Application of machine learning in river water quality management: A review

Short title: Machine learning in river water quality management

Sanja Radovic*, Sonja Dmitrasinovic*^, Marija Kostic*, Maja Turk Sekulic*, Jelena Radonic*, Ana Dodig**, Milan Stojkovic**

*University of Novi Sad, Faculty of Technical Sciences, Department of Environmental Engineering and Occupational Safety and Health, Trg Dositeja Obradovica 6, 21 000 Novi Sad, Serbia
(E-mail: sanjaradovic@uns.ac.rs, dmitrasinovic@uns.ac.rs, kosticmarija@uns.ac.rs, majaturk@uns.ac.rs, jelenaradonic@uns.ac.rs)

**Institute for Artificial Intelligence R&D Serbia, Novi Sad, Fruškogorska 1
(E-mail: ana.dodig@ivi.ac.rs, milan.stojkovic@ivi.ac.rs)

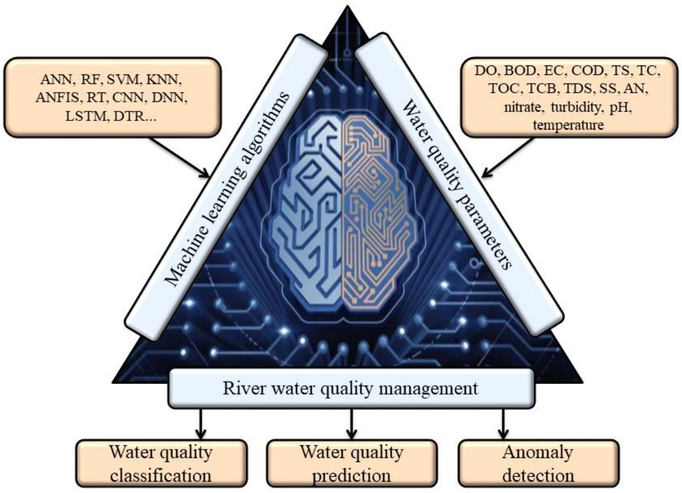
Abstract Machine learning (ML), a branch of artificial intelligence (AI), has been increasingly used in environmental engineering due to the ability to analyze complex nonlinear problems (such as ones connected with water quality management) through data-driven approach. This study provides an overview of different ML algorithms applied for monitoring and prediction of river water quality. Different parameters could be monitored or predicted, such as dissolved oxygen (DO), biological and chemical oxygen demand (BOD and COD), turbidity levels, concentration of different ions (such as Mg^{2+}, Ca^{2+} etc.), heavy metal or other pollutant's concentration, pH, temperature and many more. Although many algorithms have been investigated for prediction of river water quality, there are several which are most commonly used in engineering practice. These models mostly include so called supervised learning algorithms, such as artificial neural network (ANN), support vector machine (SVM), random forest (RF), decision tree (DT) and deep learning (DL). To further enhance prediction power, novel hybrid algorithms which merges the different approaches, could be used. However, the quality of prediction is not only dependent on applied algorithm, but also on availability of previously mentioned water qulity parameters, their selection and combination as input data used to train ML models.

Keywords: artificial intelligence, environmental engineering, machine learning algorithms, water quality index

Highlights:

- Classification, prediction and anomaly detection algorithms were reviewed.
- Hydrometeorology data can be used to compensate for missing parameter data.
- Algorithms can struggle with generalization aspect important for real applications.
- Covering critical sampling points and periods could enhance prediction accuracy.
- Hybrid models could overcome limitations of single models.

