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Environmental and Climate-Resilient Approaches to Scour Depth Prediction: From Empirical Equations to Advanced Machine Learning Models

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Abstract: Scour around bridge structures is a major cause of bridge failure, disturbing sediments and aquatic habitats; therefore, accurate prediction for structural safety and river ecosystem protection is necessary. This study bridges the gap between research and practice by highlighting the disconnect between Machine Learning (ML)- based prediction and current conventional design methods, and systematically compares their performance using consistent statistical indicators. The analysis showed that dataset size ranged from 100 to 871 samples, with an inconsistent relationship between sample size and predictive accuracy (R^2 = 0.850–0.959), whereas a mid-sized dataset of 500 samples performed best (R^2 = 0.959), indicating that no single factor determines optimal model performance. Therefore, this study recommends applying large-scale field datasets alongside laboratory datasets in different machine learning models to achieve more precise and reliable results. Such advancements can reduce unnecessary streambed disturbance and improve prediction reliability, supporting more sustainable river infrastructure.

Keywords: bridge pier, scour depth prediction, sustainable, mathematical equations, Machine Learning, river infrastructure

1. Introduction

Bridges play a vital role in the transportation system by connecting across waterways, which facilitates people to travel and goods to be transported from one place to another. However, their safety and serviceability are often compromised by substructure failure. One of the main causes is scour around bridge piers. Scour around the bridge piers has become one of the major causes of bridge failures over the past few decades (Chang et al., 2004; Kothyari et al., 2007; Kumar, 2008; Mia & Nago, 2003; Muzzammil et al., 2008; Muzzammil et al., 2015; Oliveto & Hager, 2002). Scour around the bridge piers is primarily caused by the complex flow structures. As the approach flow hits the pier, it moves in the downward direction and results in the formation of a horseshoe vortex that starts removing the sediments around the pier base, while wake vortices carry and lift away the sediment dislocated by the horseshoe vortex (Baranwal et al., 2023; Kaveh et al., 2021; Kothyari et al., 1992). Together, these effects create a deep local scour hole, as shown in Figure 1, which can significantly reduce the stability of bridge structures (Federal Highway Administration, 2001). Several factors affect scour depth development around bridge piers, including hydraulic parameters, sediment parameters, and geometry.

Many researchers contributed towards better understanding of the effects of flow conditions, sediment properties and pier geometry on scour development (Arneson et al., 2012; Chaudhuri, 2022; Jain et al., 2021; Lai et al., 2009; Oliveto & Hager, 2002; Sheppard et al., 2014; Wang et al., 2017). Kothyari & Kumar (2012) developed a model for computing the temporal variation of scour depth around circular uniform and compound piers. The researchers used Kothyari et al. (1992) mathematical model as a base and proposed a new method to compute the temporal variation of scour depth around uniform and compound circular piers. Despite extensive experimental, theoretical, and mathematical research, traditional equations for predicting the scour depth around bridge structures remain limited in specific respects, as most of the studies were derived using dimensional analysis and regression on laboratory-scale datasets with fixed ranges of pier geometry, sediment size, and flow conditions (Melville & Chiew, 1999; Oliveto & Hager, 2002; Richardson & Davis, 2001); therefore, these methods do not predict well when applied to the field scale or large dataset conditions. Furthermore, reported R^2 values for mathematical equations observed range from (0.008–0.34) when evaluated against standalone test datasets (Kumar et al., 2024a; Kumar et al., 2024b). Most mathematical equations use simple, fixed relationships that cannot fully capture the non-linear effects of sediment gradation, scour time, and pier geometry. The equations are also developed for specific scour conditions, so their accuracy reduces under

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unsteady or live-bed conditions. These limitations, and the evolution of advanced computational algorithms, motivated the researcher to apply data-driven approaches to estimate scour depth at bridge piers. (Eini et al., 2023; Eini et al., 2024; Khan & Ismael, 2026; Kumar et al., 2023; Link & Dey, 2025).

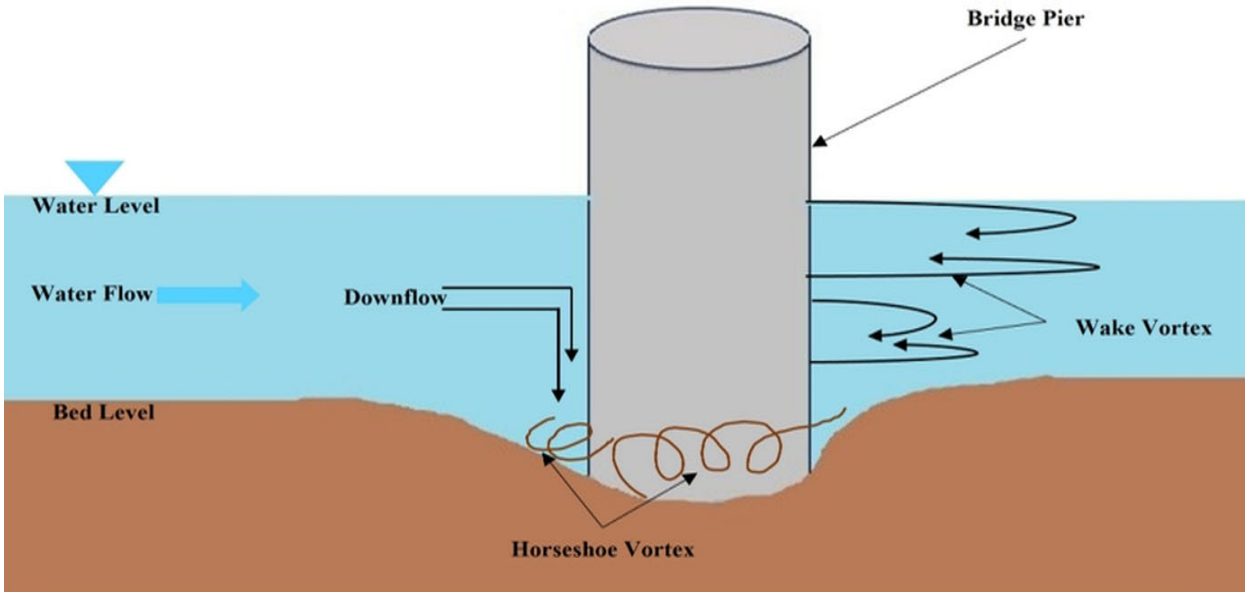

Fig. 1. Scour pattern developing around a circular shape of the bridge pier

Advancements in artificial intelligence (AI) and machine learning (ML) have gained significant attention, and researchers have used these methods in recent years to predict scour depth around bridges. Machine learning models can handle these complex relationships directly from large datasets without requiring the predefined interaction among different factors, making them effective for analysing and predicting scour development under various hydraulic conditions (Akhani et al., 2019; Ali et al., 2022; Rahman & Chavan, 2024; Sparks et al., 2020; Worden & Manson, 2007; Zounemat et al., 2021). Machine learning (ML) algorithms learn from input data by identifying patterns, enabling them to make accurate predictions (Salehi & Burgueño, 2018). As a result, researchers have applied machine learning (ML) techniques to predict scour depth development around bridge structures. Among these techniques, Artificial Neural Networks (ANNs) have been widely adopted due to their adaptability of this model to work with complex and non-linear datasets for scour prediction (Dang et al., 2021; Khan et al., 2017; Shin & Park, 2010; Toth & Brandimarte, 2011; Bateni et al., 2007a; Bateni et al., 2007b; Firat & Gungor, 2009). Machine learning models have gained importance as an alternative to conventional mathematical equations for predicting scour depth because they can handle complex, non-linear datasets. The investigators utilized data-driven machine learning approaches like Adaptive Neuro Fuzzy Inference Systems (ANFIS), Gene Expression Programming (GEP), and M5 model trees for predicting the scour depth around bridge structures (Abd El-Hady Rady, 2020; Ahmadianfar et al., 2021; Akib et al., 2014; Choudhary et al., 2023; Khan et al., 2012; Mohammed et al., 2019; Moussa, 2013).

Researchers applied Support Vector Machine (SVM) and ANN model to predict the scour depth around grade-control structure like check dams, sluice gates and weirs was predicted using both field and experimental data. The study showed that SVM performed better than back-propagation ANN, indicating the robustness and superior predictive capabilities of the SVM model for water-based learning approaches (Goel & Pal, 2009). Keshavarzi et al. (2012) addressed the limitations of the ANN model and highlighted that the ANFIS model combines the learning capabilities of neural networks with the reasoning of fuzzy logic, demonstrating more reliable performance than the ANN model for circular bridge piers. Jung et al. (2015) applied Auto Regressive (AR) and Moving Principal Component Analysis (MPCA), along with a non-parametric Kullback–Leibler Divergence (KL) model, for anomaly detection in piezometer data and demonstrated that the KL divergence method outperformed AR and MPCA, providing more consistent anomaly detection. Balouchi et al. (2015) applied Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), and M5 models to predict the maximum development of scour depth under live-bed conditions. The study concluded that MLP and RBF models performed better in the low and high scour-depth development ranges, respectively. Further, ANFIS showed better predictive performance than ANN and Multiple Non-Linear Regression (MNLR) models for predicting scour depth development in the study by Hosseini et al. (2016). Further study by Ebtehaj et al. (2018) demonstrated the superior predictive capabilities of Extreme Learning Machine (ELM) models over ANN and SVM models.

Hassanzadeh et al. (2019) applied ANFIS and Teaching–Learning-Based Optimization (TLBO) models and reported improved prediction performance for scour depth development compared with the conventional ANFIS model. Similarly, (Sihag et al., 2020) conducted their study on estimating the soil infiltration rate and applied Random Forest Regression (RFR), ANN, and SVM models, and the study highlighted superior predicted accuracy of the ANN model among RF and SVM models, while (Abd El-Hady Rady, 2020) applied Genetic Programming (GP), which showed superior performance to the ANFIS model.

