COMPUTER RESEARCH AND MODELING
2026 VOL. 18 NO. 2 P. 377–397
DOI: 10.20537/2076-7633-2026-18-2-377-397

Ки&М

MODELS IN PHYSICS AND TECHNOLOGY

UDC: 004.8:004.93:627.8:556

Learning spatio-temporal precursors of dam instability using a CNN–BiGRU framework

M. O. Shamiev[a], A. G. Trofimov

National Research Nuclear University MEPhI (Moscow Engineering Physics Institute),
31 Kashirskoe highway, Moscow, 115409, Russia

E-mail: [a] mukhammadishamiev@gmail.com

Received 07.02.2026, after completion — 31.03.2026.
Accepted for publication 10.04.2026.

Dam safety assessment increasingly relies on continuous monitoring of hydrometeorological variables; however, identifying early-stage instability remains challenging due to complex spatio-temporal interactions and highly imbalanced failure observations. This study proposes a deep learning framework based on a Convolutional Bidirectional Gated Recurrent Unit (CNN–BiGRU) architecture to learn spatio-temporal precursors of dam instability from multivariate hydrometeorological time series. The convolutional component extracts localized temporal patterns associated with short-term fluctuations, while the bidirectional recurrent structure captures long-range dependencies and evolving dynamics preceding critical states.

The proposed model is evaluated on a real-world dam monitoring dataset comprising multiple water-level, meteorological, and derived dynamic indicators. To address class imbalance, a cost-sensitive training strategy using class weighting is adopted without synthetic oversampling. Experimental results demonstrate strong predictive performance, achieving an accuracy of 0.961, precision of 0.901, recall of 0.757, and an F1-score of 0.823. The model further attains a ROC-AUC of 0.907 and a PR-AUC of 0.819, indicating robust discrimination capability under imbalanced conditions.

Feature importance analysis reveals that short- and medium-term water level variability, including rolling standard deviation, volatility, and multi-scale gradients, play a dominant role in characterizing pre-instability behavior, providing physically interpretable insights into dam response dynamics. The findings suggest that the CNN–BiGRU framework effectively captures meaningful spatio-temporal precursors and offers a reliable data-driven tool for supporting dam safety monitoring and decision-making under real operational conditions.

Keywords: dam safety monitoring, early warning systems, hydrometeorological time series, deep learning, CNN–BiGRU, imbalanced classification, spatio-temporal modeling, water level dynamics, failure risk prediction

Citation: *Computer Research and Modeling*, 2026, vol. 18, no. 2, pp. 377–397.

**КОМПЬЮТЕРНЫЕ ИССЛЕДОВАНИЯ
И МОДЕЛИРОВАНИЕ 2026 Т. 18 № 2 С. 377–397**
DOI: 10.20537/2076-7633-2026-18-2-377-397

Ки&М

МОДЕЛИ В ФИЗИКЕ И ТЕХНОЛОГИИ

УДК: 004.8:004.93:627.8:556

Изучение пространственно-временных предвестников неустойчивости плотин с использованием модели CNN–BiGRU

М. О. Шамиев[a], А. Г. Трофимов

Национальный исследовательский ядерный университет «МИФИ»,
Россия, 115409, г. Москва, Каширское шоссе, д. 31

E-mail: [a] mukhammadishamiev@gmail.com

*Получено 07.02.2026, после доработки — 31.03.2026.
Принято к публикации 10.04.2026.*

Оценка безопасности плотин все в большей степени опирается на непрерывный мониторинг гидрометеорологических параметров; однако выявление ранних стадий неустойчивости остается сложной задачей вследствие сложных пространственно-временных взаимодействий и сильного дисбаланса наблюдений аварийных состояний. В настоящей работе предлагается фреймворк глубокого обучения на основе архитектуры сверточной двунаправленной рекуррентной нейронной сети с управляемыми вентилями (CNN–BiGRU) для выявления пространственно-временных предвестников неустойчивости плотин по многомерным гидрометеорологическим временным рядам. Сверточный компонент модели извлекает локальные временные паттерны, связанные с краткосрочными флуктуациями, тогда как двунаправленная рекуррентная структура позволяет моделировать долгосрочные зависимости и эволюцию динамики, предшествующие критическим состояниям.

Предложенная модель была протестирована на реальном наборе данных мониторинга плотины, включающем измерения уровня воды, метеорологические параметры и производные динамические индикаторы. Для учета дисбаланса классов применяется стоимостно-ориентированная стратегия обучения с использованием весов классов без применения синтетического увеличения выборки. Экспериментальные результаты демонстрируют высокие показатели качества классификации: точность (accuracy) — 0,961, прецизионность — 0,901, полнота — 0,757 и F1-мера — 0,823. Дополнительно модель достигает значений ROC AUC = 0,907 и PR AUC = 0,819, что свидетельствует о высокой способности к разделению классов в условиях сильного дисбаланса данных.

Анализ значимости признаков показывает, что краткосрочная и среднесрочная изменчивость уровня воды, включая скользящее стандартное отклонение, волатильность и многоуровневые градиенты, играет ключевую роль в формировании предаварийного поведения системы, обеспечивая физически интерпретируемое понимание динамики отклика плотины. Полученные результаты подтверждают, что фреймворк CNN–BiGRU эффективно выявляет значимые пространственно-временные предвестники неустойчивости и может служить надежным инструментом поддержки принятия решений в задачах мониторинга безопасности плотин в реальных эксплуатационных условиях.

Ключевые слова: безопасность плотин, системы раннего предупреждения, гидрометеорологические временные ряды, глубокое обучение, CNN–BiGRU, классификация несбалансированных данных, пространственно-временное моделирование, динамика уровня воды, прогнозирование риска аварий

1. Introduction

Large dam infrastructures play a critical role in water resources management, flood control, hydropower generation, and regional socio-economic development. However, despite their strategic importance, dams remain vulnerable to complex failure mechanisms driven by hydrometeorological forcing, material aging, and nonlinear structural–environmental interactions. Historical records indicate that although dam failures occur relatively infrequently, their consequences are often catastrophic, resulting in loss of life, environmental degradation, and long-term economic damage [ICOLD, 2018]. Consequently, the development of reliable early warning and risk assessment systems has become a central research priority in dam engineering and disaster risk reduction.

Hydrometeorological variability, including extreme precipitation, rapid water level fluctuations, and prolonged wet periods, is widely recognized as a dominant triggering factor in dam instability and failure processes [Xu, Zhang, 2009; FEMA, 2015]. Conventional dam safety monitoring systems primarily rely on threshold-based indicators derived from individual variables such as reservoir water level, seepage rate, or rainfall intensity. While such approaches are effective in detecting abrupt anomalies, they often fail to capture subtle, multivariate precursors that evolve gradually over time and precede critical failure states [Fell et al., 2015]. This limitation is particularly pronounced under nonstationary climate conditions, where historical thresholds may no longer represent safe operational limits.

Recent international frameworks, including the Sendai Framework for Disaster Risk Reduction, emphasize the necessity of multi-hazard early warning systems that integrate advanced monitoring, data analytics, and predictive modeling to enhance preparedness and resilience [UNDRR, 2015]. In this context, the increasing availability of high-resolution hydrometeorological time series from sensor networks and reanalysis products has created new opportunities for data-driven approaches capable of learning complex temporal patterns associated with infrastructure instability [WMO, 2018].