Graphical Abstract



1. Introduction

In the recent decades, surface water quality (WQ) of the river streams has been negatively impacted by pollutants and wastes (*Khullar and Singh, 2021*). The deteriorated WQ may bring about serious negative consequences on humans, aquatic life, and environment in general. Moreover, climate change represents an additional pressure on surface WQ by reducing WQ during the low-flow seasons and increasing the river water temperature over the year. The required quality of surface water is defined by the framework directive on water and the law on water. In accordance with the Directive (*2000/60/EC*), the main goal is the sustainable management of all water systems, and it refers to determining the impact and pressure on water bodies because these are the main causes of pollution. The Law on Water includes decrees that define the issue in more detail. The most significant is the decree on limit values of emission of polluting substances in water, as well as the decree on limit values of priority and priority hazardous substances that pollute surface waters. The given decrees specify the limit values of the main parameters that define the required WQ *("Sl. glasnik RS", br. 50/2012, 24/2014*). In order to define WQ, different data collection techniques could be applied, such as sampling and analysis in the field, laboratory analyses, and the application (*appl.*) of monitoring sensors that oparate in real time. High-quality sensors can be quite expensive, need regular maintenance to function optimally, and require calibration to ensure accurate water qulity data parameters. With the development of technology, research goes towards an optimized way of managing WQ (*Ahmed et al., 2019, Park et al., 2020*). This research intends to analyze the existing challenges and to find opportunities for *appl.* of ML algorithms (*algo.*) in the river WQ management. It envelops several aspects of ML *appl.* within the following issues: (a) WQ estimation and prediction (*Khullar and Singh, 2021; Wagle et al. 2020*); (b) WQ classification (*Abuzir and Abuzir, 2022*); (c) WQ anomaly detection (*Russo et al. 2021*). Exhaustive investigation throughout these issues enables development of ML *algo.* as a tool for decision making process in the river basin, with an ultimate goal to improve the river health and maintain wildlife.

2. Water quality

Term 'water quality' can often be defined in terms of the chemical, physical, and biological water indicators (*Antanasijević et al., 2013*). Different parameters could affect and serve as indicators of WQ, which could be expressed through Water quality index (WQI) and Water quality classes (WQC). Among most frequently monitored parameters are DO, COD, BOD, total dissolved solids (TDS), nitrates (NO_3^-), pH etc.), physical (water temperature (WT), turbidity, conductivity (EC), solids, etc.) and biological (chlorophyll-a). Precise definitions of several of them and their contribution to WQ are prevously published *(Khullar and Singh, 2022; Syeed et al., 2023*).

Water quality index and water quality classes

WQI is dimensionless, single number which indicates the status of WQ *(Gorde and Jadhav, 2013; Sutadian et al., 2016*). As mentioned, it depends on different water parameters that reflects WQ (*Ahmed et al., 2019)*. WQI is calculated by the following equation:

$$WQI = \frac{\sum q_i x w_i}{\sum w_i} \quad (1)$$

where q_i is value of a parameter in the range of 0-100 and w_i is the weight of a particular parameter *(Ahmed et al., 2019*).

Based on the WQI, WQC for each water body could be established. Example of such classification is provided in Table 1 (*Ahmed et al., 2019*).

Table 1 WQ classification (*Ahmed et al., 2019*)

WQI rate	**Classification**
0-25	Very bad
25-50	Bad
50-70	Medium
70-90	Good
90-100	Excellent

3. ML algorithms in environmental engineering and water quality management

ML has a wide *appl.* in environmental science (ES) and engineering (EE), thanks to its high precision, flexible customization, and ability in solving complex data patterns (*Tharsanee et al., 2020*). According to (*Zhong et al., 2021*) from 1990-2020, 5855 publications were generated, as a result of ML *appl.* in EE in fields of water (47.63%), air (27.32%), soil (21.02), and sediment (4.02%). Four general *appl.* of ML in the field of ES and EE are provided by *Zhu et al., 2022*, and they are 1) making predictions, 2) identifying feature importance, 3) detecting anomalies, and 4) discovering new materials or chemicals. *Appl.* of 1) and 3) techniques are mostly reflected in supervised (regression or classification) learning (SupVL), but also through unsupervised (clustering) learning (unSupVL), to a lesser extent. Techniques within 2) and 4) can be implemented through SupVL, using for example Linear Discriminant Analysis (LDA), a classification technique for 2). SupVL is dominantly applied for EE issues, such as the prediction of particulate matter ($PM_{2.5}$), water resource availability, modeling of biochemical wastewater treatment systems, etc. (*Zhong et al., 2021*). Over the past few decades, different ML models have been developed to solve various water engineering management problems (*Syeed et al., 2023*). Surface WQ profiling is one of the high priorities especially in developing countries. According to *Zhu et al., 2022*, ML *algo.* applied in WQ evaluation of surface river waters are bootstrapped wavelet neural network (BWNN), ANN, autoregressive integrated moving average (ARIMA), bootstrapped artificial neural network (BANN), long short-term memory (LSTM), Nash-Sutcliffe efficiency (NSE), polynomial neural network (PNN), cascade correlation neural network (CCNN), Tsinghua/Temporary DeepSpeed (TDS), deep neural network (DNN), support vector regression (SVR), RF, SVM, convolutional neural network (CNN). Significance of ML *appl.* in the river research is evident in the number of publications from 2000-2020, which increased from 310 (in 2000) to 3444 (in 2020). Until the 2000s, SupVL *appl.* was dominant, but after 2000s, gradually equalized with unSupVL. Trend analysis also showed that unSupVL and SupVL dominated the field of river research (1990-2020), while NN and DL have gained more attention in this field, featuring in 15%–21% of the total publications over the last two decades (*Long & Goethals, 2022*). Frequently used ML models for WQ classification, WQ estimation and prediction, and anomaly detection as parts of river WQ management, are tree-structured *algo.*DT and RF (**Figure** 1), SVM and ANN (**Figure 2**) and LSTM (**Figure** 3) as a type of ANN.

