AquaMap: Empowering Communities to Report and Map Water-Related Issues in Real-Time with Deep Learning

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Abstract. In today's era of rapid urbanization and environmental challenges, effective disaster and crisis management demand innovative solutions. This paper presents a novel approach focusing on community-level water-related issues through an intelligently designed application. The primary objective is to develop a user-friendly platform facilitating the reporting of water-related problems by both social media posts and the general public, subsequently enabling prompt action by relevant government authorities. Leveraging deep learning techniques and user-generated data, our solution introduces real-time detection and classification of six distinct water-related problems. A custom dataset is curated to train a ResNet-18 model, achieving an impressive accuracy of 73%. The application, developed with a React-based frontend and Flask-powered backend, acts as a centralized hub for reporting and managing water issues. Notably, it employs user-inputted data to accurately pinpoint problem locations, thereby enhancing the precision of reporting. By presenting a holistic approach, this research significantly contributes to the development of efficient crisis management and response strategies for water-related disasters.

Keywords: Water-related issues · Disaster response · Sustainable Development · Deep Learning · Custom Data · web application

1 Introduction

In recent years, the escalating frequency and severity of water-related disasters have underscored the critical need for innovative solutions in crisis management [1]. Rapid urbanization, coupled with environmental challenges, has exacerbated the vulnerability of communities to water-related issues such as floods, potholes, water leakages, water contamination, and inadequate supply [2]. Swift detection, precise classification, and prompt response to these challenges are crucial for the social welfare and municipal departments of the government, as they are essential in mitigating the adverse impact on both lives and infrastructure.

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Traditional approaches to crisis management often rely on manual reporting mechanisms, which are prone to inefficiencies and delays. Moreover, existing technological solutions often lack the capability to harness real-time data and user-generated inputs effectively [3]. Recognizing these limitations, our research work aims to bridge this gap by introducing an advanced application that leverages deep learning techniques and user-generated data for the real-time detection and classification of water-related problems at the community level.

Real-time detection of water-related problems plays a pivotal role in effective crisis management and response strategies. Real-time detection, enabled by advanced technologies like deep learning, allows for prompt identification of problems as they occur, facilitating timely intervention and response by relevant authorities [4, 5]. This proactive approach not only reduces response times but also enhances the overall efficiency and effectiveness of crisis management efforts, ultimately leading to better outcomes for affected communities.

Deep learning techniques, particularly convolutional neural networks (CNNs), play a fundamental role in enabling real-time detection of water-related problems [6]. By leveraging deep learning algorithms, these systems can analyze and interpret large volumes of data, including images and sensor readings, to accurately identify and classify various types of water-related issues. The inherent ability of deep learning models to learn complex patterns and features from data allows for robust and reliable detection capabilities, even in dynamic and challenging environments. Additionally, deep learning models can adapt and improve over time through continuous training and refinement, further enhancing their performance in real-world scenarios [7, 8]. Overall, the integration of deep learning techniques into crisis management applications enables more proactive and effective responses to water-related disasters.

This paper presents a comprehensive framework for building an application that empowers communities to report water-related issues promptly, facilitating swift action by relevant authorities. Custom datasets are required to address the novel problems using machine learning approaches [9]. The proposed solution utilizes a custom dataset comprising six distinct water-related problem classes, enabling the training of a ResNet-18 model for accurate detection and classification [10]. Additionally, the application, developed with a React-based frontend and Flask-powered backend, offers a user-friendly interface for seamless reporting and management of water issues.

By adopting a holistic approach that integrates cutting-edge technology with community engagement, this research seeks to enhance the efficiency of crisis management and response strategies for water-related disasters. Through the development and implementation of this innovative application, we aim to contribute significantly to the resilience and sustainability of communities facing water-related challenges.

The primary contributions of this work include

- The design and implementation of a user-friendly mobile application, facilitating seamless reporting and management of water-related issues within communities.
- The construction of a custom dataset encompassing five prominent water-related challenges, namely floods, drainage issues, water contamination, potholes, and water leakages. Subsequently, a baseline model is trained using this dataset.

- Augmentation of the dataset through the incorporation of user-provided images depicting the identified problems. Furthermore, a validation mechanism is implemented to verify the accuracy of the uploaded content, thereby enhancing the overall reliability of the dataset

2 Methodology

This section delineates the methodological approach employed in crafting the application. The primary components of the application encompass Data Collection and Model Training, Capturing and Uploading Images, Obtaining Model Inferences, and Marking Problem Locations on the Map. The methodological approach is clearly described in Fig. 1.

