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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN PREDICTION OF SCOUR - A REVIEW

DHIMMAR P.[1*], POPAWALA R.[2]

[1] Research Scholar, Department of Civil Engineering, Gujarat Technological University, Ahmedabad, Gujarat, India
[2] Professor, Department of Civil Engineering, C.K. Pithawala College of Engineering and Technology, Surat, Gujarat, India

(*) pdhimmar17@gmail.com

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ABSTRACT

Scour around bridge piers is one of the major attributes of bridge failure. Scour prediction has primarily depended on physical modelling and empirical formulas. Traditional empirical formulas are often insufficient for accounting for the intricate interactions of hydraulic, sediment, and geometric parameters. This paper presents a state-of-the-art review of artificial intelligence and machine learning approaches to local scour prediction, spanning the literature from 2004 to 2025, with a focus on ML, hybrid, and physics-informed models. The study reviewed various models, including artificial neural networks, adaptive neuro-fuzzy inference systems, support vector machines, gene expression programming, particle swarm optimization-based hybrids, and physics-informed neural networks, and compared early-warning Internet of Things systems. The paper offers a comprehensive evaluation of the strengths and limitations of existing machine learning models for scour estimation, considering factors such as data availability, interpretability, and adaptability to changing environmental conditions. The study also emphasizes recent advances such as deep learning, long short-term memory, convolutional neural network architectures, and physics-guided networks. Case studies and methodological comparisons are supplied to show predictive supremacy and limitations of varying approaches. The study evaluates performance, challenges, and future directions like physics-constrained learning, digital twins, and real-time monitoring. AI and physics-informed models outperform traditional empirical equations in bridge scour prediction and enable real-time monitoring through digital twin frameworks.

Keywords: Artificial intelligence (AI), Artificial neural networks (ANN), Machine learning (ML), Pier, Scour, Support vector machines (SVM).

INTRODUCTION

Sediment erosion caused by flowing water around bridge piers is termed bridge scour (Ghasemi and Heidarnejad, 2023; Dalal and Deb, 2024; Dalal and Achour, 2025). The traditional approaches of Hydrologic Engineering Centres (HEC) are based on empirical equations obtained using controlled flumes, which are inaccurate in field conditions. However, HEC has been widely used in solving several problems of hydraulics, especially related to hydrology field (Faregh and Benkhaled, 2016; Atallah et al., 2024).

Artificial Intelligence (AI) and Machine Learning (ML) are flexible methods involving numerical simulations that can represent natural, nonlinear, and site-dependent behaviour without assuming simplified physical equations; these methods focus on hydraulics and water engineering, so its AI/ML studies are applied to environmental and hydraulic problems rather than purely theoretical AI research. The following relevant articles leverage machine learning algorithms, neural networks, support-vector machines, gradient boosting, etc., part of the broader field of artificial intelligence (Fellous et al., 2023; Zaidi et al., 2023; Bouriche et al., 2023; Fatemi and Molavi, 2025).

The integration of Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Gene Expression Programming (GEP), and Support Vector Machines (SVM/SVR) has significantly advanced the field of hydraulics by enhancing the capability to model highly nonlinear, multivariate, and uncertain hydraulic processes that are often inadequately described by traditional empirical or deterministic approaches; ANN models, for example, have demonstrated strong predictive performance in rainfall-runoff simulation and hydrological forecasting as shown by Molavi (2025), while their application to reservoir thermal regime modelling has provided improved accuracy and sensitivity interpretation in surface water temperature studies (Belouz et al., 2025), and their effectiveness in long-term discharge, water quality relationship analysis under semi-arid climatic variability has been confirmed, and sustainable hydraulic engineering design, by Chabokpour et al. (2025a; 2025b); similarly, ANN-based approaches have enhanced sediment transport estimation reliability in river basins, reducing dependence on simplified empirical sediment formulas (Bougamousa et al., 2022); beyond pure neural networks, ANFIS has contributed a hybrid framework that combines learning capability with fuzzy rule-based reasoning, improving interpretability and robustness in hydraulic applications such as sediment removal efficiency prediction in vortex settling basins (Ansari et al., 2024) and reservoir temperature modelling (Belouz et al., 2025), while also strengthening discharge-water quality modelling under long historical datasets (Chabokpour et al., 2025b); more advanced evolutionary techniques such as Gene Expression Programming have further contributed by generating explicit predictive hydraulic equations rather than remaining black-box models, thus improving transparency and physical interpretability in estimating key hydraulic parameters such as Manning's roughness coefficient (Chaplot et al., 2021); additionally, Support Vector Machines and Support Vector Regression approaches have strengthened hydraulic modelling through structural risk minimization and improved generalization capacity, particularly in runoff prediction contexts where SVM was evaluated alongside neural networks (Molavi, 2025), in advanced soft-computing frameworks for discharge-water quality dynamics (Chabokpour et al., 2025b), and in wastewater sludge production forecasting using hybrid decomposition-machine learning techniques that included SVR (Zaidi et al., 2023); collectively, these contributions highlight a clear paradigm shift within hydraulic engineering from empirical and semi-theoretical formulations toward adaptive, data-driven, and hybrid intelligent modelling frameworks that enhance predictive accuracy, manage environmental uncertainty, and support more reliable design and operational decision-making in water resources systems.

