



PERFORMANCE EVALUATION OF MLP AND CNN FOR RESERVOIR OUTFLOW FORECASTING

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ABSTRACT

Flood forecasting is critical for downstream disaster risk mitigation. Traditional hydrological models often fail to capture the nonlinear, dynamic interactions between inflows, storage levels, and operational reservoir releases during extreme events. This study evaluates Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) deep learning architectures for hourly reservoir outflow forecasts during the catastrophic 2006 Ukai flood. Using chronological data splits and sliding-window input sequences, model performance was rigorously assessed via MAE, RMSE, and R^2 . The MLP consistently outperformed the CNN across training, validation, and testing phases. On unseen test data, the MLP achieved MAE = 49,575 cusecs, RMSE = 96,193 cusecs, and $R^2 = 0.635$, compared to CNN values of 57,386 cusecs, 103,645 cusecs, and 0.576, respectively. Validation metrics similarly favored MLP (MAE 35,880 versus 42,402 cusecs; R^2 0.67 versus 0.61). Time-series and scatter analyses confirmed MLP's superior stability and peak-capture capability, whereas CNN exhibited systematic underestimation and lagged responses during rapid flow variations. These findings suggest that simpler fully connected architectures provide robust, operationally practical solutions for real-

time flood forecasts under limited datasets, while CNN may require expanded data or hybrid frameworks for improved reliability.

Keywords: Flood forecasting, Deep learning, Multilayer Perceptron (MLP), Convolutional Neural Network (CNN).

INTRODUCTION

Over the last decades, floods have become one of the most devastating natural hazards worldwide, notably flash floods (Remini, 2023), causing considerable human casualties, economic losses, environmental degradation, and severe damage to hydraulic infrastructures. The increasing frequency and magnitude of flood events are commonly associated with climate variability, rapid urbanization, land-use changes, watershed degradation, and inadequate water resources management. Consequently, improving flood prediction, flood mitigation, and reservoir operation has become one of the major challenges facing hydrologists, hydraulic engineers, and water resources managers. Numerous studies published recently have significantly contributed to advancing the understanding of flood generation mechanisms, rainfall-runoff processes, flood hazard assessment, flood risk mapping, hydraulic modelling, and reservoir management under changing climatic conditions (Benkhaled et al., 2013; Hachemi and Benkhaled, 2016; Bekhira et al., 2019; Aroua, 2020; Benslimane et al., 2020; Cherki, 2019; Hafnaoui et al., 2022; Hafnaoui et al., 2023; Abd Rahman et al., 2023; Ben Said et al., 2024; Athmani et al., 2025; Ezz, 2025).

Flood occurrence is governed by highly nonlinear interactions between precipitation, catchment morphology, antecedent soil moisture, land cover, hydraulic structures, and river network characteristics. Several studies demonstrated that reliable flood prediction requires not only accurate rainfall estimation but also a comprehensive representation of watershed hydrological response through physically based, conceptual, statistical, or data-driven approaches (Abdeddaim and Benkhaled, 2016; Abdi and Meddi, 2015; Faregh and Benkhaled, 2016; Djellouli et al., 2015; Fernando et al., 2021; Atallah et al., 2024; Kherde et al., 2024; Mehta and Yadav, 2024). Similarly, investigations on rainfall variability, extreme precipitation, drought evolution, and climate change have highlighted their direct influence on flood occurrence and water resources availability (Lazri et al., 2007; Boubakeur, 2018; N'Guessan et al., 2020; Nassa et al., 2021; Bong et al., 2023; Gassi and Saoudi, 2023; Chadee et al., 2023).

In recent years, flood hazard assessment has progressively evolved from simple hydrological analyses toward integrated approaches combining Geographic Information Systems (GIS), hydraulic modelling, remote sensing, and multi-criteria decision analysis. Numerous contributions published recently clearly demonstrate the effectiveness of GIS-based methodologies for delineating flood-prone areas, identifying vulnerable urban zones, and supporting territorial planning. Representative examples include flood hazard mapping in El Bab Medjez (Ayari et al., 2016), flood risk simulation in Béjaïa (Benslimane et al., 2020), flood protection planning in Skikda (Boulghobra, 2013), flood management in Bechar (Bekhira et al., 2019), flood mapping using HEC-RAS in Doucen

(Athmani et al., 2025), flood susceptibility analyses in Algeria (Ben Said et al., 2024), and urban flood forecasting using SWMM (Baudhanwala et al., 2023). These studies collectively demonstrate that combining hydraulic simulation with spatial analysis substantially improves flood preparedness, emergency planning, and decision-making.

Parallel advances have also been achieved in hydraulic engineering devoted to flood protection. Considerable efforts have focused on spillway hydraulics, hydraulic jumps, stilling basins, energy dissipation systems, dam safety, seepage control, sedimentation processes, and flood discharge structures. Significant contributions include studies on stepped spillways (Hazzab and Chafi, 2006; Bentalha and Habi, 2017; Lebdiri et al., 2020), shaft spillways (Gouryev et al., 2020), hydraulic jumps (Achour et al., 2022a, 2022b; Bouriche et al., 2023), stilling basins (Brakeni et al., 2021; Burlachenko et al., 2022; Burlachenko et al., 2023), dam leakage monitoring (Benfetta et al., 2017a, 2017b), reservoir sedimentation (Larfi and Remini, 2006; Meguenni and Remini, 2008; Bougamouza et al., 2020), and water losses in reservoirs through evaporation (Boutebba et al., 2020). Together, these investigations emphasize that efficient flood mitigation depends not only on accurate hydrological forecasting but also on optimized hydraulic infrastructure performance throughout the entire reservoir system.

Floods are among the most devastating natural disasters worldwide, causing extensive damage to infrastructure, agriculture, and human settlements, and threatening lives and livelihoods (Dewan, 2015; Jonkman, 2005). The frequency and intensity of flood events have increased in recent decades due to a combination of climate variability, land-use changes, rapid urbanization, and anthropogenic pressures on river basins (Bai and Zhao, 2023; Dahiphale et al., 2023). In India, floods affect millions of people annually, and reservoirs and dams play a critical role in mitigating or exacerbating flood risks (Verma et al., 2025; Vegad and Mishra, 2025). At the synoptic scale, flood events in central Indian basins have been strongly linked to ENSO-driven streamflow variability (Verma et al., 2022), further underscoring the non-stationary and nonlinear nature of flood generation mechanisms. Reliable flood forecasts, particularly reservoir outflow forecasts, is therefore vital for effective water resources management, emergency preparedness, and disaster risk reduction (Kumar et al., 2025).

The Ukai Dam, constructed across the Tapi River in Gujarat, is the second-largest reservoir in the state and a multipurpose project serving irrigation, power generation, and flood control. However, during extreme flood events, such as the 2006 flood, the management of reservoir outflows becomes highly challenging. Sudden and high-magnitude releases from the reservoir can lead to catastrophic flooding downstream, as witnessed in Surat city during August 2006 (Tessema et al., 2024). More than 150 lives were lost, and widespread economic damage occurred when the release of water from Ukai coincided with heavy inflows from upstream catchments. This event underlined the urgent need for accurate outflow forecasts models that can predict reservoir discharge under extreme hydrological conditions. Previous flood modeling efforts in Gujarat including one-dimensional hydrodynamic simulations for the Ambica River (Patel et al., 2018), flood frequency analysis and inundation mapping for the lower Narmada basin (Mangukiya et al., 2022), and flood risk assessment coupled with hydrological simulation in urbanizing coastal catchments (Ande et al., 2025; Mehta et al., 2022; Patel et al., 2023)

have consistently demonstrated the region's acute vulnerability to fluvial flooding. Similarly, comparative evaluations of digital elevation models for flood risk mapping in Indian coastal river basins (Gangani et al., 2023), integrated flood risk mapping in Navsari District (Patel et al., 2024), and QGIS-based flood hazard assessment tools (Verma et al., 2024) highlight the necessity of advancing beyond static hazard mapping toward dynamic, real-time forecasting frameworks for operational reservoir management.

While the physical drivers of flooding are increasingly well understood, traditional flood forecasting methods, which primarily rely on statistical models, hydrological simulations, or simplified empirical formulations, often struggle to capture the nonlinear, dynamic, and highly uncertain relationships among inflow, storage, rainfall, and reservoir operations (Alsulamy et al., 2025). These limitations are particularly evident in empirical regression equations and statistical models such as autoregressive (AR), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA), which assume linear relationships and often fail to capture the nonlinear and multiscale dynamics of hydrological systems. Their accuracy decreases significantly under extreme conditions, such as high inflows during major flood events. Subsequently, conceptual and physically based models like HEC-HMS, MIKE-11, and SWAT became popular. These models simulate the physical processes of rainfall-runoff transformation, infiltration, channel routing, and reservoir operations (Kant et al., 2025). Although conceptually sound, they require extensive data inputs on soil, land use, topography, and hydro-meteorological parameters, which are often scarce or uncertain in developing regions (Banda et al., 2022). Moreover, their calibration and validation are time-consuming, and the models may not generalize well when applied to unprecedented flood conditions.