The growing application of machine learning approaches has encouraged researchers to apply hybrid, data-driven machine learning models to achieve better scour-depth prediction results. Khosravi et al. (2021) applied hybrid models, including Bagging-Kstar (BA-Kstar), Dagging-Kstar (DA-Kstar), Random Committee-Kstar (RC-Kstar), Random Subspace-Kstar (RS-Kstar), and Weighted Instance Handler Wrapper-Kstar (WIHW-Kstar), to datasets generated from flume experiments. The study demonstrated the effectiveness of hybrid machine learning models in predicting scour depth development under clear-water conditions. In addition, Seyedian et al. (2022) applied various soft computing models, including GEP, ELM, and Least Squares Support Vector Machine (LSSVM), and showed satisfactory performance in predicting scour depth development. Furthermore, Kumar et al. (2023) used a laboratory dataset from previous studies to predict the temporal variation of scour depth around bridge piers. Researchers compared two ensemble learning models, Bagging Regressor (BR) and AdaBoost Regression (ABR), with a self-contained machine learning model, Support Vector Regression (SVR). The study showed that BR and ABR outperformed SVR and conventional mathematical equations, highlighting the superior capabilities of ensemble machine learning approaches for predicting temporal variation in scour depth. Studies on scour depth estimation using ML techniques have highlighted the potential of using hybrid and ensemble machine learning models for accurately predicting the scour depth around the bridge structures (Kumar et al., 2023; Deepak Verma & Parveen Berwal et al., 2023; Link & Dey, 2025; Khan & Ismael, 2026).

Although various studies have examined machine learning models for accurately predicting scour depth development around bridge structures, comprehensive evaluations of ensemble and hybrid machine learning approaches, based on their performance characteristics for complex and non-linear hydraulic datasets, remain limited. Therefore, a systematic review and assessment of these machine learning techniques is needed to better understand their reliability and accuracy in predicting scour processes. One of the study's main objectives is to bridge the gap between research and practice by highlighting the disconnect between ML-based prediction and the use of current conventional design methods. The comparative analysis of conventional methods and ML-based models will provide a basis for field engineers to select the most reliable scour-prediction method for a given site condition, including flow conditions, pier shape, and sediment characteristics, rather than relying on conservative empirical formulas that sometimes provide inaccurate scour depths. Moreover, the study aims to focus on the use and availability of data to apply machine learning approaches in scour prediction research and to raise awareness among the next generation of water resources professionals about using new, advanced, appropriate data-driven tools for scour depth prediction.

2. Review Methodology

In this study, a systematic review approach is adopted to evaluate the machine learning techniques for predicting scour depth development around bridge structures. The methodology includes data identification, collection, and analysis of relevant research studies published in recent years. The selected studies evaluating scour depth using mathematical equations and machine learning techniques are comprehensively reviewed and assessed based on their datasets, input parameters, modelling approaches, evaluation criteria, strengths, and limitations. The papers were searched mainly in Web of Science, Scopus, and Google Scholar (Figure 2). A total of 350 papers were initially identified; after screening and applying inclusion/exclusion criteria, 100+ papers were finally considered for this literature review.

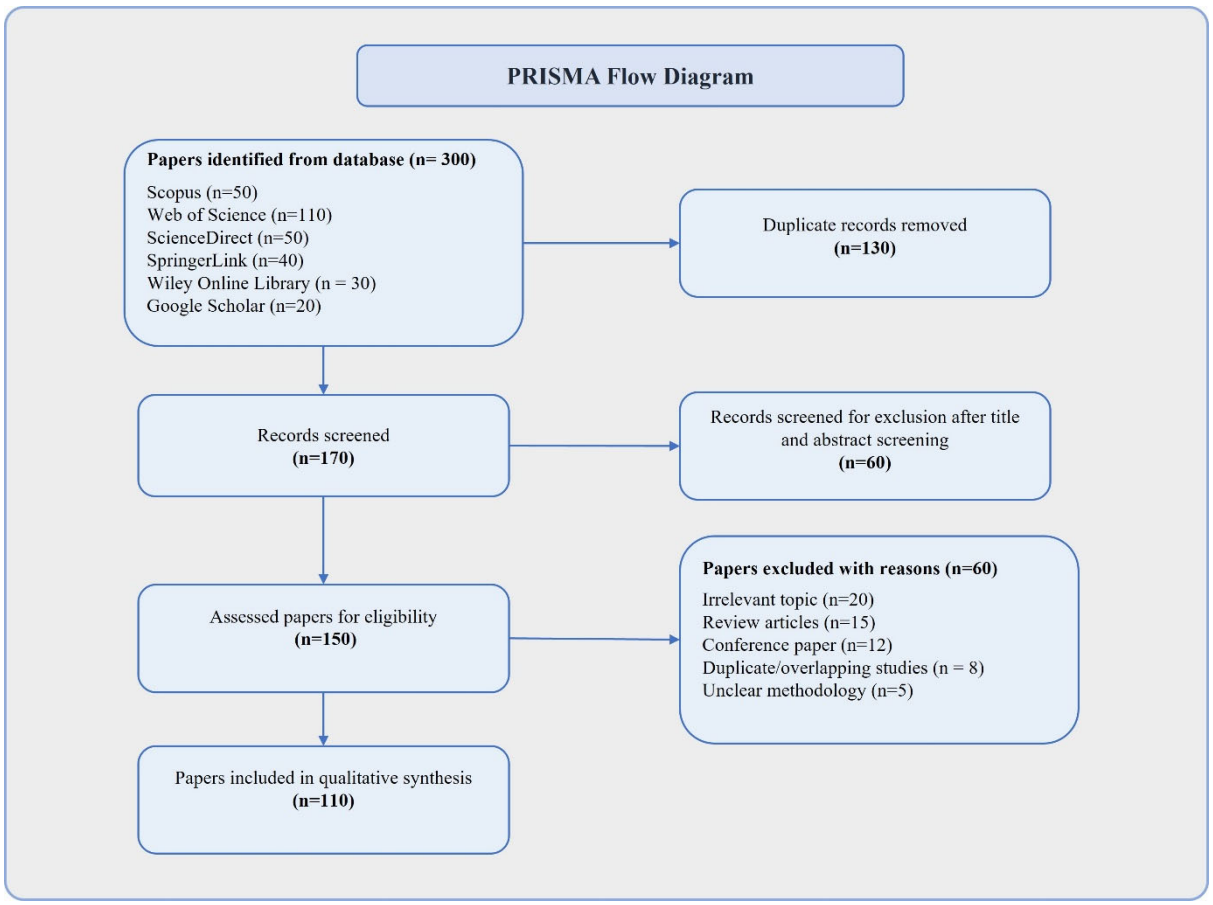

Fig. 2. Flow chart for representation of the literature selection process

2.1. Scope and Literature Selection Criteria

This review focuses mainly on approaches developed to predict local scour depth around bridge piers (equilibrium scour depth, dse, and time-dependent scour depth, d_{st}). We evaluated studies based on model-specific performance data, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), which studies reported most consistently. The Nash–Sutcliffe efficiency (NSE) and index of agreement (Id) were summarized in Table 2(a). These metrics enabled a quantitative, standardized comparison of predictive performance between traditional mathematical equations and machine learning models across the reviewed literature.

2.2. Classification of the Present Framework

Instead of listing individual studies and reflecting the conceptual evolution of scour-depth prediction approaches, the present study is systematically organized into four categories of increasing model complexity, including (1) Mathematical equations, (2) Traditional (standalone) machine learning models, (3) Ensemble machine learning models, and (4) Deep learning models. This analysis enables a systematic comparison of predictive capabilities, data utilized, and physical interpretability as presented in Section (2.2.1–2.2.4).

2.2.1. Mathematical Equations for Local Scour

Mathematical equations, derived using dimensional analysis and laboratory-scale datasets, represent the earliest and most widely used approach to scour-depth prediction (Neill, 1964; Colorado State University (CSU), 1975; Johnson, 1992; Melville & Chiew, 1999; Oliveto & Hager, 2002; Richardson & Davis, 2001; Kothyari et al., 2007; Ettema et al., 2011; Kim et al., 2015; Pandey et al., 2018; Coleman, 2005; Sheppard & Renna, 2005; Arneson et al., 2012) as represented in section (2.3). More recent equations have also combined flow depth, flow intensity, sediment characteristics, and pier geometry using larger experimental datasets as described in Table 2(a). These developments show a shift from geometry-based equilibrium scour prediction toward more comprehensive local scour approaches that include flow, sediment, and time effects. However, most equations use fixed, predefined functions and are generally developed for specific experimental conditions, which limits their ability to capture complex, non-linear relationships in local scour development. These limitations have motivated the use of machine-learning approaches to predict local scour depth.

2.2.2. Traditional (Standalone) Machine Learning Models

Traditional machine learning models learn a non-linear mapping between input parameters and scour depth directly using a single learning algorithm, without breaking the problem into sub-models in an ensemble approach. These models include Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines/Regression (SVM/SVR), Gene Expression Programming (GEP), M5 model tree, Multiple Linear Regression (MLR), Gaussian Process Regression, K-Nearest Neighbours, and Least Angle Regression as presented in Table 2(a). These models subsequently outperformed mathematical equations by capturing non-linear parameter interactions. Still, their accuracy depends on data quality, architecture selection, and hyperparameter tuning of the training dataset, with limited physical interpretability (Verma D. et al., 2023).

2.2.3. Ensemble and Advanced Machine Learning Models

Ensemble models combine multiple weak learners, typically decision trees, to reduce prediction errors and improve accuracy compared to a single standalone model. These models include Random Forest Regression (RFR), AdaBoost Regression (ABR), Extreme Gradient Boosting (XGBoost), Gradient Boosting Regression (GBR), CatBoost, LightGBM, Extra Trees Regressor, and Stacking Regressors as discussed in Table 2(a). Across the reviewed comparative studies, ensemble models consistently achieved the highest predictive accuracy among all machine learning categories, with reported R^2 improvements of 0.23–0.84 over mathematical equations evaluated on identical test datasets (Kumar et al., 2024b; Nandi et al., 2025).