Researchers have explored a variety of approaches to predict scour depth, from traditional ML like Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), to more advanced techniques, Gene Expression Programming (GEP) and Support Vector Machines (SVM). In recent years, deep learning (Long Short-Term Memory (LSTM)) networks and Convolutional Neural Networks (CNN) have also been applied. Hybrid approaches, such as those combining Genetic Algorithms (GA), ANN, and Particle Swarm Optimization (PSO), have shown enhanced precision. More cutting-edge strategies include physics-inspired neural networks (SPINNs) and real-time forecasting systems that integrate Internet of Things (IoT) technologies. At present, the primary approaches used to investigate scour around bridge piers include experimental studies, theoretical analyses, and numerical simulations. A detailed review of these research areas can be found in the works of Baranwal et al., (2023); Hong et al., (2012); Kumar et al., (2012); Singh et al., (2020); and Zaid et al., (2019).

The review includes studies (2004-2025) that apply AI and ML techniques, such as ANN, ANFIS, SVM, GEP, PSO-hybrid methods, physics-informed neural networks, deep learning, and ensemble learning, to bridge scour prediction. The works integrate laboratory, field, or numerical datasets into predictive frameworks, emphasize physics-constrained or hybrid approaches linking empirical hydraulic principles with ML models, and address digital twins, real-time monitoring, or sensor-based scour detection.

Baranwal et al. (2024) reviewed the problem of local scour around bridge piers and its implications for structural stability. The study synthesized the effectiveness of various scour countermeasures, including riprap, collar plates, slots, submerged vanes, and sacrificial piles, applied individually or in combination. The authors highlighted that countermeasure selection depends on flow velocity, bed sediment characteristics, and bridge geometry, with device performance strongly influenced by installation depth and position. Review showed that scour protection measures are more effective under clear-water scouring conditions ($V/V_c \leq 1$) than live-bed scouring conditions, and that combined flow-altering devices, particularly collar plates used with slots, provide greater scour reduction than single countermeasures.

Early studies comparing ANN, ANFIS, general regression neural networks (GRNN), and feedforward neural networks (FFNN) found that GRNNs outperformed FFNNs for pier-related applications. Bateni et al. (2007) demonstrated strong ANN performance, identifying channel width and sediment size as effective predictors, while ANFIS performed well under clear-water conditions. Oğuz et al. (2022) further improved the GP accuracy ($R^2 > 0.8$) using cluster analysis to give cluster-specific scour formulations that outperformed standard empirical formulations. The Fig. 1 illustrates a general framework for applying ML methodologies within engineering disciplines.

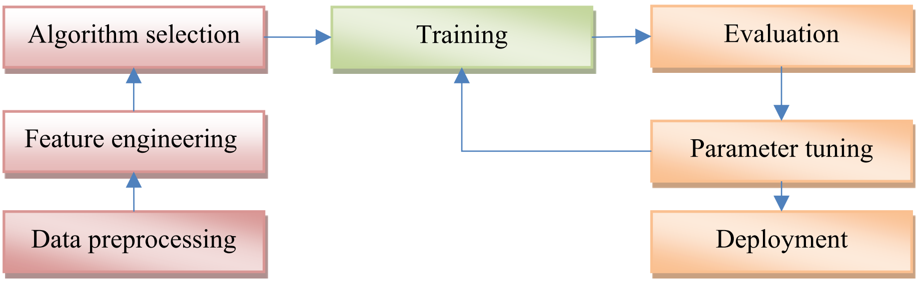

Figure 1: Conceptual framework for ML application (Rahman et al., 2025)

Achour et al. (2022) investigated the hydraulic response of flow around structures and its influence on local scour development. The study demonstrated that increased flow intensity significantly amplifies scour depth and highlighted the strong dependence of scour on hydraulic conditions and structural geometry. By improving empirical approaches, the authors achieved better agreement with observed and experimental data than conventional prediction methods. While the findings provide useful guidance for scour prediction and hydraulic design, the study is limited by simplified modelling assumptions, restricted hydraulic conditions, and the lack of long-term field data for extreme flow events. Ardiclioglu et al. (2022) investigated the influence of bridge configuration on river hydraulics, focusing on changes in water surface profile and flow velocity induced by the backwater effect. Using experimental measurements and HEC-RAS simulations, the study examined five discharges and four bridge opening ratios. Results showed substantial velocity reduction upstream (92.59%) and a smaller reduction downstream (11.95%), with HEC-RAS significantly overestimating upstream velocities.

Sultana et al. (2025) investigated bridge pier scour as a major source of structural instability. The study evaluated twelve collar shapes with respect to placement, normalized dimensions, and scour reduction efficiency, and assessed effective collar elevations for oblong and circular configurations. Based on a comparative analysis of hydraulic and geometric parameters, the authors concluded that oblong collars provide the most effective reduction in local scour, particularly below the bed level, outperforming circular and octagonal collars.

Dang et al. (2020) determined vital input ratios, such as channel width-to-flow depth (b/y) and particle size-to-flow depth (d_{50}/y), using PSO. ANN LM and ANN for the prediction of clear water scour and GA-ANN using previously trained data flow, pier geometry, skew, and sediment size attained greater accuracy in varied scenarios; ensemble and tree based strategies (Marulasiddappa et al., 2024), SVM (Gaussian/quadratic) kernels (Pal et al., 2011), BO-optimized XGBoost, MARS, and GMDH (Rahman et al., 2023), showed a good performance with a lower RMSE and higher percentage of R^2, with GTB and MARS performing significantly better for specific abutment morphologies; and, physics-inspired and transferable models as in SPINNs (Chen et al., 2025) where empirical scour equations are embedded into the deep learning frameworks to help minimize forecasting errors by as much as 50% and improve generalizability cross site, and LSTM/CNN architectures to long term sensor data (Hashem et al., 2024; Yousefpour et al., 2022) high temporal prediction accuracy (MAE = 0.1-0.5) with effective early warning capabilities and reduced computational cost.