Tree-structured algorithms

DT is a SupVL classifier, consisting of Decision and Leaf Nodes. Decision nodes are used to make any decision and have multiple branches, whereas the leaf nodes are the output of those decisions, and don't contain any further branches. Each node represents features in a category to be classified and each subset defines a value that can be taken by the node. (*Abuzir & Abuzir, 2022*). For the best splitting feachure selection, there are several selection measures for gaining the purest subset, such as Information Gain. Information Gain evaluate feature for splitting based on the difference in entropy (**equation x**), before and after the split is calculated. Feature with highest Information Gain value, split nodes and DT is builded (**equation x**). Also, quite often applied RF *algo.* represents the ensemlbe of DTs, which provides fits of multiple DTs on various sub-samples of the dataset and makes the predictions by averaging the predictions from each DT. As a result, possible DT overfitting can be controlled and better prediction accuracy is provided (*Quinlan, 1993*).

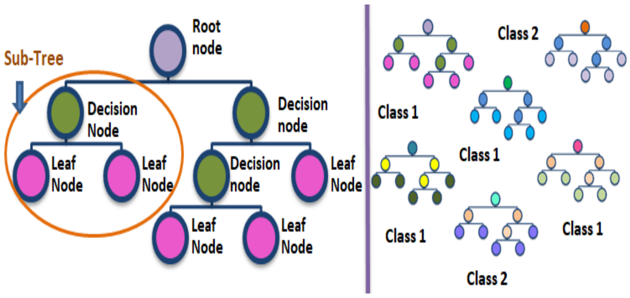


Figure 1 Single DT and RF (*Quinlan, 1993*)

$$Entropy\ (p) = -\sum_{i=1}^{N} p_i\ log_2 p_i \tag{2}$$

where *p* is whole dataset, *N* is number of classes and *pi* is frequency of class *i* in the same dataset.

$$Information\ Gain = Entropy\ (bef) - \sum_{j=1}^{K} Entropy\ (j, aft) \tag{3}$$

where *bef* is dataset before split, *K* is humber of subsets generated by the split and *(j, aft)* is subset after split.

Support vector machine algorithms

Although ANN model is oftenly examined and proved as suitable for different predictions, SVM model has been recognised as more reliable for the same purpose, by several authors (*Haghiabi et al., 2018; Liu and Lu, 2014; Park et al., 2015; Zhu et al., 2022*). Hence, general architecture of SVM model is presented in Figure 2. K(.) is a kernel function, while n represents number of support vectors (*Liu and Lu, 2014*).The following equation presents SVM regression function:

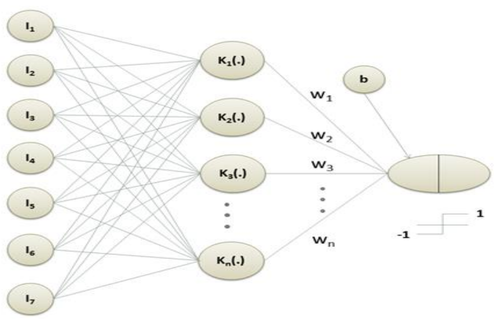


Figure 2 SVM architecture (*Liu and Lu, 2014*)

$$f(x) = [w * \varphi(x)] + b \tag{4}$$

where φ *(x)* is the nonlinear mapping function, w is the weight vector, and b is the bias term *(Liu and Lu, 2014*).