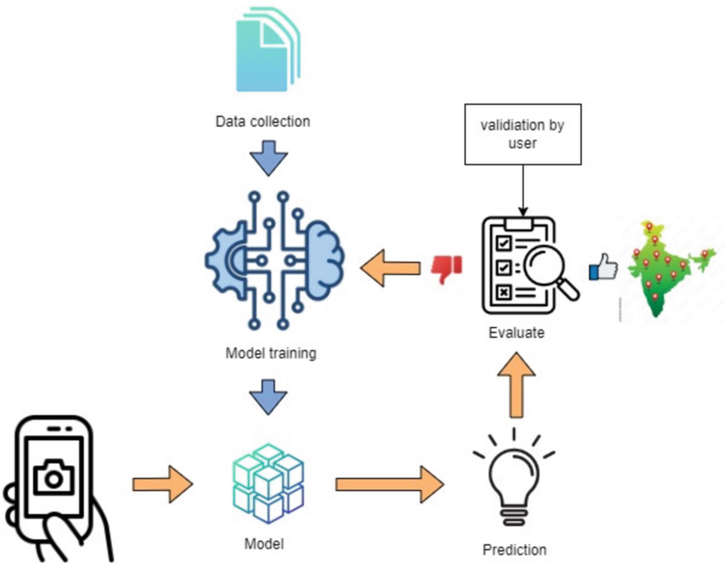

Fig. 1. Approach for building aquaMap by incorporating deep learning and user generated data.

2.1 Data Collection and Model Training

Given the absence of a dedicated dataset for the identified water-related issues [11], images representing all six classes were amassed and curated to form a comprehensive dataset. The six classes comprise drainage, potholes, floods, water contamination, water leakages, and a non-water class. Subsequently, the ResNet-18 model underwent training utilizing this custom dataset.

2.2 Capturing and Uploading Images

The application facilitates an intuitive method for issue reporting, allowing users to upload images relevant to the reported problem. Users are empowered to either capture photographs using the in-app camera feature or select pre-existing images shared by others. Concurrently, alongside uploading problem-related images, the application enables users to furnish a description of the encountered issue, thereby streamlining the resolution process with enhanced accuracy.

2.3 Model Inference

Upon user submission of an image, the trained ResNet model is leveraged for classification. User validation of the prediction is solicited to refine existing data, thereby augmenting the model's future performance [12]. It is imperative to acknowledge the inherent unpredictability of machine learning models; thus, in instances of misclassification, the model undergoes retraining to rectify errors and enhance its efficacy [13]. Notably, if a user submits an image that does not align with any pre-defined classes, manual specification of the problem is necessitated, ensuring meticulous classification.

2.4 Marking Problem Locations

The crux of the proposed AquaMap application lies in marking and discerning the locations of reported issues. Leveraging the user's location, the application automatically retrieves the problem location when an image is uploaded via the camera functionality. Conversely, when users share images, they are prompted to manually input the location details. Subsequently, the accumulated data is depicted on a map, with distinctive colors assigned to each problem type; for instance, floods are denoted in red. This mapping feature serves as a pivotal tool for administrators and community members to swiftly identify issues and their precise locations, potentially mitigating their impact. Furthermore, the application's data collection capability, coupled with mapping functionalities, holds promise in diverse domains such as emergency management, urban planning, and environmental monitoring, facilitating informed decision-making processes.

3 Dataset Creation and Model Training

The dataset utilized in this study comprises five crucial community-level water-related challenges: drainage, potholes, floods, water contamination, and water leakages. Additionally, a sixth class, designated as the non-water class, has been introduced, resulting in a comprehensive dataset comprising a total of six classes. To ensure robust representation, 100 images were collected for each class, culminating in an extensive dataset of 600 images. Sample images from each class are depicted in Fig. 2. These images were sourced from various locations across India, with some obtained from social media platforms, Google, Pinterest, and Flickr. Emphasis was placed on creating a diverse and balanced dataset to facilitate the training of a generalized model.