Kumar et al. (2023) evaluated multiple ML methods for streamflow prediction in the Garudeshwar watershed, emphasizing their relevance to flood management and water supply planning. Using temporally lagged and seasonally contextualized features tailored to Indian climatic conditions, the study compared algorithms including CatBoost, XGBoost, LGBM, Random Forest, and neural networks. CatBoost consistently outperformed other models across MAE, RMSE, and R^2 for both training and testing datasets, while XGBoost and LGBM showed higher error rates for moderate to high inflows. The findings demonstrate CatBoost's robustness in hydrological time-series modelling and highlight the broader potential of ML for improving hydrological predictions.

Over the past decade, AI has developed as a transformative technology, largely propelled by rapid developments in big data and high-performance computing. A core component of AI, ML, is defined as a computational paradigm capable of autonomously learning and improving its performance through experience, without the need for explicit programming. While previous papers have given practitioners a general overview of how ML techniques are used across several branches of civil engineering, a clear knowledge gap remains regarding their specific application to predicting scour around bridge piers.

In recent years, the publications applying ML methods to scour-related problems in bridge engineering have grown substantially. Given the increasing prevalence of ML across scientific disciplines, it is expected that its adoption in scour analysis research will continue to expand. Consequently, a detailed investigation into how ML has been applied to the calculation of scour around bridge piers is both essential and timely.

Ensemble learning approaches such as Random Forest, Gradient Boosting, and XGBoost were not explicitly emphasized in this review due to their limited application within the bridge scour prediction literature relative to neural network-based and physics-informed models. The thematic focus of this review on the contrast between data-driven and physics-informed or hybrid AI approaches, priority was placed on models that explicitly incorporate physical knowledge, empirical scour formulations, or digital twin integration.

Digital twins for bridge scour are conceptualized as dynamic, virtual replicas of physical bridge-river systems that continuously update using real-time and near–real-time data streams, such as flow velocity, sediment transport, and riverbed elevation. Unlike static numerical models, these twins evolve alongside the physical system, reflecting changing hydraulic and geomorphic conditions. The primary purpose of a bridge scour digital twin is to simulate the initiation and progression of scour processes, predict risk levels under varying hydraulic and flood conditions, and enable proactive, data-driven decision-making to support bridge safety management, inspection planning, and maintenance interventions. Implementations and conceptual designs typically integrate the following components: The bridge scour digital twin integrates multi-layered sensing, modeling, and simulation capabilities. An IoT-enabled sensor and data acquisition layer provides continuous monitoring through MEMS-based vibration and tilt sensors, embedded scour depth probes, and vision-based systems enhanced with deep learning frameworks, enabling real-time observation of structural response and hydraulic-sediment interactions. AI and ML, including LSTM networks and CNNs, are utilized for temporal and spatial pattern recognition. Meanwhile, hybrid PINNs incorporate empirical scour formulations to enhance physical consistency and generalization. These data-driven models are coupled with hydrodynamic and morphodynamic solvers such as HEC-RAS to simulate local flow and sediment transport conditions around bridge foundations. A centralized data integration and update mechanism synchronizes sensor data, simulation outputs, and predictive models, allowing continuous model updating, adaptive recalibration during extreme events, and alignment between physical observations and virtual predictions.

Although digital twins for bridge scour are not yet standardized, several practical implementations are emerging. Early warning digital twins integrate real-time sensor data with AI-based scour prediction models to operate in near real time and issue alerts when projected scour depths approach critical thresholds during flood events. Hybrid monitoring and simulation twins integrate hydrodynamic modeling, AI-driven sensor analytics, and laboratory- and field-scale validation.

This review paper aims to fill that gap by offering an inclusive assessment of ML approaches used for bridge scour prediction. It integrates findings from studies to evaluate the performance and efficiency of various ML models. It identifies key gaps in existing literature and suggests promising directions for future research.

PRACTICAL CASES

The reviewed literature was classified according to data source and methodological integration into four categories: laboratory, field, numerical, and hybrid studies. Laboratory investigations primarily employed controlled flume experiments with scaled bridge pier models to generate benchmark datasets for ML training, including ANN, ANFIS, and SVM, albeit with inherent scale limitations. Field-based studies relied on real-time bridge monitoring using sensor technologies and ultrasonic probes, providing sparse yet high-value datasets for validating AI predictions and supporting digital twin development. Numerical studies utilized CFD and hydrodynamic solvers (FLOW-3D) to produce synthetic datasets and enable scenario analysis under diverse hydraulic conditions. Hybrid approaches integrated empirical scour equations (HEC-18) with ML corrections, physics-informed neural networks, and emerging digital twin frameworks that couple sensor data, AI, and CFD simulations.

Advanced AI techniques have been effectively applied to pier scour prediction, demonstrating significant performance improvements over traditional methods. Numerous real-world and laboratory-based studies show promising results: Pal (2019) employed a dataset of 232 real-world scour depth extents 154 for training and 78 for testing using input variables such as flow depth, velocity, sediment size, and pier geometry to train a deep neural network (DNN) with three hidden layers (100, 80, 50 nodes) via adaptive learning rate optimization, achieving superior performance (R = 0.957; RMSE = 0.306 m) compared to a traditional single hidden-layer ANN (R = 0.938; RMSE = 0.388 m), thereby demonstrating enhanced non-linear modelling capabilities of deeper architectures even with modest datasets. Sreedhara et al. (2019) developed a hybrid PSO-ANN trained on laboratory and field data encompassing both clear-water and live-bed scour circumstances, utilizing input variables such as median sediment size (d_{50}), sediment quantity, flow velocity, pier shape, and time, where particle swarm optimization was employed to optimize neural network weights, and performance evaluated using Correlation Coefficient (CC), Normalized RMSE, Nash–Sutcliffe Efficiency (NSE), and Normalized Mean Bias (NMB) demonstrated superior accuracy compared to conventional regression and standard ANN across varying pier geometries and scour regimes. Fujail (2022) developed a GA-ANN to estimate upstream scour depth using literature-derived datasets with six input variables: pier length, pier width, flow velocity, flow depth, pier skew, and median sediment size, where genetic algorithms optimized network parameters, resulting in superior prediction accuracy compared to empirical equations and a standalone ANN.

