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Integrating Artificial Intelligence for Urban Drainage Systems Aided Decision: State of the Art

S. BOUGHANDJIOUA [1], F. LAOUACHERIA[1], N.AZIZI[2]

[1]Laboratory of Soils and hydraulic, Faculty of Technology Badji-Mokhtar Annaba University Annaba, Algeria
[2]LABGED Laboratory, Faculty of Technology Badji-Mokhtar Annaba University Annaba, Algeria

CORRESPONDING AUTHOR: S. Boughandjioua (e-mail: samira.boughandjioua@univ.annaba.dz).

ABSTRACT Urban drainage systems may derive advantages from the implementation of machine learning methods for decision-making and cleansing operations. Conventional decision support systems are rendered ineffective in tackling the intricate and indeterminate aspects of urban planning concerns. It aims to improve model evolution and use while facilitating simpler access using suggested open sources provided in this research. This paper provides an overview of machine learning methods applied in modeling urban drainage systems, and it compares the proposed methods among different machine learning models., which are classified into five distinct approaches: Supervised learning, unsupervised learning, deep learning, Reinforcement learning, and finally hybrid approaches combining two or more previous algorithms. This study explores also diverse datasets and open sources related modelling in urban drainage system that researchers can utilize in their scientific investigations. From the study it can be concluded that the choice of machine learning for urban irrigation systems depends on the specific goals and the nature of the problem. Additionally, studies demonstrate that hybrid and deep learning approaches can solve problems with urban irrigation systems, increase system performance, and yield correct results. Accurately interpreting data and successfully resolving urban irrigation systems' problems are the goals of deep learning. Furthermore, hybrid methods facilitate advances in model development through the integration of mathematical and machine learning models.This study helps researchers improve models and promote their applications to prevent natural disasters.

INDEX TERMS Datasets, Machine Learning, Reinforcement Learning, Urban Drainage System.

I. INTRODUCTION

Urban drainage system modeling using machine learning has been a topic of interest in recent research. Several studies have explored the use of machine learning methods to improve the operation and control of drainage systems [1]. Machine learning techniques have been increasingly used in urban drainage systems as an alternative to classical models due to their numerous benefits [2]. These benefits include improved accuracy and predictive capabilities [3], the ability to handle complex and non- linear relationships [4], and the potential for real-time monitoring and control [5]. Machine learning algorithms can effectively analyze large and diverse datasets, allowing for more comprehensive and detailed modeling of urban drainage systems [6]. Additionally, machine learning techniques can adapt and learn from new data, making them suitable for dynamic and evolving urban environments [6]. Overall, the use of machine learning in urban drainage systems offers the potential for more efficient and effective management of stormwater and flood control [7]. The previous study investigated the application of machine learning (ML) in urban drainage systems (UDS) to enhance model performance, efficiency, and understand data distribution patterns. It specifically focused on real-time operational control, flood prediction, and pipeline maintenance, while also emphasizing the limitations associated with physically based fluid dynamics and hydraulic models [8].

In our research, the proposed method provides an overview of various machine learning methods, including supervised learning, unsupervised learning, deep learning, reinforcement learning, and hybrid approaches, applied to model urban drainage systems. The study also compares the learning models in selected studies and involves both local and reference datasets. The research is distinguished by the inclusion of open-source datasets for prediction and expansion, proposing datasets for urban drainage systems, as well as model development. This facilitates easy use for researchers and engineers in predicting and improving expansion. Additionally, a comparison is made with the previous study [8], which lacked open data sources, representing an enhancement in providing information for researchers and engineers. The obtained results indicate that deep learning and hybrid approaches are the best models for utilizing machine learning. The focus of the review was on five categories: supervised learning, unsupervised learning, deep learning, reinforcement learning, and hybrid approaches. To gather relevant literature, the following methods were employed: web databases such as Web of Science, Scopus, and Google Scholar, in addition to AI assistants such as Perplexity and ChatPDF.There are multiple sections in this paper. The second section discusses the kind of machine learning employed for the investigation. The subsequent segment examines and groups prior studies based on machine learning types. The main topic of the fourth section is the comparison of the machine learning models applied in these investigations. Section five provides an overview of open-source datasets and suggested datasets for urban drainage systems. The discussion concludes with the sixth section, and the seventh section offers conclusions.