2.2.4. Deep Learning Models

Deep learning models learn feature representations directly from raw data using multiple hidden layers, thereby reducing the need for manual feature engineering. In the present study, this category includes one-dimensional Convolutional Neural Networks (1D-CNN) and standard Deep Neural Networks (DNN), applied by (Huynh et al., 2025) to predict scour depth around complex pier and pile-group configurations. Recurrent architectures like Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN), which are conceptually suited to model the temporal variation of scour depth, were applied in the local pier scour-depth prediction studies conducted by (Behera et al., 2025; Huynh et al., 2025).

2.3. Summary of Traditional Mathematical Equations for Scour Depth Prediction

Table 1 summarizes selected mathematical equations proposed in previous studies to predict both equilibrium and temporal scour depth around bridge piers. These equations show a clear progression: Neill (1964) proposed the simplest relation, presenting scour depth as a function of the pier diameter-to-flow-depth ratio (D_P/y). This treated scour primarily as a geometric problem, without considering flow velocity or sediment characteristics. Richardson & Davis (1975) introduced the Froude number (F_r), which represents flow velocity relative to gravitational effects, along with correction factors (K_1, K_2, K_3) for pier nose shape, flow angle of attack for flow and bed condition. By separating hydraulic, geometric, and sediment effects, this equation became one of the most widely adopted in bridge design practice, such as in HEC-18. Johnson (1992) proposed an equation that incorporated sediment gradation through the standard deviation of sediment size (σ_g), highlighting that non-uniform sediment forms a protective layer that reduces scour depth compared with predictions from equations based on uniform sediment. Melville & Chiew (1999) introduced the concept of time-dependent scour depth development using a temporal factor (K_t), which represents the ratio of the critical velocity for sediment movement to the approach velocity, and predicts an equilibrium scour time (t_e). Their findings separate total scour depth into components for flow depth, flow intensity, particle size, and time. Equations proposed by Kothyari et al. (2007), Modified Richardson & Davis (2001), and Oliveto & Hager (2002) replaced the standard Froude number with the densimetric Froude number (Fd), which considers the submerged relative density of sediment and provides better predictions of the threshold for sediment motion. Studies by Kothyari et al. (2007) and Oliveto & Hager (2002) further proposed a dimensionless time parameter (T) and reference length (R_L), proposing their equations to make predictions based on dimensional analysis rather than purely mathematical equations.

In contrast, Lee & Sturm (2009) proposed a simple geometric-based relation for the pier diameter-to-sediment-size ratio (DP/d_{50}) and applied it across a range of sizes. Their study highlighted that simplified formulas remain relevant even in recent literature. The most recent studies (Kim et al., 2015; Kim et al., 2024; Pandey et al., 2018; Yanmaz, 2001) integrated multiple parameters, such as flow depth, Froude number, sediment gradation, and relative grain size, and used larger, more diverse experimental datasets. Overall, the equations summarized in Table 1 show an evolution in equations for predicting scour depth around bridge piers. This progression showed a growing understanding of scour-depth predictions, including the combined interaction of flow, sediment, and time, rather than pier geometry alone.

Table 1. Mathematical equations proposed in the literature for evaluating the scour depth around bridge pier structure

S. No.	Author Reference	Formula Used		#Description
1	Neill (1964)	$\frac{d_{st}}{y} = 1.35\left[\frac{D_P}{y}\right]^{0.7}$	(1)	D_P, y
2	Colorado State University (CSU), (1975)/ Richardson & Davis (2001)	$\frac{d_{st}}{y} = 2.0\ K_1K_2K_3\ \left(F_r{}^{0.43}\right)\left[\frac{D_P}{y}\right]^{0.65}$	(2)	D_P, y, $F_r = \frac{U}{\sqrt{g\,y}}$, U, g $K_1K_2K_3$ = Correction factor for pier nose shapes, Correction factor for angle of attack of flow, Correction factor for bed condition, respectively.
3	Johnson (1992)	$\frac{d_{se}}{y} = 2.0\ y\left[\frac{D_P}{y}\right]^{0.98} F_r{}^{0.21}\sigma_g{}^{-0.24}$	(3)	D_P, Y, F_r, σ_g
4	Melville & Chiew (1999)	$K_t = \frac{d_{st}}{d_{se}} = \exp\left\{-0.03\left\lvert\frac{U_c}{U}\ ln\left(\frac{t}{t_e}\right)\right\rvert^{1.6}\right\}$	(4)	$t_e = 48.26\ \frac{D_P}{U}\left(\frac{U}{U_C} - 0.4\right);\ \frac{y}{D_P} > 6$ $te = 30.89\ \frac{D_P}{U}\left(\frac{U}{U_C} - 0.4\right)\left(\frac{y}{D_P}\right)^{0.25};\ \frac{y}{D_P} \le 6$ To calculate the equilibrium scour depth around the bridge piers, $d_{se} = K_{yD}\ K_I\ K_d K_t$. Here, K_t is a time-dependent factor, (KyD) represents the Flow Depth-to-Pier Width Ratio, (KI) represents the Flow Intensity, and (Kd) represents the particle size; refer to the Scour depth estimation factors proposed by Melville (1997).
5	Yanmaz (2001)	$\frac{d_{st}}{D_P} = 1.564\left[\frac{y}{D_P}\right]^{0.405} F_r{}^{0.413}$	(5)	y, D_P, F_r
6	Modified Richardson & Davis (2001)	$\frac{d_{st}}{y} = 2.6\left[\frac{D_P}{y}\right]^{0.65} F_d{}^{0.43}$	(6)	$F_d = \frac{U}{\sqrt{g'\,d_{50}}}$ $g' = g\left(\rho_s - \rho_f/\rho_f\right)$
7	Oliveto & Hager (2002)	$\frac{d_{st}}{R_L} = 0.068\,\sigma_g^{-0.5}\,F_d^{1.5}\,logT$	(7)	$R_L = \left(D_p^2\,y\right)^{\frac{1}{3}}$ $T = \frac{\sqrt{g'\,d_{50}}}{R_L}\,t$

Table 1. cont

S. No.	Author Reference	Formula Used		#Description
8	Kothyari et al. (2007)	$\frac{d_{st}}{(yD_p)^{1/3}} = 0.272\,\sigma_g^{-0.5}\left(F_{d\beta}\right)^{2/3} logT$	(8)	$F_{d\beta} = \phi_\beta F_{di}$ Here, Φ_β is the entrainment effect, F_{di} is the densimetric particle Froude number for incipient motion in the approach flow channel bed, which can be calculated using the equations below. $F_{di} = 2.33{D_*}^{-1/4}\left(\frac{R_h}{d_{50}}\right)^{1/6}$; $D_* \le 10$ $F_{di} = 1.08{D_*}^{1/12}\left(\frac{R_h}{d_{50}}\right)^{1/6}$; $10 < D_* < 150$ $F_{di} = 1.65\left(\frac{R_h}{d_{50}}\right)^{1/6}$; $D_* \ge 150$
9	Lee & Sturm (2009)	$\frac{d_{st}}{D_P} = 5.0\,Log\left[\frac{D_P}{d_{50}}\right] - 4.0,\ \ for\ 6 \le \frac{D_P}{d_{50}} \le 25$ $\frac{d_{st}}{D_P} = \left[\frac{1.8}{\left[0.02\frac{D_P}{d_{50}} - 0.2\right]^2 + 1}\right] + 1.3,$ $for\ 25 < \frac{D_P}{d_{50}} \le 10000$	(9a) (9b)	D_P and d_{50}
10	Kim et al. (2015)	$\frac{d_{st}}{D_P} = 0.69\left[\frac{D_P}{y}\right]^{0.35}\left[\frac{d_{50}}{y}\right]^{-0.10}{\sigma_g}^{0.39}{F_r}^{0.56}$	(10)	D_P y, d_{50}, σg, F_r
11	Pandey et al. (2018)	$\frac{d_{se}}{D_P} = 0.987\,{F_d}^{-0.302}\left[\frac{y}{D_P}\right]^{-0.566}\left[\frac{D_P}{d_{50}}\right]^{0.079}$	(11)	D_P, y, d_{50}

#Description: D_P = Diameter of the pier, y = Flow depth, F_r = Froude number, U = Approach flow velocity, g = gravitational acceleration, σ_g = Standard deviation of sediment size, F_d = densimetric Froude number, g' = Relative gravitational acceleration, d_{50} = Mean diameter of the sediment, R_L = Reference length, T = Dimensionless parameter

2.4. Limitations of Traditional Mathematical Equations

Despite extensive experimental, theoretical, and mathematical research, traditional approaches for predicting scour depth remain limited in some respects. Most of the equations were derived using dimensional analysis and regression modelling on small laboratory-scale datasets with fixed ranges of pier geometry, sediment size and flow conditions including the studies conducted by (Melville & Chiew, 1999; Oliveto & Hager, 2002; Richardson & Davis, 2001), so the performance of coefficients of determination do not show good performance when applied to a field-scale or large scale datasets, reported R^2 values for these equations fall in the range (0.008–0.34) when evaluated against independent datasets (Kumar et al., 2024a; Kumar et al., 2024b). These equations typically assume a fixed functional form (logarithmic relationships between a small set of dimensionless groups), which cannot capture the non-linear, interacting effects of sediment size, temporal scour depth, and pier geometry observed experimentally. Most equations were developed for a single scour condition (clear-water, equilibrium), which reduces accuracy when applied under unsteady or live-bed conditions outside that regime. These structural limitations, rather than a general lack of effort in research, motivate the researchers for application of data-driven techniques, capable of learning non-linear, multi-parameter relationships directly from dataset (Eini et al., 2023; Eini et al., 2024; Khan & Ismael, 2026; Kumar et al., 2023; Lee & Sturm 2009; Link & Dey, 2025; Pandey et al., 2018; Wang et al., 2020).