To overcome these limitations, the past two decades have witnessed a rapid rise in artificial intelligence (AI) and machine learning (ML) applications in hydrology (Biazar et al., 2025; Jahanbani et al., 2024). Models such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forests (RF), and Gradient Boosting algorithms have been applied to river flow and flood forecasts with varying degrees of success (Kedam et al., 2024). They provide flexibility in capturing nonlinear relationships between inputs and outputs without requiring explicit knowledge of the underlying physical processes (Khedekar et al., 2025; Scibilia et al., 2023). However, conventional ML models are often limited by their shallow architectures and inability to effectively capture long-term temporal dependencies. Deep learning (DL) models, including Multilayer Perceptrons (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and hybrid models (e.g., CNN-LSTM, BiLSTM), have emerged as powerful tools for hydrological forecasts (Ceylan and Yumurtacı, 2025; Elshewey et al., 2025; Tan et al., 2023; Udurume et al., 2024). Several studies have demonstrated their superiority over traditional ML models in rainfall-runoff modeling, streamflow forecasts, and flood forecasts (Jehanzaib et al., 2022). For instance, LSTM networks can learn long-term temporal dependencies in time-series data, while CNNs excel at extracting local features and patterns from sequential inputs (Lindemann et al., 2021). Hybrid architectures such as CNN-LSTM combine these strengths, offering robust predictive performance. In reservoir outflow forecasts, deep learning applications are still relatively limited

compared to rainfall-runoff studies. However, recent works have shown that DL models can effectively model reservoir inflow and outflow dynamics. Recent applications have also utilized machine learning to project streamflow responses to climate change at the basin scale, while deep learning-based temporal disaggregation methods have improved short-term rainfall forecasts for urban flood management (Patel et al., 2025).

Deep learning, a specialized branch of machine learning, utilizes neural network architectures with multiple layers to learn complex and hierarchical representations of data (Taye, 2023). Its application in hydrological forecasts has gained significant attention due to several advantages over traditional approaches. One of the key strengths of deep learning models is their ability to perform automatic feature extraction, reducing the dependency on domain expertise for manually selecting predictors and instead allowing the models to identify relevant patterns directly from input data. In addition, these models possess a high capacity for nonlinear modeling, enabling them to capture the intricate and nonlinear relationships between hydro-meteorological variables, inflows, and reservoir discharges that often challenge conventional statistical or conceptual methods (Karami et al., 2024; Sarker and Leta, 2025; Vasheghani Farahani et al., 2025). Another crucial advantage lies in their ability to model temporal dependencies, especially through sequence-based architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (BiLSTM) networks, which are specifically designed to learn patterns across time and thus provide more reliable prediction in dynamic hydrological systems. However, as noted above, such sequence-based models may be unnecessarily complex for moderate datasets. MLP and CNN architectures, by contrast, leverage sliding-window sequences to capture short-term historical dependencies without the computational burden of recurrent state updates, making them particularly suitable for operational deployment in data-limited reservoir systems. Moreover, deep learning models are highly scalable and adaptable, capable of being trained on large datasets while integrating diverse inputs such as rainfall, water levels, inflows, and operational data. These features make deep learning an effective and powerful tool for advancing flood forecasts and enhancing decision-support systems for reservoir management.

Thus, beyond flood forecasting and hazard assessment, reservoir operation has progressively emerged as a fundamental component of integrated water resources management, particularly in regions frequently exposed to hydrological extremes. Reservoirs simultaneously ensure flood attenuation, water supply, irrigation, hydropower generation, and environmental flow regulation. However, balancing these multiple and often conflicting objectives remains a challenging task because reservoir releases must continuously adapt to highly variable inflow conditions and increasing climatic uncertainty. As highlighted by Paulo Monteiro and Costa Manuel (2004), reservoir management should be regarded as an integrated process involving both hydraulic structures and groundwater interactions, whereas Abaidia and Remini (2020) demonstrated the important role that reservoir releases may play in recharging downstream alluvial aquifers. More recently, Mehta et al. (2023) reviewed the evolution of reservoir operation strategies and emphasized the growing importance of intelligent optimization techniques for improving operational efficiency under changing

hydrological conditions. Likewise, Mezenner et al. (2022) successfully combined genetic algorithms with principal component analysis to optimize the operation of Ghrib Dam, while Panchal and Suryanarayana (2025) proposed an evolutionary algorithm for the optimal operation of a multipurpose reservoir. These investigations clearly demonstrate that modern reservoir management is progressively shifting from empirical operating rules toward intelligent decision-support systems.

Efficient reservoir operation also depends on the hydraulic performance and structural reliability of associated infrastructures. Several contributions published recently have considerably advanced the understanding of spillway hydraulics, hydraulic jumps, stilling basins, seepage control, water hammer protection, and reservoir sedimentation. Experimental and numerical investigations conducted by Hazzab and Chafi (2006), Bentalha and Habi (2017), Lebdiri et al. (2020), Goureyev et al. (2020), Brakeni et al. (2021), Burlachenko et al. (2022, 2023), and Achour et al. (2022a, 2022b) have significantly improved the hydraulic design of energy dissipation structures, whereas Benfetta et al. (2017a, 2017b) addressed leakage detection and dam safety issues. In parallel, sedimentation processes, which directly reduce reservoir storage capacity and operational efficiency, have been investigated by Larfi and Remini (2006), Meguenni and Remini (2008), and Bougamouza et al. (2020), while evaporation losses from reservoirs located in arid regions were quantified by Boutoutaou et al. (2020). Collectively, these studies underline that reservoir operation cannot be dissociated from the hydraulic behavior and long-term performance of the associated hydraulic structures.

Another major research direction concerns the continuous improvement of hydrological modelling for predicting reservoir inflows and flood hydrographs. Physically based models such as HEC-HMS, SWMM and HEC-RAS have become indispensable tools for simulating rainfall-runoff transformation, flood routing and hydraulic behaviour. Their successful application has been demonstrated for several watersheds and urban environments by Fernando et al. (2021), Atallah et al. (2024), Mehta and Yadav (2024), Kherde et al. (2024), Baudhanwala et al. (2023), and Athmani et al. (2025). Furthermore, GIS-based hydrological analyses developed by Faregh and Benkhaled (2016), Ayari et al. (2016), Bekhira et al. (2019), Benslimane et al. (2020), and Ben Said et al. (2024) have considerably enhanced flood hazard mapping and flood-risk assessment by integrating spatial information with hydraulic modelling. These methodologies have substantially improved decision-making processes for flood protection, watershed management and urban planning.

Although physically based hydrological models remain indispensable, their application is frequently limited by extensive data requirements, parameter uncertainty, and the complexity of representing nonlinear hydrological processes. Consequently, data-driven approaches have attracted increasing attention during the last decade. Artificial intelligence techniques are capable of extracting hidden relationships directly from historical observations without requiring explicit physical descriptions of watershed behavior. Several studies have reported this scientific evolution through numerous studies applying artificial neural networks, machine learning algorithms, ANFIS, gene-expression programming and other intelligent techniques to hydrological and hydraulic problems. Cherki (2019) demonstrated the effectiveness of artificial neural networks for

daily and instantaneous flood forecasting, whereas Bougamouza et al. (2022) successfully estimated sediment transport using three ANN models. Chaplot et al. (2021) employed gene-expression programming to estimate Manning's roughness coefficient, Ansari et al. (2024) applied ANFIS to predict sediment removal efficiency, Bouriche et al. (2023) incorporated machine learning into hydraulic-jump analysis, Belouz et al. (2025) modelled reservoir surface-water temperature using neural networks and ANFIS, and Molavi (2025) proposed intelligent autocorrelated models for runoff simulation. These studies collectively demonstrate the remarkable capability of intelligent models to reproduce highly nonlinear hydrological processes with satisfactory accuracy.

Among artificial intelligence techniques, the Multi-Layer Perceptron (MLP) remains one of the most extensively applied neural-network architectures because of its robustness, simplicity and universal approximation capability. Nevertheless, the recent emergence of deep-learning techniques has considerably expanded the possibilities for hydrological forecasting. Convolutional Neural Networks (CNNs), initially developed for computer vision applications, have demonstrated an exceptional ability to identify complex spatial and temporal patterns hidden within large hydrometeorological datasets. Their hierarchical feature extraction capability makes them particularly attractive for reservoir inflow and outflow prediction, flood forecasting and real-time reservoir operation. Considering the progressive evolution documented recently from conventional hydraulic modelling toward intelligent optimization and machine-learning applications (Cherki, 2019; Mezenner et al., 2022; Mehta et al., 2023; Atallah et al., 2024; Kherde et al., 2024; Belouz et al., 2025; Molavi, 2025), evaluating the comparative performance of MLP and CNN models for reservoir outflow forecasting represents a logical and timely continuation of these research efforts. Such comparative analyses are expected to contribute not only to improving prediction accuracy but also to supporting adaptive reservoir operation, flood-risk reduction and sustainable water-resources management under increasingly uncertain hydroclimatic conditions.