II. Preliminaries

At this stage, the proposed methods will delve into various types of machine learning and explore their applications. Machine learning is an expansive field within artificial intelligence, focusing on the creation and utilization of algorithms enabling computers to learn from data and make predictions or decisions. It involves the development of models or algorithms capable of automatic learning and improvement without explicit programming. These algorithms are crafted to analyze pat- terns, extract meaningful information from vast datasets, and render precise predictions or decision [8] In the context of urban drainage systems, machine-learning techniques have been increasingly utilized to improve various aspects of these systems. From storm water drainage systems to overflow forecasting in early warning systems, machine learning algorithms have demonstrated their potential in enhancing the efficiency and effectiveness of urban drainage systems by making use of the vast amounts of data generated by sensors installed in these systems [9]. Machine Learning Approaches can address several significant challenges in UDSs, such to divide approaches in machine learning studies; you can consider the following sections (Fig.1).

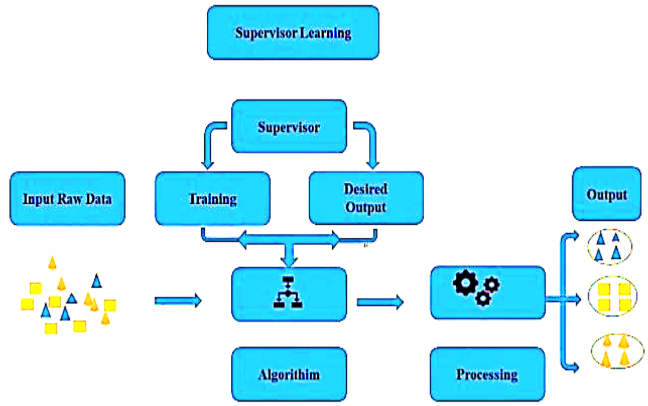

FIGURE 1. The main stages of supervised learning Based approaches.

A. Supervised Learning

Supervised learning is a type of machine learning algorithm that learns from labeled data. Labeled data consists of input data and the corresponding output labels. The algorithm learns from the labeled data to make predictions about new, unseen data [10]. The applications of supervised learning in Urban Drainage System Modeling include:

1) Predicting rainfall-runoff relationships: By analyzing historical rainfall and runoff data, a supervised learning model can be trained to predict future runoff based on forecasted rainfall [11].
2) Improving the accuracy of flood inundation mapping: By combining high-resolution topographic data and historical flood events, a supervised learning model can be trained to predict the extent and depth of flooding for different rainfall scenarios [12].
3) Optimizing the design of drainage systems: By simulating different drainage system designs under various rainfall scenarios, a supervised learning model can be used to identify the most efficient and cost-effective design [13].

B. Unsupervised Learning

This is a type of machine learning algorithm that learns from unlabeled data. Unlabeled data consists of input data without any corresponding labels. The algorithm learns from the unlabeled data to identify patterns and structure in the data [10]. The applications of unsupervised learning in Urban Drainage System Modeling include:

1) Classifying land use types: By analyzing satellite imagery or other geospatial data, an unsupervised learning model can be used to classify different land use types based on their impact on runoff [14]
2) Identifying potential sources of pollution: By analyzing water quality data, an unsupervised learning model can be used to identify potential sources of pollution in a drainage system [15].
3) Detecting anomalies in drainage system performance: By analyzing sensor data from a drainage system, an unsupervised learning model can be used to detect leaks, blockages, or other anomalies [16].

It is a type of machine learning that uses artificial neural networks (ANNs) with multiple layers to learn from data. ANNs are inspired by the structure of the human brain, and they can learn complex patterns from data [17]. The applications of deep learning in Urban Drainage System Modeling include:

4) Enhancing Rainfall-Runoff Prediction Accuracy: DL models can effectively capture the intricate physical processes governing rainfall-runoff relationships, leading to more accurate runoff predictions [18].
5) Developing Real-time Control Systems for Drainage Systems: Deep reinforcement learning (DRL) models can optimize drainage system operations in real-time, considering factors like rainfall intensity and drainage capacity [19].
6) Automating Drainage System Inspection and Maintenance: DL models can analyze sensor data and inspection images to identify potential issues and prioritize maintenance needs [20].

C. Reinforcement Learning

This is a type of machine learning algorithm that learns by interacting with its environment. The algorithm learns to take actions that maximize a reward signal [21]. The applications of Reinforcement Learning in Urban Drainage System Modeling include:

1) Optimizing Pump and Valve Operation: RL models candetermine the optimal operation of pumps and valves in a drainage system, balancing stormwater removal with energy conservation [22].
2) Developing Adaptive Control Systems for Drainage Systems: RL models can adapt drainage system operations to changing conditions, such as rainfall patterns or land use changes [23].