3. Evolution of Machine Learning Approaches

Machine Learning (ML) is an important concept in artificial intelligence and data science. It involves using computer programs that can learn from data and perform tasks without being explicitly programmed at every step. Researchers have made significant improvements by applying regression-based machine learning models, as discussed below.

3.1. Artificial Neural Networks (ANN)

ANN is one of the oldest machine learning methods used for scour depth estimation because it can learn non-linear relationships among hydraulic, geometric, and sediment parameters. ANN model consists of small units called neurons that are connected. These neurons are arranged mainly in three layers: the input layer, hidden layers, and the output layer, as shown in Figure 3. The model works on the principle of collecting raw data through the input layer, which is then passed to the hidden layers where the main calculations take place, and then the output layer provides results (Jatoliya et al., 2024; Raikar et al., 2016). Studies conducted by Ali & Günal (2021) and Ali et al. (2022) demonstrated that the ANN model outperformed traditional regression methods by achieving R^2 values greater than 0.92, highlighting that the model is best suited for analysing small, well-structured laboratory datasets with a moderate number of input parameters, making it a practical first choice for a preliminary scour depth prediction model where a limited experimental dataset is available.

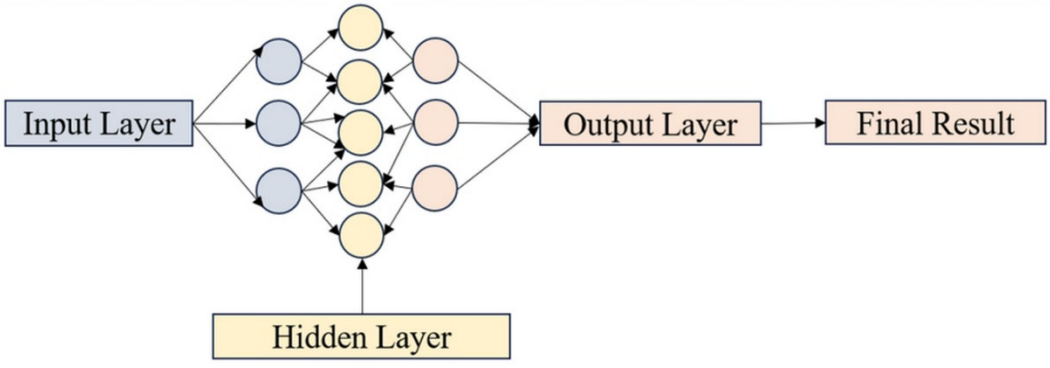

Fig. 3. Architecture illustration of an ANN model (Jatoliya et al., 2023)

3.2. Adaptive Neuro-fuzzy Inference System (ANFIS)

ANFIS is a powerful machine learning method first introduced by Jang (1993). The model combines neural networks with fuzzy logic to solve complex non-linear problems by establishing relationships between input and output data (Jatoliya et al., 2024; Najafzadeh et al., 2016). Integrating a hybrid function by combining the Fuzzy Inference System (FIS) with a Feed-Forward Neural Network (FFNN), as shown in Figure 4, improved the model's prediction accuracy (Jang, 1996). A study on predicting time-dependent scour depth using the ANFIS model and comparing its performance with GEP demonstrated that ANFIS effectively captured the

non-linear, complex behaviour of scour depth while providing satisfactory prediction performance. However, the ANFIS model performs similarly well on small to moderate datasets but becomes computationally expensive as the number of input parameters increases, limiting its application in multi-dimensional parameter scour predictions (Kumar et al., 2024a).

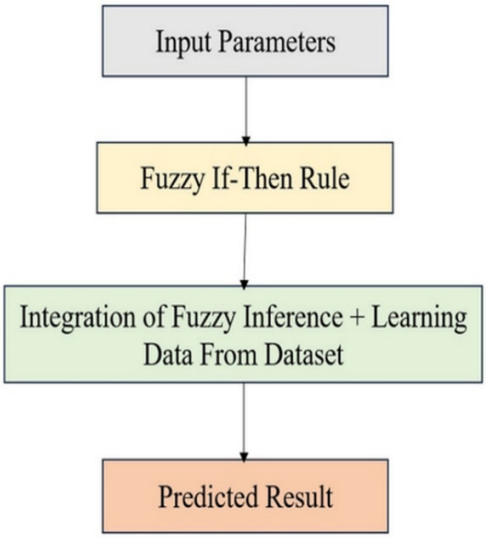

Fig. 4. Architecture illustration of an ANFIS model (Choudhary et al., 2023)

3.3. Random Forest Regression (RFR)

RFR is an ensemble machine learning model first proposed by Breiman (2001). The model is composed of multiple decision trees trained on different datasets. The model does not train on the entire dataset at once; instead, it selects random samples of subsets and features to train each tree independently, as shown in Figure 5. This randomness is referred to as random vectors, which makes the model robust (Bakhtiary et al., 2020; Bakhtiary et al., 2022; Bakhtiary et al., 2023; Kotu & Deshpande, 2015). The bagging structure of the model makes it robust to noise and outliers with moderate dataset sizes, and it works efficiently with datasets having a larger number of input features, making the model suitable for multi-parameter scour datasets integrating hydraulic, sediment, and geometric parameters (Huynh et al., 2025; Nandi et al., 2025).

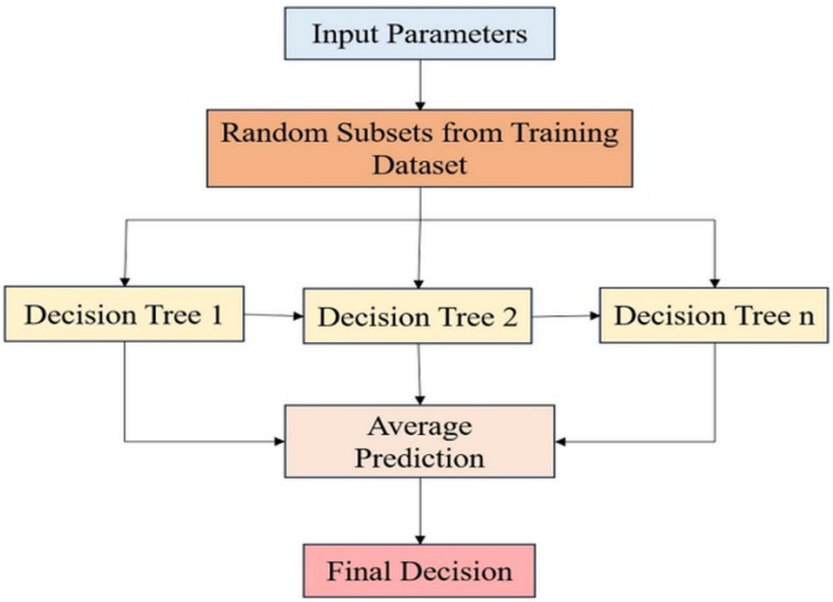

Fig. 5. Architecture illustration of an RFR model (Rahman & Chavan, 2024)

3.4. AdaBoost Regression (ABR)

ABR is an ensemble machine learning model that combines multiple weak trees to build a strong predictive model (Freund & Schapire, 1997). Studies by Kumar et al. (2023) and Nandi et al. (2025) applied the ABR model to predict temporal variations in scour depth. The study demonstrated that the ABR model achieved higher prediction accuracy than all other models applied. Although ABR improves prediction accuracy through sequential error corrections, as shown in Figure 6, it offers lower transparency and interpretability than traditional equations, making it difficult to physically understand how individual parameters influence scour depth (Ghanim et al., 2025; Schapire, 2013). The ABR model performs well with complex, non-uniform datasets, but its sequential training makes it sensitive to noisy or small datasets compared to the RFR model; therefore, it is best suited for moderate-to-large, relatively clean datasets (Kumar et al., 2023; Nandi et al., 2025).

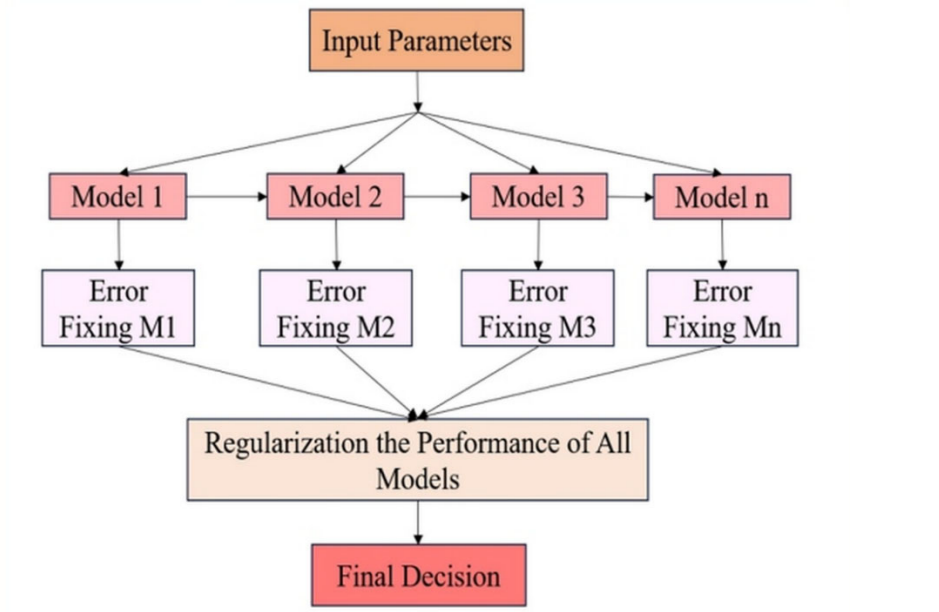

Fig. 6. Architecture illustration of ABR Algorithm Working Process (Ghanim et al., 2025)

3.5. Extreme Gradient Boosting Regressor (XGBR)

XGBR is one of the most advanced tree-based ensemble learning approaches. The model sequentially constructs decision trees while minimizing prediction errors through gradient optimization, reducing overfitting as shown in Figure 7. These characteristics enable XGBR to efficiently model highly non-linear relationships among hydraulic, sediment, geometric, and temporal variables (Chen & Guestrin, 2016). Kumar et al. (2024b) reported that the XGBR model achieved superior prediction performance compared with RF and ETR models. The gradient-optimized structure of the XGBR model makes it particularly well suited to large, high-dimensional datasets with strong non-linear interactions among parameters, consistently achieving the highest accuracy among ensemble models across the reviewed studies, making the model a preferred choice for multi-parameter, temporal evaluation of scour depth evaluation (Kumar et al., 2024b; Khan & Ismael, 2026).