Long short-term memory (LSTM)

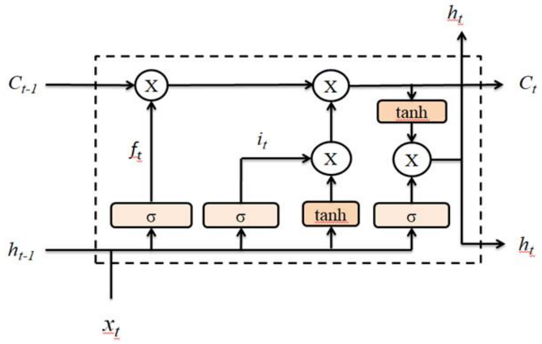


Figure 3 The Structure of LSTM Cell (*K. and K., 2022*)

Figure 3 depicts the structure of commonly used deep learning based *algo.*-LSTM, for anomaly detection.

$$f_t = \sigma\, (W_f \,.\, [\, h_{t-1}, x_t] + b_f) \quad (5$$

where f_t is the forget gate at t, t is the timestep, x_t is the input, h_{t-1} is the previus hidden state, W_f is the weight matrix between forget gate and input gate, and b_t is the connection bias at t (*K. and K., 2022*).

4. Results and Discussion - Application of ML algorithms in river water quality management

a. Water quality classification

Anthropological activities from urban and rural areas are the most common causes of deteriorated water quality (*Nazzir et al., 2016*), hence WQ assessment and WQI estimation are vital for preserving human and environmental health (*Syeed et al., 2023, Wang et al., 2017, Zhu et al., 2022*). WQ parameters that were mostly used in selected articles are DO, BOD, nitrate (NO_3^-), pH, EC (*Hassan et al., 2022, Sillberg et al.,2021, Al-Adhaileh et al., 2021, Bui et al., 2020*), and in lesser extent COD, total solids (TS), phosphate ($PO4^{2-}$) (*Bui et al., 2020*), turbidity (*Sillberg et al., 2021, Abuzir et al., 2022, Bui et al., 2020*), fecal colifrom (FC) (*Al-Adhaileh et al., 2021, Bui et al., 2020*), total coliform (TC) (*Hassan et al. 2022*), total coliform bacteria (TCB), salinity, TDS, suspended solids (SS) (*Sillberg et al.,2021*), total organic carbon (TOC) (*Abuzir et al., 2022*) and ammonia nitrogen (AN) (*Shamsuddin et al., 2022*). **Table 2** contains applied ML *algo.* regrading this assessments within reviewed papers.

Table 2 Commonly used ML *algo.* used for WQ classification

Domain of application:	**Type of algorithm:**	**References**
	Neural network (NN) (ANN, FFNN)	*Hassan et al., 2022; Al-Adhaileh et al., 2021; Shamsuddin et al., 2022*
Water quality classification (determination of water quality index (WQI) and water classes)	Random forest (RF)	*Hassan et al., 2022; Bui et al., 2020*
	Multinomial logistic regression (MLR)	*Hassan et al. 2022*
	Support vector machine (SVM)	*Hassan et al., 2022; Shamsuddin et al., 2022*
	Bagged tree model (BTM)	*Hassan et al. 2022*
	Decision tree (DT) (M5P)	*Bui et al., 2020; Shamsuddin et al., 2022*
	K-nearest neighbor (KNN)	*Al-Adhaileh et al., 2021*
	Random tree (RT)	*Bui et al., 2020*
	Reduced error pruning tree (REPT)	*Bui et al., 2020*
	Hybrid models: 12 hybrid *algo.* as combinations of standalones with bagging (BA), CV parameter selection (CVPS) and randomizable filtered classification (RFC)*;*	*Bui et al., 2020; Sillberg et al., 2021; Al-Adhaileh et al., 2021*

	attribute-realization (AR) and SVM (AR-SVM)*;* Adaptive neuro-fuzzy inference system (ANFIS)	