D. Hybrid Approaches

A hybrid approach in urban drainage systems combines decentralized and centralized strategies to manage excess stormwater and enhance urban flooding resilience1. This integrated approach aims to address the challenges of urban water management by combining various techniques and technologies to optimize water resources and reduce the risk of flooding [24]. The hybrid approach can be applied in urbandrainage systems through the following components:

1) Decentralized Strategies: These strategies focus on capturing and storing stormwater at the source, therebyreducing the flow of water to the centralized stormwater drainage system. Examples of decentralized strategies include green roofs, infiltration trenches, and permeable pavements [25].
2) Centralized Strategies: These strategies involve the useof traditional stormwater drainage systems, such as storage and infiltration (SWDTs), located downstream. Of subcatchments1. These systems help attenuate the peak flow of stormwater and reduce the risk of flooding [24].
3) The Hybrid Approach for Excess Stormwater Management (H-SM): This approach combines both decentralized and centralized strategies to optimize urban flooding resilience [24].
4) Real-time flood forecasting: Hybrid models can be used to combine real-time rainfall data with historical data and physical models to make more accurate pre- dictions of flood inundation and potential damage [26].
5) Optimizing water resource management: Hybrid models can be used to develop integrated water resource management plans that balance the needs of various water users, such as municipalities, industry, and agriculture [27].

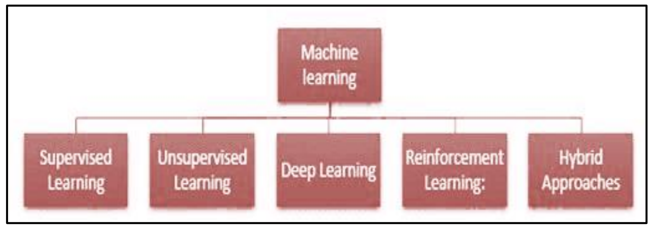

FIGURE 2. Types of machine learning studies.

III. Review Of Current Machine Learning Algorithms In Urban Drainage Systems

An intensive analysis of the literature on a number of research studies that focus on using machine learning techniques in flood prediction and control has been conducted. Depending on the datasets employed, the evaluated studies cover a wide variety of methodologies, including reinforcement learning, deep learning, supervised learning, and hybrid approaches.

A. Supervised learning context

Several studies had focused on classical supervised machine learning algorithms. In 2017, Bhakthavathsalam et al., [28], explored the use of machine learning models in conjunction with sensor networks for real-time urban flood prediction. They evaluated different machine learning techniques and proposed new methods based on rainfall thresholds to pro- vide accurate and timely flood risk assessment and warnings. Noymanee & Theeramunkong (2019) [29], presented a method to enhance real-time flood water level forecasting byintegrating hydrological modeling with five machine learning techniques which are Linear regression and Neural network, regression, Bayesian, linear regression, Boosted decision tree regression, Alternative regression techniques. They usedthe MIKE-11 hydrologic forecasting model and water level records from 2012-2016 to create a better early warningsystem for urban flooding in Thailand. In the paper by H. Wang & Song (2020)

[30] a machine learning-based approach utilizing the support vector machine (SVM) algorithm was developed to predict water levels in stormwater pipe networks, improving flood warning in urban areas. This paper presents a machine learning-based method using the Support Vector Machine algorithm to predict water levels in rainwater pipe networks for improved flood warning in urban areas. Ke et al. (2020) [31] studied urban pluvial flooding prediction in Shenzhen, China, using machine learn- ing methods. They proposed a new flood prediction method based on rainfall thresholds that efficiently assess flood risk and provide valuable lead-time for citizens in flood-prone areas. Dtissibe et al. (2020) [32] proposed an efficient flood forecasting system using an artificial neural network scheme, achieving good forecasting capacity through intensive exper- iments. Kwon & Kim (2021) [8] conducted a state-of-the- art review of machine learning-based urban drainage system (UDS) modeling and applications. The review emphasized the potential of ML technology in addressing UDS- related challenges and promoting developments in UDSs.

B. Deep learning techniques

Five studies for flood forecasting were employed by:

Jeily et al. (2017) [33] developed a flooding forecast system (FFS) using the Nonlinear Auto Regressive with eXogenous inputs (NARX) neural network to alert UDS managers for potential flooding. Cruz et al. (2018) [34] developed a flood prediction system using real-time monitoring sensors and a multi-layered artificial neural network with MATLAB. Le et al. (2019) [35] suggested a Long Short-Term Memory (LSTM) neural network model for flood forecasting on the Da River in Vietnam, achieving impressive predictive ability. Mousavi et al. (2021) [36] developed flood early detection systems using deep learning models and IoT-based data collection, comparing their performance with physical and statistical models. Chen et al. (2023) [37] proposed a new method for fast prediction of urban flooding risk by combining a numerical model with an LSTM artificial neural network model, showing high prediction accuracy and fast calculation speed.