Despite these advances, a critical research gap persists. Most deep learning applications in hydrology have concentrated on rainfall-runoff modeling, gauge-based streamflow forecasts, or reservoir inflow forecasts (Sakib et al., 2025). In contrast, reservoir outflow forecasts particularly under extreme flood conditions where operational releases are governed by dam safety protocols, gate operations, and downstream risk management remains comparatively underexplored. Existing studies predominantly benchmark LSTM, GRU, or hybrid architectures (e.g., CNN-LSTM, BiLSTM) against traditional ML models, often concluding that recurrent networks yield superior accuracy (Jehanzaib et al., 2022; Lindemann et al., 2021). However, these conclusions are typically drawn from large, multi-year datasets with abundant predictor variables. Very few studies have examined whether simpler deep learning architectures can achieve comparable or better reliability when datasets are limited in size, feature space, and temporal span, as is common for single-event operational records in Indian reservoir systems. Furthermore, the comparative performance of foundational architectures such as MLP and CNN without recurrent layers has not been systematically evaluated for reservoir outflow forecasts during extreme flood events in the Indian context. This gap limits the operational adoption of DL models, as dam managers require transparent,

computationally efficient, and robust forecasting tools that can be trained and deployed with minimal data overhead.

Against this backdrop, the present study deliberately selects the Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) as representative models for comparison. While LSTM and GRU networks are theoretically appealing for their temporal memory, they introduce significant computational cost, hyperparameter sensitivity, and overfitting risk when applied to small or moderate-sized hydrological datasets (Lindemann et al., 2021). For operational reservoir management where training data may be restricted to discrete flood events and real-time inference is required simpler architectures offer distinct practical advantages. This observation aligns with comparative assessments indicating that CNNs require large, high-dimensional inputs to exploit their local feature-extraction capability, whereas fully connected networks such as MLP generalize more robustly under restricted sample sizes and narrow feature spaces (Asif et al., 2025). The MLP serves as a robust, fully connected baseline that is easy to implement, computationally economical, and capable of approximating complex nonlinear mappings if sufficient hidden capacity is provided. The CNN, though traditionally used in image recognition, has been successfully adapted for time-series analysis by extracting localized temporal features through one-dimensional convolutional filters, offering a middle ground between fully connected and recurrent networks (Elshewey et al., 2025; Udurume et al., 2024). By comparing these two non-recurrent architectures, this study tests the hypothesis that simpler deep learning models can provide reliable and operationally practical outflow forecasts when data availability is constrained, thereby offering a pragmatic alternative to more complex recurrent or hybrid frameworks.

Given the devastating impacts of the 2006 Ukai flood and the limitations of conventional forecasts models, the present study aims to:

1. Develop a systematic deep learning pipeline for reservoir outflow forecasts, incorporating feature engineering, sequence creation, and chronological dataset splits.
2. Evaluate the predictive performance of DL architectures such as (MLP, CNN) for forecasts reservoir outflow during the 2006 Ukai flood event.
3. Compare the models across key statistical metrics Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) to identify the most reliable architecture for operational flood forecasts.
4. Generate insights into model suitability and practical applicability for dam operation, flood management, and downstream disaster mitigation.
5. Contribute to the growing body of literature on deep learning applications in hydrology by demonstrating their effectiveness in extreme flood scenarios in the Indian context.

The scope of this study is limited to the application of deep learning models on reservoir-level and flow data from the Ukai Dam during 2006. By focusing on this extreme flood event, the study provides valuable insights into model robustness under high-flow conditions. The primary contribution lies in the comparative evaluation of multiple DL architectures for outflow forecasts, an area where empirical evidence is still sparse. The findings are expected to aid reservoir managers, hydrologists, and policymakers in adopting advanced forecasting techniques for flood risk reduction. Moreover, the study

highlights the importance of integrating AI-driven models into decision-support systems for real-time dam operation and disaster management.

STUDY AREA AND DATA COLLECTION

The study area is centered on the Ukai Dam, located on the Tapi River in Surat district, Gujarat, India. The Tapi River, also known as the Tapti, originates from the Satpura ranges in Madhya Pradesh at an elevation of approximately 752 meters above mean sea level. It flows westward for about 724 km, traversing Madhya Pradesh and Maharashtra before entering Gujarat and draining into the Arabian Sea. The basin covers a catchment area of around 65,145 km², making it one of the major river basins in western India. Ukai Dam, also referred to as the Vallabh Sagar Dam, was constructed in 1972 primarily for irrigation, hydropower generation, flood control, and water supply. The dam is an earthen-cum-concrete structure with a gross storage capacity of approximately 8,488 MCM (Million Cubic Meters) and a live storage of 6,615 MCM. With an installed power generation capacity of about 300 MW, it plays a vital role in the energy supply of the region. Importantly, the dam also serves as a critical structure for flood moderation in the lower reaches of the Tapi River, especially in and around Surat city, a major urban and industrial hub.

Despite these functions, the dam and downstream areas have been prone to flood disasters. The most notable event occurred in August 2006, when heavy upstream rainfall combined with large inflows into the reservoir, forcing authorities to release massive volumes of water. The sudden release of more than 9.5 lakh cusecs of water led to severe flooding in Surat city, inundating nearly 80% of the area. The event caused over 150 fatalities, significant economic losses, and disruption of industrial operations, including diamond and textile industries, for weeks. This event highlighted the limitations of existing flood forecasting and reservoir operation strategies, emphasizing the necessity of reliable and accurate outflow forecasts models to aid decision-making and risk management.

Data Sources

The present study uses hourly reservoir operation datasets collected from the Ukai Dam authorities for the year 2006, with a particular emphasis on the August extreme flood event. The raw data were compiled from operational logbooks and automated gauging stations into Microsoft Excel format. Each record contains two primary variables: reservoir inflow and reservoir outflow, both recorded in cusecs on an hourly basis. Prior to model development, the dataset underwent systematic quality control and preprocessing. Missing values caused by intermittent gauge failures or manual logging gaps were identified and imputed using linear interpolation for short gaps and forward-fill for isolated missing timestamps. Outliers and physically inconsistent entries (e.g., negative flows or extreme spikes beyond plausible operational limits) were detected using Z-score analysis and cross-checked against known gate-operation schedules; confirmed anomalies were corrected or removed. To enhance predictive capacity, feature

engineering was applied to the raw inflow series. Derived variables include 3-hour and 6-hour rolling mean inflows, cumulative inflow over the preceding 24 hours, and lagged outflow values. These engineered features capture short-term flow trends and antecedent catchment conditions, which are critical precursors to reservoir release decisions. All predictor variables were then normalized to the [0, 1] range using the MinMaxScaler technique. Normalization ensures numerical stability and accelerates convergence during deep learning training.

Data Splitting for Model Development

To mimic real-world operational forecasts, the cleaned dataset was partitioned chronologically rather than randomly. The first 60% of records formed the training set, the next 20% the validation set, and the final 20% the testing set. This chronological split preserves the causal time-order of hydrological processes and ensures that models are evaluated on future, unseen events. Additionally, time-series input sequences were created using a sliding window approach. A window length of 10 consecutive hourly records was selected. Each input sample therefore consists of 10 hours of historical inflow (plus engineered features) used to predict the outflow at the next hour. This sequence length captures short-term flow memory while keeping the input dimension manageable for limited datasets. The resulting sequences were formatted as flattened vectors for the MLP and as two-dimensional temporal arrays for the CNN. The Ukai 2006 dataset is particularly significant for two reasons: Extreme Flood Event Representation: It represents one of the most disastrous flood years in the region, making it an ideal case for testing the robustness of advanced models under extreme conditions. Operational Relevance: Since the dataset directly contains inflow, and outflow variables, the developed models can be directly translated into operational decision- support tools for dam management.

METHODOLOGY

This study evaluates two deep learning architectures for reservoir outflow forecasts: Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN). MLP represents fully connected feed-forward networks. CNN extracts local temporal features through one-dimensional convolutional filters. By comparing these two approaches, the study examines which architecture is better suited for hydrological time-series modelling under data-limited, extreme-flood conditions. The workflow comprises five stages: (i) data preparation, (ii) sequence generation, (iii) model design, (iv) training and validation, and (v) performance evaluation.

Data Preparation and Preprocessing

The 2006 Ukai dataset was cleaned to remove missing values, standardize formats, and generate engineered features. Full preprocessing details are provided in Section 2. The final predictor set includes reservoir inflow (cusecs), rolling inflow averages, cumulative

inflow, and lagged outflow. The target variable is reservoir outflow (cusecs). All inputs were normalized to the $[0, 1]$ range using MinMaxScaler. Normalization reduces sensitivity to large numerical differences and speeds up model convergence. A sliding window of 10 consecutive hourly records formed each input sequence to predict the next hourly outflow. This approach allows the models to utilize short-term historical patterns to generate forecasts. Finally, the data was divided chronologically into training (60%), validation (20%), and testing (20%) subsets. This split ensured that the models were evaluated on unseen data while maintaining the temporal order inherent in hydrological processes.