Mehta et al. (2020) studied the influence of flow conditions, pier geometry, pier size, and sediment characteristics on scour depth in alluvial streams. Using a hydraulic approach, the stability of the Sardar Bridge on the Tapi River was assessed by evaluating scour profiles under various flood events and estimating scour depths at piers and abutments based on flow velocity. The results indicated that constructing a new parallel bridge upstream of the existing structure provides greater hydraulic stability than downstream placement, while accurate scour depth estimation during design can substantially reduce foundation construction costs.

Baudhanwala et al. (2024) investigated the performance of ML for precipitation forecasting in the flood-prone Ambica River Basin of South Gujarat, India. The study compared Support Vector Regression, Random Forest, Decision Tree, and Multiple Linear Regression using long-term meteorological data (1981-2021) and performance metrics. Results showed that SVR and Random Forest consistently outperformed conventional models, achieving strong predictive accuracy across stations. The findings demonstrate the effectiveness of ML for precipitation prediction in monsoon-dominated, semi-arid regions, while also highlighting limitations related to geographic specificity, input variable selection, and the need for future integration of advanced deep learning and broader climate drivers.

Each modelling approach highlights distinct methodological strengths: deep neural networks (DNNs) and PSO/GA-optimized ANN hybrids perform effectively on static, scattered datasets due to their capacity for non-linear mapping and global optimization, SPINNs integrate empirical domain knowledge, enabling transferable and interpretable modelling across diverse bridge sites, LSTM networks and CNNs are well-suited for real-time forecasting tasks using temporally sequenced sensor data, offering robust predictive performance in dynamic environments.

IoT-enabled real-time monitoring systems have integrated vibration-based MEMS sensors with Mask R-CNN image analysis from CCTV feeds to track scour development during flood events, while a hybrid hydrodynamic AI simulated scour evolution and demonstrated effective early warning capabilities through successful validation in both laboratory and field situations.

Physics-constrained and physics-guided learning approaches address the fundamental data scarcity challenge in bridge scour prediction, where field-scale measurements are limited due to the hazard of flood events. Purely data-driven machine learning models, therefore, struggle to generalize beyond observed conditions. By embedding empirical scour equations and fundamental conservation laws governing flow and sediment transport into learning architectures, physics-guided models introduce strong prior knowledge that reduces dependence on large datasets and acts as an effective against overfitting. Table 1 illustrates the relative feasibility of ML and physics-guided approaches when data are scarce.

Table 1: Comparative feasibility under low-data regimes

Approach	Data Requirements	Generalization Ability	Error Reduction	Operational Feasibility
Pure ML	High - needs large, diverse field datasets	Low - struggles to extrapolate beyond training data	Moderate - prone to overfitting with sparse data	Limited - difficult to deploy in data-scarce river systems
Physics-Constrained ML	Moderate - can work with small datasets since physics reduces hypothesis space	High - guided by universal fluid mechanics and sediment transport laws	High - studies show ~40–50% error reduction compared to pure ML	Strong - feasible for early warning systems with limited sensor data
Hybrid Physics-Guided ML	Moderate to High - combines empirical/CFD baselines with ML corrections	Very High - site-specific calibration improves transferability	Very High - ensemble approaches outperform both pure ML and empirical models	Strongest - practical for operational bridge management, especially with synthetic CFD data augmentation

Physics-constrained and physics-guided learning approaches are highly feasible in low field-data regimes because they exploit universal hydraulic and sediment-transport principles to constrain model behaviour and reduce data dependence. Their effectiveness depends on the intelligent integration of empirical formulations and CFD-derived knowledge, careful calibration using available field observations, and uncertainty-aware implementation to support reliable, risk-informed operational decision-making.

Coverage across AI models was ensured by organizing the reviewed studies into methodological groups, including classical ML, optimization-enhanced hybrids, deep learning architectures, and physics-informed approaches. Within each, studies were synthesized comparatively rather than selectively, with emphasis on reported performance metrics, dataset characteristics, and methodological strengths and limitations. In addition to predictive accuracy, operational relevance-including computational demand, data requirements, and feasibility for sensor integration or digital twin deployment-was evaluated, enabling a balanced assessment beyond model popularity alone. Table 2 synthesizes the comparative evaluation of diverse AI/ML paradigms.