Hassan et al., 2022 utilized ML *algo.* from **Table 2** and developed a software *appl.* that used MLR to predict WQ in India in real-time for three classes (good, poor, and unsuitable for drinking). RF model was used to handle missing data. Performance for MLR, RF, BT, NN, and SVM classification models was 99.83%, 98.99%, 98.99%, 98.65%, and 96.98%. The highest variable importances obtained by NO_3^-, pH, EC, DO, TC, and BOD were with NN (19.67), BT (36.805), BT (81.494), BT (147.558), BT (105.166) and BT (130.173). Similarly to the previous article *Shamsuddin et al., 2020* utilized ANN, DT, and SVM for multiclass classification of river WQ of Langat River Basin, but showed the opposite results in the best classification model. The efficiency of ANN handling big data sets and predicting WQI was overcome by SVM, whose applicability to small data sets was surpassed and improved by the kernel function. The most numerous WQC was III and II defined as water supply/fisheries. Preferences for ANN, DT, and SVM utilization were the ability to model non-linear and complex relationships between input and output variables, easy and widely used classification techniques, and modeling of non-linear relationships between input variables. So all three models achieved more than 85% performance, with macro accuracies and precision values of 96.35%, 91.97% for SVM, 95.62%, 92.06% for ANN, and 94.71%, 89.22% for DT. *Sillberg et al., 2021* applied an integrated approach AR-SVM, along with 11 WQP to classify Chao Rivers WQ. Linear regression proved to be the most suitable function for WQ classification, with six QP, and accuracy, and precision of 0.94, 0.84. WCs variated, however poor WQ class III prevailed. The main WQP in WQC and their confidence values were NH_3-N (0.80), TCB (0.79), FCB (0.78), BOD (0.76), DO (0.69), and Sal (0.64). A smaller number of significant variables aided the AR-SVM model by minimizing some limitations. AR-SVM had the same results for 15 of the 16 data sets (93.75%) approving good correspondence with traditional WQI calculation. With applied three to six WQP, the AR-SVM model showed a potent approach in classifying river WQ with an accuracy of 0.86-0.95. *Al-Adhaileh et al., 2021* for WQI prediction utilized an ANFIS and KNN, FFNN for WQC of different water bodies across India. WQI determined by ANFIS showed high efficiency and accuracy and a regression coefficient of 96.17%. FFNN model showed superior robustness in classifying the WQC with high accuracy and precision of 100% and 99.961%, while KNN had 80.63% and 82.50%. ANFIS and FFNN as ANN, compared to *Hassan et al., 2022* and *Shamsuddin et al., 2020,* showed the best performances for the prediction of WQI. ANFIS confirmed its ability to monitor drinking and contaminated water with high accuracy. Determined WQ was classified as poor, hence proposed method has been defined as helpful in water treatment and management. The determination of monthly WQI of Iran River by *Bui et al., 2020,* implied the *appl.* of 4 standalones and 12 hybrid data-mining models, presented in **Table 2** Main WQPs in QWC were FC and TS. Different WP combinations provided different levels of model performances for each one of them. The rank of the *algo.* based on the prediction power (best to worst) was BA-RT, BA-RF, BA-M5P, CVPS-RF, RF, RFC-RF, BA-REPT, M5P, CVPS-M5P, RFC-REPT, RFC-M5P, REPT RT, RFC-RT, CVPS-RT, CVPS-REPT. Among 16 validated *algo.* all models performed well, but BA-RT have the highest power (R2=0.941), while CVPS-REPT had the lowest (R2=0.853) in predicting WQI. Hybrid tree-based models (especially the bagging *algo.*) were more robust and flexible than standalone models. Among standalone, RF outperformed M5P, REPT, and RT. Nearly all *algo.* overestimated WQI values, but RT, BA-RT, and CVPS-REPT did not. Even though hybrid BA-RT outperformed the other models it didn't predict extreme WQI accurately.

