote sensing technology has brought major advances that allow for more accurate mapping and analysis of flood-prone areas. But the real breakthrough came with the use of deep learning tools that increased the accuracy and efficiency of flood forecasting models.

2.2. Deep Learning Models for Flood Prediction

Deep learning, a subset of machine learning, has revolutionized flood forecasting by facilitating the analysis of large amounts of data, including satellite images and environmental data. Convolutional neural networks (CNN), in particular, have played an important role in analyzing spatial data to predict flood events with high accuracy. Research shows the effectiveness of CNNs in extracting meaningful patterns from complex data, thereby improving the predictive ability of flood forecast models. Flood forecasting using ResNet-18 and other deep learning methods demonstrates the ability of these methods to adapt and learn from changing data, making predictions more reliable, accurate, and timely.

2.3. Mobile Technologies and Integration with Existing Systems for Enhanced Flood Management

A number of approaches are required to maximize the effectiveness of mobile technology in flood control. This includes not only using smartphones to collect information and issue alerts, but also connecting these digital devices to the emergency response system. This integration increases confidence in forecast accuracy, facilitates communication, and supports joint response strategies.

Strict data verification procedures and personal protection measures must be implemented to resolve personal data issues and the accuracy of the data stack. Additionally, efforts to close the digital divide, such as increasing the use of mobile technology and improving digital literacy, can ensure that the benefits of these changes reach all citizens, especially those living in poor and remote areas.

In fact, the integration of mobile technology with existing disaster management systems should revolutionize flood management. By encouraging community participation, providing accurate information and strengthening communication, we can increase flood protection and reduce its impact on people.

3. METHODOLOGY

Our strategic plan to solve India's flood-related challenges through technology and data solutions includes several key steps, including the use of data collection and prioritization, deep learning models, early warning system development, community engagement, user-driven data validation and flood monitoring. and warning systems. Here we explain the methods used in our project:

3.1. Data Collection and Preprocessing:

The first phase of our approach involves collecting historical and current data on water levels, flood data and geographic maps. Historical flood data is a valuable resource that provides insight into patterns and trends in past flood events. On the other hand, real-time data collection captures current flood conditions, providing a better understanding of changing conditions. Additionally, georeferenced images shared by citizens are an important source of ground truth that provides immediate visibility to people on the ground.

The data we use to calibrate the ResNet-18 model is the 2016 Louisiana Floods, which contains satellite images of floods in Louisiana where heavy rains in August caused local water levels to reach flood history. The original data contains a total of 332 images with their tags as a csv archive. We use 52 images for testing and 270 images for training.

3.2. Deep Learning Model Development:

Deep learning is a subfield of machine learning that focuses on developing and using neural networks designed to model and solve complex tasks. In deep learning, the term "deep" refers to the use of deep neural networks, which are neural networks with multiple layers of input and output processing (deep architectures). These networks learn the hierarchical structure of data, allowing them to capture and understand complex patterns and features.

In traditional machine learning, extraction and selection are usually done manually by experts [5]. For example, deep learning algorithms can learn relevant features from raw data, making them particularly useful for tasks such as image [6] and speech recognition, language, grammar, and other structural problems.

The core of our interventions revolves around the development and continuous improvement of deep learning models with a focus on neural networks (CNN). More importantly, the model is designed to allow for continuous learning from ad-hoc ideas. The flexibility of CNN ensures that the model can be adjusted to changing conditions, thus maintaining accuracy in flood prediction. At the same time, the learning process plays an important role in refining the model, making it effective in predicting and predicting floods and providing a solid foundation for our early warning system.

The training data mentioned in the first step is further improved by using random image cropping and training pattern of crop image; this represents improvement in the level of educational evaluation. Since the data we have is very small, we use the weight presets that come with ResNet-18 and are fine-tuned to our data.