C. Reinforcement learning techniques

Two studies for real-time control of stormwater systems wereutilized by:

Mullapudi et al. (2020) [38] trained reinforcement learning agents to control valves in stormwater basins, demonstrating the effectiveness of reinforcement learning in controllingstormwater systems and mitigating flooding. Bowes et al. (2020) [39] proposed the use of reinforcement learning (RL) for real-time control (RTC) of stormwater infrastructure, reducing flooding volume by 70.5% on average compared to passive systems using the Deep Deterministic Policy Gradient (DDPG) algorithm.

D. Hybrid approaches

These techniques were proposed in five studies:

Wang et al. (2019) [40] introduced an intelligent water resources system combining a BP neural network with a genetic algorithm and an expert system to improve flood forecasting accuracy. Kan et al. (2020) [41] proposed a novel hybrid machine learning (HML) hydrological model that combined the artificial neural network (ANN) with the K-nearest neighbor method, overcoming local minimum issues using genetic algorithms and Levenberg–Marquardt-based methods. Keum et al. (2020) [42] developed a classification-based real-time flood prediction model for urban areas, combining a numerical analysis model based on hydraulic theory with a machine learning model. Researchers Kan et al. (2020) [43] built hybrid models for flood forecast purposes by combining artificial neural networks with the K-nearest neighbor method and using genetic algorithms and Levenberg–Marquardt-based methods. Motta et al. (2021) [44] developed a flood prediction system using a combination of Machine Learning classifiers and GIS techniques, serving as an effective tool for urban management and resilience planning.

Table 1 summarizes the findings from the reviewed studies, including the used dataset, the nature of the machine learning model employed, and the results, which represent the model accuracy.

TABLE 1. Machine Learning For Urban Drainage Systems: A Study

Authors	Data set used	The used Methods	Results	Type of machine learning
Bhakthavathsalam et al., 2017[28]	Real-time sensor data	- Geographical Information Systems techniques - Machine Learning models with sensor network	- Application of machine learning models for flood prediction - Use of sensor network for real-time forecasting	Supervised Learning
Rjeily et al. 2017 [33]	Rainfall Intensity and Water depth variation in manholes	- NARX neural network	the FFS is capable of accurately forecasting the water depth variation in manholes during storm events	Deep Learning
Cruz et al. 2018[34]	real-time monitoring sensors rain gauge, water level, and soil moisture sensors	- Multi-layered artificial neural network with MATLAB - Real-time monitoring sensors and systems	- Goodness-of-fit values: 0.99889 (training), 0.99362 (test), 0.99764 (validation), 0.99795 (overall) - Root Mean Square value: 2.2648 (small overall difference between predicted and actual flood level)	Deep Learning
Noymanee et al. 2019[29]	water-level records during 2012-2016 data	- Linear regression - Neural network regression - Bayesian linear regression - Boosted decision tree regression	- Hydrological modeling augmented with machine learning techniques - Reduction in error in runoff forecasting	Supervised Learning

