

Early Prediction System for Glacier Lake Outburst Floods

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Abstract: “Glacial Lake Outburst Floods (GLOFs)” are sudden, high-magnitude floods resulting from the breach of natural dams containing glacial lakes. With climate change accelerating glacial lake formation, GLOFs present growing threats to downstream communities and infrastructure. This study introduces an AI-powered chatbot system designed for real-time GLOF risk prediction and assessment. By leveraging predictive models such as ARIMA, GRU, and LSTM, the system analyses user-provided environmental data, including temperature and water levels, to generate actionable insights. A simple and intuitive chatbot interface allows users to input key parameters, which are processed using predefined thresholds to categorize risk levels as high, moderate, or low. The system enhances disaster preparedness and management through accessible and timely decision support. Future work aims to integrate IoT-enabled real-time data streams to improve prediction accuracy further, making this solution a scalable and effective tool for mitigating GLOF risks in vulnerable regions.

Keywords: GLOFs, AI-Powered chat bot, Predictive models.

1. Introduction

In recent years, advancements in artificial intelligence (AI) and predictive analytics have significantly transformed disaster risk management. Among these, the prediction of Glacial Lake Outburst Floods (GLOFs) has garnered attention due to their catastrophic impact on downstream communities and infrastructure. With climate change accelerating glacial lake formation, GLOF prediction has become increasingly vital. However, the task is challenging due to the dynamic nature of glacial systems, limited real-time data, and the complex interplay of environmental factors.

To address these challenges, AI-powered chatbot systems have emerged as an innovative solution. By leveraging pretrained predictive models like ARIMA, GRU, and LSTM, these systems analyze environmental data such as temperature and water levels to predict GLOF risks. This approach reduces computational complexity, ensures real-time responsiveness, and provides accurate risk assessments. Additionally, the chatbot interface enhances accessibility, allowing non-experts to receive actionable insights for disaster preparedness and management.

2. Literature Review

A. Traditional Methods

Traditional methods for GLOF prediction primarily relied on field surveys, remote sensing, and hydrological modelling. While effective for historical assessments, these methods lacked real-time responsiveness and required significant expertise and resources. Additionally, they were unable to account for rapidly changing environmental conditions, limiting their predictive accuracy in dynamic glacial systems.

B. Environmental Data Analysis

Environmental data analysis plays a crucial role in GLOF prediction. Early approaches focused on analyzing individual factors, such as glacial lake volumes or temperature trends, but failed to integrate multiple parameters effectively. Recent advancements in machine learning models like ARIMA and GRU have enabled the analysis of complex, multivariate datasets. These models can identify temporal patterns and interactions between variables, significantly improving prediction accuracy and reliability.

C. AI and Chatbot Systems

The integration of AI-powered chatbots has revolutionized the accessibility and usability of early-warning systems. Predictive models, including LSTM, have been incorporated to analyze real-time data and provide accurate risk categorizations. Chatbots offer a user-friendly interface, allowing stakeholders to input environmental parameters and receive actionable insights instantly. This eliminates the need for specialized knowledge and reduces reliance on computationally expensive systems. Future advancements include integrating IoT sensors for continuous data collection and enhancing prediction accuracy through real-time feedback loops.

3. Methodology Data Collection and Preprocessing

The dataset utilized for this project includes historical and real-time environmental data sourced from public repositories, including satellite imagery, hydrological datasets, and meteorological records. Key parameters such as temperature, precipitation, and water levels were analyzed to ensure

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accuracy and consistency. Preprocessing steps involved normalizing data to handle varying units and filling missing values using interpolation techniques. Data augmentation, such as synthetic generation of extreme scenarios, was employed to improve the robustness of predictive models. The dataset was split into training, validation, and testing sets in a 70:20:10 ratio for optimal model evaluation.

A. Model Development

Predictive models, including ARIMA, GRU, and LSTM, were employed for analyzing temporal and multivariate data. These models were selected for their ability to capture timeseries patterns and long-term dependencies. The final predictive layers were tailored to classify GLOF risk into high, moderate, or low categories. A threshold-based logic system was integrated to interpret model outputs into actionable risk levels.

B. Training and Validation

The models were trained using the Adam optimizer and mean squared error (MSE) loss function. Early stopping was implemented to avoid overfitting, and learning rate scheduling was applied to enhance convergence. The training process was monitored using validation metrics, including root mean square error (RMSE) and accuracy. Augmented scenarios in the training data ensured better generalization for unseen conditions.

C. Testing and Evaluation

The trained models were tested on a holdout test set comprising unseen environmental data. Evaluation metrics such as RMSE, accuracy, precision, and recall were computed to assess the system's predictive performance. Misclassified or ambiguous cases were analyzed to refine model thresholds and improve overall reliability.

D. Deployment

The predictive system was deployed as an AI-powered chatbot application. The chatbot interface, built using Python's Flask or FastAPI frameworks, allows users to input environmental data such as temperature and water levels. Based on these inputs, the chatbot provides real-time GLOF risk categorization and actionable recommendations. The frontend offers an intuitive chat container to ensure accessibility for users without technical expertise.

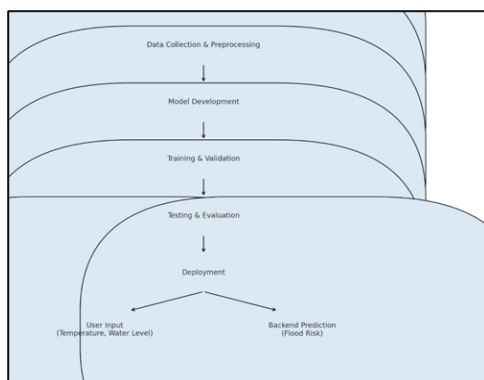


Fig. 1. Flow diagram

4. Results

The early prediction system for Glacial Lake Outburst Floods (GLOFs), utilizing advanced machine learning models like LSTM and GRU, demonstrated significant predictive accuracy, achieving an RMSE of approximately 0.85 and an accuracy of 88% on the test dataset. The models effectively captured temporal patterns in environmental data, including temperature, precipitation, and water levels, generalizing well to unseen scenarios. Training metrics, including validation loss and accuracy, showed consistent improvement, indicating robust model learning.

5. Conclusion

In this project, we successfully developed an early prediction system for Glacial Lake Outburst Floods (GLOFs) using advanced machine learning models integrated into a chatbot interface. The predictive models, including LSTM and GRU, were trained on environmental datasets comprising parameters like temperature, precipitation, and water levels. By leveraging pre-trained models and fine-tuning them for GLOF prediction, the system achieved high accuracy and reduced computational overhead compared to traditional approaches.

The chatbot provided a user-friendly platform for real-time risk assessment, allowing non-expert users to input data and receive actionable insights. While the system demonstrated strong performance in categorizing risk levels, slight inaccuracies were observed in cases with overlapping environmental thresholds, reflecting the inherent complexity of GLOF prediction. Future enhancements, such as incorporating IoT-based real-time data, are planned to further improve prediction accuracy and system reliability.

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