The ResNet18 model underwent fine-tuning using the custom dataset collected. Pretrained on the ImageNet dataset, the ResNet model possesses extensive knowledge of

Fig. 2. Sample image for every class of the curated dataset.

visual features and patterns [14]. This pre-training was further enhanced with the newly curated custom dataset to adapt the model's understanding to the six classes. During fine-tuning, the final fully connected layer was replaced with a new linear layer, configured to output size matching the number of classes, which is six. The dataset was split into three sets: training (70%), validation (15%), and testing (15%), to ensure a robust evaluation. PyTorch DataLoader was employed to efficiently load and preprocess the datasets, with a batch size of 32 chosen to balance computational efficiency and model performance. To optimize the model's performance during training, the Adam optimizer was utilized with a learning rate set to 0.001. Adam dynamically adapts learning rates for individual parameters, leveraging both first-order momentum and second-order acceleration of gradients [15]. The CrossEntropyLoss function served as the loss criterion for multi-class classification, evaluating the difference between the predicted probability distribution and the ground truth labels, which were one-hot encoded. This comprehensive model training methodology yielded impressive validation and test accuracies of 70.89% and 77.50%, respectively, demonstrating the model's capability to accurately identify various water-related challenges at the community level.

4 Application Development

The frontend component of the application was meticulously crafted using React, a framework known for its user-friendly and responsive design capabilities [16]. This choice ensures a seamless and aesthetically pleasing user experience. The interface allows users to effortlessly upload images or capture real-time pictures using their device's camera, enhancing the usability of the disaster and crisis management application.

The application provides robust functionality for reporting water-related issues within communities. Users can easily submit reports by uploading images or capturing photos of the encountered problems. Additionally, they can provide detailed descriptions to streamline the resolution process, ensuring accurate and prompt responses from relevant authorities. To enhance the application's capabilities, a Flask-powered backend was seamlessly integrated to facilitate communication between the frontend and the deep learning model. This backend handles crucial operations such as responding to user queries, interacting with the deep learning model, and managing image uploads. This integration ensures a smooth flow of data between the computational engine and the user interface, enabling real-time detection and classification of water-related issues.

The application implements robust user input validation mechanisms to ensure the accuracy and reliability of reported issues. Users are prompted to provide detailed information along with images, facilitating precise problem classification and location marking. Leveraging user-provided data, the application accurately pinpoints the locations of reported issues on a map, enabling authorities to swiftly address community-level water-related challenges.

5 Results and Discussion

The performance of the trained model on the custom dataset was assessed using key metrics suitable for multi-class classification tasks, including accuracy, precision, recall, and F1-score. Precision measures the model's ability to accurately identify instances of a specific class, while recall evaluates its capability to capture all instances of that class. The F1-score, as the harmonic mean of precision and recall, offers a comprehensive assessment of the model's overall performance [17] (Fig. 3).

The model exhibited excellent accuracy across images related to water issues, with particularly commendable performance in identifying potholes as illustrated in Table 1. However, it displayed suboptimal performance in accurately addressing drainage problems. This comprehensive evaluation provided valuable insights into the model's strengths and areas for improvement, guiding potential refinements in subsequent iterations. To assess the model's generalization ability, further testing was conducted using randomly selected images not included in the original dataset. A sample inference on the unseen image is shown in Fig. 4. The model demonstrated its capacity to extend its learned knowledge beyond the training set, showcasing promising predictions for these unseen images. To enhance performance further, augmentation techniques can be explored to increase the diversity of the training data.

The application interface allows users to view problem locations on a map, facilitating easy identification and reporting of water-related issues. The app's camera feature enables users to capture and upload pictures along with their location details, while manual entry of location information is also supported. The map displays problem locations with specific colors corresponding to the type of issue, such as red for flood-related problems. A sample set of application images were shown in Fig. 5.

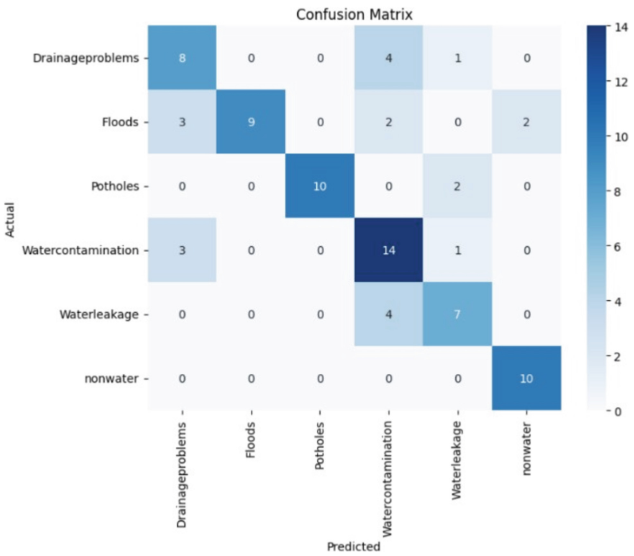

Fig. 3. Confusion matrix of the performance of the base- line model

Table 1. Performance of the ResNet model on the custom dataset of six classes.