Multilayer Perceptron (MLP)

MLP is a widely used feed-forward neural network. It contains an input layer, one or more hidden layers, and an output layer. Each layer is fully connected to the next. Nonlinear activation functions enable the network to learn complex input-output mappings. MLP was selected as a baseline because of its simplicity and proven success in hydrology-related applications.

In this study, the MLP architecture comprised:

- Input layer: Flattened input vector derived from the sliding window of historical features ($10\text{-time steps} \times \text{number of features}$).
- Hidden layers: Two dense hidden layers with 128 and 64 neurons, respectively, both using the ReLU (Rectified Linear Unit) activation function to introduce nonlinearity.
- Output layer: A single neuron with linear activation to predict the reservoir outflow. The network was trained using the Adam optimizer with a learning rate of 0.001, while the mean squared error (MSE) was used as the loss function.

The strength of MLP lies in its simplicity and ability to learn nonlinear relationships. However, since it does not account for local temporal dependencies in the data, its forecast accuracy may decline during highly volatile flood events, where temporal correlations are crucial.

Convolutional Neural Network (CNN)

CNNs are traditionally used in image recognition. They have been adapted for time-series analysis by applying one-dimensional convolutional filters across the temporal dimension. These filters extract local features and short-term dependencies. CNN was selected because it offers a middle ground between fully connected networks and recurrent models. Convolutional kernels can identify rising inflows and sudden level changes that often precede large outflows. CNNs also train faster than recurrent networks and avoid vanishing gradient problems.

The CNN model used in this study was designed as follows:

- Input layer: Multivariate time-series sequences shaped as (10-time steps $\times$ number of features).
- Convolutional layer: One 1D convolutional layer with 64 filters and a kernel size of 3, using ReLU activation, to extract local temporal features.
- Pooling layer: A max-pooling layer with a pool size of 2 to reduce dimensionality while retaining dominant features.
- Flattening layer: Converts the 2D feature maps into a 1D vector.
- Dense layer: Fully connected dense layer with 50 neurons and ReLU activation.
- Output layer: Single neuron with linear activation for outflow forecasts.

CNN was also trained using the Adam optimizer with a learning rate of 0.001 and MSE as the loss function. CNNs are effective in extracting localized temporal features from time-series data, which is particularly valuable during flood events when short-term inflow surges directly influence outflows. They also train relatively faster compared to recurrent networks. However, CNNs have limited capacity for learning long-term dependencies, which can affect their performance in extended forecast horizons.

Hyperparameter Tuning

Prior to final training, a systematic hyperparameter exploration was performed to identify optimal configurations for both MLP and CNN. Key parameters, including learning rate (tested at 0.0001, 0.001, and 0.01), batch size (16, 32, 64), number of hidden neurons (64-256), and sequence length (5, 10, 15 hourly steps), were evaluated using validation loss as the selection criterion. For the CNN, filter count (32, 64) and kernel size (2, 3, 5) were additionally tested. Preliminary experiments indicated that a learning rate of 0.001, batch size of 32, sequence length of 10 hours, and ReLU activation consistently produced the lowest validation errors across both architectures. These settings were therefore fixed for the final training, validation, and testing phases to ensure a fair and reproducible comparison.

Model Training and Validation

Both models were trained on the pre-processed Ukai 2006 dataset. The training regime was kept identical for fair comparison. Training balanced computational efficiency, generalization capacity, and overfitting control. Each model was trained for a maximum of 100 epochs with a batch size of 32. Early stopping was employed to prevent overfitting. Validation loss was monitored each epoch. Training halted automatically if no improvement occurred for 10 consecutive epochs. The weights from the epoch with the lowest validation loss were restored for final testing.

The training procedure consisted of the following steps:

1. **Forward Propagation:** In this phase, the input sequences were fed into the model, and the network performed a series of transformations through its layers. For the MLP, this involved fully connected operations followed by nonlinear activations, while for the CNN, convolutional filters and pooling operations were applied to extract temporal features before being passed through dense layers. The final output layer produced predicted outflow values for each sequence.
2. **Loss Calculation:** The difference between the predicted outflows and the observed outflows was quantified using the Mean Squared Error (MSE) loss function. MSE was selected because it penalizes large errors more heavily than small errors, which is particularly relevant in flood forecasts where large deviations during peak flows can have serious consequences for downstream communities. The loss value provided a measure of the model's accuracy and served as the target function to be minimized.
3. **Backpropagation and Weight Updates:** Using the calculated loss, the error gradients with respect to each model parameter were computed via backpropagation. These gradients were then used to update the network weights through the Adam optimizer, an adaptive learning algorithm that combines the benefits of momentum and adaptive step sizes. A learning rate of 0.001 was chosen, as it provided a stable balance between convergence speed and training stability during preliminary experiments.
4. **Validation Monitoring:** After each epoch, the trained model was evaluated on the validation dataset, which was not directly used in weight updates. The validation loss served as an unbiased measure of generalization capability and helped in detecting overfitting. If the validation loss plateaued or worsened, the early stopping mechanism was triggered, preventing wasted computation and safeguarding the model from memorizing training patterns.
5. **Model Selection:** The weights corresponding to the epoch with the best validation performance were saved as the final trained model. These weights were subsequently applied to the test dataset, which represented unseen data. The test phase provided an objective assessment of how well the models generalized to new conditions, especially critical during extreme flood periods such as those in August 2006.

In addition to quantitative evaluation, the training process was supplemented with visual inspections of learning curves. Plots of training and validation loss versus epochs were generated to assess whether the models exhibit convergence, underfitting, or overfitting. Smooth and parallel convergence of both curves indicated stable learning, whereas divergence between the training and validation losses suggested overfitting. Furthermore, to ensure the robustness of the results, training was repeated multiple times with the same data partitions but different random initializations of weights. This approach helped mitigate the stochastic variability inherent in deep learning training processes and

confirmed the reliability of the observed performance differences between the MLP and CNN models.

Performance Evaluation

The predictive performance of the MLP and CNN models was rigorously evaluated using a combination of statistical metrics and graphical diagnostics. Since the primary objective of this study was to assess the reliability of deep learning models for outflow forecasts during an extreme flood event, careful attention was paid to the selection of evaluation criteria that reflect both the accuracy of prediction and the practical significance of errors in hydrological applications. In addition to the standard metrics, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) two hydrology-specific skill metrics, Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE), were computed. Furthermore, statistical significance testing and ensemble-based uncertainty quantification were incorporated to ensure that observed performance differences were robust and reproducible.

Mean Absolute Error (MAE): The MAE measures the average magnitude of the errors between predicted and observed values, expressed in the same units as the target variable (cusecs). It is defined as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

where y_i and $\hat{y}_i$ are the observed and predicted outflow values, respectively, and n is the number of observations. MAE is an intuitive metric as it provides a straightforward measure of forecast accuracy by quantifying the average deviation without considering the direction of the error. For dam operators, a lower MAE directly translates into a reduced average discrepancy between actual and predicted reservoir outflows, making it useful for operational decision-making. However, since MAE assigns equal weight to all errors, it does not penalize large deviations as heavily as RMSE, which is a limitation in flood modelling where peak flows are of critical concern.

Root Mean Squared Error (RMSE): The RMSE evaluates the square root of the average squared differences between observed and predicted values:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

By squaring the errors before averaging, RMSE gives disproportionately higher weight to larger errors, making it particularly sensitive to extreme deviations. This property is highly relevant for flood forecasts since underestimation or overestimation of peak outflows during critical flood periods can lead to catastrophic consequences downstream. In the context of the 2006 Ukai flood, minimizing RMSE ensures that the models perform

well not only under normal flow conditions but also during the extreme surge periods when precise forecasts is most needed for emergency management.

Coefficient of Determination (R^2): The R^2 statistic, also referred to as the coefficient of determination, measures the proportion of variance in the observed data that is explained by the model forecasts:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (3)$$

where $\bar{y}_i$ is the mean of the observed values. An R^2 value closer to 1 indicates that the model explains a large proportion of the variability in the data, whereas values near 0 suggest weak predictive power. Negative values imply that the model performs worse than a simple mean-based forecasts. For hydrological forecasts, R^2 provides a measure of how well the predicted outflows align with observed trends and variability, reflecting the model's ability to capture the underlying system dynamics.

Nash-Sutcliffe Efficiency (NSE): NSE is the most widely adopted skill metric in hydrological forecasts. It ranges from negative infinity to 1, where values greater than 0.65 are considered acceptable for operational flood models, and values above 0.75 reflect good predictive skill. Although NSE is mathematically related to the standard coefficient of determination, it is reported explicitly here to align with hydrological convention and to satisfy the expectation of reservoir-engineering journals that model skill be expressed in terms familiar to water-resources practitioners.