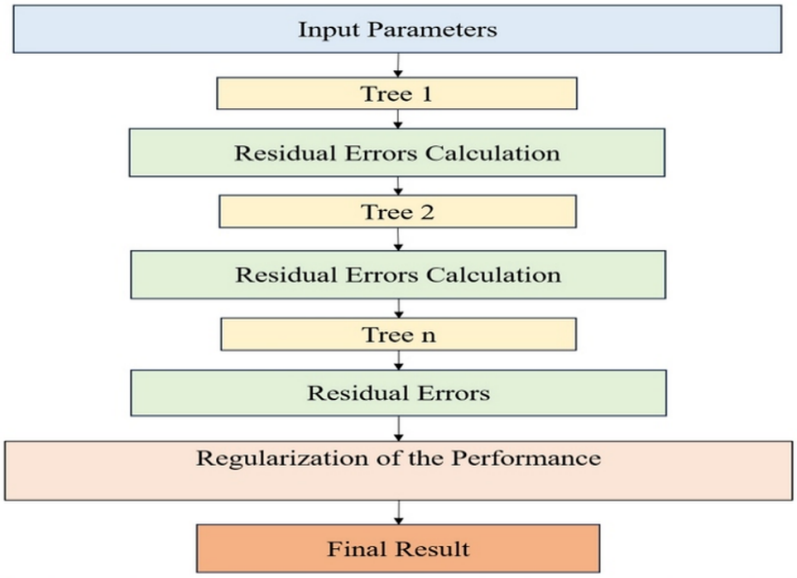

Fig. 7. Architecture illustration of XGBR model (Rahman & Chavan, 2024)

3.6. Deep Machine Learning

Deep learning is an advanced machine learning approach that has gained growing attention in engineering for solving complex problems. Deep learning models learn directly from raw data through multiple hidden layers, without the need for manual feature engineering, as shown in Figure 8. Some popular deep learning models include: (Deep Neural Networks) DNN, (Convolutional Neural Networks) CNN, and (Recurrent Neural Networks) RNN (Hamdia et al., 2021; Kumari & Toshniwal, 2021; Shyam, 2021). Huynh et al. (2025) applied a one-dimensional Convolutional Neural Network (1D-CNN) to predict scour depth around complex bridge pier configurations. CNN models have shown strong performance in handling complex spatial features, while RNN models have shown significant potential for predicting temporal variations in scour depth around bridge structures (Miao et al., 2021; Kim, 2020). Deep learning models require substantially larger datasets than the models above to avoid overfitting and are best reserved for complex, high-dimensional problems and spatial configurations like pile groups, rather than for single-bridge-pier datasets of limited size (Huynh et al., 2025).

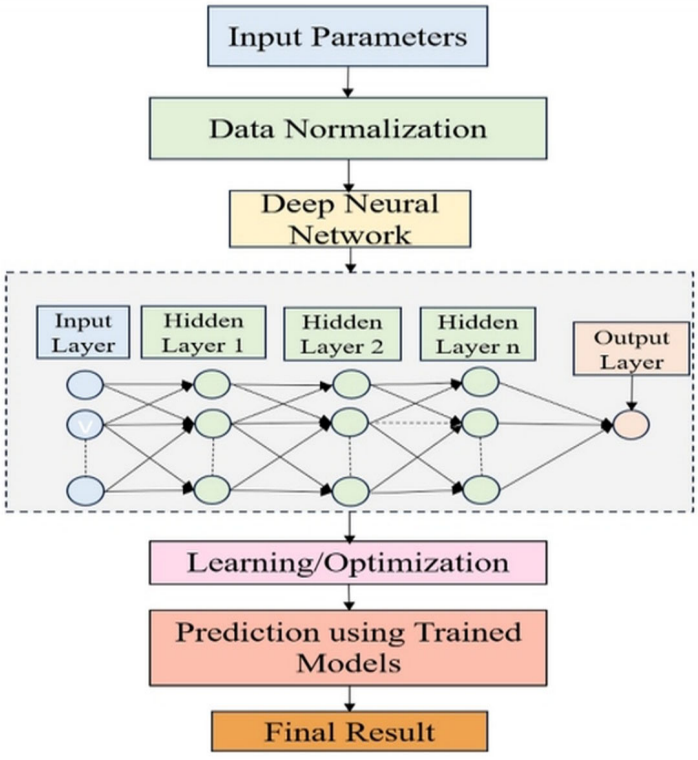

Fig. 8. Architecture illustration of Deep Learning model (Pal, 2022)

4. Critical Discussions

4.1. Critical Assessment of Traditional Mathematical Equations for Predicting Scour Depth

The mathematical equations summarized in Table 1 (Section 2.3) highlight the progressive development of scour-depth prediction around bridge piers, which has gained considerable attention over the past decades, reflecting researchers' consistent efforts to improve understanding of the scour process. Neill (1964) proposed a mathematical approach that relates scour depth primarily to pier diameter and flow depth, providing a simple way to estimate scour depth. However, this approach remains limited under varying hydraulic conditions, such as flow intensity, sediment characteristics, and pier geometry. The Colorado State University (CSU) equation (Colorado State University, 1975) was later included in HEC-18 by Richardson & Davis (2001) and considers the effects of Froude number, pier shape, flow angle, and bed conditions. Because of its simplicity and reliability, the CSU equation remains one of the most widely adopted approaches in bridge engineering. However, recent studies conducted by (Xiong et al., 2025), corroborated this limitation by reporting quantitative analysis, demonstrated that (HEC-18 and Melville, 1997) equations overestimated live-bed scour depth by up to 40% when evaluated against field measurements, with the most economical benchmark equation incurring 5–37% higher cost than the corrected alternative approach while (Wilson, 1995) equation underestimated scour depth with a 72% probability under live-bed conditions, highlighting the inconsistent bias of mathematical formulations on field scale applications. Similarly, Kim et al. (2024) demonstrated that four widely used mathematical equations, including HEC-18 ($R^2 = 0.35$) and Wilson (1995) ($R^2 = 0.11$), showed low correlation with field-representative scour depth evaluation from the USGS Pier Scour Database, further confirming that the predictive reliability of mathematical equations declines substantially when applied beyond controlled laboratory conditions.

Johnson (1992) improved the physical representation of the scour process by accounting for sediment gradation through the standard deviation of sediment size, improving scour-depth predictions for non-uniform sediments. Melville & Chiew (1999) developed an improved mathematical equation to estimate equilibrium scour depth, incorporating correction factors such as flow depth, flow intensity, sediment size, and time effects. This approach provided a more realistic view of scour development by separating the hydraulic and sediment effects governing scour depth and incorporating a time factor into equilibrium scour-depth prediction, indicating that scour develops progressively over time rather than instantaneously. Despite this improved physical basis, Xiong et al. (2025) reported that the Melville (1997) formulation overestimated live-bed scour by up to 40% and about 30% for clear-water conditions relative to field measurements, while Kim et al. (2024) reported an R^2 of only 0.34 against laboratory and field data, highlighting that the added physical complexity did not improve the predictive accuracy. Yanmaz (2001) proposed a time-dependent scour equation using the Froude number and relative flow depth, while Oliveto & Hager (2002) proposed a densimetric Froude number to describe temporal variation in scour depth. Kothyari et al. (2007) further included sediment entrainment and incipient particle motion. Later studies, including Kim et al. (2015), Lee & Sturm (2009), and Pandey et al. (2018), incorporated sediment and hydraulic parameters to improve prediction accuracy. However, these time-dependent equations have not been validated against large-scale field datasets in the reported literature, limiting their reliability under unsteady flow conditions relative to the equilibrium-depth equations discussed above.

4.2. Critical Assessment of Machine Learning Models for Predicting Scour Depth

The machine learning approaches listed in Table 2(a) show significant improvement in scour-depth prediction by mitigating limitations associated with traditional mathematical equations. The findings highlight that the ANN model achieved high prediction accuracy, with (R^2) values exceeding 0.92, demonstrating the capability of the model to capture the non-linear behaviour of scour processes. Ensemble learning techniques, including BR, XGBoost, GBR, AdaBoost, RFR, CatBoost, and stacking-based ensemble models, outperformed other machine learning models, showing better prediction accuracy and lower prediction errors. Among the studies reviewed in Table 2(a), GBR ($R^2 = 0.959$), XGBoost ($R^2 = 0.932$), and BR ($R^2 = 0.913$) performed best. CatBoost and stacking-based ensemble models ($R^2 \approx 0.90$) demonstrated more reliable predictive performance, highlighting the effectiveness of ensemble learning techniques for estimating scour depth. Although deep learning models such as one-dimensional Convolutional Neural Networks (1D-CNN) also showed satisfactory predictive accuracy, their performance remained dependent on the availability of large datasets. Sensitivity analyses across the reviewed studies consistently identified pier diameter (DP), dimensionless time (T), and scour depth time (d_{st}) as the most influential parameters, despite differences in dataset size and modelling approach. Feature importance techniques such as the Gamma Test, permutation importance, and SHAP analysis further improved model transparency by quantifying each input's relative contribution.