Wang et al. 2019 [40]	Historical hydrological data	- Combination of BP neural network with genetic algorithm - Integration of expert system with local data	- Combination of BP neural network and genetic algorithm improves flood forecasting accuracy. - Expert system incorporates local knowledge for flood forecasting.	Hybrid approaches
Le et al. 2019[35]	daily discharge data	Data based methods	94.5%, 86.2%	Deep Learning
Wang et al. 2020[30]	Water levels	SVM-based machine learning method.	- Model accuracy and running speed are key issues. - Traditional hydrodynamic models have rigo [illegible] ysical mechanism.	Supervised Learning
Kan et al. 2020[41]	Rainfall and Antecedent Runoff	- Artificial neural network (ANN) - K-nearest neighbor method	- The [illegible] hydrological model successfully forecasts peak flow values within a 20% error threshold. - The model performs well in terms of the Nash-Sutcliffe coefficient of efficiency (NSCE), with most flood events achieving NSCE higher or equal to 0.9.	Hybrid Approaches
Mullapudi et al. 2020[38]	Simulated strom scenarios	- Real-time control approach based on Reinforcement Learning (RL) - Use of Deep Neural Network for control strategy learning	- RL can effectively control individual stormwater sites. - RL controller's performance is sensitive to reward formulation.	Rienforcement Learning
Ke et al. 2020[31]	Rainfall Intensity	Machine learning Approaches	- ML models classify flooding with 96.5% accuracy - ML models lower false alert rate to 25%	Supervised Learning
Keum et al. 2020 [42]	Flood Data bases	Combination of hydraulic theory and machine learning - Latin hypercube sampling and probabilistic neural network classification techniques	- Developed model has 85% goodness-of-fit - Required run time is 1 min 12 s	Hybrid Approaches
Bowes et al. 2020 [39]	Sensor and forecast data	- Deep Deterministic Policy Gradient (DDPG) algorithm - Comparison with a passive flood control policy	- RL implementations reduced flooding volume by 70.5% on average - RL implementations performed within a range of 5% compared to the passive system.	Reinforcement Learning
Dtissibe et al. 2020 [32]	Discharge	Physical-based flood forecasting methods - Artificial neural network scheme (multilayer perceptron)	- The designed flood-forecasting model showed effectiveness. - The model had a good forecasting capacity.	Supervised Learnnig
Kwon et al. 2021 [8]	Hydrological data	Machine learning techniques sach as ANN CNN, LTM	ML is utilized extensively in UDSs to advance model performance and efficiency	Supervised and Unsupervised, Deep Learning, Reinforcement Learning
Mousavi et al. 2021[36]	Collected from 4 gauging stations at brandy wine christina watershed Pennsylvania from 2013 to 2019	IoT approach using LoRaWAN for communication technology - Deep learning models for flood forecasting	- Deep learning models are more accurate than physical and statistical models. - Results can help implement flood detection systems.	Deep Learning
Motta et al. 2021 [43]	local weather measurements and fire department	Machine Learning classifiers (Random Forest) - GIS techniques (Hot Spot analysis)	- Random Forest model: MCC = 0.77, Accuracy = 0.96 - Flood risk index created using Random Forest and Hot Spot analysis.	Hybrid Approaches
Kumar et al. 2022 [44]	Past Rainfall measurements with Rainfall in divers duration and flow of water	Neural network model with past rainfall measurements - Fuzzy and sigmoid function for identification of runoff rainfall process	- Proposed model has the best outcome - Effective prediction compared to existing approach	Hybrid Approaches
Chen et al. 2023 [37]	rainfall scenarios	combining the Long Short Term Memory (LSTM) neural network model and hydrological hydrodynamics model	Prediction results of the method are less inaccurate compared with the measured waterlogging monitoring data and numerical simulation results, and the prediction accuracy is high	Deep Learning

In the provided text, several studies utilizing machine learning techniques for flood forecasting and control are discussed. Research uses various machine learning models such as neural networks, support vector machines [30] and reinforcement learning to improve the accuracy of flood fore- casts and provide timely warnings [23]. Key findings include the combined use of geographic information system (GIS) [43] technology and machine learning models to predict flood events in real time, the successful application of NARX [33] neural networks to predict water depth fluctuations, and the use of multi-layered artificial neural networks using MATLAB to predict flood levels in real time [34]. Additionally, these studies demonstrate the effectiveness of machine learning techniques in reducing runoff forecast errors, optimizing flood prediction models, and controlling stormwater systems in real time.

I. Comparison

The provided text discusses various studies that employ machine learning techniques for flood prediction and control, utilizing different types of machine learning algorithms. Here's a comparison between the types of machine learning mentioned in the Table 2:

TABLE 2. Comparison of Varied Machine Learning Models in Urban Drainage Systems

Approach	Strengths	Weaknesses	Scenarios	Citation Reference
Supervised Learning	- Effective for predicting flood patterns in real-time using labeled data. - Well-suited for tasks where historical data can be used to train models. - Provides accurate and timely flood risk assessments with the integration of sensor networks.	- Relies on the availability of labeled data, which might be challenging to obtain. - May struggle with adaptability to rapidly changing urban environments.	Effective in scenarios where historical data on rainfall and drainage system performance is available.	Bhakthavathsalam et al., 2017; Noymanee and Theeramunkong, 2019; Wang et al., 2020
Unsupervised Learning	- Useful for identifying patterns or structures in datasets without labeled examples. - Provides insights into underlying dynamics of stormwater data.	- Interpretability can be a challenge as it discovers patterns without predefined labels. - May not be as effective in tasks requiring labeled data for prediction.	Valuable for understanding complex relationships and identifying potential flood risk areas.	Rjeily et al., 2017; Cruz et al., 2018; Le et al., 2019
Deep Learning	- Exceptional at handling complex datasets and extracting high-level features. - LSTM, a form of deep neural network, has shown effectiveness in maintaining time-series data.	- Requires a large amount of data and computational resources for training. - Interpretability can be a challenge due to the complexity of neural networks.	Highly effective in predicting water levels and discharge levels for reliable flood forecasting.	Mullapudi et al., 2020; Bowes et al., 2020; Dtissibe et al., 2020
Reinforcement Learning	- Effective in optimizing stormwater system control in real-time. - Can adapt to diverse storm scenarios by maximizing rewards through decision-making.	- Sensitive to the formulation of reward structures. - Requires careful tuning and training for practical applications.	Ideal for real-time control of stormwater systems to mitigate flooding.	Kwon et al., 2021; Mousavi et al., 2021; Motta et al., 2023
Hybrid Approaches	- Combines the strengths of different approaches to improve accuracy and stability. - Integrates physical models with machine learning classifiers for comprehensive solutions.	- Complexity may lead to challenges in model interpretability. - Requires expertise in multiple domains for effective implementation.	Effective in enhancing flood forecasting accuracy and resilience planning.	Kumar et al., 2022; Chen et al., 2023

