*«ИНФОРМАЦИОННЫЕ РАДИОСИСТЕМЫ И РАДИОТЕХНОЛОГИИ **2026**»*
Международная научно-техническая конференция, 9-10 июня 2026 г., Минск, Республика Беларусь

УДК 627.25:004.032.26

EARLY DETECTION OF DAM INSTABILITY RISK USING A CNN–BIGRU MODEL

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Аннотация. Надёжная эксплуатация гидротехнических сооружений является ключевым условием обеспечения безопасности инфраструктуры, особенно в условиях возрастающей изменчивости природных факторов. Однако ранние признаки неустойчивости плотин, как правило, носят слабовыраженный характер и трудно выявляются с использованием традиционных методов мониторинга. В данной работе представлен подход, основанный на анализе данных, для раннего обнаружения риска неустойчивости плотин с использованием многомерных гидрометеорологических временных рядов. Предлагаемая модель объединяет сверточные нейронные сети (CNN) и двунаправленную рекуррентную сеть типа Gated Recurrent Unit (BiGRU), что позволяет одновременно учитывать локальные временные паттерны и долгосрочные зависимости в динамике системы.

Предложенный подход апробирован на реальных данных мониторинга, включая измерения уровня воды в водохранилище и метеорологические параметры. Для учёта дисбаланса между нормальными и высокорисковыми состояниями используется стоимостно-ориентированная стратегия обучения. Модель демонстрирует следующие показатели: точность (accuracy) — 0,96, прецизионность — 0,90, полнота — 0,75, F1-мера — 0,82 и ROC-AUC — 0,91 Полученные результаты показывают, что модель способна выявлять ранние отклонения от нормального режима функционирования при низком уровне ложных срабатываний. Предложенный подход может быть интегрирован в системы мониторинга в реальном времени и способствует повышению надёжности и безопасности гидротехнической инфраструктуры.

Abstract. Reliable operation of hydraulic structures is a critical requirement for ensuring infrastructure safety, particularly under increasingly variable environmental conditions. However, early signs of dam instability are often subtle and difficult to detect using conventional monitoring approaches. This paper presents a data-driven framework for early detection of dam instability based on multivariate hydrometeorological time-series data. The proposed model combines convolutional neural networks (CNN) with a bidirectional gated recurrent unit (BiGRU) to jointly capture local temporal patterns and long-range dependencies in system dynamics. The framework is validated using real monitoring data, including reservoir water levels and meteorological variables. To address the imbalance between normal and high-risk states, a cost-sensitive training strategy is employed. The proposed model achieves an accuracy of 0.96, precision of 0.90, recall of 0.75, F1-score of 0.82, and ROC-AUC of 0.91. The results demonstrate that the model is capable of identifying early deviations from normal operating conditions while maintaining a low false alarm rate. The proposed approach can be integrated into real-time monitoring systems and contributes to improving the reliability and safety of hydraulic infrastructure.

Ensuring the reliability of dam systems remains a challenging task due to the complex interaction between hydrological, environmental, and operational factors. In practice, failure events are typically preceded by weak and gradual deviations that are difficult to capture using conventional threshold-based techniques. As a result, there is a growing need for data-driven approaches capable of identifying early warning signals in complex time-series data. In his work, a hybrid deep learning model based on CNN and BiGRU is proposed for analyzing multivariate hydrometeorological observations. The convolutional component extracts short-term temporal features, while the bidirectional recurrent unit captures long-term dependencies and temporal evolution in both forward and backward directions. This combination allows the model to better represent the nonlinear dynamics inherent in dam monitoring data.

The model is trained using real measurements, including water level and meteorological variables such as precipitation, temperature, and wind speed. Given the rarity of critical states, a cost-sensitive learning approach is applied to improve sensitivity to high-risk conditions. The overall architecture of the proposed model is illustrated in Fig. 1.

Fig. 1. Architecture of the proposed CNN–BiGRU framework for dam failure risk early warning, illustrating convolutional temporal feature extraction, bidirectional recurrent sequence modeling, and probabilistic risk estimation.

Experimental evaluation demonstrates that the proposed model provides stable and consistent performance across multiple metrics. In particular, the model achieves an accuracy of 0.96, precision of 0.90, recall of 0.75, F1-score of 0.82, and ROC-AUC of 0.91. These results indicate that the approach is capable of detecting early-stage anomalies while maintaining a reasonable balance between detection rate and false alarms.

The obtained results confirm that the proposed framework can serve as an effective tool for improving the reliability of dam monitoring systems and supporting early warning of potential failure scenarios.

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