Table 2: AI/ML Approaches in Scour Prediction

Model Type	Typical Dataset Source	Strengths	Limitations	Operational Relevance
ANN	Laboratory datasets; small-scale flume experiments	Flexible, widely applied; good at capturing nonlinear scour dynamics	Needs large datasets; prone to overfitting	Early benchmark model, widely cited but less robust for field-scale
ANFIS	Laboratory, limited field data	Combines rule-based reasoning with learning; interpretable	Sensitive to input fuzzification; moderate scalability	Useful for hybrid monitoring, but less common in recent works
SVM	Small datasets; lab/field	Strong with limited data; avoids overfitting	Less effective with highly nonlinear scour processes	Good for sparse-data regimes, but less adaptable
GEP	Laboratory datasets	Symbolic regression; generates explicit equations	Complex tuning; limited adoption	Provides interpretable models, but niche usage
PSO-Hybrid	Laboratory, numerical	Improves parameter optimization; reduces training error	Computationally intensive; site-specific calibration needed	Effective in hybrid setups, but not widely standardized

PINNs/SPINNs	Lab, synthetic CFD, sparse field	Embed hydraulic laws; generalize well with limited data	Require careful physics formulation; still emerging	Highly promising for digital twins and low-data regimes
Deep Learning (CNN, LSTM, Ensembles)	Large lab datasets; synthetic CFD	Excellent at capturing temporal/spatial scour evolution	Data-hungry; black-box nature limits explainability	Strong potential for real-time monitoring, especially with sensor integration

ARTIFICIAL NEURAL NETWORK

An ANN is a computational model inspired by the structure and operation of the human brain. These systems consist of interrelated processing units, or neurons, that work collectively to identify patterns, learn from data, and generate predictions or decisions based on that information. However, it is only within the past decade that ANNs have gained significant attention, becoming a foundational component of modern artificial intelligence technologies.

An ANN typically comprises three main layers: an input layer, one or more hidden layers, and an output layer. The input layer receives raw data, which is then processed through the hidden layers, where complex transformations occur. Finally, the output layer produces the model's prediction or decision. Various architectures of ANNs exist, each designed to address specific types of problems or data structures.

The adoption of AI-based scour prediction is constrained by several regulatory and standardization challenges. A key issue is the lack of standardized validation and benchmarking protocols, as AI models trained on limited laboratory and field datasets can produce site-dependent predictions, making regulatory certification difficult. Data quality and availability further complicate approval, since field-scale scour data are sparse and noisy, and there are no clear guidelines on minimum data requirements or the admissibility of synthetic CFD-generated datasets (Yousefpour et al., 2023). Integration with existing bridge design codes, such as HEC-18 or IRC provisions, remains limited because these frameworks are based on empirical equations and do not formally recognize AI-derived predictions, preventing their legal substitution in design or assessment (Yousefpour et al., 2023). Additionally, the opacity of black-box models raises concerns regarding transparency and explainability, necessitating standards for explainable AI in safety-critical infrastructure. Unclear liability in the event of system failure and underdeveloped cybersecurity and data governance standards for IoT-enabled monitoring systems further hinder operational deployment, underscoring the need for regulatory frameworks that address accountability, certification, and secure data management before widespread adoption is feasible. Table 3 highlights issues, identified gaps, and directions for future improvements.

Table 3: Standardization Requirements for AI-Based Scour Prediction

Issue	Current Gap	Needed Standardization
Validation	No benchmarks for accuracy	Unified test datasets & error thresholds
Data Quality	Sparse, site-specific	Guidelines for minimum data and synthetic augmentation
Code Integration	AI not recognized in design codes	Formal inclusion in HEC-18, IRC, Eurocodes
Transparency	Black-box predictions	Explainable AI standards
Liability	Undefined responsibility	Clear certification and accountability frameworks
Cybersecurity	Weak IoT/cloud safeguards	Infrastructure-grade security protocols

Model generalizability in AI-based scour prediction is strongly influenced by how key physical factors are represented in training datasets and model formulations. Across the reviewed studies, sediment properties are often oversimplified, with most models relying on a single characteristic grain size (d_{50}) and rarely accounting for sediment gradation or cohesion. Cohesive and mixed-bed conditions are particularly underrepresented, as the majority of datasets originate from non-cohesive sandy beds in laboratory flumes, limiting applicability to prototype bridges founded in clayey or heterogeneous sediments. Pier geometry is more consistently included, typically through diameter and basic shape descriptors; however, complex configurations such as pile groups, skewed piers, and pier caps are seldom represented, reflecting the idealized nature of laboratory experiments. Flow unsteadiness represents the weakest dimension of generalization, as most AI models are trained under steady-flow assumptions, with limited consideration of flood hydrographs, seasonal variability, or transient hydraulic loading. While emerging approaches using IoT-enabled monitoring and CFD-based simulations show potential for capturing unsteady flow effects, their integration into ML training remains limited. Consequently, reviewed models demonstrate the strongest generalization with respect to simplified pier geometry, reduced robustness for sediment heterogeneity, and poorest transferability under unsteady flow conditions, explaining persistent challenges in applying AI-based scour predictions to real-world bridge environments.

AI-based scour prediction is promising but cannot yet replace code-based methods due to regulatory and standardization gaps. Moving forward, agencies must establish validation benchmarks, explainability requirements, and liability frameworks before AI can be fully integrated into bridge safety management.

SUPPORT VECTOR MACHINE

The SVM is widely regarded as one of the most powerful and reliable techniques in supervised learning. It is particularly effective for smaller datasets that exhibit complex patterns. SVM is a versatile ML approach applicable to both classification and regression tasks, though it is most renowned for its strong performance in classification problems.

Originally, the method was developed based on the principle of structural risk minimization. The earliest version of SVM was designed to identify an optimal hyperplane that maximizes the margin between data classes in the feature space, a Support Vector Classification (SVC). Subsequently, the framework was extended to handle regression problems, forming the basis of Support Vector Regression.

In situations involving nonlinear relationships, where data points cannot be separated using a straight hyperplane, SVM employs a technique known as the kernel trick. This approach maps the input data into a higher-dimensional feature space, enabling the algorithm to construct an optimal separating hyperplane that effectively captures the underlying data structure (Pérez et al., 2004).