While early investigations focused on identifying the most suitable machine learning algorithm, recent studies have shifted toward hybrid frameworks and feature selection techniques that integrate traditional mathematical equations directly into ML models to combine physical knowledge with data-driven learning. Kumar et al. (2023) incorporated the equations of (Ettema et al., 2011; Kothyari et al., 2007; Oliveto & Hager, 2002), while Kumar et al. (2024a) integrated six widely used mathematical equations, including those proposed by (CSU 1975; Kim et al., 2015; Melville & Chiew, 1999; Neill, 1964; Oliveto & Hager, 2002; Pandey et al., 2018). Similarly, Kumar et al. (2024b) combined equations from Ettema et al. (2011), Johnson (1992), Oliveto & Hager (2002), and Richardson & Davis (2001), whereas Huynh et al. (2025) integrated Coleman (2005), HEC-18 methods, and Sheppard & Renna (2005). Nandi et al. (2025) integrated 11 mathematical equations from the literature studies in their machine learning framework. These studies demonstrated that embedding physical knowledge into ML frameworks improves accuracy, robustness, and practical applicability beyond what a standalone approach can achieve alone. Across all the reviewed studies listed in Table 2(a), it is concluded that dataset sizes in the range of 100–871 samples have shown an inconsistent correlation between sample size and predictive accuracy (R^2 = 0.850–0.959). The smallest dataset in Huynh et al. 2025 (100 samples) showed the lowest value (R^2 = 0.85), while the largest dataset in Nandi et al. 2025 (871 samples) showed moderate accuracy (R^2 = 0.896). In contrast, Khan & Ismael (2026), with a sample size of 569, and Kumar et al. (2024), with a sample size of 500, show the highest values (R^2 = 0.959) and (R^2 = 0.952), respectively, with mid-sized datasets. This suggests that feature selection and problem complexity, rather than dataset size alone, more strongly determine model performance in scour depth prediction.

Based on this integration of mathematical formulation into ML frameworks, several investigations provide quantitative evidence of the resulting higher accuracy. Kim et al. (2024) proposed an interpretable XGBoost model with SHAP analysis for evaluating scour depth, achieving R^2 = 0.75 and RMSE = 0.23 on an unseen dataset, outperforming HEC-18 (R^2 = 0.35, RMSE = 0.73) and Wilson (1995) (R^2 = 0.11, RMSE = 1.06) on the same dataset. Uzun & Kumcu (2025) similarly reported that the RFR model achieved R^2 = 0.9956 and MAPE below 10% for evaluating time-dependent scour depth around a bridge abutment, outperforming Linear Regression (R^2 = 0.4547, MAPE> 80%). This gap remained robust across 10-fold cross-validation and multiple train-test splits. Li et al. (2025) proposed a Transformer designed to focus more on input parameters physically important for scour development, based on fluid mechanics knowledge, reducing RMSE from 0.189 to 0.061 and increasing R^2 from 0.868 to 0.986. Hosseini et al. (2024) demonstrated that high R^2 values do not always indicate reliable performance. Although RBF, MLP, ANFIS, SVM, and MLR achieved R^2 values of 0.99, 0.98, 0.97, 0.96, and 0.90, respectively, ANFIS performance dropped to R^2 (0.97–0.23) on the training dataset from (80–50%) with a small training dataset, while RBF remained stable with R^2 (0.99–1.00).

The analysis in the present study indicated that the importance of ML-derived input parameters is largely consistent with established scour mechanics and empirical formulations. Pier diameter was identified as the most important input parameter in the study conducted by Khan & Ismael (2026). This finding is consistent with empirical equations such as HEC-18 and Melville (1997), which highlight that increasing pier diameter can form a stronger horseshoe vortex that removes large amounts of sediment, with scour depth generally increasing with pier width. Similarly, Kim et al. (2024) identified flow shallowness as the most important parameter, although HEC-18 indicates that scour depth increases gradually with flow depth. For time-dependent scour, dimensionless time was identified as the most important input parameter by Kumar et al. (2023), which is consistent with the established empirical observation that scour grows rapidly at the initial stage and then progressively slows as scour depth reaches the final equilibrium stage (Melville & Chiew, 1999). The importance of parameters varies across studies because it depends on the data and inputs used (Rahman & Chavan, 2024). Therefore, ML-derived models should be supported by data-dependent evidence and established physical scour mechanisms.

Table 2(a). Summary of machine learning-based studies used in the literature for evaluating the scour depth around bridge pier structures

Authors	Datasets Used	*Input Parameters	**Modelling Approaches	***Model Assessment and Key Findings
Ali & Gunal, (2021)	Total Dataset = 400 Training Dataset = (70%) Testing Dataset = (15%) Validating Dataset = (15%)	$D_p, d_{50}, \sigma_g, U, U_C, y, \mu, g, \rho, \rho_s, d_{se}, \alpha$ and β, Υ	Models used are: 1. ANN 2. Training Algorithms DM-1 (TRAINLM), DM-2 (TRAINRP), DM-3 (TRAINGDA), DM-4 (TRAINCGF), DM-5 (TRAIN-CGP), DM-6 (TRAINCGB), DM-7 (TRAINBFG), NDM-1 (TRAINLM)	Model assessment is based on R^2 and MSE. The best-performing model is ANN DM-1 (TRAINLM) with (R=0.929, MSE=0.0032). D_P = most influential parameter (sensitivity analysis).
Ali et al., 2022	Total Dataset = 400 Training Dataset = (70%) Testing Dataset = (15%) Validating Dataset = (15%)	$D_P, y, U, d_{50}, \sigma_g, U_C, d_{se}$	Models used are: 1. ANN-1 (TRAINBR) 2. ANN-2 (TRAINLM) 3. ANN-3 (TRAINSCG) 4. MLR (Multiple linear regression)	Model assessment is based on R^2 and MSE. Best Performing model ANN-1 (TRAINBR) with (R2=0.926, MSE=0.0066) D_P= most influential parameter (sensitivity analysis).
Kumar et al., 2023	Total Dataset = 587 Training Dataset = (53%) Testing Dataset = (47%)	$d_{50}, \sigma_g, U, y, t, D_p, \rho_f, \mu, g, \rho_s, U_{cr}, Al, Sh, t_R, d_{st}/D_P$	Models used are: 1. BR 2. ABR 3. SVR Mathematical Equations used are: 1. Oliveto and Hager (2002) 2. Kothyari et al. (2007) 3. Ettema et al. (2011)	Model assessment is done based on R, R^2, NSE, MAE, MSE, and PBIAS BR outperformed mathematical equations on the same testing dataset: Oliveto and Hager (R^2=0.615), Kothyari et al. (R^2=0.390), and Ettema et al. (R^2=0.224), showing an R^2 improvement from (0.30-0.69) over classical formulas. Best model performance of the BR model with (R^2=0.913, R=0.956, NSE=0.913, MAE=0.06, MSE=0.013, and P BIAS=0.329). log(T1) is the most sensitive dimensionless input parameter (sensitivity analysis).

Table 2(a). cont.

Authors	Datasets Used	*Input Parameters	**Modelling Approaches	***Model Assessment and Key Findings
Kumar et al., 2024a	Total Dataset = 500 Training Dataset = (80%) Testing Dataset = (20%)	D_P, y, U, U_C, F_r, d_{50}, σ_g, t, d_s, μ, g, ρ	Models used are: 1. ANFIS 2. GEP 3. Gamma Test Mathematical Equations used are: 1. Neill (1964) 2. CSU (1975) 3. Melville and Chiew (1999) 4. Oliveto and Hager (2002) 5. Kim et al. (2015) 6. Pandey et al. (2018)	Model assessment is based on R^2, RMSE, MAPE, and I_d. GEP outperformed all six mathematical equations on the same testing dataset: Neill (R^2=0.328, MAPE=165.41%), CSU (R^2=0.329, MAPE=35.71%), Melville & Chiew (R^2=0.050, MAPE=205.13%), Oliveto & Hager (R^2=0.008, MAPE=212.5%), Kim et al. (R^2=0.187, MAPE=90.82%), and Pandey et al. (R^2=0.307, MAPE=146.9%), showing an R^2 improvement of 0.62-0.94 over classical formulas. ANFIS also outperformed all six equations (R^2=0.825, MAPE=17.17%). The best-performing model reported is GEP (R^2=0.952, MAPE=8.67%, RMSE=0.02, Id=0.986), also b/y (relative pier width) identified as the most essential parameter for scour depth modelling
Kumar et al., 2024b	Total Dataset = 555 Training Dataset = (52.3%) Testing Dataset = (47.7%)	D_P, y, U, d_{50}, σ_g, t, d_{st}/D_p	Models used are: 1. XGBR 2. RFR 3. ETR Mathematical Equations used are: 1. Oliveto & Hager (2002) 2. Johnson (1992) 3. Ettema et al. (2011) 4. Richardson & Davis (2001)	Model assessment is based on R, R^2, NSE, MSE, CRMSE, MAE, SI, and A_gI. XGBR outperformed all four mathematical equations on the same testing dataset: Oliveto & Hager (R^2=0.615, +34.04%), Johnson (R^2=0.350, +62.45%), Ettema et al. (R^2=0.344, +63.16%), and Richardson & Davis (R^2=0.148, +84.16%), showing an R^2 improvement of 0.148-0.615 (34-84%) over classical formulas. XGBR also outperformed 8 other ML methods (R^2=0.729-0.905), highlighting an improvement of 2.89-21.76% The best-performing model is XGBR (Model 3) with (R=0.966, R^2=0.932, NSE=0.932, A_gI=0.982, CRMSE=0.095, SI=0.209) log(T3) is identified as the most sensitive dimensionless input parameter using sensitivity analysis.