3.2.1 ResNet-18 Architecture:

ResNet-18 is a specific modification of the well-known ResNet (residual network) architecture [7] with the use of residual blocks, which helps solve the training problems of deep neural networks. ResNet-18, as the name suggests, is an 18-layer ResNet model. The main innovation of the ResNet architecture is the use of redundancies. Residual blocks have cross-connects (also called fast connections or cross-connects) that allow the input to bypass one or more layers and be added directly to the output. This helps solve the incomplete problem and makes deep networks easier to train.

ResNet-18 is an inferior version of ResNet compared to other variants such as ResNet-50 or ResNet-101. It aims to balance model depth and computational efficiency, making the model suitable for many applications, especially when computing resources are limited. ResNet architectures, including ResNet-18, are widely used in computer vision tasks such as image classification, object detection, and image segmentation due to their effectiveness in training deep neural networks.

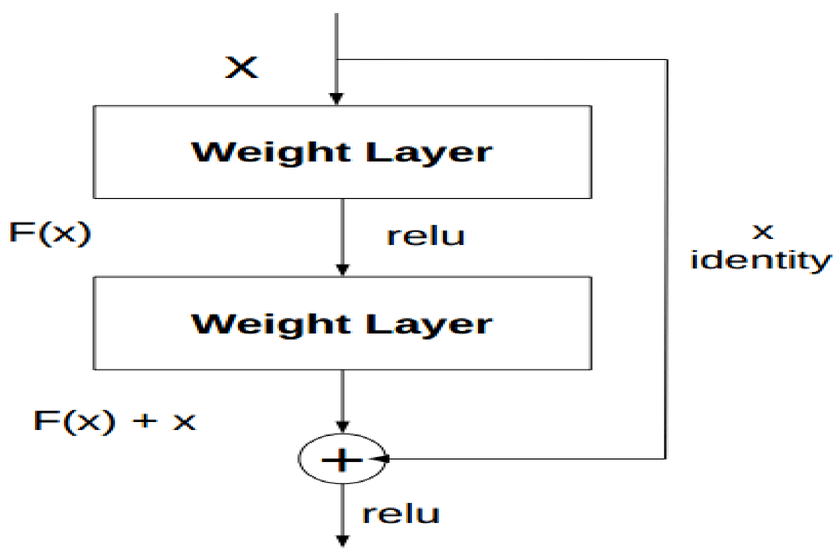

Fig.2: Skip connections in Res-Net

3.2.2 Model Training:

We trained our model on the training dataset for 9 epochs which was decided based on trial and error, training for more epochs resulted in overfitting. The term "loss" refers to the measure of how well a machine learning model is performing with respect to its predictions compared to the actual ground truth labels. The loss function quantifies the difference between the predicted output and the true label for each example in the dataset. We used binary cross entropy [8] as our loss function which is defined as follows:

$$L(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N} \quad [y_i \cdot log\ log\ (\hat{y_i})\ + (1-y_i) \cdot log\ log\ (1-\hat{y_i})\ ]$$

Where:

- N is the number of samples or instances in the dataset
- yi is the true label for the i-th sample (0 or 1 for binary classification).
- yi is the predicted probability that the i-th sample belongs to class 1.

The binary cross-entropy loss penalizes the model more when its predicted probability diverges from the true label. In other words, if the true label is 1, the loss increases as the predicted probability for class 1 deviates from 1; if the true label is 0, the loss increases as the predicted probability for class 1 deviates from 0.

The error rate metric is used which is a common metric used for classification tasks, such as image classification. The error rate is a measure of classification performance and is calculated as the ratio of incorrectly classified samples to the total number of samples. The formula for error rate can be expressed as:

Error Rate = Number of Misclassified Samples / Total Number of Samples

In the context of a classification problem, a lower error rate indicates better model performance, as it reflects a smaller proportion of incorrectly classified samples. At the end of training with the augmented dataset the error rate was 0.057692.

Finally, the Adam optimizer[9] is used, Adam (short for Adaptive Moment Estimation) is an optimization algorithm commonly used in training deep neural networks. It is an extension of stochastic gradient descent (SGD) and combines ideas from RMSprop (Root Mean Square Propagation) and momentum. Adam is a popular choice for training deep neural networks due to its adaptive learning rates, momentum, and efficiency in handling sparse gradients. It often converges faster than traditional SGD and requires less tuning of hyperparameters.