The utilized methods can summarize the key points about different machine learning approaches used in urban drainage systems as follows:

1) The Supervised Learning approaches leverage traditional ML algorithms for various tasks, showcasingversatility in addressing different aspects of flood prediction.
2) Deep Learning Techniques excel in handling complex tasks and real-time monitoring, providing impressive predictive abilities in flood forecasting scenarios.
3) Reinforcement Learning Techniques focus on real-time control, demonstrating their effectiveness in adaptive control of stormwater systems to mitigate flooding.
4) Hybrid Approaches leverage the strengths of different ML techniques, combining neural networks with genetic algorithms, expert systems, and GIS techniques for improved accuracy and resilience in flood prediction systems.

In conclusion, the features of the issue, the data that are accessible, and the computational resources should all be taken into account when choosing a machine learning strategy for urban drainage systems. Hybrid systems, which combine many techniques, may provide a comprehensive answer to the problems caused by the complexity of urban drainage. Further study should concentrate on enhancing interpretability, managing scenarios with limited data, and maximizing computing efficiency in order to propel machine learning's applicability in urban drainage.

II. Proposed Datasets For Urban Drainage Decision Systems And Open-Source Datasets

A. Type of datasets

Datasets play a crucial role in understanding and managing Urban Drainage Decisions Systems. Here is an introduction to local and reference datasets for urban drainage systems.

Local datasets for urban drainage systems are used for managing and analyzing data related to urban drainage systems, while reference datasets are used as a standard or a point of reference for comparison or analysis. Both types of datasets are important for understanding and managing urban drainage systems. Here are some websites that may be useful for urban drainage systems, as shown in Table 3, including:

1) Data.world: There are 40 drainage datasets available on data. World, contributed by thousands of users and organizations across the world [45].
2) DTU Orbit: to develop tools for model evaluation in urban drainage systems, specifically to determine if a model can be applied for a specific objective at a specific site and transform data to useful information [46], [47].
3) Dataset for Bellinge: An urban drainage case study, which includes comprehensive sensor data, models, and background information for the urban drainage system in Bellinge, Odense, Denmark[48] also The Bellinge data set: open data and models for community-wide urban drainage systems research ,This website has a paper describing a comprehensive and unique open-access dataset for research within hydrological and hydraulic modeling of urban drainage systems, called The Bellinge dataset open data and models for community-wide urban drainage systems research.
4) Asset database - urban drainage system, which is an asset database of an urban drainage system [49].
5) data.gov.ie: This website has a database containing location and description information for sustainable urban drainage systems (SUDs) completed in Dublin City Council area [50].
6) Data collection in urban drainage and stormwater management systems – case studies: This book chapter contains several urban drainage and stormwater management metrology case studies selected to cover a wide range of scopes, scales, objectives, climates, data validation methods, and data storage approaches. These case studies are initiated by academics and institutions from the water industry [51].
7) National Hydrography Dataset (NHD): This dataset represents the water drainage network of the United States with features such as rivers, streams, canals, lakes, ponds, coastline, dams, and stream gages. It is widely used as a reference dataset for hydrological modeling and analysis in the United States [52].