Table 2(a). cont

Authors	Datasets Used	*Input Parameters	**Modelling Approaches	***Model Assessment and Key Findings
Huynh et al., 2025	Total Dataset = 100 Training and validation Dataset = (80% training, 20% validation) Testing Dataset = (20%)	y, U, U_C, d_{50}, σ_g, b_{col}, l_{col}, T, b_{pc}, l_{pc}, D_{pb}, S_n, S_m, m, n and h_0, h_1	Models used are: 1. SVM 2. GPR 3. LR 4. RFR 5. XGBoost 6. DNN 7. NN 8. 1D CNN Mathematical Equations used are: 1. Coleman (2005) Method 2. Sheppard and Renna (2005) Method (Method of FDOT) 3. Method of HEC-18	Model assessment is based on R2, MSE, RMSE, MAE, SI, Se, and B. 1D CNN reduced RMSE by 21.07%, 57.48% and 76.77% relative to HEC-18 (RMSE=0.299), FDOT (RMSE=0.555), and Coleman (RMSE=1.016), respectively. Best performing model 1D CNN (One-Dimensional Convolutional Neural Network) with (R^2=0.85, RMSE=0.1125, MAE=0.1078, SI=0.1149, Se=0.1147, B=-0.0194)
Nandi et al., 2025	Total Dataset = 871 Training Dataset = 75% Validation Dataset = 25%	y, D_P, σ_g, U, U_C, d_{50}, ρ_f, ρ_s, t, g, B, μ, s/d (S), i/i_c (I), d/d_{50} (D), T, R_e, F_r	Models used are: 1. LRS 2. ANN 3.KNNK 4. MARS 5. SVR 6. ABR 7. RFR 8. GBR 9. LARS 10. ETR 11. XGBoost 12. LightGBM 13.MachineHGB 14. CatBoost Ensemble Models: 1. Voting Regressor 2. Stacking Regressor Mathematical Equations used are: Used 11 mathematical equations from literature study	Model assessment is based on R2, MSE, MBE, MAE, KGE, IA, STDev, and TSS. Both CatBoost and the Stacking ensemble outperformed all 11 mathematical equations: the best classical performance achieved is R^2=0.659 (Nandi and Das, 2023) and R^2=0.648 (Franzetti et al., 2022), as compared to the R^2= (0.887-0.896) for the ML models; an improvement of 0.23-0.60 in R^2 is observed. Best performing model CatBoost (CB) with (R^2=0.887, MSE=0.044, MAE=0.157, KGE=0.879, and IA=0.968) Among ensemble methods, Stacking Regressor using the top 7 ML models with six input parameters performed best with (R^2=0.896, MSE=0.041, MAE=0.148, KGE=0.906, and IA =0.971) Flow shallowness (S) is the most influential input variable (sensitivity analysis)

Table 2(a). cont.

Authors	Datasets Used	*Input Parameters	**Modelling Approaches	***Model Assessment and Key Findings
Khan & Ismael, 2026	Total Dataset = 569 Training Dataset = 455 (80%) Testing Dataset = 114 (20%)	D_P, y, U, d_{50}, σ_g, U_C, t, d_{se}	Models used are: 1. GBR 2. AdaBoost 3. XGBoost 4. GPR 5. Polynomial kernel	Model assessment is based on R2, RMSE, MAE, and SHAP. Best performing model GBR with (R^2 = 0.959, RMSE = 0.145, MAE = 0.064) Pier width normal to flow (D_{Pn}) is the most important parameter, accounting for about 70.6% of total importance (SHAP analysis).

***Input Parameters:** U_c (critical sediment velocity), μ (dynamic viscosity), t (time for start of scour depth), ρ (mass density), ρs (mass density of the sediment), d_{se} (equilibrium scour depth), α and β (correction factors for flow angle of attack and pier shape), Υ (is the correction factor for bed form), μ (dynamic viscosity of fluid), (critical velocity for sediment movement), Al (pier alignment), Sh (pier shape), t_R (time scale for scour), d_s (time dependent scour depth), d_{st}/d_P (scour depth at any time t), b_{col} (width of the column), l_{col} (length of the column), (T) thickness of the pile, b_{pc} (width of the pile), l_{pc} (length of the pile), D_{pb} (diameter of the pile), S_n (perpendicular spacing), S_m (parallel spacing), m (perpendicular flow direction), n (parallel flow direction) and h_0,h_1 (pile cap elevation relative to the sediment bed elevation), B (width of the flume), s/d (S) (flow shallowness), i/i_c (I) (intensity of the flow), d/d_{50} (D) (sediment coarseness), R_e (Reynolds number).

****ML-Models:** ANN (Artificial Neural Network), MLR (Multiple linear regression), BR (Bagging Regressor), ABR (AdaBoost Regressor), SVR (Support Vector Regressor), ANFIS (Adaptive Neuro-Fuzzy Inference System), GEP (Gene Expression Programming), Gamma Test (GT), XGBR (Extreme Gradient Boosting Regressor), RFR (Random Forest Regression), ETR (Extra Trees Regressor), Support Vector Machine (SVM), Gaussian Process Regression (GPR), Logistic regression (LR), Deep neural network (DNN), Neural Network (NN), 1D convolutional neural networks (1D CNN), LRS (Linear Regression), KNNK (Nearest Neighbors), MARS (Multivariate Adaptive Regression Splines), GBR (Gradient Boosting Regression), LARS (Least Angle Regression), ETR (Extra Trees Regressor), LightGBM (Light Gradient Boosting), MachineHGB (Histogram-Based Gradient Boosting), CatBoost (Categorical Boosting), GPR (Gaussian Process Regression, RBF kernel), Kernel Ridge Regression (polynomial kernel).

*****Statistical Indicators:** R (Correlation Coefficient), R^2 (Coefficient of Determination), NSE (Nash-Sutcliffe Efficiency), MAE (Mean Absolute Error), MSE (Mean Squared Error), PBIAS (Percent Bias), MAPE (Mean Absolute Percentage Error), I_d (Index of Agreement), A_gI (Agreement Index, CRMSE (Centered Root Mean Square Error), SI (Scatter Index), S_e (Standard Deviation of Prediction Errors), B (Mean Prediction Error/Bias), MBE (Mean Bias Error), KGE (Kling-Gupta Efficiency), IA (Index of Agreement), St_{Dev} (Standard Deviation), TSS (Taylor Skill Score), SHAP (SHapley Additive ExPlanations).

Table 2(b) presents the data sources, validation methods, number of predictors, principal limitations, and interpretability methods used in the reviewed studies in Table 2(a). All models used in the literature are trained on laboratory datasets; most are under clear-water conditions, so their accuracy under field conditions remains untested. Most studies listed in Table 2(a) and (b) used a single training-and-testing dataset split. Only Huynh et al. (2025) and Khan & Ismael (2026) utilized k-fold cross-validation. So, model performance may partly depend on the dataset split. The number of predictors ranged from 5 to 16, and most models used dimensionless input parameters. Table 2(b) shows that interpretability methods were mainly limited to sensitivity analysis. Nandi et al. (2025) and Khan & Ismael (2026) applied SHAP, and only Kumar et al. (2024a) used the Gamma Test for input selection and Sensitivity analysis as the interpretability method. Therefore, this review suggests that future studies should include field data, cross-validation, and interpretability tools to make ML models more reliable for evaluating scour depth around bridge structures.

Table 2(b). Summary of data characteristics, validation and interpretability of the reviewed ML studies

Authors	Data Source	Laboratory /Field Classification	Validation Method	Number of Predictors	Principal Limitations	Interpretability Method
Ali & Gunal, (2021)	400-data points are utilized from different literature studies	Laboratory studies	The performance of the model is checked using training, testing and validation of the model	Input variables used for validating the results = 6	The results of ANN model are only compared regression model; no established scour equations are utilized	Sensitivity analysis
Ali et al., 2022	400-data points are collected from different literature studies				The results of ANN model are only compared regression model; no established scour equations are utilized	Sensitivity analysis
Kumar et al., 2023	587-data points are collected from different literature studies.			Input variables used for validating the results = 5	Unbalanced dataset, Chang et al. 2004 was dominated by about 75% of data from total data used in their study	Sensitivity analysis
Kumar et al., 2024a	500-data points are collected from different literature studies.				Performance accuracy of the model depends on data normalisation (GEP R^2 = 0.952 on normalised data and 0.814 on raw data) which is limited to the data ranges tested.	Gamma Test for input selection and Sensitivity analysis
Kumar et al., 2024b	555-data points are collected from different literature studies.				Limited to the laboratory datasets for clear-water, steady flow conditions. Performance for live-bed scour, unsteady flow, and natural water beds was not tested	Sensitivity analysis

Table 2(b). cont.

Authors	Data Source	Laboratory /Field Classification	Validation Method	Number of Predictors	Principal Limitations	Interpretability Method
Huynh et al., 2025	100-data points are collected from prominent research sources across different geographical and institutional backgrounds	Laboratory studies	The performance of the model is checked using training, testing and k-fold cross-validation of the model	Input variables used for validating the results = 16	Small dataset (100 points) is utilized for a deep-learning model.	Correlation analysis
Nandi et al., 2025	871-data points are collected from different literature studies.		The performance of the model is checked using training and testing of the model	Input variables used for validating the results = 12	unbalanced dataset is utilised in which a few sources are dominate (e.g. Ettema 1980 =115 data, Pandey et al. 2020 = 85)	SHAP analysis
Khan & Ismael, 2026	569-data points from 2014 U.S. Geological Survey Pier-Scour Database			Input variables used for validating the results = 7	Trained on laboratory data. V_c and T for the field site were estimated rather than measured, and the variation in d_{50} and σ_g was limited.	SHAP analysis

4.3. Rationale and Contribution of this Review

While several studies have proposed new mathematical equations or machine learning models for predicting scour depth around bridge structures, to the best of the authors' knowledge, no existing review has systematically compared these approaches within a hierarchical framework based on their relationship to standalone, ensemble, and hybrid ML techniques and their mathematical predecessors. Moreover, the extent of performance improvement among studies has not been consistently quantified using statistical criteria. This gap makes it difficult to select an appropriate predictive approach based on reliability, computational cost, data availability, and physical interpretability. This review study addresses this gap by critically comparing traditional and data-driven approaches among a common set of performance metrics (R^2, RMSE, MAPE). It concludes with a model selection guide summarizing the conditions under which mathematical equations, standalone ML models, ensemble methods, or hybrid physics-informed frameworks are most appropriate for evaluating local scour depth around bridge piers.