Class label	Precision	Recall	F1-Score
Drainage Problems	0.57	0.62	0.59
Floods	1.00	0.56	0.72
Potholes	1.00	0.83	0.91
Water contamination	0.58	0.78	0.67
Water leakage	0.64	0.64	0.64
Nonwatery	0.83	1.00	0.91
Accuracy	0.73		

In comparison with existing solutions, the developed application offers several advantages, including real-time detection and classification of water-related issues, user-friendly interface design, and seamless integration of the deep learning model. This innovative approach empowers communities to report and manage water problems promptly, contributing to efficient crisis management and response strategies. Through the implementation of the application and evaluation of the trained model, valuable insights were gained regarding the effectiveness of deep learning techniques in addressing community-level water-related challenges. Lessons learned from this research include the importance of diverse and balanced datasets, the need for ongoing model refinement, and the significance of user input validation for accurate problem classification and location marking.

Fig. 4. Model Generalizability on the Unseen Data

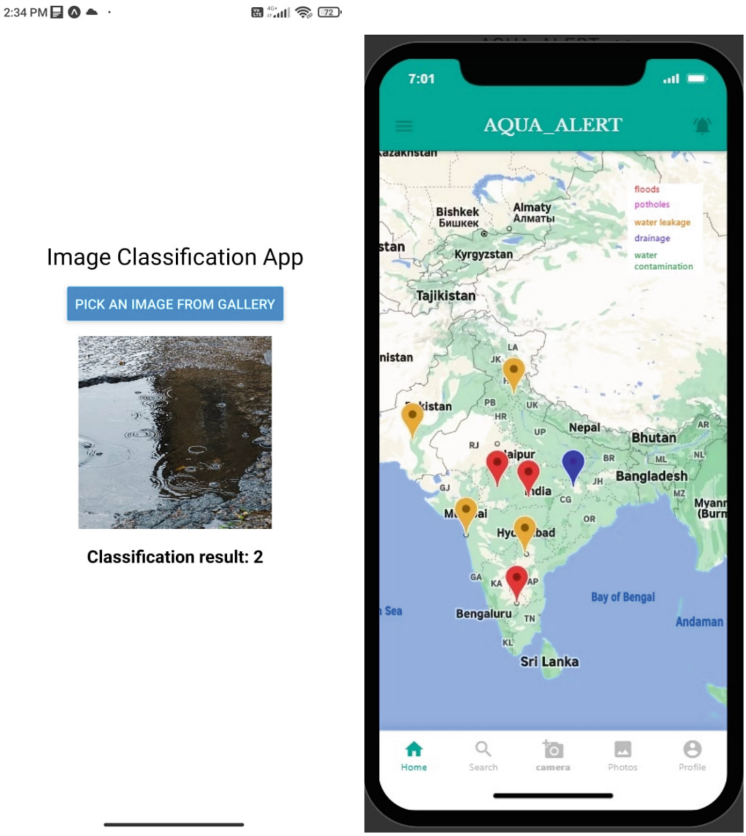

Fig. 5. Interface of the Final application

6 Conclusion

In this research, we developed an innovative application utilizing deep learning and user-generated data to swiftly detect and classify water-related issues in real-time. Our aim was to create a platform for public reporting and management of such problems, aiding governmental and emergency response efforts effectively. Through meticulous design, the frontend component crafted with React offers a user-friendly interface, while seamless integration with a Flask-powered backend facilitates communication with the deep learning model. Our dataset, comprising six distinct classes and 600 images, underpinned robust model training and evaluation. Leveraging the ResNet model, we achieved commendable accuracy in classifying uploaded images, further validated by user input, streamlining issue reporting for prompt resolutions.

Looking ahead, our research sets a foundation for advancing water-related crisis management. Future endeavors could focus on refining the deep learning model to bolster accuracy and robustness, exploring augmentation techniques to diversify the dataset, and implementing strategies to enhance user engagement. Integration with IoT devices also holds promise for real-time monitoring and detection of water-related issues. By addressing these avenues, we aspire to contribute further to the efficacy and efficiency of crisis management strategies, ensuring communities are better equipped to address water-related challenges promptly and effectively.

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