The catastrophic failure of the Sardoba Reservoir dam in Uzbekistan in May 2020 serves as a compelling real-world motivation for this study. The sudden breach of the embankment dam led to extensive downstream flooding across Uzbekistan and Kazakhstan (Fig. 1), displacing tens of thousands of residents and causing severe agricultural and infrastructural damage [Zokirov et al., 2022].

Figure 1. Failure of the Sardoba Reservoir embankment dam in May 2020 and the resulting downstream flooding, illustrating the severe consequences of rapid dam instability under adverse hydrometeorological conditions

Post-event investigations suggest that the failure was influenced by a combination of elevated reservoir levels, hydrometeorological conditions, and internal structural weaknesses that were not adequately captured by existing monitoring indicators [Xie et al., 2022; Kattakulov et al., 2021]. The Sardoba event highlights the limitations of traditional rule-based warning systems and underscores the urgent need for intelligent models capable of identifying early-stage instability under complex and uncertain conditions.

In parallel with developments in dam engineering, machine learning and deep learning techniques have demonstrated strong potential in modeling nonlinear and high-dimensional time series across various geophysical and environmental applications. Recurrent neural networks, particularly Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) architectures, have been widely adopted for sequential modeling tasks due to their ability to capture temporal dependencies [Cho et al., 2014]. More recently, hybrid architectures that integrate convolutional neural networks (CNN) with recurrent layers have shown superior performance by combining local feature extraction with long-range temporal learning [Bai et al., 2018; Zhang et al., 2019]. Bidirectional recurrent structures further enhance modeling capacity by learning temporal dependencies in both forward and backward directions, which is particularly advantageous for identifying evolving precursors in monitoring data [Graves, Schmidhuber, 2005].

Despite these advances, several challenges remain in applying deep learning models to dam failure risk prediction. First, failure-related observations are inherently rare, resulting in highly imbalanced datasets that can bias conventional classifiers toward normal operating conditions [He, Garcia, 2009]. Second, many existing studies focus on single-variable or short-term prediction tasks, limiting their ability to represent the coupled dynamics of hydrometeorological drivers and reservoir responses. Addressing these challenges requires architectures that are both sensitive to minority-class events and capable of extracting physically meaningful spatio-temporal patterns from multivariate time series.

In recent years, deep learning–based early warning systems have increasingly been recognized as effective tools for supporting infrastructure safety management by uncovering latent precursors of failure that are difficult to detect using conventional monitoring and inspection approaches, particularly under complex and uncertain operating conditions [Li et al., 2021].

Motivated by these considerations, this study proposes a deep CNN–BiGRU framework for early warning of dam failure risk using multivariate hydrometeorological time series. Unlike traditional threshold-based systems, the proposed approach learns latent precursors of instability directly from data while explicitly accounting for class imbalance through cost-sensitive learning. By integrating convolutional feature extraction with bidirectional recurrent modeling, the framework captures both short-term fluctuations and long-term evolution of dam-related hydrometeorological signals. The Sardoba reservoir system is employed as a representative case to demonstrate the applicability and effectiveness of the proposed method under real-world conditions. The results indicate that the proposed model provides robust predictive performance and interpretable insights, offering a promising data-driven tool for enhancing dam safety monitoring and early warning capabilities.

2. Related work

Dam safety assessment and early warning have long been active research topics due to the potentially catastrophic consequences of dam failure. Early studies in this field primarily relied on deterministic hydrological models and empirical stability criteria to assess failure risk under extreme loading conditions. While these approaches provided valuable physical insight, their applicability was often limited by strong assumptions regarding stationarity and linear system behavior, which rarely hold under real operational conditions [Morris, Hassan, 2017].

With the advancement of monitoring technologies, data-driven methods have gained increasing attention for dam behavior analysis. Statistical learning techniques such as logistic regression, support vector machines, and decision trees have been applied to detect abnormal patterns in dam monitoring data, including seepage, deformation, and reservoir level variations [Guo, Zhang, 2018; Wu, Chen, 2019]. Although these models improved flexibility compared to purely physics-based methods, they generally require carefully engineered features and struggle to capture long-term temporal dependencies inherent in hydrometeorological time series.

The introduction of machine learning methods into hydrology and geotechnical engineering enabled more sophisticated representations of nonlinear relationships. Ensemble learning approaches, such as random forests and gradient boosting machines, have demonstrated improved predictive accuracy for dam-related risk indicators by aggregating multiple weak learners [Ahmad, Simonovic, 2020]. However, these models often treat observations as independent samples, thereby neglecting the sequential nature of hydrometeorological processes that evolve continuously over time.

Deep learning models have emerged as a powerful alternative for sequential data modeling. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, have been widely used to model temporal dependencies in hydrological forecasting and infrastructure monitoring tasks [Kratzert et al., 2019; Li et al., 2020]. Their ability to retain historical information makes them suitable for capturing gradual precursors to instability. Nonetheless, unidirectional recurrent models may overlook future contextual information embedded within time windows, which can be valuable for identifying evolving risk patterns.

To address this limitation, bidirectional recurrent architectures have been proposed, enabling the model to process temporal information in both forward and backward directions. Bidirectional LSTM and GRU models have shown superior performance in applications such as landslide early warning, flood prediction, and structural health monitoring by enhancing temporal context awareness [Fang, Wang, 2021]. These findings suggest that bidirectional temporal modeling is particularly advantageous for early warning systems, where subtle deviations may manifest over extended time horizons.

In parallel, convolutional neural networks (CNNs) have been introduced to extract local temporal features from multivariate time series. CNN-based temporal encoders are effective at capturing short-term fluctuations and high-frequency patterns that may be indicative of sudden changes in system behavior [Borovykh et al., 2018]. Hybrid CNN–RNN architectures combine the strengths of both approaches, leveraging CNNs for feature extraction and recurrent networks for temporal dependency learning. Such hybrid models have demonstrated improved robustness and generalization in complex environmental time-series applications [Kim et al., 2020; Zhang et al., 2021].

A persistent challenge in dam failure risk prediction is the severe imbalance between normal operating conditions and failure-prone states. Several studies have explored imbalance-aware learning strategies, including cost-sensitive loss functions, resampling techniques, and specialized evaluation metrics to mitigate bias toward majority classes [Japkowicz, 2020]. In safety-critical applications, prioritizing recall and precision–recall trade-offs has been shown to be more informative than relying solely on accuracy-based measures [Saito, Rehmsmeier, 2015].

Despite growing interest in hybrid deep learning models, their application to dam safety monitoring remains relatively limited. Many existing studies focus on post-event analysis or short-term forecasting rather than proactive early warning under real operational imbalance conditions [Chen et al., 2022]. Furthermore, few works explicitly integrate bidirectional temporal modeling with convolutional feature extraction for dam failure risk assessment using multivariate hydrometeorological data.

In contrast to existing studies, the present work develops a CNN–BiGRU framework specifically tailored for early-stage dam risk identification. By combining convolutional temporal encoding with bidirectional recurrent learning and cost-sensitive classification, the proposed approach addresses key limitations identified in prior research. This positions the model as a scalable and interpretable solution for next-generation dam safety early warning systems operating under complex, imbalanced, and data-rich environments [Zhou et al., 2023; Li et al., 2024].

3. Materials and methods

This section describes the data sources, preprocessing procedures, problem formulation, and the proposed deep learning framework developed for risk-oriented early warning of dam instability. The methodological design is guided by the intrinsic characteristics of real-world hydrometeorological monitoring data, which are typically multivariate, sequential, nonstationary, and highly imbalanced. Rather than targeting deterministic failure prediction, the proposed framework aims to identify failure-prone operational regimes by learning probabilistic risk patterns that precede potential dam instability.