Table 3 summarizes comparisons from previous review studies. Literature review studies addressed scour processes and estimation methods (Pizarro et al., 2020), evaluated deterministic empirical equations (Shahriar et al., 2021), focused on scour evaluation and monitoring (Tola et al., 2023), and summarised some ML studies (Rahman & Chavan, 2024), as shown in Table 3. The table shows that systematic comparisons of empirical equations with standalone, ensemble, and hybrid ML models tested on the same dataset for bridge pier scour are limited in these studies. Therefore, this review addresses this gap through a quantitative comparison and a model-selection guide, as presented in Table 2(a).

Table 3. Summary of comparison of previous review studies

Previous Reviews	Scope	Methods	Limitations	Specific contribution to present study
Pizarro et al. (2020)	To address the problem of scour at bridge foundations	Sediment motion, physical modelling and controlling dimensionless scour parameters, scour estimates encompassing empirical models, numerical frameworks, data-driven methods, non-deterministic approaches, monitoring and design	Machine learning models are not compared to predict the reliable model for predicting the scour depth	This review compares different machine learning models with existing mathematical models based on the statistical matrix to evaluate scour depth around bridge structures.
Shahriar et al. (2021)	This study was carried out to evaluate the scour around a bridge pier. Error statistics and accuracy, precision, and probabilistic distribution of predictions from these models are discussed in this study.	Four pier scour models, Wilson (1995), Melville (1997), Hydraulic Engineering Circular No. 18 (2012), and Briaud (2014), are used to comparatively analyse laboratory-experiment data and evaluate the pier scour database.	Their study is limited to deterministic equations only; no machine learning models are used to predict the most reliable model, so probabilistic/reliability-based approaches remain limited.	Machine learning models, including standalone, ensemble, and hybrid models, are used to evaluate the most reliable model for estimating scour depth.
Tola et al. (2023)	This literature review was carried out to present the recent scour detection techniques and approaches.	Direct and indirect monitoring and machine learning algorithm-based studies are investigated in their study. The approaches, models, data characteristics, and other input properties are outlined.	Their study focuses on detection and monitoring of scour detection techniques; no depth prediction related to scour estimation was carried out.	Scour depth prediction for bridge structures is carried out.

Table 3. cont.

Previous Reviews	Scope	Methods	Limitations	Specific contribution to present study
Rahman & Chavan (2024)	This study was carried out to analyze the scour depth predictive equations around bridge piers under clear-water and live-bed scouring conditions	Their study consolidated the following (1) Available experimental and field data sets on different types of bridge pier scouring (2) The influence of flow and roughness parameters on both clear-water scouring (CWS) and live-bed scouring (LBS) (3) Existing empirical equations suitable for computing equilibrium scour depth around a bridge pier under CWS and LBS conditions.	In this study, based on the performance of different empirical models in predicting scour depth ratio, suitable models are recommended for CWS and LBS conditions. However, the study's analysis of the most reliable model based on side-by-side performance values using statistical indicators is limited.	A detailed comparison of machine learning models and empirical models, as shown in Table 2(a), is presented. The review also presents a model-selection guide based on the comparison matrix of statistical indicators to select the most reliable model for evaluating scour depth prediction.
Murtaza et al. (2025)	This review critically analysed hybrid machine learning models used to predict scour depth around bridge abutments.	The reviewed techniques used ANN, ANFIS, GEP, SVM, and ELM models, including their hybrid versions. Their predictive performance was assessed using the correlation coefficient (R), mean square error (MSE), Taylor diagrams, and sensitivity analysis.	Their study is limited to evaluating scour around abutments; therefore, their findings cannot be directly applied to local scour evaluation around bridge piers. Also, no model-selection guide based on dataset size and complexity is provided.	This review focuses on evaluating local scour around bridge piers and provides a full hierarchy of empirical, standalone machine learning, ensemble, and hybrid models. Also, the performances of these models are compared with empirical equations on the same datasets as shown in Table 2(a) and provide a model selection guide to select accordingly.

4.4. Engineering and Environmental Benefits of Accurately Predicting the Scour Depth

Accurate scour-depth prediction can reduce environmental impact through a simple chain: a small design error leads to smaller protection works. Existing scour design equations are intentionally conservative. For example, HEC-18 and Melville (1997) overestimate scour depth by about 40% under live-bed conditions and about 30% under clear-water conditions (Xiong et al., 2025). Overestimating scour depth can lead to deeper foundation designs, larger riprap aprons, more excavation, and more material placed in the streambed. This increases construction material consumption, construction time, and disturbance to the riverbed and aquatic habitat, thus disturbing the ecology. Improved prediction models can reduce this overestimation without compromising safety. An enhanced HEC-18 equation was reported to maintain a safety level as compared to existing equations while achieving predictions that were 5–37% closer to the field measurements (Xiong et al., 2025).

5. Gaps and Future Perspectives

The traditional mathematical equations and machine learning models reviewed in this study were developed and validated using laboratory datasets under controlled hydraulic conditions, limiting their applicability to complex field conditions. These limitations are not merely theoretical, as discussed in Section 4.1; equations such as HEC-18 and Melville (1997) have shown results that overestimate the field-measured scour depth, while Wilson (1995) equation exhibited a probability of underestimation under live-bed conditions, highlighting the unreliability of laboratory-scaled experimental equations when extrapolated to field conditions. A similar limitation was observed for several machine learning models as discussed in Section 4.2; ANFIS-based models exhibited substantial degradation in predictive accuracy when the training dataset size was reduced, whereas ensemble methods such as RF maintained stable performance, indicating that robustness under limited or field-representative data availability is not yet consistently achieved across ML architectures. Additionally, the lack of standardized datasets makes direct comparisons of model performance difficult because dataset size, input parameters, and evaluation metrics vary. All researchers used different datasets based on availability, so the models show different predictive capabilities. The deviation in results can be minimized with a large dataset. The U.S. Geological Survey published pier-scour data in a digital spreadsheet called the 2014 USGS Pier-Scour Database (PSDb-2014). It consists of 569 laboratory and 1,858 field measurements. These data cover a wide range of laboratory and field measurements from 23 states in the United States and 6 other countries (Benedict & Caldwell, 2014). Because scour is a complex phenomenon, more real-time bridge-scour data and hydraulic datasets are needed to understand pier-scour relationships and develop reliable pier-scour relationships. The current study aims to focus on integrating machine learning approaches with hydraulic engineering data, alongside conventional design methods already used in research, and to raise awareness among the next generation of water resources professionals about applying new, advanced, appropriate data-driven tools for scour depth prediction. Although recent studies integrated mathematical equations with ML approaches, further research is needed to develop interpretable, field-validated models using large, standardized datasets that adequately represent sediment, flow, and pier conditions in practice.

6. Summary

This review examined scour depth prediction using traditional mathematical equations and modern machine learning techniques, highlighting a clear shift from physics-based mathematical formulations to data-driven frameworks. Beyond implications for structural safety, accurate scour-depth prediction also has direct environmental relevance, since scour development governs disturbance of sediment bed material and aquatic habitat around bridge piers. Traditional mathematical equations have played a fundamental role in understanding the hydraulic mechanisms responsible for scour depth development and have provided a foundation for understanding the scour mechanism. However, these equations' dependence on scour-influencing parameters, predefined mathematical relationships, and laboratory-scale datasets limits their ability to represent the complex, non-linear interactions governing scour depth development under various hydraulic conditions.

This review demonstrated that machine learning models have shown superior predictive performance for scour depth development by learning complex relationships directly from experimental datasets, without requiring predefined functional equations like traditional mathematical models. This progressive transition of machine learning algorithms towards ensemble learning and hybrid modelling frameworks has significantly improved prediction accuracy, robustness, and model interpretability. Ensemble learning techniques, including GBR, XGBoost, BR, CatBoost, and stacking models, consistently achieved superior predictive performance using the statistical indicators (MSE, RMSE, MAE, and R^2) as described in Table 2(a), where machine learning

techniques outperformed traditional mathematical equations in the majority of comparisons in reviewed studies. The integration of traditional mathematical equations into machine learning frameworks suggests that combining hydraulic knowledge with data-driven techniques can provide more reliable and consistent predictive capabilities than a single machine learning approach alone. This improved reliability has practical environmental benefits, as overly conservative mathematical predictions often lead to overestimation and additional scour countermeasures, resulting in excess use of construction materials and greater disturbance of the streambed and habitat around bridge piers, whereas more accurate hybrid predictions can support right-sized, less disruptive design solutions.

Despite these advancements, this review concludes that the practical applicability of existing models remains constrained by reliance on laboratory datasets and limited validation under real field conditions. Therefore, it is suggested that there is a need for a large number of field datasets, along with laboratory datasets, which may be applied with different data-driven tools like machine learning models, to check their capabilities to get more precise and accurate results. The research community needs updated, available hydraulic data on bridge scour to develop more reliable methods based on advanced data-driven technologies like machine learning. Training hydraulic engineers and staff in the latest data-driven tools, along with greater access to scour data, will help the community develop more realistic hybrid empirical-ML formulas. The Comprehensive review aims to promote a pathway for advancing bridge scour risk management by applying hybrid empirical-ML methods, based on greater availability of data (field and experimental), and by building interdisciplinary capacity within the water resources community, educators, policymakers, and researchers. In this context, the present review aims to encourage prediction practices that minimize unnecessary material use and habitat disturbance, contributing to more environmentally sustainable infrastructure development.

Statements and Declarations

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Data Availability Statement

The data used in the study can be obtained from the authors upon request.

Consent to Publish

The authors declare that there are no potential conflicts of interest and all the authors consent to the publication of this manuscript.

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