TABLE 3. **Urban Drainage System Datasets: A Comprehensive Compilation with Objectives, Types, and Sources**

Dataset Name	Objectives	Type	source
Data.world	Various drainage datasets contributed globally by users and organizations.	Reference	[45]
DTU Orbit	to develop tools for model evaluation in urban drainage systems, specifically to determine if a model can be applied for a specific objective at a specific site and transform data to useful information	Reference	[46], [47]
Dataset for Bellinge	Urban drainage case study with comprehensive sensor data, models, and background info.	Local	[48]
Asset database - urban drainage system	Asset database of an urban drainage system.	Local	[49]
data.gov.ie	Database with location and description info for sustainable urban drainage systems.	Local	[50]
Data collection in urban drainage and stormwater	Book chapter with metrology case studies initiated by academics and institutions	Reference	[51]
National Hydrography Dataset (NHD)	Represents the water drainage network of the United States, widely used for hydrological modeling.	Reference	[52]

The Table 3 provides a summary of well-known datasets for urban drainage systems that can be utilized byresearchers, engineers, and programmers in developingmachine-learning models for flood forecasting and control. The datasets listed offer valuable information on various aspects of urban drainage systems, including sensor data, models, background information, customer service requests, natural drainage basins, and sustainable urban drainage systems.

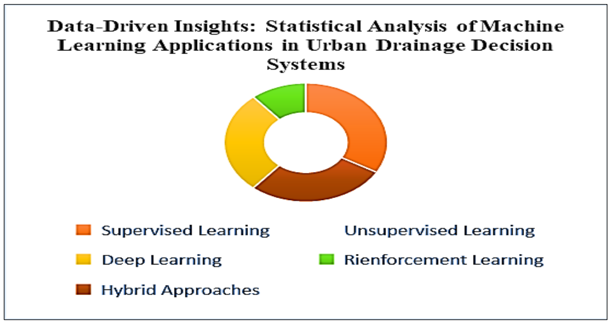

FIGURE 3. **Data-Driven Insights: Statistical Analysis of Machine Learning Applications in Urban Drainage Decision Systems**

B. Open-source datasets

Open sources for urban drainage systems refer to publicly available information, data, and tools that can be used to design, plan, and manage urban drainage systems.

Open-source datasets play a crucial role in enabling the development and application of machine learning techniques for urban drainage systems. These datasets provide the necessary training data for machine learning algorithms to learn from and make accurate predictions or decisions There are several open-source systems available for urban drainage systems as shown Table 4. Some of them are:

a) swmm_mpc: The swmm_mpc is a Python package for model predictive control (MPC) for EPASWMM5 models. It can be used to perform model predictive control for EPASWMM5[53].
b) Norfolk_Groundwater_Model: This repository contains scripts to model and forecast shallow groundwater table level in Norfolk, VA with artificial neural networks[54].
c) smart_stormwater_swmm_models: This repository contains SWMM5 models for studying active stormwater control[55].
d) stormwater-iot: This is an IoT application for visualizing flooding in Norfolk, Virginia[56].
e) MatSWMM: This is an open-source toolbox for designing real-time control of urban drainage systems[57].
f) rl-storm-control: This repository contains source code and data used in the Deep Reinforcement Learning for the Real Time Control of Stormwater Systems paper. The related paper is "Deep Reinforcement Learning for the Real Time Control of Stormwater Systems"[58], [59].
g) pyswmm: This is a Python Wrappers for SWMM. Stormwater-Management-Model: This is the Open Water Analytics Stormwater Management Model repository[60].
h) pystorm: This is a python to JavaScript compiler based on Niall McCarroll's py2js released under MIT license[61].
i) CityDrain2: This is an open-source toolbox for integrated modelling of urban drainage systems realized in Matlab/Simulink. The related paper or study is not explicitly mentioned in the search results[62].
j) Stormwater-Management-Model is the Open Water Analytics Stormwater Management Model repository[63].

These open-source systems can be used for analyzing and designing urban drainage systems and improving stormwater management.

TABLE 4. **Open-Source Datasets for Urban Drainage Systems**

Package	Description	Created	source
pystorm	Python to JavaScript compiler.	27-Jun-12	[61]
CityDrain2	Open-source toolbox for integrated modelling of urban drainage systems realized in Matlab/Simulink.	19-Apr-16	[62]
stormwater-iot	IoT application for visualizing flooding in Norfolk, Virginia.	20-Aug-18	[56]
smart_stormwater_swmm_models	Repository that contains SWMM5 models for studying active stormwater control.	20-Mar-19	[55]
swmm_mpc	Python package for model predictive control (MPC) for EPASWMM5 models.	13-May-19	[53]
rl-storm-control	Repository that contains source code and data used in the Deep Reinforcement Learning for the Real Time Control of Stormwater Systems paper.	16-May-19	[58], [59]
MatSWMM	Open-source toolbox for designing real-time control of urban drainage systems.	17-Sep-20	[57]
Norfolk_Groundwater_Model	Repository that contains scripts to model and forecast shallow groundwater table level in Norfolk, VA with artificial neural networks.	10-Nov-20	[54]
Stormwater-Management-Model	Open Water Analytics Stormwater Management Model repository.	28-Mar-23	[63]
pyswmm	Python package that provides wrappers for EPA's SWMM5 stormwater modeling tool.	28-Apr-23	[60]

In conclusion, the evidence presented leads to conclusions that emphasize a variety of stormwater management techniques and tools, with a focus on modeling, real-time control, and the integration of deep learning and Internet of Things technology.