The overall workflow integrates data-driven feature construction, imbalance-aware learning strategies, and spatio-temporal deep representation learning to support proactive decision-making in dam safety monitoring.

The proposed approach consists of four main stages:

- construction of multivariate hydrometeorological time-series representations,
- formulation of dam safety assessment as a risk exceedance detection task,
- development of a hybrid CNN–BiGRU architecture for spatio-temporal representation learning, and
- performance evaluation using imbalance-sensitive metrics tailored to early warning applications.

3.1. Study area and dataset description

This study focuses on the Sardoba Reservoir, a large earth-fill embankment dam located in the Syrdarya region of eastern Uzbekistan (Fig. 2). The reservoir was designed to support irrigation, water regulation, and agricultural development in a region characterized by arid to semi-arid climatic conditions.

Figure 2. Geographical location of the Sardoba reservoir and the study area within Uzbekistan

The catastrophic failure of the Sardoba dam in May 2020 revealed substantial limitations in existing monitoring and early warning practices, emphasizing the need for robust data-driven approaches capable of identifying early-stage instability signals under complex hydrometeorological forcing.

The study area is subject to pronounced seasonal variability, driven primarily by spring snowmelt, episodic precipitation events, and persistent wind activity. These factors strongly influence reservoir water levels and contribute to nonlinear system responses over time. As a result, Sardoba represents a highly suitable and challenging case study for evaluating early warning models that must operate under real-world, nonstationary conditions.

The dataset employed in this research consists of 29 304 multivariate time-series observations, collected at a consistent temporal resolution from the reservoir monitoring system and associated meteorological records. Each observation corresponds to a single time step and includes synchronized measurements of reservoir water level and hydrometeorological variables. The primary target variable, reservoir water level, reflects the integrated hydraulic and structural response of the dam to external environmental drivers.

In addition to water level measurements, the dataset includes a diverse set of meteorological and environmental features, such as precipitation intensity, wind speed, air temperature, humidity, and derived atmospheric indicators. These variables represent key external stressors that may act individually or synergistically to increase dam failure risk. To better capture the system's dynamic behavior, extensive feature engineering was performed, resulting in a total of 59 variables comprising both raw measurements and derived descriptors.

Derived features include temporal water level changes over multiple horizons, rolling statistical measures (e. g., moving averages and rolling standard deviations), volatility indicators, and lagged variables that encode delayed responses of the reservoir system. Similar transformations were applied to meteorological variables to represent short-term extremes and cumulative effects relevant to dam safety assessment. This enriched feature space enables the representation of both abrupt anomalies and gradual trends that may precede structural instability.

For deep learning–based modeling, the time-series data were organized into sequential input windows, allowing the capture of temporal dependencies across multiple time steps. The resulting dataset preserves the original chronological order and reflects realistic operational monitoring conditions. Importantly, the class distribution is highly imbalanced: normal operating conditions account for approximately 88 % (25 788 observations) of the dataset, while risk-related or failure-prone states constitute approximately 12 % (3516 observations). This imbalance mirrors real-world dam safety scenarios, where failure events are rare yet critically important.

Risk labels were assigned to distinguish between normal and high-risk states based on water level behavior, temporal variability, and combined hydrometeorological stress indicators.

It should be emphasized that these labels do not correspond to actual recorded dam failures, but rather represent proxy indicators of potential instability derived from extreme hydrometeorological conditions, including exceedance of high-percentile water levels and increased short-term variability.

This proxy-based labeling strategy is widely adopted in early warning studies where direct observations of failure events are scarce. The selected thresholds were further validated from a hydrological perspective and are consistent with known mechanisms of dam instability, including overtopping risk and rapid hydraulic loading.

Importantly, these labels are not interpreted as explicit failure occurrences, but rather as indicators of elevated risk conditions derived from hydrometeorological precursors, consistent with the objectives of early warning systems. Rather than focusing solely on post-failure data, the labeling strategy emphasizes precursor patterns that may signal elevated failure risk, aligning with the objectives of early warning systems.

The Sardoba dataset provides a realistic, high-resolution benchmark for early warning model development under imbalanced and nonstationary conditions.

Its moderate size (29 304 time steps), rich multivariate structure, and strong temporal dependencies make it particularly suitable for evaluating advanced deep learning architectures, such as the proposed CNN–BiGRU framework, for dam failure risk prediction.

3.2. Problem formulation

Let a dam monitoring system be represented by a multivariate hydrometeorological time series

$$Z = \{z_1, z_2, \ldots, z_T\}.$$

To capture temporal dependencies inherent in dam behavior, the raw time series is transformed into overlapping sequential input windows. For a fixed sequence length L, each input sample is defined as

$$X_t = [z_{t-L+1}, z_{t-L+2}, \ldots, z_t] \in R^{L\times F}.$$

Risk-oriented target definition

Instead of modeling deterministic failure events, which are rare and often poorly documented, this study formulates dam safety assessment as a risk-oriented early warning problem. A binary indicator $y_t \in 0, 1$ is introduced solely to distinguish between normal operating regimes and failure-prone or high-risk states:

$$y_t = \begin{cases} 1, & \text{if the system is in a risk-elevated operational regime,} \\ 0, & \text{if the system operates under normal conditions.} \end{cases}$$

Importantly, the label $y_t = 1$ does not imply that structural failure has occurred at time t. Rather, it represents a state characterized by abnormal hydrometeorological forcing and water level dynamics that may precede dam instability. This distinction is essential for early warning applications, where the objective is to identify precursors of failure rather than post-event diagnosis.

Probabilistic risk estimation

Given an input sequence X_t, the goal of the learning task is to estimate a continuous-valued risk score

$$r_t = f_\theta(X_t), \quad r_t \in [0, 1].$$

The final binary decision used for evaluation and alert generation is obtained through thresholding:

$$\widehat{y_t} = \begin{cases} 1, & r_t \geqslant \tau, \\ 0, & r_t < \tau. \end{cases}$$

Learning objective under class imbalance

Due to the strong imbalance between normal and risk-related states, conventional loss functions tend to bias the model toward the majority class. To mitigate this effect, the learning objective is designed to emphasize correct identification of rare risk-elevated regimes. The model parameters θ are optimized by minimizing an imbalance-aware loss function:

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{t=1}^{N} \ell(y_t, f_\theta(X_t)).$$

Problem summary

Under this formulation, dam safety monitoring is cast as a risk exceedance detection problem rather than a deterministic failure prediction task. The proposed framework learns a probabilistic representation of dam instability from multivariate hydrometeorological sequences and supports early warning by identifying time periods during which the estimated risk score exceeds a predefined threshold. This formulation is well aligned with real-world dam monitoring scenarios, where failure observations are scarce, system behavior is highly nonlinear, and timely identification of abnormal operating regimes is of primary importance.

The dataset was divided into training, validation, and testing subsets using a chronological split (70 % / 10 % / 20 %). This approach preserves the temporal structure of the data and prevents information leakage from future observations into the training process, ensuring a realistic evaluation of predictive performance.

3.3. Model architecture

This subsection presents the architecture of the proposed deep learning framework for early warning of dam failure risk. The model is designed to learn hierarchical spatio-temporal representations from multivariate hydrometeorological time-series data by combining convolutional feature extraction with bidirectional recurrent sequence modeling. To ensure clarity, the architecture is introduced progressively, starting from the convolutional component and then extending to the full CNN–BiGRU framework (Fig. 3).