DEEP LEARNING

In recent years, an advanced subset of neural networks known as deep learning has gained significant attention as an effective solution for managing large and complex datasets. This growing interest is primarily driven by two key advantages. First, deep learning is highly scalable with respect to data volume; its performance tends to improve as the dataset size increases. In contrast, conventional ML algorithms, often referred to as shallow learning methods, typically reach a performance plateau even when additional training data are provided. Second, deep learning can automatically extract relevant features directly from raw data, thereby minimizing the need for manual feature engineering. This feature makes them particularly well-suited for high-dimensional and data-intensive applications. Among the most commonly used deep learning algorithms in supervised learning are: DNN, Recurrent Neural Networks (RNN), and CNN.

The primary distinction between an ANN and a DNN lies in the network depth. DNNs consist of two hidden layers, as illustrated in Fig. 2, and their ability to model complex relationships generally increases with the number of hidden layers (Hamdia et al., 2021).

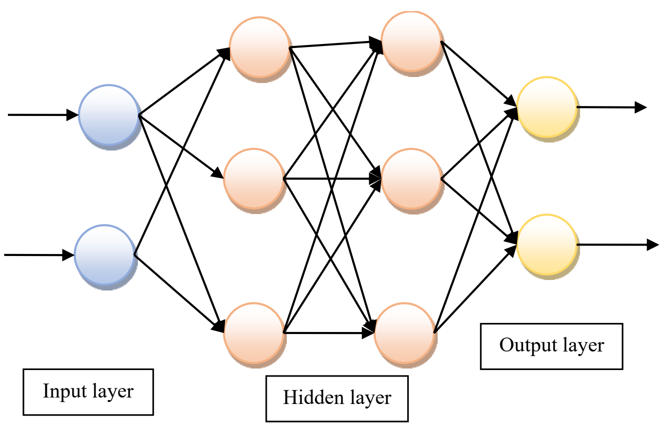

Figure 2: A typical architecture of a DNN

Kumar et al. (2023) reviewed the application of deep learning in flood forecasting and management, highlighting its potential to improve prediction accuracy and decision-making. The study examined commonly used data sources, deep learning architectures, and evaluation metrics, while critically assessing their strengths and limitations. The review also outlined future research directions, such as uncertainty-aware forecasting, multi-source data integration, hybrid modeling approaches, and improved transparency.

UTILIZING MACHINE LEARNING MODELS TO FORECAST BRIDGE SCOUR

AI/ML methods consistently outperform empirical formulas in accuracy, particularly for nonlinear scour conditions. Black-box like LSTM offer high predictive power but low interpretability, whereas SPINNs and GEP strike a balance between transparency and performance. Challenges include data requirements, transferability, and computational cost. The scope of AI/ML in scour prediction lies in their ability to provide data-driven alternatives to traditional empirical equations by capturing complex, nonlinear relationships from historical field and laboratory data; over the past two decades, diverse models have been explored, including ANN, SVM, GRNN, and RBF networks; advanced techniques (ANFIS, GEP, LSTM, and CNN); and hybrid frameworks (GA-ANN, PSO-ANN), Physics-Informed Neural Networks (PINNs).

Jatoliya et al. (2024) addressed scour-induced instability in offshore structures by estimating scour depths using physics-based numerical modelling and ML approaches. ML models were trained on datasets from previous studies and evaluated using statistical performance measures, while numerical simulations were conducted for current-only and combined wave–current conditions using the REEF3D framework. The results showed that ANN and adaptive neuro-fuzzy inference systems outperformed, and numerical predictions agreed well with reported experimental data. For current-only conditions, normalized scour depths (S/D) of 0.65 and 0.81 were observed at the front and rear of the pier, respectively, while wave–current interaction reduced S/D to 0.26.

The comparison between purely data-driven models and hybrid or physics-informed approaches was framed along multiple complementary dimensions. Predictive performance was assessed using consistently reported error metrics, including RMSE, MAE, R^2, and NSE, with emphasis on relative error reduction under comparable training conditions. Data dependency was evaluated by contrasting model behavior under low- and high-data regimes, recognizing that purely data-driven models generally require large and diverse datasets, whereas hybrid and physics-informed models benefit from embedded physical constraints that improve learning efficiency with sparse data. Third, interpretability and physical consistency were examined by assessing whether model outputs adhered to governing hydraulic and sediment transport principles, particularly under extreme or unseen flow conditions. Fourth, operational feasibility was considered in terms of computational demand, transferability from laboratory to field scales, and suitability for real-time monitoring or digital twin integration. Finally, the validation context was compared, distinguishing laboratory-only benchmarks from mixed validation strategies incorporating numerical simulations and limited field observations. Table 4 presents the model performance accuracy across the approaches.

Table 4: Model performance accuracy

Model	Accuracy (RMSE)	Interpretability	Data Demand	Use Case
ANN	0.1-0.25 m	Low	High	General scour
ANFIS	0.1-0.3 m	Medium	Moderate	Rule-based modeling
GEP	0.07-0.25 m	High	Moderate	Formula derivation
SVM	0.08-0.22 m	Medium	Low	Small datasets
LSTM	0.1-0.15 m	Low	High	Real-time forecasts
SPINNs	0.04–0.12 m	High	Moderate	Physics, ML
PSO-ANN	0.06–0.2 m	Medium	Moderate	Optimized architecture
CNN	0.08–0.14 m	Low	High	Time-series scour shape
XGBoost	0.05–0.18 m	Medium	High	Ensemble predictions

Operational relevance was considered by assessing whether models were validated using real flood events, integrated with in situ sensing systems, or proposed within digital twin architectures. This qualitative approach enabled the identification of the relative strengths and limitations of different AI-based scour prediction methodologies without imposing a rigid scoring framework.