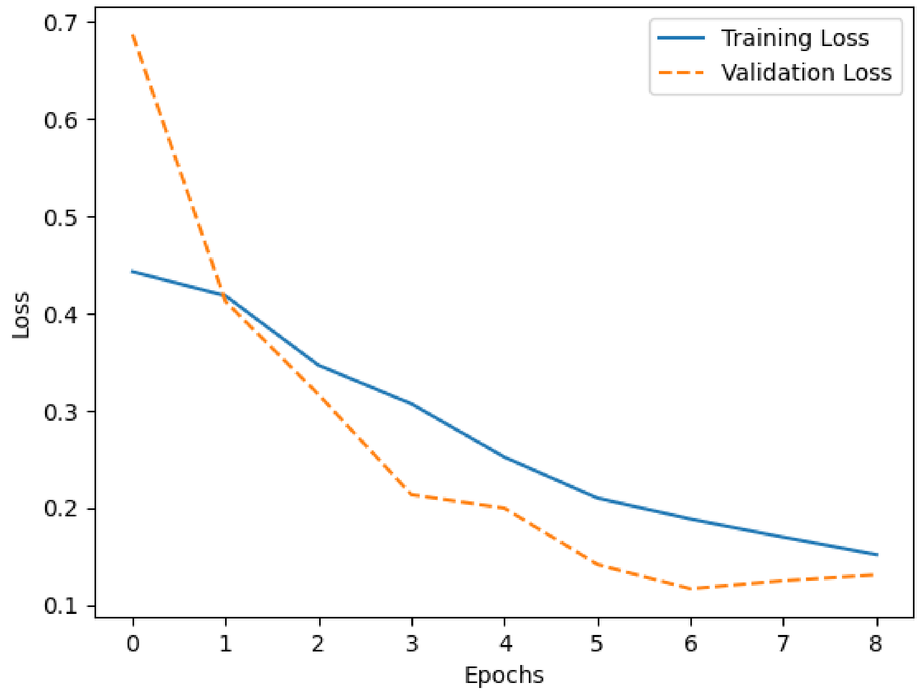

Fig.2: Training and Validation Loss

3.2.3. Model Evaluation:

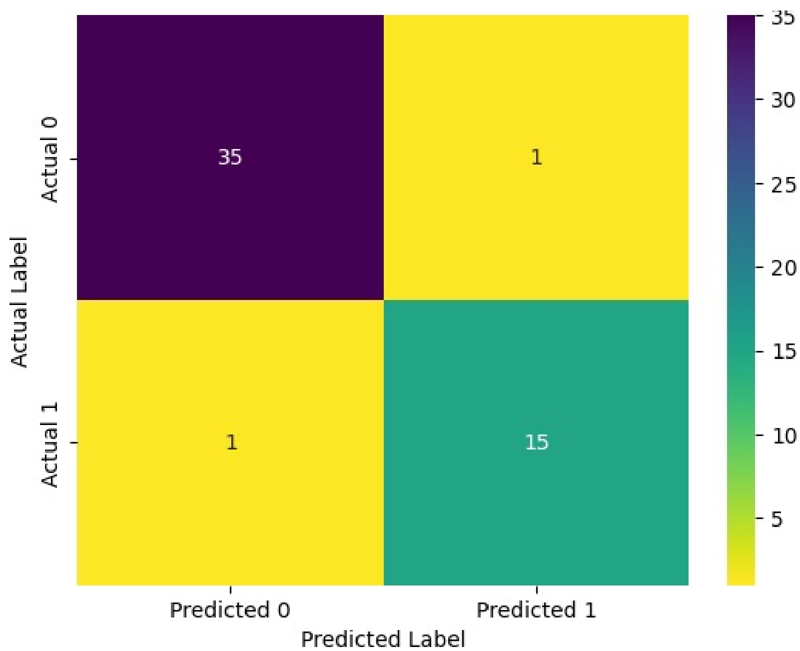

Fig.4: Final Confusion Matrix after Data Augmentation

3.3. Early Warning System:

Building on the capabilities of our deep learning model, the next step in our approach involves the implementation of early warning systems. Advanced algorithms have been developed to monitor real-time data to reveal flooding patterns. These algorithms continuously evaluate important signals and trigger automatic alerts when confidence estimates exceed a predetermined threshold. This approach ensures that communities and authorities are informed in a timely manner, allowing them to take action quickly and efficiently to respond to flood events.