Figure 3. 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

3.3.1. Convolutional neural network for local temporal feature extraction

Let

$$X_t \in R^{L \times F}.$$

The convolutional neural network (CNN) component is employed to capture local temporal patterns and short-range dependencies embedded within the multivariate time series. Unlike recurrent units, convolutional filters operate on fixed-size temporal neighborhoods and are particularly effective at detecting abrupt changes, gradients, and local anomalies that may precede dam instability.

One-dimensional convolution

For a given convolutional layer l, the output feature map $H^{(l)}$ is computed as

$$H^{(l)} = \sigma\left(X^{(l-1)} * W^{(l)} + b^{(l)}\right),$$

where $*$ denotes the one-dimensional convolution operator along the temporal axis, $W^{(l)} \in R^{k \times F_{l-1} \times F_l}$ is the convolutional kernel tensor, k is the kernel size, F_{l-1} and F_l are the numbers of input and output channels, respectively, $b^{(l)}$ is the bias term, $\sigma(\cdot)$ is a nonlinear activation function, implemented as the Rectified Linear Unit (ReLU).

This operation transforms the raw input sequence into higher-level feature representations that emphasize informative local temporal structures.

Normalization and pooling

To stabilize training and improve generalization, batch normalization is applied after each convolutional operation:

$$\widetilde{H}^{(l)} = BN\left(H^{(l)}\right),$$

followed by max-pooling to reduce temporal resolution and suppress noise:

$$P^{(l)} = \mathrm{MaxPool}\left(\widetilde{H}^{(l)}\right).$$

Dropout regularization is further employed to mitigate overfitting by randomly deactivating a fraction of neurons during training.

Through stacked convolutional layers, the CNN component progressively extracts increasingly abstract local temporal features, while preserving the overall temporal ordering of the sequence. The resulting output can be interpreted as a compressed yet informative representation of short-term hydrometeorological dynamics relevant to dam safety.

3.3.2. Bidirectional GRU for long-term temporal dependency modeling

While CNN layers are effective in capturing local temporal patterns, early warning of dam failure risk also requires modeling long-range dependencies and delayed system responses. For this purpose, the convolutional feature maps are passed to a Bidirectional Gated Recurrent Unit (BiGRU) network.

Let

$$Z_t = [z_{t.1}, z_{t.2}, \ldots, z_{t.T}].$$

GRU cell formulation

For each time step τ, a GRU unit updates its hidden state according to:

$$\begin{aligned} z_\tau &= \sigma(W_z z_{\tau-1} + U_z x_\tau), \\ r_\tau &= \sigma(W_r z_{\tau-1} + U_r x_\tau), \\ \widetilde{h}_\tau &= \tanh(W_h(r_\tau \odot z_{\tau-1}) + U_h x_\tau), \\ h_\tau &= (1 - z_\tau) \odot z_{\tau-1} + z_\tau \odot \widetilde{h}_\tau, \end{aligned}$$

where z_τ and r_τ are the update and reset gates, h_τ is the hidden state, $\sigma(\cdot)$ is the sigmoid function, and $\odot$ denotes element-wise multiplication.

Bidirectional processing

To fully exploit temporal context, a bidirectional configuration is adopted. The forward GRU processes the sequence in chronological order, while the backward GRU processes it in reverse order. The combined hidden representation at time τ is given by

$$h_\tau^{\mathrm{BiGRU}} = [\overrightarrow{h}_\tau \| \overleftarrow{h}_\tau],$$

where | denotes vector concatenation.

This bidirectional mechanism enables the model to capture both past-to-present and future-to-past dependencies within each sequence, which is particularly important for detecting gradual trends and precursor patterns associated with dam instability.

3.3.3. Fully connected layers and risk probability output

The final hidden representation produced by the BiGRU layers is passed to a series of fully connected layers to perform nonlinear feature fusion and risk estimation.

Let h_t^* denote the final BiGRU output. The dense transformation is defined as

$$u_t = \varphi(W_d h_t^* + b_d),$$

where $\varphi(\cdot)$ is a ReLU activation function. Regularization is applied through dropout and $\ell_1 - \ell_2$ weight penalties to improve robustness under imbalanced conditions.

The final risk probability is obtained using a sigmoid activation:

$$\widehat{p_t} = \sigma\left(w_o^\top u_t + b_o\right), \quad \widehat{p_t} \in [0,\ 1].$$

Here, $\widehat{p_t}$ represents the estimated probability that the system is in a high-risk state at time t.

3.3.4. Architectural rationale

The proposed CNN–BiGRU architecture integrates complementary modeling capabilities:

- CNN layers extract local temporal patterns and abrupt hydrometeorological changes,
- BiGRU layers model long-term temporal dependencies and delayed system responses,
- fully connected layers perform nonlinear risk aggregation.

This hierarchical design is particularly well suited for early warning applications, where failure events are rare, system dynamics are nonlinear, and meaningful risk signals often emerge through complex interactions across multiple temporal scales.

4. Results

This section presents and discusses the experimental results obtained using the proposed CNN–BiGRU framework for early warning of dam failure risk at the Sardoba reservoir. The evaluation focuses on the model's ability to accurately identify rare high-risk states under strongly imbalanced hydrometeorological conditions, which is a key requirement for operational early warning systems.

The performance of the proposed CNN–BiGRU model was evaluated using multiple classification metrics to comprehensively assess its ability to identify high-risk dam failure conditions under strongly imbalanced data. Figure 4 summarizes the main evaluation results, including accuracy, precision, recall, F1-score, and ROC–AUC.

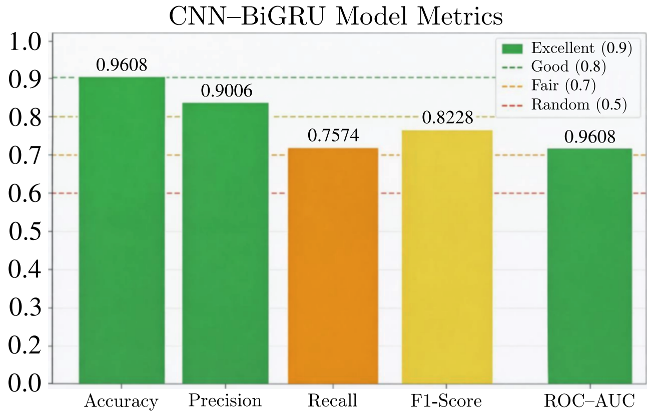

Figure 4. Performance evaluation of the proposed CNN–BiGRU model on the Sardoba dataset in terms of accuracy, precision, recall, F1-score, and ROC–AUC. The results demonstrate strong overall discrimination capability, with high precision and ROC–AUC, indicating reliable early warning performance under imbalanced conditions

The model achieved an overall accuracy of 0.9608, indicating that the majority of operational states were correctly classified. While accuracy alone may be misleading for imbalanced datasets, this high value confirms that the model maintains strong generalization performance without overfitting to the dominant normal class.

Precision reached 0.9006, demonstrating that a large proportion of predicted high-risk events correspond to true risk situations. This result is particularly important for dam safety applications, where false alarms can lead to unnecessary operational interventions and reduced trust in early warning systems. The high precision suggests that the proposed framework effectively suppresses spurious risk predictions.