Model performance in AI-based scour prediction studies is most commonly evaluated using the R^2 and RMSE, which together quantify goodness-of-fit and error magnitude, with RMSE particularly relevant due to its sensitivity to extreme scour events. Mean absolute error (MAE) is reported less frequently but provides a more robust measure of average deviation, while the Nash–Sutcliffe efficiency (NSE) appears mainly in hydrology-influenced studies and is less common in scour-focused applications. Direct comparison across studies remains challenging because of heterogeneity in datasets (laboratory, field, numerical), scale, input variables, and validation strategies. Consequently, most comparisons are conducted within identical datasets through relative model ranking or benchmarking against empirical scour equations (CSU), with broader cross-study synthesis remaining largely qualitative.

A comprehensive synthesis of ML applications for predicting scour around bridge piers and abutments, integrating diverse datasets, algorithms, and target variables. Kumar et al. (2023) utilized 942 datasets from 18 prior studies to clear-water pier scour using an ANN-PSO hybrid, identifying pier width-to-flow depth ratio and Froude number as dominant predictors. Hong et al. (2012) employed a Deep Neural Network and SVR on 417 datasets, capturing time-dependent scour dynamics under both uniform and non-uniform sediment conditions. Muzzammil (2008) and Firat et al. (2009) benchmarked ANN and GRNN against empirical formulas, revealing superior performance in estimating equilibrium scour depth. Ebthehaj et al. (2018) leveraged ensemble (ELM, XGBoost, LightGBM) on 295 datasets from Dey et al. (2005), with abutment geometry, sediment size (d_{50}) emerging as key features, and applied ELM to 321 datasets from Ataie-Ashtiani et al. (2012), demonstrating the importance of pile diameter and spacing in group pier scour. Real-time monitoring was addressed by Yousefpour et al. (2023) using RNN and

LSTM on 11 years of Alaska scour sensor data, incorporating seasonal features via sine–cosine transformations. Kohansarbaz et al. (2021) introduced ANFIS-FA for dual-pier scour prediction, outperforming standalone ANFIS via Monte Carlo validation. Khosravi et al. (2021) and Mohammadpour et al. (2016) explored hybrid Kstar and ANFIS for abutment scour in cohesive soils. Collectively, these studies underscore the efficacy of ML in capturing complex hydrodynamic interactions, outperforming empirical methods across varied sediment regimes and structural configurations.

ML offers improved accuracy over empirical formulas, particularly under complex flow sediment conditions. While black-box offer high accuracy, symbolic models provide both accuracy and interpretability. ML methods for scour prediction offer notable strengths alongside key limitations and deployment challenges:

- Accuracy and Nonlinearity: ML effectively captures the complex, coupled nonlinear dynamics of scour processes, consistently outperforming empirical equations across various studies.
- Data Needs and Generalizability: High-quality, large-scale datasets are critical, yet scarce field data, especially for extreme events limits model generalizability, with purely data-driven models often failing to transfer well across different bridge sites.
- Interpretability and Overfitting: Many models function as "black boxes," complicating error tracing and limiting engineering trust, while ANFIS can suffer from overfitting, particularly with small datasets.
- Computational Cost and Practical Deployment: Deep learning may involve high computational costs, though FCN variants reduce these burdens, and hybrid physics-informed approaches offer improved robustness, interpretability, and site transferability.

The reviewed studies rely predominantly on laboratory-scale datasets, with most AI/ML models trained and validated using controlled flume experiments. Laboratory data dominate due to their ability to precisely control hydraulic variables, such as flow velocity, sediment characteristics, and pier geometry, resulting in consistent and repeatable measurements well suited for model training. In contrast, field measurements remain limited, primarily because of logistical constraints, high costs, environmental variability, and incomplete long-term monitoring records. Numerical and CFD-based simulation datasets represent an emerging but still minor component of the literature; these are typically employed to supplement laboratory data or to test model robustness under extended hydraulic scenarios, given their computational demands and calibration requirements.

Scale effects and data scarcity were explicitly acknowledged as critical challenges in transferring AI-based scour prediction models from laboratory flume experiments to prototype bridge conditions. The reviewed studies recognize that laboratory and empirically derived datasets often fail to fully represent prototype-scale scour dynamics due to differences in hydraulic regimes, sediment heterogeneity, and structural geometry. To mitigate scale-transfer limitations, physics-informed machine learning approaches, structured and physics-informed neural networks embed empirical scour formulations and hydraulic constraints within data-driven models, thereby improving generalization beyond laboratory scales. Several studies further employ cluster-based strategies, including hierarchical clustering coupled with genetic programming, to derive site-specific formulations that reduce scaling bias across diverse field conditions. Data scarcity at the prototype scale is addressed through hybrid optimization techniques, which enhance robustness and reduce overfitting when training on limited data. Transfer learning, clustered training schemes, and physics-inspired neural architectures enable efficient use of sparse site-specific observations while maintaining broader generalization capability. Collectively, these strategies position data scarcity and scale transferability as central research frontiers, while demonstrating that physics-informed, hybrid, and sensor-integrated approaches offer viable pathways toward operational, real-world scour prediction.

Despite demonstrated predictive advantages, the adoption of AI/ML scour models by bridge designers and agencies remains limited due to multiple barriers. Key challenges include the lack of large-scale field datasets for extreme events, poor generalization across diverse rivers, sediments, and hydraulic conditions, and low interpretability of black-box models. Additional obstacles are high computational and expertise demands, the absence of regulatory standards, liability concerns for safety-critical infrastructure, and integration difficulties with existing workflows, software (HEC-RAS), and monitoring systems. Addressing these barriers requires a combination of strategies: expanding multi-event, multi-river datasets through sensors, remote sensing, and crowdsourced data; embedding physical laws via hybrid or physics-informed ML to improve generalization; adopting explainable AI techniques to enhance trust; creating lightweight, user-friendly computational tools; and collaborating with regulatory agencies to establish standards and validation protocols.