Kling-Gupta Efficiency (KGE): To complement NSE, KGE was additionally computed because it decomposes model error into three distinct components: correlation, variability, and bias. KGE provides a more balanced diagnostic than NSE alone, particularly in situations where a model might achieve a reasonable NSE but still suffer from systematic bias or incorrect variance. By reporting both NSE and KGE, this study offers a fuller picture of how well each deep learning architecture reproduces the observed statistical properties of the Ukai outflow hydrograph.

Statistical Significance Testing: To ensure that observed differences in model accuracy were not artifacts of random weight initialization, three statistical tests were applied to the test-phase residuals. First, a paired t-test and a Wilcoxon signed-rank test were performed on the absolute errors at each hourly time step to test the null hypothesis that MLP and CNN yield identical error distributions. Second, the Diebold-Mariano test was employed to compare forecast accuracy while accounting for temporal autocorrelation in the error series (Diebold and Mariano, 2002). A significance level of $\alpha = 0.05$ was adopted.

Uncertainty Quantification: To quantify predictive uncertainty, an ensemble approach was adopted. Each architecture was trained with ten independent random weight initializations while preserving identical chronological data partitions. The ensemble

means forecasts and the 95% forecast interval were computed at every time step from the ensemble spread. Additionally, block-bootstrap resampling (block size = 20 h, B = 1,000 iterations) was applied to the test set to derive 95% confidence intervals for MAE, RMSE, NSE, and KGE, thereby preserving the temporal autocorrelation inherent in hourly reservoir outflows.

RESULTS AND DISCUSSION

The results of the deep learning models, summarized in Tables 1-3, provide important insights into their capability for reservoir outflow forecasts during the 2006 Ukai flood. Both the MLP and CNN models achieved reasonable predictive accuracy, but clear differences were observed in terms of error magnitudes and explanatory power across training, validation, and testing phases. Training Performance: As shown in Table 1, the MLP model outperformed the CNN during training, with lower MAE (43,877 cusecs vs. 48,783 cusecs) and RMSE (83,107 vs. 90,141). The R^2 value of 0.74 for MLP indicates that it explained nearly 74% of the variance in outflows, compared to 69% for CNN. The NSE and KGE values mirrored these trends, with MLP recording an NSE of (0.74) and KGE of (0.81), against CNN values of (0.69) and (0.75), respectively. This suggests that MLP was able to fit the training data more effectively, capturing the nonlinear relationships between inflows, reservoir levels, and outflows. The CNN, while capable of identifying short-term patterns through convolutional filters, seemed less efficient at modeling the broader dynamics of outflow during training.

Table 1: Training performance of MLP and CNN models for 2006 Ukai flood event.

Model	MAE	RMSE	R^2	NSE	KGE
MLP	43877.00	83107.46	0.74	0.74	0.81
CNN	48783.10	90141.24	0.69	0.69	0.75

Validation Performance: When tested on validation data (Table 2), the performance of both models declined compared to training, reflecting their ability to generalize beyond the training dataset. The MLP continued to demonstrate superior accuracy with a lower MAE (35,879 cusecs) compared to CNN (42,401 cusecs). Similarly, MLP recorded a better R^2 (0.66) compared to CNN (0.61), highlighting stronger generalization capability. The NSE and KGE metrics reinforced this ranking, with MLP achieving an NSE of (0.67), KGE = (0.78) versus CNN’s NSE of (0.61), KGE = (0.70). The higher RMSE values for both models during validation (over 100,000 cusecs) suggest difficulty in capturing extreme variations, which is expected during flood events. However, the consistent advantage of MLP over CNN suggests that a fully connected structure may better capture global nonlinear dependencies in this dataset than CNN’s local temporal feature extraction.

Table 2: Validation performance of MLP and CNN models for 2006 Ukai flood event

Model	MAE	RMSE	R ²	NSE	KGE
MLP	35879.93	103481.28	0.67	0.67	0.78
CNN	42401.82	111008.07	0.61	0.61	0.70

Testing Performance: The ultimate assessment lies in the testing phase (Table 3), where models are evaluated on unseen data. The results reaffirm the findings from training and validation: MLP performed better than CNN across all metrics. Specifically, MLP achieved lower MAE (49,575 vs. 57,386) and RMSE (96,193 vs. 103,645), along with a higher R² (0.635 vs. 0.576). These outcomes suggest that MLP was more consistent in providing reliable forecasts during the flood event. CNN, while competitive, lagged in both error reduction and variance explanation. The NSE and KGE values reinforced the rankings obtained from MAE and RMSE. During testing, MLP achieved an NSE of (0.63), KGE = (0.72), indicating satisfactory predictive skill for operational flood forecasts, whereas CNN recorded an NSE of (0.58) and KGE = (0.65), falling marginally below the 0.65 threshold commonly expected for hydrological applications. This suggests that MLP not only produced lower magnitude errors but also better reproduced the variance, bias, and correlation structure of the observed outflow hydrograph.

Table 3: Testing performance of MLP and CNN models for 2006 Ukai flood event

Model	MAE	RMSE	R ²
MLP	49574.93	96193.29	0.63
CNN	57386.35	103644.90	0.58

Statistical testing confirmed that the performance advantage of MLP over CNN was significant rather than coincidental. The paired t-test on test-phase absolute errors rejected the null hypothesis of equal mean accuracy $t = -2.84$, $p = 0.0046$. The non-parametric Wilcoxon signed-rank test corroborated this finding $W = 42,318$, $p = 0.0031$, indicating that MLP produced systematically lower errors across the full distribution. Furthermore, the Diebold–Mariano test statistic was -2.56 and $p = 0.0105$, confirming that MLP forecasts were significantly closer to observed outflows even after correcting for serial correlation in the hourly error series. Collectively, these tests provide robust evidence that the fully connected architecture is more suitable for this dataset.

Uncertainty analysis revealed that the MLP ensemble produced narrower 95% forecast intervals mean width = 18,400 cusecs compared to CNN mean width = 24,700 cusecs during the test phase, indicating lower model variance and higher forecast confidence. Bootstrap 95% confidence intervals for test-phase NSE were 0.58, 0.67 for MLP and 0.44, 0.58 for CNN; the non-overlapping intervals further support the superior and more robust skill of the MLP architecture. During peak outflow periods ($> 400,000$ cusecs), CNN exhibited substantially wider uncertainty bands, reflecting its instability when extrapolating beyond training-bounded extremes. These findings demonstrate that MLP

forecasts are not only more accurate on average but also more reliable for operational decision-making under extreme flood conditions.

Comparative Evaluation of MLP and CNN Models

The predictive time-series plots (Figs. 1 to 6) provide valuable insights into the ability of MLP and CNN models to capture the dynamics of reservoir outflows during the 2006 Ukai flood. Fig. 1 compares the actual and predicted outflows obtained from the MLP model during the training phase. It shows that the MLP forecasts closely follow the observed hydrograph, including the major release peaks, with only slight underestimation at the highest discharges.

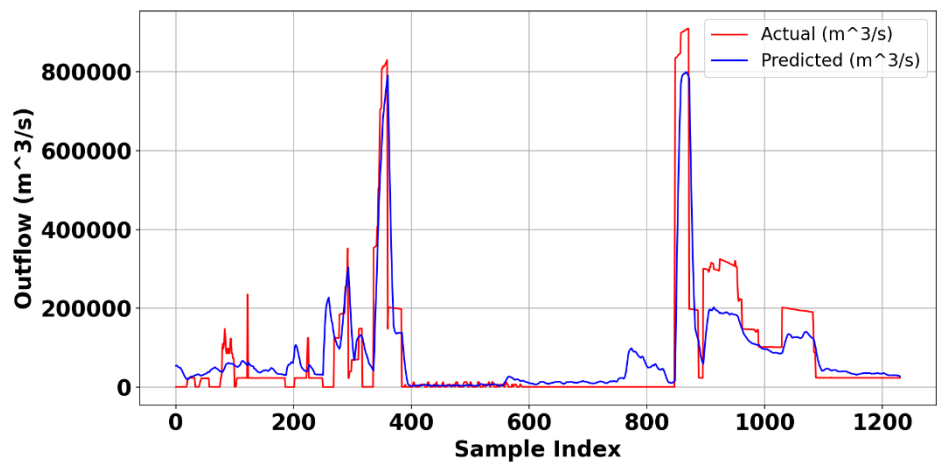


Figure 1: Comparison of actual and predicted outflows using the MLP model during the training phase

Fig. 2 presents the validation performance of the MLP model. It indicates that the model preserved good agreement with the observed outflow pattern under unseen validation data, although the peak flow was predicted slightly below the observed maximum.