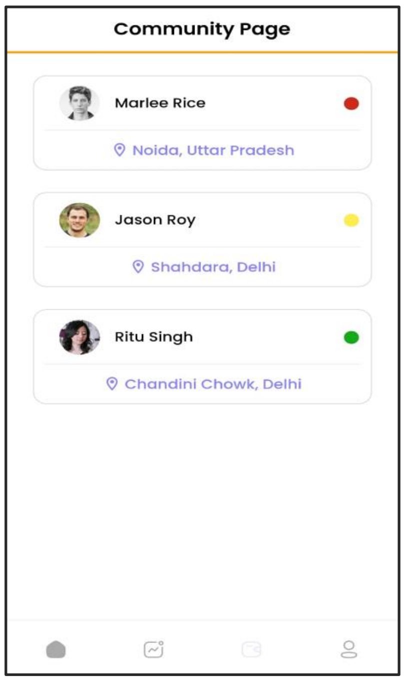

Fig.5: Community Page for showing alerts and SOS calls of other users

3.4. Image Analysis:

To improve the accuracy and precision of flood-related data, our method uses deep learning models to integrate image analysis. These algorithms are specifically designed to analyze publicly available georeferenced images. This systematic analysis serves two main purposes: to identify community reports and to provide detailed information about similar flood events. Image analysis adds a layer of validity to the data, greatly increasing the overall reliability of flood monitoring. By ensuring the information obtained from publicly available images is accurate, these devices can help emergency responders better understand the situation at the scene and therefore make sense of their responses. The developed deep learning model is deployed using Flask to facilitate fast API calls for improved usability.

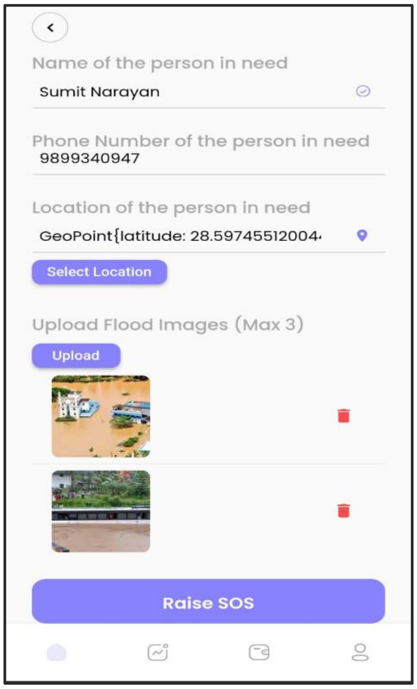

Fig.6: SOS Call generation page with real-time image and location adding feature

3.5. Flood Monitoring and Alerting:

Our approach is focused on the development of rapid flood and automatic warning systems, drawing on the capabilities of early warning systems and deep learning models. This system continuously monitors important data such as water levels, rainfall and geographic maps, providing a comprehensive and dynamic view of flood changes. Automated alerts resulting from early warning systems play an important role in ensuring timely communication and coordination among stakeholders. This comprehensive approach ensures that policymakers and emergency workers have the information necessary to take rapid and informed action in the event of a flood. Flood monitoring and warning systems that combine technology with up-to-date information to improve the overall protection of society from monsoon flooding are crucial to our approach.