Real-time scour monitoring systems that integrate sensors, IoT devices, and AI analytics face interconnected challenges affecting reliability, sustainability, and security. Data reliability is compromised by sensor drift, environmental noise from turbulence and debris, data gaps during extreme floods, and limited ground-truth validation. Maintenance challenges arise from harsh riverine conditions that cause corrosion and mechanical damage, dependence on constrained power supplies, unreliable network connectivity in remote or flood-prone areas, and high lifecycle costs. Cybersecurity further complicates deployment, as real-time data streams are vulnerable to tampering, unauthorized access, denial-of-service attacks, and expanded attack surfaces through system interoperability, while also requiring compliance with cybersecurity standards. Overcoming these issues demands robust calibration and validation methods, durable and low-maintenance sensor designs, resilient power and communication infrastructure, and secure, standardized cybersecurity frameworks to ensure long-term operational trustworthiness.

CONCLUSION

The present review synthesizes insights from key studies, highlighting the growing adoption of sophisticated, data-driven approaches that have substantially improved the accuracy and reliability of scour depth predictions. AI and ML techniques, particularly hybrid and deep learning, are transforming the way scour prediction is approached. While empirical methods remain useful for baseline analysis, intelligent models enable real-time monitoring, forecasting, and integration into digital twins for resilient infrastructure management. AI and ML approaches from ANFIS, GP, SVM, ensemble methods to deep learning and physics-inspired hybrids have demonstrated significant promise in predicting scour depth around bridge piers. They offer superior predictive performance compared to traditional empirical models, particularly in complex flow and sediment conditions. Key challenges persist regarding data availability, interpretability, and generalization across different sites. AI and ML have transformed how engineers model local scour around bridge piers. While data availability and generalization remain challenges, advances like PINNs, hybrid optimization, and digital twins offer promising solutions. Future progress lies in physics-informed architectures, real-time digital twin systems, and methods that adapt to site-specific clusters of conditions.

While ML for bridge pier scour prediction has demonstrated promising accuracy within controlled datasets, its generalization capability across diverse river systems and sediment regimes remains insufficiently evaluated. Most studies validate performance using single-river datasets or laboratory flume experiments, which limits the operational relevance of the findings. Sediment characteristics, such as grain size distribution, cohesion, and transport dynamics, are acknowledged as critical drivers of scour depth, yet models are often trained on relatively uniform sediment conditions. As a result, predictive reliability under contrasting regimes (e.g., fine silts versus coarse gravels) is uncertain. The absence of systematic, multi-river validation frameworks highlights a significant research gap: without rigorous cross-system testing, the transferability of these models to real-world applications cannot be assured.

A concise overview is provided on the theoretical foundations of several representative ML algorithms. Many of the reviewed studies compared their proposed models against other algorithms or established empirical formulas, such as Melville–Sheppard, MBW, HEC-18, Laursen & Toch. Across these comparisons, ML-based approaches consistently outperformed traditional empirical models in predicting scour depth. This demonstrates the capacity of ML to learn and interpret complex nonlinear relationships among scour-related parameters, offering a promising paradigm for future research in the field.

Future research directions

The difficulties of finding locally optimal solutions and the high computational demands of evolutionary algorithms can be mitigated by combining different standalone algorithms into hybrid approaches. Such hybrid algorithms are particularly useful for modelling a wide range of phenomena in water resources engineering. By integrating the strengths of multiple methods, hybrid models aim to enhance a system's overall performance, robustness, and generalization ability. These often blend traditional statistical techniques with modern machine learning approaches to achieve better results.

AI/ML models for scour prediction generally struggle under extreme flow conditions, as most are trained on steady-flow laboratory datasets that do not capture flood-scale hydraulic variability. Traditional models such as ANN and SVM perform reasonably well under moderate flows but systematically underpredict maximum scour depths and exhibit instability when confronted with rare, high-velocity events. Hybrid approaches offer improved robustness for small datasets but remain limited when extrapolating beyond laboratory ranges. Physics-informed neural networks demonstrate greater resilience, embedding empirical scour relations and hydraulic constraints that enable more reliable extrapolation to flood conditions. Emerging strategies leveraging IoT-enabled real-time monitoring and numerical simulations (CFD coupled with ML) offer additional potential to capture unsteady flows and prototype-scale scour dynamics, though they are not yet mainstream. The review highlights that operationally reliable flood-scale scour prediction will require integrating physics-informed models with real-time sensor data, event-aware input features, and digital twin frameworks, supported by robust validation protocols that encompass pre-, peak-, and post-flood conditions.

Future research in scour prediction should focus on enhancing model accuracy, interpretability, and transferability through several promising directions: (1) advancing physics-informed or hybrid ML approaches such as SPINNs to embed established scour mechanics into learning frameworks for improved generalization; (2) integrating real-time sensor data into AI-driven digital twins to enable dynamic simulation and predictive monitoring of scour evolution; (3) developing hybrid time-series models (LSTM, CNN, MGGP) to forecast cyclic and temporally evolving scour conditions rather than static equilibrium depths; and (4) improving model adaptability and transferability using ensemble techniques and clustering based approaches, such as hierarchical clustering with GP, to create site-specific or regional applicable to diverse bridge scenarios.

Declaration of competing interest

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

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