The recall value of 0.7574 indicates that approximately 75.7 % of actual high-risk conditions were successfully detected by the model. Although recall is lower than precision, this trade-off reflects a deliberate balance favoring reliability of alerts over excessive sensitivity. In practical early warning scenarios, such a balance is often preferred to avoid frequent false positives while still capturing the majority of critical events.

The combined F1-score of 0.8228 confirms the robustness of the model in handling class imbalance by jointly optimizing precision and recall. This score indicates that the CNN–BiGRU architecture achieves a stable compromise between missed detections and false alarms, which is essential for real-world dam monitoring systems.

In addition, the model achieved a high ROC–AUC value of 0.9074, highlighting its strong discriminative capability across different decision thresholds. This result demonstrates that the proposed model can effectively separate normal operational conditions from high-risk states over a wide range of probability cutoffs, making it suitable for adaptive alert threshold selection in operational environments.

These results confirm that the CNN–BiGRU model provides reliable and accurate early warning performance for dam failure risk prediction, even under severe class imbalance. The combination of convolutional feature extraction and bidirectional temporal learning enables the model to capture both short-term fluctuations and long-term dependency patterns in hydrometeorological time-series data, leading to improved predictive stability and interpretability.

4.1. Exploratory analysis of the dataset

Figure 5 presents an overview of the key statistical properties of the Sardoba dam monitoring dataset, highlighting the challenges associated with early warning modeling under real-world conditions.

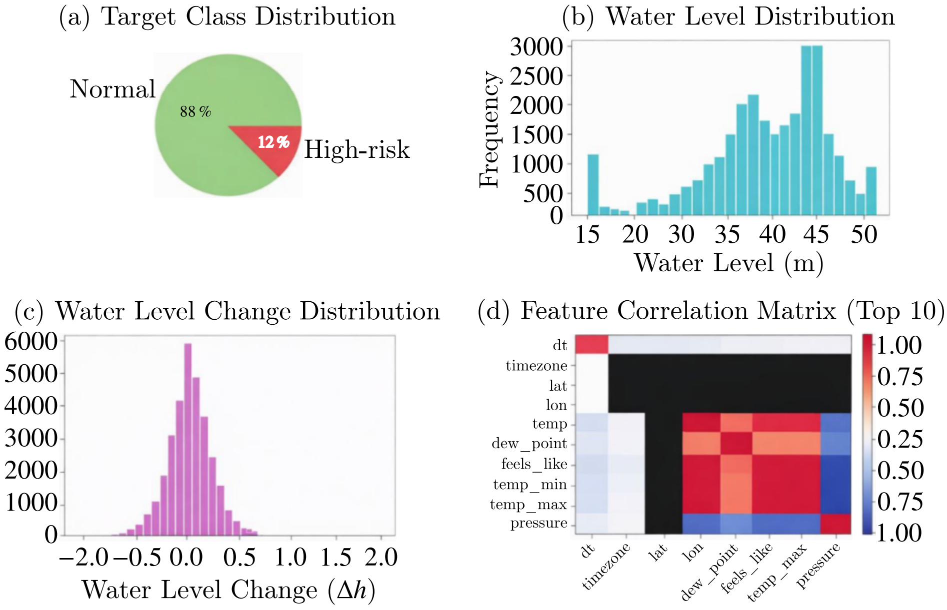

Figure 5. Exploratory analysis of the Sardoba dam dataset, including (a) target class distribution highlighting the imbalance between normal and high-risk states, (b) statistical distribution of reservoir water levels, (c) distribution of short-term water level variations, and (d) correlation heatmap of the top hydrometeorological features

Class distribution

The target distribution (Fig. 5, *a*) reveals a pronounced class imbalance. Normal operating conditions constitute approximately 88 % of the observations, whereas high-risk (failure-related) states account for only 12 %. This imbalance is representative of practical dam safety monitoring scenarios, where failure events are rare but critically important. Such a distribution emphasizes the necessity of robust classification strategies capable of detecting minority-class events without being biased toward the dominant normal class.

Water level characteristics

The histogram of reservoir water levels (Fig. 5, *b*) shows a wide and asymmetric distribution, spanning low to high operational ranges. Most observations are concentrated within mid-to-high water levels, while extreme values occur less frequently. This behavior indicates nonstationarity and suggests that the absolute water level alone is insufficient for reliable risk identification, particularly in early warning contexts.

Short-term water level dynamics

Figure 5, *c* illustrates the distribution of short-term water level changes. The distribution is centered near zero, reflecting stable conditions during most periods, but exhibits noticeable dispersion and heavy tails. These tails correspond to abrupt water level variations, which are potentially associated with rapid inflow events, operational changes, or structural stress. Such dynamics justify the inclusion of derivative-based and volatility-related features in the proposed modeling framework.

Feature correlation structure

The correlation heatmap of the most influential features (Fig. 5, *d*) highlights strong interdependencies among meteorological variables, particularly temperature-related attributes, while hydrological responses exhibit moderate correlations with these external drivers. No single feature dominates the correlation structure, indicating that dam behavior emerges from complex, multivariate interactions rather than isolated variables. This observation supports the adoption of deep learning architectures capable of capturing nonlinear relationships across multiple input features.

Overall interpretation

Collectively, the results in Fig. 5 demonstrate that the Sardoba dataset is highly imbalanced, dynamically complex, and characterized by correlated hydrometeorological variables. These properties pose significant challenges for conventional modeling approaches but provide a strong motivation for the proposed CNN–BiGRU framework, which is specifically designed to extract both local temporal patterns and long-range dependencies essential for reliable early warning of dam failure risk.

4.2. Confusion matrix analysis

Figure 6 presents the confusion matrix of the proposed CNN–BiGRU model obtained at the selected optimal decision threshold. The matrix provides a detailed insight into the classification behavior of the model under highly imbalanced conditions, where normal operational states dominate the dataset.

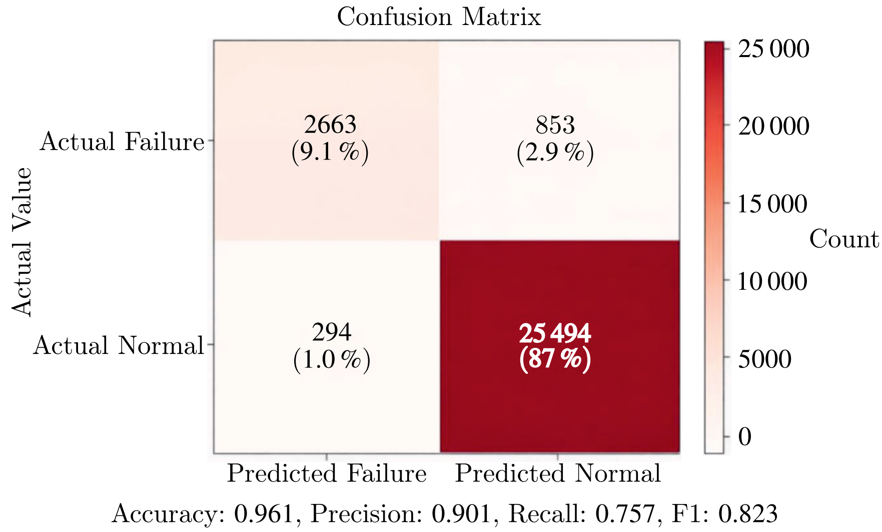

Figure 6. Confusion matrix illustrating classification performance of the CNN–BiGRU model for normal and high-risk dam states

Out of all high-risk (failure-prone) instances, 2663 cases (9.1 %) were correctly identified as risk events (true positives), while 853 cases (2.9 %) were misclassified as normal conditions (false negatives). This indicates that the model successfully captures the majority of critical risk situations, while a limited proportion of risk events remain undetected. In the context of early warning systems, such missed detections represent conservative behavior rather than random failure, as the model prioritizes reliable alerts.