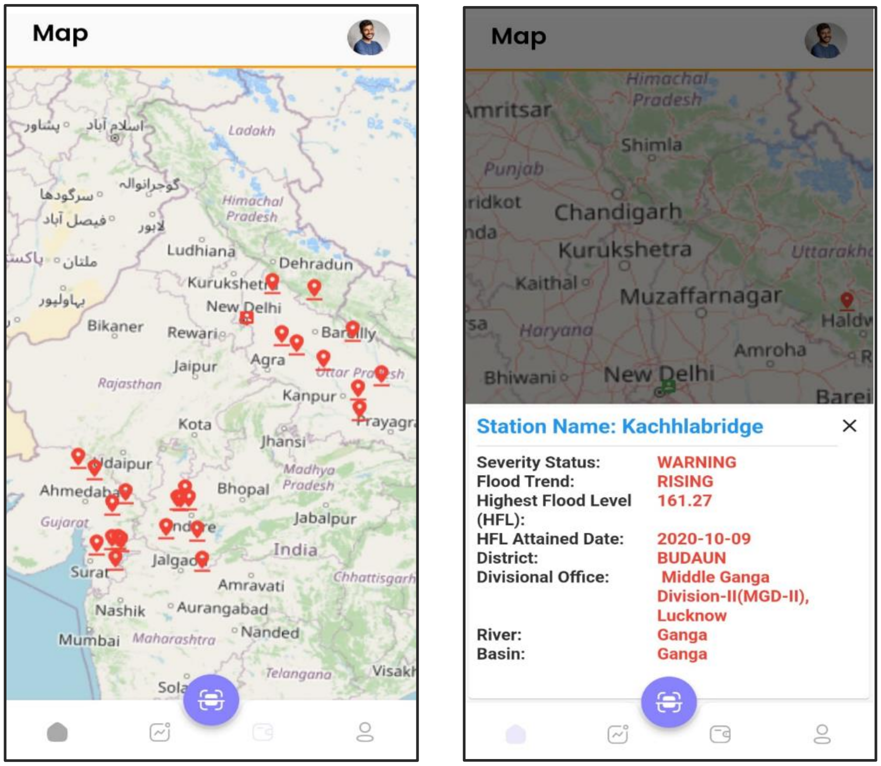

Fig.7: Flood Monitoring Panels
(Red markers showing water stations with water level above warning)

4. FUTURE SCOPE

By expanding our peak flood forecast, we aim to support our deep learning models with more environmental data, including real-time satellite imagery. This integration is expected to increase the accuracy and timeliness of flood forecasting through the acquisition of geographical and meteorological information. Using high-resolution satellite imagery, we can again make more accurate predictions by detecting early signs of flooding, such as rising water levels and rainfall patterns. At the same time, we are committed to increasing social cohesion through mobile applications, providing better interactive communication and educational resources to encourage comprehensive participation in flood control. Incorporating new technologies such as Internet of Things (IoT) sensors will strengthen the predictive capabilities of our systems and enable real-time monitoring of environmental change. Strong partnerships with government agencies and non-governmental organizations ensure our predictive tools reach and benefit the most vulnerable communities. This multifaceted strategy aims to increase global resilience by not only improving the technical performance of flood forecasting models, but also demonstrating the globally adaptable potential of our approach by promoting support, information and coordination for disaster management.

5. CONCLUSION

In particular, the suite of deep learning models in convolutional neural networks (CNN) is important for our flood predictions. Through extensive training and continuous improvement, these models achieved the best accuracy in flood prediction, demonstrating the early adaptability and reliability of their findings. The integration of our early warning systems and community engagement measures plays an important role in increasing the effectiveness of flood management. Leveraging user-friendly mobile applications, we create a powerful communication system to support communities and authorities, thereby increasing the time and efficiency of response in emergency situations. Additionally, image analysis techniques significantly increase the reliability of crowdsourced data. By analyzing accurate information from geographical maps, we ensure that emergency response teams receive reliable information that improves their situational awareness and decision-making processes. Additionally, our flood monitoring and coordination efforts benefit from real-time tracking of critical data, including water levels and rainfall, supported by non-automated alerts. This generalization not only facilitates communication between participants but also improves resource allocation, leading to major advances in managing the sensitivity and speed of flood emergencies.

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