Certain instruments' spatial uniqueness indicates that local environmental conditions are taken into account. Furthermore, the continuous development of new packages points to a dynamic and changing field of study and instruments for stormwater management.

I. Discussion

The application of machine learning techniques in urban drainage systems offers several advantages over traditional models. Conventional decision support systems often struggle to tackle the intricate and indeterminate aspects of urban planning concerns, especially in the context of rapidly urbanizing areas with uncertain rainfall patterns and aging infrastructure. Supervised learning has shown promisein utilizing labeled data to predict flood patterns in real-time. By leveraging sensor networks and rainfall thresholds, researchers have developed accurate and timely flood risk assessments and warning systems. This approach has the potential to enhance flood management strategies and improve response times during extreme weather events. Unsupervised learning techniques, such as clustering and dimensionality reduction, offer valuable insights into the patterns and structures present in datasets without labeled examples. These methods can be instrumental in understanding the underlying dynamics of stormwater data and identifying potential flood risk areas. Deep learning approaches, particularly deep neural networks like LSTM, have demonstrated their ability to handle complex datasets and extract high-level features. They have shown exceptional performance in predicting water levels and discharge levels, enabling more reliable flood forecasting and early warning systems. Reinforcement learning algorithms have proven effective in optimizing stormwater system control in real-time. By training agents to make decisions to maximize rewards, these models can efficiently mitigate flooding during diverse storm scenarios, leading to improved flood management and reduced flood volumes. Hybrid approaches combining different machine learning techniques have shown potential in enhancing flood forecasting accuracy and stability. By integrating physical models with machine learning classifiers and GIS techniques, researchers can identify flood-prone areas and develop effective flood risk indices for urban management and resilience planning.

II. Conclusion

The paper examines how to forecast and manage floods using machine learning in urban drainage systems. The current study emphasizes the efficacy of several machine learning techniques, including supervised learning, unsupervised learning, deep learning, reinforcement learning, and hybrid methodologies, for handling the intricate details of urban planning. The results of the literature evaluation demonstrate that deep learning and reinforcement learning methodologies have outperformed conventional machine learning techniques in terms of impact the accuracy of flood predictions has increased thanks to the integration of real- time sensor data with machine learning models, which has also enhanced stormwater system control during severe weather events.

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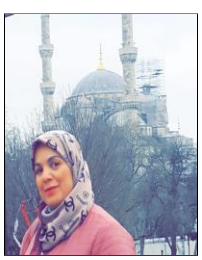
AUTHORS BIOGRAPHY

Samira Boughandjioua She is a Ph.D. student at the University Badji Mokhtar Annaba in Algeria, specializing in urban hydraulic studies at the Faculty of Technology, particularly within the laboratories of soils and hydraulics. Her primary research areas include hydraulics, hydrology, machine learning, data science, and climate change. She focuses on Hydrological-Hydraulic modeling, Urban Drainage Systems, and the impact of climate change, employing machine learning techniques in her research.

Dr. Fares LAOUACHERIA was graduated from the Badji Mokhtar Annaba University, he obtained his Ph.D. in 2015 in Hydraulic. He defended his HDR from the Badji Mokhtar Annaba University in 2019. He is a research professor at hydraulic department of Badji-Mokhtar Annaba University and a head team in Laboratory of Soils and Hydraulic. He supervises Master's and Ph.D. students to this day. Dr Fares LAOUACHERIA is closely associated with several international journals as a reviewer. His main research is: urban Hydrology, Hydrological-Hydraulic modelling, Urban drainage systems, Water Resources and Environment, Remote Sensing and GIS, Natural Hazards, Artificial Intelligence.



Prof. Nabiha AZIZI was graduated from the University of Badji Mokhtar Annaba, She has her Ph.D. (2011) in Pattern recognition. She is an associate professor at computer science department of Annaba University and member of LABGED laboratory. Dr Nabiha AZIZI is one of Editorial Board Members of International Journal of Image Mining (IJIM) and International Journal of Rough Sets and Data Analysis (IJRSD). Dr. Nabiha AZIZI is closely associated with several international journals as a reviewer. her main research are: Computing in Mathematics, Natural Science, Engineering and Medicine, Data Mining Artificial Intelligence

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