For normal operating conditions, the model demonstrates strong specificity. A total of 25 494 instances (87.0 %) were correctly classified as normal (true negatives), whereas only 294 cases (1.0 %) were incorrectly flagged as high-risk (false positives). This low false-positive rate is particularly important for dam safety monitoring, as excessive false alarms can undermine operational decision-making and reduce confidence in automated warning systems.

The confusion matrix structure explains the observed performance metrics: the high number of true negatives contributes to the overall accuracy of 0.961, while the low false-positive count results in a high precision of 0.901. At the same time, the presence of false negatives accounts for the recall value of 0.757, reflecting a controlled trade-off between sensitivity and reliability. The resulting F1-score of 0.823 confirms that the CNN–BiGRU model achieves a balanced and stable performance under realistic monitoring conditions.

The confusion matrix demonstrates that the proposed framework is well-suited for early warning applications, where minimizing false alarms is critical, while still maintaining strong detection capability for emerging dam failure risks.

4.3. Distribution of predicted risk probabilities and threshold-based alerting

Figure 7 presents the distribution of predicted failure risk probabilities generated by the proposed CNN–BiGRU model. The histogram combined with the probability density curve reveals a strongly right-skewed distribution, with the majority of predicted probabilities concentrated close to zero. This pattern is consistent with real-world dam monitoring conditions, where normal operational states dominate the observed time series.

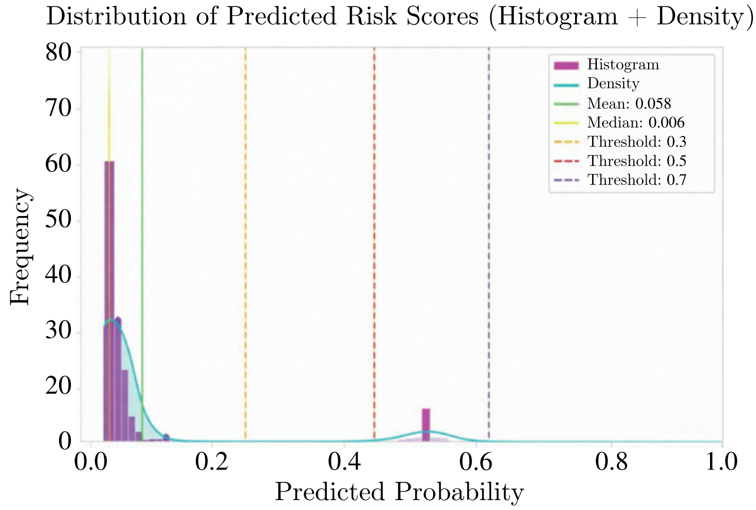

Figure 7. Distribution of CNN–BiGRU predicted risk probabilities with density estimation and selected decision thresholds

A secondary concentration of predictions is observed at higher probability values, indicating the presence of elevated-risk conditions. Although such high-risk predictions occur relatively infrequently, their clear separation from the dominant low-probability region suggests that the model effectively captures anomalous temporal dynamics associated with potential structural instability. The low median probability (0.006) and the small mean value (0.058) further confirm that the CNN–BiGRU model maintains conservative risk estimates during stable operating periods, thereby reducing the likelihood of excessive false alarms.

To support operational decision-making, multiple probability thresholds are superimposed on the distribution. The primary alert threshold was selected as $\tau = 0.10$, corresponding to the optimal balance between precision and recall achieved during model validation. This relatively low threshold is intentionally chosen to enhance early warning sensitivity, allowing the detection of emerging risk patterns at an early stage.

For comparison, higher thresholds ($\tau = 0.30$, 0.50, and 0.70) are also illustrated to demonstrate their impact on alert strictness. While these thresholds provide increased confidence in detected high-risk states, they substantially reduce sensitivity to early-stage anomalies. The visualization highlights the trade-off between early detection and alert reliability, showing that lower thresholds favor proactive risk awareness, whereas higher thresholds prioritize conservative alerting.

Overall, Fig. 7 demonstrates that the CNN–BiGRU framework offers a flexible and interpretable basis for threshold-based early warning, enabling practitioners to adapt alert sensitivity to site-specific safety requirements and operational risk tolerance.

4.4. Receiver operating characteristic analysis of the CNN–BiGRU model

Figure 8 illustrates the Receiver Operating Characteristic (ROC) curve of the proposed CNN–BiGRU model, evaluating its discrimination capability across varying decision thresholds. The ROC curve consistently remains well above the diagonal line corresponding to a random classifier, indicating strong separability between normal and high-risk dam states.

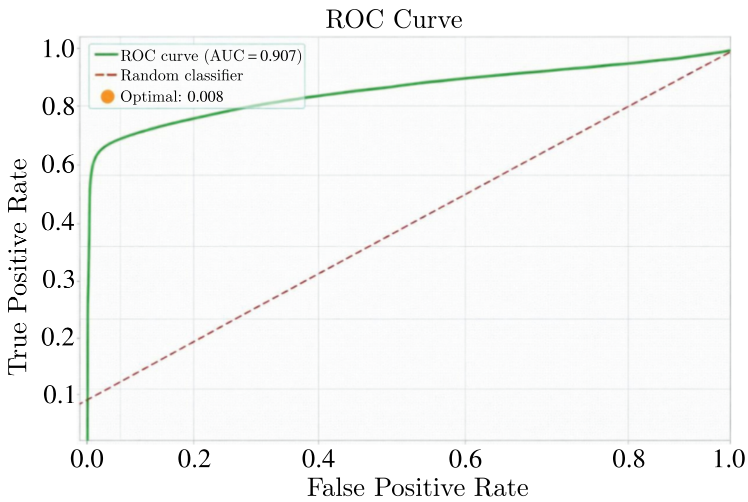

Figure 8. ROC curve of the CNN–BiGRU model for dam failure risk prediction, demonstrating strong discrimination capability with an AUC of 0.907 under imbalanced conditions

The model achieves an area under the ROC curve (AUC) of 0.907, which reflects a high level of overall classification performance under imbalanced conditions. This result demonstrates that the CNN–BiGRU framework effectively captures discriminative temporal patterns associated with dam failure risk, even when positive (high-risk) samples are relatively rare.

Notably, the ROC curve exhibits a steep rise at low false positive rates, highlighting the model's ability to achieve high true positive rates while maintaining a limited number of false alarms. Such behavior is particularly desirable for early warning systems, where timely detection of emerging risk must be balanced against operational stability and alert fatigue.

An optimal operating point is indicated near a low false positive rate, corresponding to a threshold that maximizes the trade-off between sensitivity and specificity. This confirms that the proposed model supports flexible threshold selection, enabling risk managers to adapt alerting strategies to different safety requirements without sacrificing predictive reliability.

4.5. Comparison with baseline models

To further assess the effectiveness of the proposed CNN–BiGRU architecture, its performance was compared against several widely used baseline approaches: Logistic Regression, Random Forest, and a standalone GRU model. All models were implemented using the same input features and evaluated under identical experimental conditions, ensuring consistency in the comparison. The evaluation was based on standard classification metrics, including accuracy, precision, recall, F1-score, and ROC–AUC.