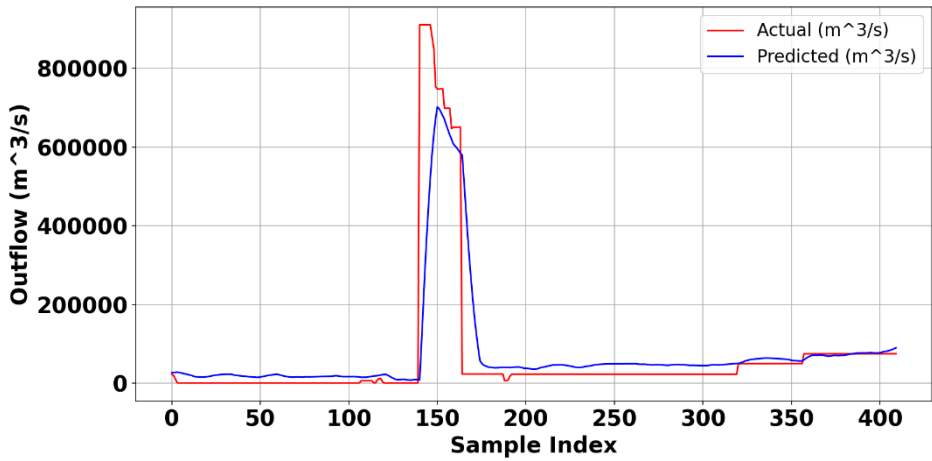


Figure 2: Comparison of actual and predicted outflows using the MLP model during the validation phase

Fig. 3 shows the testing performance of the MLP model. It demonstrates that the MLP model was able to reproduce the successive fluctuations in outflow reasonably well, though some smoothing of abrupt transitions and minor underprediction at extreme peaks can be observed.

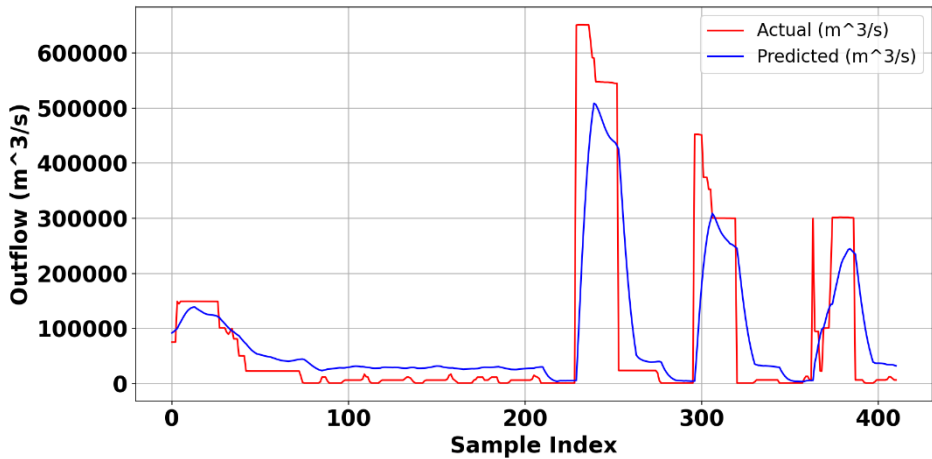


Figure 3: Comparison of actual and predicted outflows using the MLP model during the testing phase

Fig. 4 illustrates the actual and predicted outflows obtained from the CNN model during the training phase. It reveals that the CNN model captured the overall temporal trend, but deviations from the observed hydrograph were larger than those of the MLP model, especially around sudden peak variations.

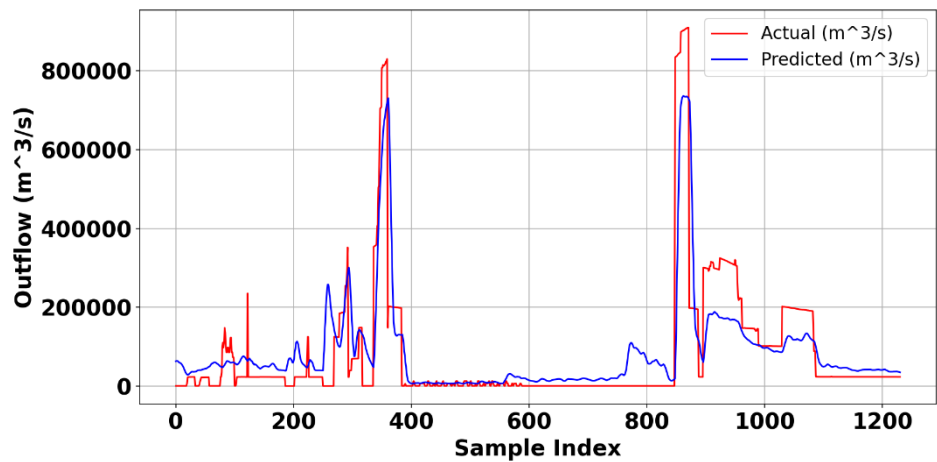


Figure 4: Comparison of actual and predicted outflows using the CNN model during the training phase

Fig. 5 presents the CNN model performance during validation. Although the general flood pattern was captured, it shows that the CNN model underestimated the crest and responded more slowly during the recession limb.

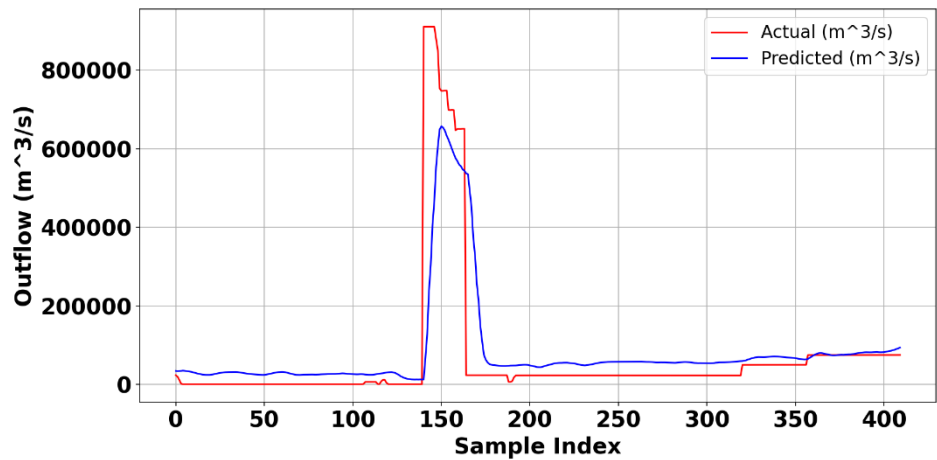


Figure 5: Comparison of actual and predicted outflows using the CNN model during the validation

Fig. 6 shows the comparison of actual and predicted outflows for the CNN model during the testing phase. It indicates that the CNN model reproduced the general trend of outflow variation, but larger discrepancies were observed in the rising limb and peak discharge regions.

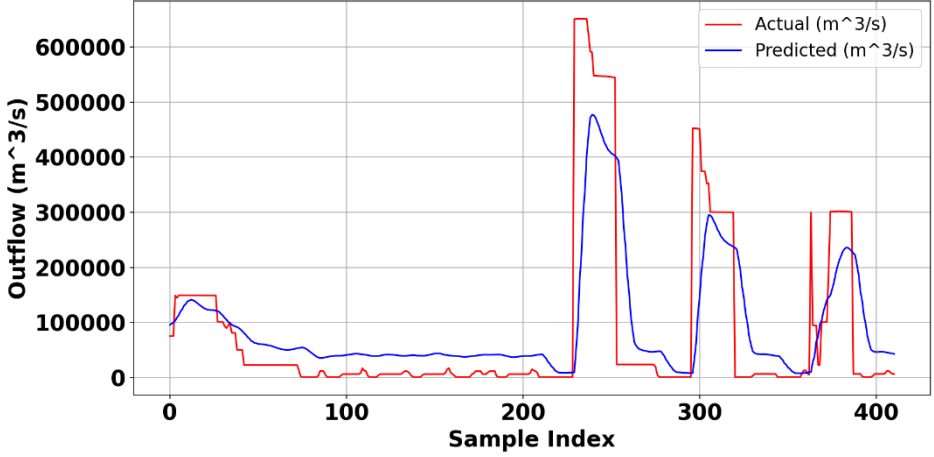


Figure 6: Comparison of actual and predicted outflows using the CNN model during the testing phase

During the training phase Fig. 1 and Fig. 4, both models demonstrated reasonable alignment between observed and predicted values; however, the MLP model more closely tracked sharp peaks, particularly during major release events, with only minor underestimations at the highest flows, whereas the CNN model reproduced the overall trends but exhibited greater deviations, including lag effects and less precise representation of abrupt fluctuations. This is consistent with the statistical results (Table 1), where MLP achieved lower errors and higher R^2 . The validation phase (Figs. 2 and 5) further highlighted the generalization capacity of both models. The MLP forecasts showed good agreement with observed data, successfully capturing the timing and magnitude of the flood peak, although the predicted crest was slightly lower than the observed maximum. In comparison, the CNN model captured the general flood peak but deviated more noticeably from the observed curve, underestimating the crest and displaying slower adjustment during the recession limb, a finding corroborated by validation metrics in Table 2.