Table 1 summarizes the quantitative results.

Table 1. Performance comparison of baseline models and the proposed CNN–BiGRU framework

Model	Accuracy	Precision	Recall	F1-score	ROC AUC
Logistic Regression	0.6808	0.5210	0.6307	0.5732	0.6233
Random Forest	0.9412	0.8114	0.6980	0.7503	0.8637
GRU	0.9517	0.8514	0.7239	0.7822	0.8816
CNN–BiGRU	**0.9607**	**0.9014**	**0.7566**	**0.8226**	**0.9071**

The proposed CNN–BiGRU model consistently outperforms all baseline approaches across all metrics. Compared to the best-performing baseline (GRU), the CNN–BiGRU achieves a 5.2 % relative improvement in F1-score (0.8226 vs. 0.7822) and a 2.9 % relative improvement in ROC AUC (0.9071 vs. 0.8816). The most notable gain is in precision, which increases from 0.8514 (GRU) to 0.9014, indicating that the hybrid architecture significantly reduces false alarms while maintaining high sensitivity.

Logistic Regression yields the lowest scores, which can be attributed to its linear nature and inability to capture nonlinear interactions inherent in hydrometeorological processes. Random Forest, while capable of modeling nonlinear relationships, does not explicitly account for temporal dependencies, which are crucial for time-series data. The standalone GRU model effectively captures sequential dynamics but lacks the ability to extract localized patterns from multivariate inputs.

The CNN–BiGRU architecture combines convolutional feature extraction with bidirectional temporal modeling, enabling it to learn both short-term fluctuations and long-range dependencies. This synergy leads to more reliable identification of complex patterns associated with evolving risk conditions, particularly under severe class imbalance. The results confirm that the proposed framework provides a robust and practically meaningful improvement over conventional and single-component models for dam risk assessment tasks.

5. Discussion

This study proposed a hybrid CNN–BiGRU framework for early warning of dam failure risk using multivariate hydrometeorological time series under highly imbalanced conditions. The discussion focuses on the interpretation of the results obtained, the role of temporal–spatial feature learning, the implications of threshold-based alerting, and the practical relevance of the proposed approach for real-world dam safety monitoring.

Interpretation of predictive performance under imbalanced conditions

The CNN–BiGRU model achieved strong overall predictive performance, with an accuracy of 0.9608, an F1-score of 0.8228, and a ROC AUC of 0.9074. More importantly for early warning applications, the model maintained a favorable balance between precision (0.9006) and recall (0.7574), indicating that a substantial proportion of high-risk states were correctly identified while limiting false alarms.

Unlike conventional classification tasks, dam failure prediction prioritizes sensitivity to rare but critical events rather than maximizing overall accuracy. In this context, the achieved recall demonstrates that the proposed model is capable of detecting a majority of risk-related conditions, even when such events represent only a small fraction of the dataset. The relatively high PR AUC value (0.8185) further confirms that the model performs robustly under severe class imbalance, where precision–recall characteristics are more informative than ROC metrics alone.

These results indicate that the CNN–BiGRU architecture effectively captures subtle precursory patterns that precede potential instability, rather than relying on dominant normal-state characteristics.

Contribution of CNN–BiGRU architecture to risk detection

The strong performance of the proposed framework can be attributed to the complementary roles of the convolutional and bidirectional recurrent components. The CNN layers efficiently extract localized temporal patterns and short-term fluctuations in hydrometeorological signals, such as abrupt water level changes and short-duration volatility bursts. These patterns are often early indicators of abnormal system behavior that may not be evident in raw time-series data.

The subsequent BiGRU layers enhance the representation by modeling long-range temporal dependencies in both forward and backward directions. This bidirectional structure allows the model to contextualize current observations with respect to both preceding and subsequent system states within each sequence window. Such capability is particularly important in dam monitoring, where instability often develops gradually and is influenced by cumulative hydrological and meteorological forcing.

The combination of CNN-based feature abstraction and BiGRU-based temporal reasoning enables the model to learn hierarchical spatio-temporal representations that are well suited for complex, nonstationary monitoring environments.

Feature importance and physical interpretability

Feature importance analysis provides additional insight into the physical relevance of the learned representations. The most influential variables were related to water level variability and volatility, including rolling standard deviation over 12 hours, overall water level volatility, and multi-hour water level changes. The observed increase in water level variability and short-term fluctuations can be interpreted as indicators of unstable hydrodynamic regimes. Such behavior may reflect intensified seepage processes within the dam body, increasing pore water pressure and reducing the effective stress that contributes to structural stability.

Rapid changes in water level can also lead to transient loading conditions, which impose additional stress on the dam structure and its foundation. These effects are particularly critical for embankment dams, where internal erosion, slope instability, and overtopping risks are closely associated with abrupt hydraulic variations.

From a physical perspective, the identified statistical features therefore capture meaningful precursors of potentially hazardous conditions. Rather than being purely data-driven artifacts, these variables reflect underlying hydromechanical processes that are known to contribute to dam instability.

This connection between data-driven indicators and physical mechanisms enhances the interpretability of the proposed model and supports its applicability in real-world early warning systems. These features directly reflect dynamic stress conditions acting on the dam structure and are consistent with known mechanisms of embankment instability.

The prominence of meteorological variables such as wind speed and short-term precipitation further highlights the interaction between hydraulic loading and external environmental forcing. Importantly, the model does not rely on a single dominant indicator but instead integrates multiple correlated signals, suggesting that failure risk emerges from the combined effect of gradual trends and short-term anomalies.

This alignment between data-driven importance rankings and physical intuition enhances confidence in the model's applicability for real-world decision support, addressing a common concern regarding the interpretability of deep learning models in safety-critical domains.

Threshold selection and early warning implications

A key contribution of this study lies in the explicit treatment of threshold-based alert generation. The primary decision threshold was set to $\tau = 0.10$, which was selected to optimize the trade-off between recall and precision during validation. This relatively low threshold reflects the operational priorities of early warning systems, where missing a true high-risk event is typically more costly than issuing a limited number of false alerts.

The probability distribution of model outputs shows a clear separation between dominant low-risk predictions and a smaller cluster of elevated-risk probabilities. This separation supports the feasibility of flexible threshold selection depending on safety requirements. Higher thresholds ($\tau = 0.30$, 0.50, and 0.70) provide increasingly conservative alerting but may delay detection of early-stage instability patterns. In contrast, the adopted $\tau = 0.10$ enhances sensitivity to emerging anomalies, offering valuable lead time for preventive action.

Rather than prescribing a single universal threshold, the proposed framework enables adaptive alerting strategies that can be tuned to site-specific risk tolerance and operational constraints.

Practical relevance and limitations

The Sardoba case study demonstrates the applicability of the CNN–BiGRU framework to real-world dam monitoring scenarios characterized by nonstationary behavior, multivariate dependencies, and severe class imbalance. The results suggest that the proposed approach can complement traditional monitoring systems by providing probabilistic risk estimates that evolve continuously over time.

Nevertheless, several limitations should be acknowledged. First, the risk labels are derived from hydrometeorological behavior and proxy indicators rather than direct structural failure measurements, which may introduce uncertainty in ground truth definition. Second, while the dataset captures rich temporal dynamics, the model's performance may vary across different dam types and climatic regimes. Future work should therefore focus on cross-site validation and the integration of structural health monitoring data to further enhance robustness.