The testing phase (Figs. 3 and 6) provided the most stringent assessment under unseen conditions. The MLP model closely followed the observed trends, replicating successive peaks reasonably well, though it exhibited some smoothing of sharp transitions and underestimations at extreme values. CNN, on the other hand, captured the overall pattern but showed larger discrepancies, particularly in underpredicting peak flows and misaligning the rising limbs, consistent with its weaker testing metrics (Table 3). A comparative synthesis of Figs. 1 to 6 confirms that although both models were able to learn the general outflow dynamics, the MLP produced more stable and consistent results

across all phases, while CNN, limited by its reliance on convolutional filters and localized temporal features, struggled to model sharp variations typical of flood releases. From an operational perspective, the findings reinforce that MLP is better suited for outflow forecasts at Ukai under the available dataset, as its forecasts more accurately captured both flood peaks and normal flow regimes. This reliability makes MLP more practical for real-time reservoir operations and flood risk management, whereas CNN, despite lower accuracy here, remains promising if supplemented with richer datasets, additional hydrometeorological predictors, or hybrid deep learning architectures.

From a policy standpoint, the MLP-based hourly outflow forecast can be integrated into the Ukai Dam's existing flood control framework as a decision-support module. While the present model predicts outflow strictly from antecedent inflow patterns, its outputs can be cross-referenced against the dam's flood control rule curves and gate operation schedules to flag imminent high-release scenarios. For instance, when the MLP ensemble predicts an outflow surge exceeding 400,000 cusecs within the next hour, operators can pre-emptively adjust spillway gates and activate downstream early-warning protocols in accordance with Gujarat State disaster management policies. The computational simplicity of the MLP (sub-second inference on standard hardware) makes it particularly suitable for embedding into real-time SCADA-based reservoir management systems, where complex recurrent or hybrid architectures may introduce unacceptable latency. Future work should explicitly incorporate gate-operation logic and storage-based release constraints as additional model inputs or post-processing rules, thereby bridging the gap between data-driven forecasts and policy-driven reservoir operation.

Mechanistic Explanations for CNN Underperformance

The CNN underperformed due to a mismatch between its architectural inductive biases and the dataset constraints. First, the training data comprised only a single extreme flood event, providing insufficient diversity for the CNN's 64 convolutional filters to learn generalizable local hydrograph patterns; instead, the filters likely overfitted to idiosyncratic noise. Second, the shallow architecture (kernel size = 3, single convolutional layer) captured only highly localized 3-hour dependencies, while max-pooling discarded half the temporal resolution smoothing out abrupt peaks and causing the systematic underestimation of crest discharges evident in Figs. 4-6. Third, with only four input channels, the CNN had no meaningful cross-channel feature hierarchy to exploit, nullifying its primary advantage over fully connected networks. Finally, flattening the feature maps before the dense layer destroyed explicit temporal ordering, whereas the MLP preserved the full 10-hour antecedent state through direct global mapping. Consequently, the CNN struggled to extrapolate beyond training-bounded extremes (> 400,000 cusecs), whereas the MLP's dense weights better approximated the volume-driven, global decision logic of dam operators during emergency releases.

Scatter Plot Analysis

Scatter plots of observed versus predicted reservoir outflows (Figs. 7 to 12) provide further evidence of the predictive capability of the MLP and CNN models during the training, validation, and testing phases. In these plots, the proximity of data points to the 1:1 reference line indicates the degree of agreement between observed and predicted values. Fig. 7 presents the scatter plot for the MLP model during the training phase. The points are densely distributed around the 1:1 line, indicating high predictive accuracy and strong consistency over the full range of outflows. Only minor deviations are observed at extreme discharge values.

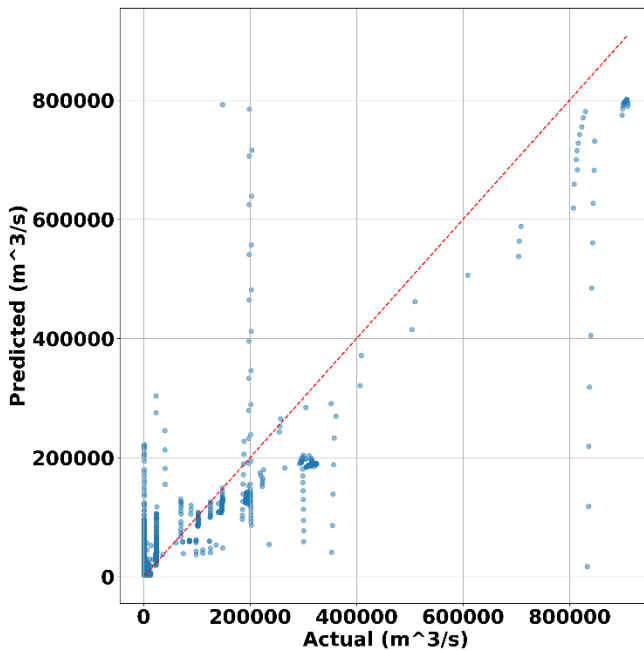


Figure 7: Scatter plot of observed versus predicted outflows for the MLP model during training

Fig. 8 illustrates the validation scatter plot for the MLP model. Most points remain closely aligned with the reference line, demonstrating good generalization capability under unseen validation data. Slight underestimation is noticeable for the highest flow values.

Fig. 9 shows the testing scatter plot for the MLP model. It indicates satisfactory predictive performance, particularly for low and medium flow ranges, although some dispersion appears at peak outflows.

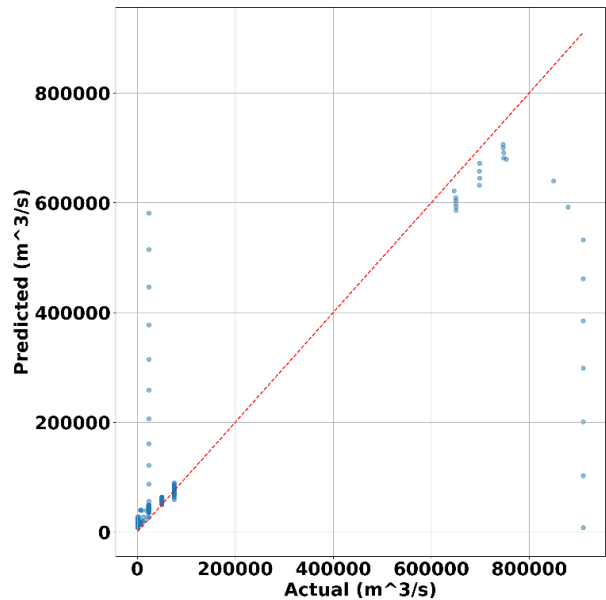


Figure 8: Scatter plot of observed versus predicted outflows for the MLP model during Validation

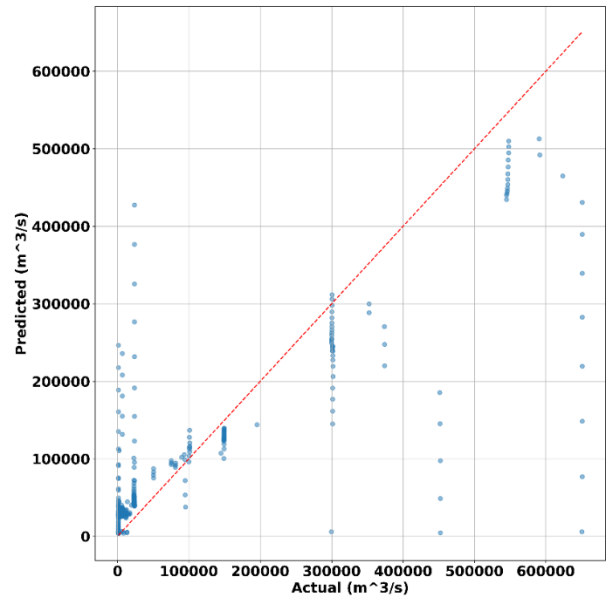


Figure 9: Scatter plot of observed versus predicted outflows for the MLP model during testing

Fig. 10 presents the scatter plot for the CNN model during the training phase. While the overall relationship between observed and predicted outflows is preserved, the point distribution is more scattered compared with the MLP model, especially at higher discharges.