Despite these limitations, the presented results indicate that hybrid deep learning architectures, when combined with imbalance-aware evaluation and interpretable thresholding, offer a promising pathway toward reliable data-driven early warning systems for dam safety.

6. Conclusion

This study presented a deep learning–based early warning framework for dam failure risk assessment using multivariate hydrometeorological time-series data under highly imbalanced conditions. By integrating convolutional neural networks with bidirectional gated recurrent units, the proposed CNN–BiGRU model was specifically designed to capture both short-term anomalies and long-term temporal dependencies that characterize the early stages of dam instability.

Using a real-world case study of the Sardoba reservoir, the proposed approach demonstrated strong predictive performance, achieving a ROC AUC of 0.9071, a PR AUC of 0.8185, and an F1-score of 0.8226, while maintaining a high precision of 0.9014 and a recall of 0.7566. These results confirm that the model is capable of identifying rare, risk-related conditions without being dominated by the majority of normal operational states, which is a critical requirement for practical dam safety applications.

A key contribution of this work lies in the explicit formulation of dam failure risk prediction as a threshold-based probabilistic early warning problem. By adopting a relatively low decision threshold ($\tau = 0.10$), the framework prioritizes early detection of emerging instability signals, offering valuable lead time for preventive intervention. At the same time, the clear separation observed in the predicted probability distribution allows for flexible adjustment of alert thresholds (e. g., $\tau = 0.30$, 0.50, and 0.70) to accommodate different operational risk tolerances and safety policies.

Feature importance analysis further demonstrated that the model's predictions are driven primarily by physically meaningful indicators, such as water level variability, multi-hour water level changes, and volatility-related features, complemented by key meteorological drivers. This alignment between data-driven learning and domain knowledge enhances the interpretability and credibility of the proposed approach, addressing a common concern in the application of deep learning models to safety-critical infrastructure monitoring.

Overall, the findings of this study suggest that hybrid CNN–BiGRU architectures provide an effective and robust solution for early warning of dam failure risk under real-world monitoring constraints. The proposed framework is not limited to the Sardoba reservoir and can be readily adapted to other dams and water infrastructure systems with similar multivariate time-series data availability. Future research will focus on cross-dam generalization, integration of structural health monitoring measurements, and the development of adaptive, context-aware thresholding strategies to further enhance operational reliability and decision support.

References

Ahmad S., Simonovic S. An ensemble machine learning framework for flood and dam risk prediction. — Water Resources Management, 2020.

Bai S., Kolter J., Koltun V. An empirical evaluation of convolutional sequence models // arXiv preprint. — 2018. — arXiv:1803.01271

Borovykh A., Bohte S., Oosterlee C. W. Conditional time series forecasting with convolutional neural networks // Journal of Computational Finance. — 2018. — Vol. 22, No. 4. — P. 37–59.

Chen J. et al. Deep learning-based dam behavior analysis under extreme hydrological events // Engineering Applications of Artificial Intelligence. — 2022. — Vol. 112. — Article 104878.

Cho K., van Merrienboer B., Gülçehre Ç, Bahdanau D., Bougares F., Schwenk H., Bengio Y. Learning phrase representations using RNN encoder – decoder for statistical machine translation // Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). — 2014. — P. 1724–1734.

Fang Z., Wang Y. Bidirectional recurrent neural networks for landslide early warning // Natural Hazards. — 2021. — Vol. 108. — P. 1–20.

Fell R., MacGregor P., Stapledon D., Bell G., Foster M. Geotechnical engineering of dams. — Boca Raton: CRC Press, 2015.

FEMA. Federal Guidelines for Dam Safety Risk Management. — Washington, DC: Federal Emergency Management Agency, 2015.

Graves A., Schmidhuber J. Bidirectional LSTM networks // Neural Networks. — 2005. — Vol. 18, No. 5–6. — P. 602–610.

Guo X., Zhang L. Application of support vector machines in dam safety monitoring // Engineering Structures. — 2018. — Vol. 166. — P. 401–413.

He H., Garcia E. Learning from imbalanced data // IEEE Transactions on Knowledge and Data Engineering. — 2009. — Vol. 21, No. 9. — P. 1263–1284.

ICOLD. Dam failures: statistical analysis and lessons learned. — Paris: International Commission on Large Dams, 2018. — Bulletin 99.

Japkowicz N. Learning from imbalanced data sets: a comparison of various strategies // AI Magazine. — 2020. — Vol. 21, No. 2. — P. 49–63.

Kattakulov F. et al. Hydrometeorological conditions preceding the Sardoba dam collapse // Central Asian Journal of Water Research. — 2021. — Vol. 7, No. 1. — P. 23–35.

Kim S. et al. Hybrid CNN–LSTM networks for environmental time-series prediction // Environmental Modelling & Software. — 2020. — Vol. 134. — Article 104847.

Kratzert F., Klotz D., Shalev G., Klambauer G., Hochreiter S., Nearing G. Towards learning universal, regional, and local hydrological behaviors via LSTM networks // Hydrology and Earth System Sciences. — 2019. — Vol. 23. — P. 5089–5110.

Li Q. et al. Data-driven early warning systems for critical infrastructure using deep neural networks // Reliability Engineering & System Safety. — 2024. — Vol. 241. — Article 109546.

Li Y. et al. GRU-based deep learning for multivariate hydrological time series prediction // Journal of Hydrology. — 2020. — Vol. 589. — Article 125176.

Li Z. et al. Deep learning-based early warning systems for infrastructure safety // Engineering Structures. — 2021. — Vol. 234. — Article 111977.

Morris M., Hassan M. Breaching processes and sediment dynamics in embankment dams // Journal of Hydraulic Engineering. — 2017. — Vol. 143, No. 9. — Article 04017033.

Saito T., Rehmsmeier M. The precision–recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets // PLOS ONE. — 2015. — Vol. 10, No. 3. — P. e0118432.

UNDRR. Sendai framework for disaster risk reduction 2015–2030. — Geneva: United Nations Office for Disaster Risk Reduction, 2015.

WMO. Multi-hazard early warning systems: A checklist. — Geneva: World Meteorological Organization, 2018.

Wu Z., Chen Y. Decision-tree-based anomaly detection for dam deformation monitoring // Structural Control and Health Monitoring. — 2019. — Vol. 26, No. 10. — P. e2425.

Xie L., Xu W., Ding X. Remote sensing analysis of the 2020 Sardoba dam failure // Journal of Applied Geodesy. — 2022. — Vol. 16, No. 3. — P. 215–228.

Xu Y., Zhang L. Breaching parameters for earth and rockfill dams // Journal of Geotechnical Engineering. — 2009. — Vol. 135, No. 12. — P. 1957–1970.

Zhang J. et al. CNN–RNN hybrid models for hydrological forecasting // Water Resources Research. — 2019. — Vol. 55, No. 6. — P. 4785–4802.

Zhang R. et al. Deep hybrid networks for hydrometeorological risk prediction // Science of the Total Environment. — 2021. — Vol. 784. — Article 147098.

Zhou H. et al. Spatio-temporal deep learning for infrastructure safety monitoring // Structural Safety. — 2023. — Vol. 102. — Article 102330.

Zokirov A., Yuldashev T., Karimov B. Hydrological conditions and damage assessment after the Sardoba dam failure // Journal of Water Resources of Central Asia. — 2022. — Vol. 5, No. 2. — P. 41–52.