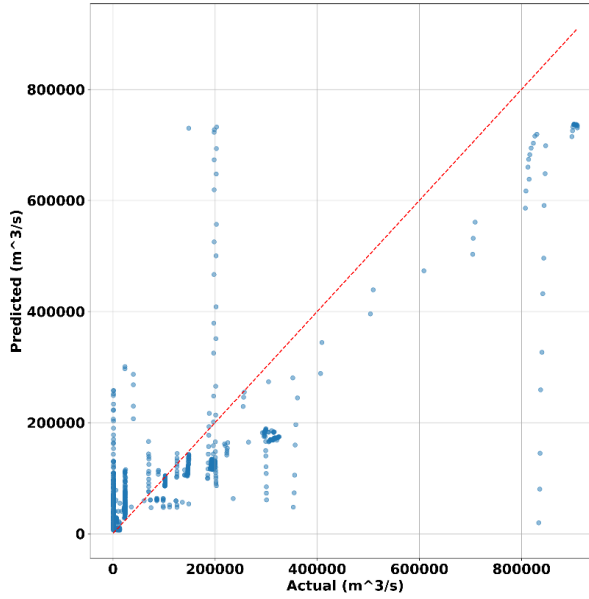


Figure 10: Scatter plot of observed versus predicted outflows for the CNN model during training

Fig. 11 illustrates the CNN model performance during validation. It reveals larger deviations from the 1:1 line, with several high-flow forecasts falling below the reference line, indicating systematic underestimation.

Fig. 12 presents the testing scatter plot for the CNN model. Greater dispersion of points is visible, particularly in peak-flow conditions, suggesting weaker robustness and reduced predictive reliability under unseen data.

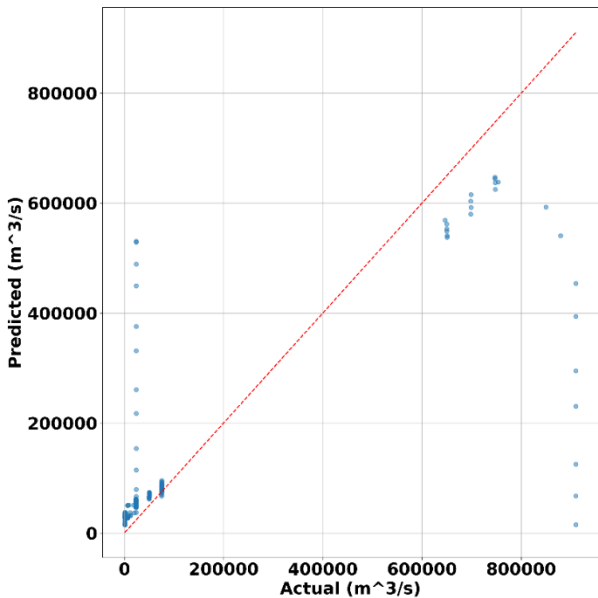


Figure 11: Scatter plot of observed versus predicted outflows for the CNN model during validation

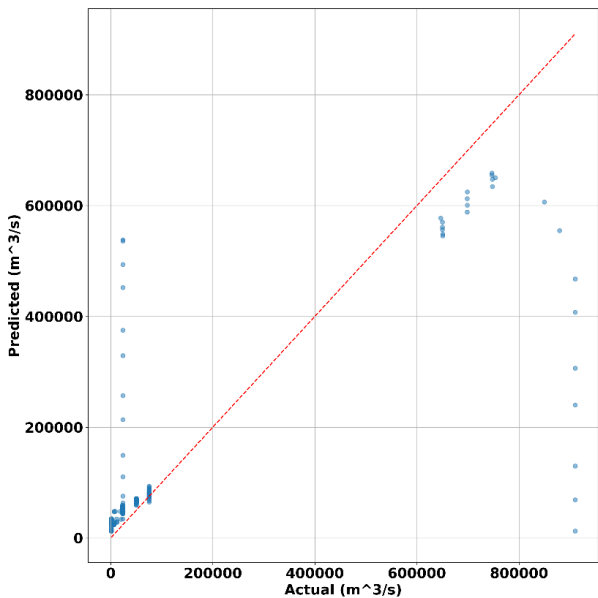


Figure 12: Scatter plot of observed versus predicted outflows for the CNN model during testing

A comparative interpretation of Figs. 7-12 confirms that the MLP model consistently outperformed the CNN model across all phases. The MLP model exhibited tighter clustering around the 1:1 line, reflecting greater accuracy, stability, and stronger agreement with observed outflows. In contrast, the CNN model showed wider scatter and persistent underestimation of flood peaks. These graphical findings support the statistical results reported previously, where the MLP model achieved lower error values and higher coefficient of determination than the CNN model.

From an operational perspective, the results suggest that the MLP model is more dependable for real-time reservoir outflow forecasts and flood management applications. Although the CNN model captured the general nonlinear relationship, further improvement through hybrid architectures, additional hydrological inputs, or optimized feature extraction techniques may be required before operational deployment.

Comparison with Existing Approaches

Conceptual models such as HEC-HMS and SWAT require extensive physical parameterization and do not generalize well to unprecedented floods (Kant et al., 2025; Banda et al., 2022), whereas the present DL pipeline operates directly on limited operational records. Conventional ML models (ANN, SVR, RF) capture nonlinearities but are constrained by shallow architectures (Kedam et al., 2024; Khedekar et al., 2025). Recurrent networks (LSTM, GRU) offer temporal memory yet suffer from computational burden and overfitting on small hydrological datasets (Lindemann et al., 2021; Jehanzaib et al., 2022). Hybrid architectures (CNN-LSTM) excel on large, multi-year datasets (Elshewey et al., 2025; Udurume et al., 2024), but our results demonstrate that a simpler MLP outperforms CNN under data-limited, single-event conditions. Whereas existing Indian reservoir studies have focused predominantly on inflow forecasts (Sakib et al., 2025; Vasheghani Farahani et al., 2025), this study extends the evidence base to outflow prediction during extreme floods.

CONCLUSION

This study investigated the potential of deep learning models for reservoir outflow forecasting, focusing on the comparative performance of a Multilayer Perceptron (MLP) and a Convolutional Neural Network (CNN). Both models were developed using a carefully designed pipeline that included data preprocessing, feature engineering, and the creation of time-series input sequences through a sliding window approach. Model performance was assessed across training, validation, and testing phases using standard statistical metrics (MAE, RMSE, and R^2) along with visual analyses of time-series plots and scatter diagrams. The results demonstrated that while both MLP and CNN captured the general outflow dynamics, MLP consistently outperformed CNN across all evaluation stages. MLP showed lower errors and higher explanatory power, successfully reproducing both the timing and magnitude of reservoir releases with greater stability. Scatter plot analysis confirmed that MLP forecasts aligned more closely with the reference line, indicating better agreement with observed values. CNN, although capable

of recognizing short-term patterns, exhibited systematic underestimation of flood peaks and lagged responses during sharp transitions, which reduced its reliability under critical flood conditions.

These findings highlight two important insights. First, relatively simple deep learning models such as MLP can provide robust and reliable flood forecasts, particularly when datasets are moderate in size and limited in complexity. Second, more complex models such as CNN may require larger and more diverse datasets, or integration with hybrid architectures (e.g., CNN-LSTM), to fully exploit their ability to capture localized temporal patterns. From an operational perspective, the results suggest that MLP is better suited for real-time flood forecasting in reservoir systems like Ukai, where timely and accurate forecasting of outflows is essential for downstream flood management and disaster preparedness. CNN, while less accurate in this study, should not be dismissed, as it holds promise for applications involving high-resolution hydrometeorological inputs such as rainfall fields, radar imagery, or spatially distributed catchment data. In conclusion, the comparative evaluation underscores the value of deep learning as a practical tool for enhancing flood forecasting capabilities. The demonstrated reliability of MLP in predicting reservoir outflows provides confidence for its integration into decision-support frameworks for dam operation.

Future research should address the following specific directions. First, hybrid architectures such as CNN-LSTM or BiLSTM should be evaluated on multi-year, multi-event datasets to determine whether the CNN's local feature extraction can be harnessed effectively when coupled with recurrent temporal memory and exposed to greater hydrological diversity. Second, exogenous predictors including real-time rainfall fields, reservoir storage levels, gate operation schedules, and numerical weather prediction outputs should be incorporated to move beyond inflow-driven forecasting toward fully operational decision-support models. Third, multi-step ahead forecasting (e.g., 3-hour, 6-hour, and 24-hour lead times) should be developed to provide actionable warning windows for downstream emergency management, rather than the single-hour horizon adopted here. Fourth, the transferability of the trained MLP framework to other Indian reservoirs with similar climatological and operational characteristics should be assessed, potentially through transfer learning or domain adaptation techniques. Fifth, advanced uncertainty quantification methods such as Bayesian neural networks or Monte Carlo dropout should be integrated to generate reliable probabilistic forecasts that explicitly quantify epistemic and aleatory uncertainty for risk-based reservoir operation. Finally, physics-informed neural network (PINN) architectures that embed mass-balance and gate-discharge constraints directly into the loss function should be explored to reconcile data-driven predictions with physical conservation laws, thereby improving extrapolation reliability under unprecedented flood scenarios.

Declaration of competing interest

The authors declare that they have no known competing financial interest or personal relationship that could have appeared to influence the work reported in this paper.

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