b. Water quality prediction

Monitoring and prediction of WQ is very important as it can enhance water management, including WQ preparation and regulation, higher quality and development of irrigation strategy, efficiency of aquaculture and improved drinking water preparation and strategies for prevention of water contamination *(Al-Adhaileh and Alsaade, 2021; Khullar and Singh, 2022*). Table 3 summerizes several ML *algo.* which can be used for prediction purposes. ANN, DNN and SVM models were more frequently used in comparison to other models. It might be due to the advantages they offer (*Krishnan et al., 2022*). Among most commonly used WQ parameters for surface WQ prediction are DO, WT, pH, SS, nitrates (NOx), TDS, EC, turbidity, BOD, COD. However, other parameters were occasionaly used such as FC, chlorides, sulphates, organic and inorganic pollutants etc. were also occasionally used, depending on the availability of data, type and locality of river (*Syeed et al., 2023*). Mentioned indicators of WQ are interconnected since one parameter can affect value of another. Hence, it is important to evaluate each parameter significance and their mutual correlations (Zhu et al., 2022). For instance, many authors have recognized that DO is one of the most globally concerned WQ indicator that had strong correlations with certain input parameters such as pH value, temperature, NOx concentration (*Zhu et al., 2022*). It consequently can affect prediction accuracy of applied ML model, and therefore, those correlations should be thoroughly investigated. Despite prediction of concentration/ level of certain parameter, or general WQ based on several parameters, other predictions, such as monthly runoff prediction (*Samantaray et al., 2022*) or water level prediction could be applied (*Baek et al., 2020*). Common approach for modeling future water status is to collect large number of data from previously published articles or public services/monitoring stations and generate data bases which could serve as input for ML model development for certain purpose. However, sometimes there is problem of missing data. That problem caused by inclomplete data could be overcomed by adding another type of data such as hydrological data (which is more often available) to model development (*Zhi et al., 2021*) or using additional data post-processing tools such as Multivariate Bayesian Uncertainty Processor (MBUP) (*Zhou, 2020*). Developing more than just one model is beneficial as it allowes comparisong between utilised models for investigated purpose and chosing the most appropriate (highest accuracy, lowest error etc.). Specific problems could occur when predicting concentrations of certain components of agricultural drainage river basins, because of existance of self-purification mechanisms and nonpoint source transport of pollutants. ML *algo.*, namely ANN and SVM succeeded to predict total nitrogen and total phosphorus concentrations in river in China. However, SVM showed better generalization as it avoided occurrence of overtraining and optimizing fewer parameters based on structural risk minimization principle. In order to optimise the parameters of models, genetic *algo.*, trial and error analysis were used (*Liu and Lu, 2014)*. Facing different limitations, single models could be outperformed by different hybrid models. For instance, although some authors report good prediction ability of deep learning LSTM model (*Liu et al., 2019*), some authors such as *Khullar and Singh (2022)* reported that single CNN and LSTM models could be oftenly characterized as highly complex and with low prediction accuracy, which could be overcomed by improved Bi-LSTM model which proved ability to be adapted for various WQ samples from different sources (*Khullar and Singh, 2022*). Hybrid models also proved efficient for important short-term WQ prediction, such as in the case when an advanced data denoising technique - complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) was integrated with extreme gradient boosting and RF to predict six WQ indicators (Lu and Ma, 2020).

Table 3 Common ML *algo.* used for water quality prediction

Domain of application:	***Type of algorithm:***	***References:***

Water quality prediction and estimation	ANN: Artificial neural network (ANN) and their variations (Backpropagation neural network (BPNN), General regression neural network (GRNN), Recurrent neural network (RNN), Deep neural networks (DNN), their variations (Convolutional neural network (CNN), Long short-term memory (LSTM) and combinations (CNN-LSTM)	*Antanasijević et al., 2013; Baek et al., 2020; Bilali and Taleb, 2020; Haghiabi et al., 2018; Khullar and Singh, 2022; Liu and Lu, 2014; Liu et al., 2019*
	Group method of data handling (GMDH)	*Haghiabi et al., 2018*
	SVM	*Haghiabi et al., 2018; Liu and Lu, 2014*
	Extra tree regression (ETR)	*Asadollah et al., 2021*
	Support vector regression (SVR)	*(Asadollah et al., 2021; Bilali and Taleb, 2020; Khullar and Singh, 2022*
	Decision tree regression (DTR)	*Asadollah et al., 2021*
	Decision tree (DT) based hybrid models: CEEMDAN-RF and CEEMDAN-XGBoost	*Lu and Ma, 2020*
	DNN based hybrid models: Bi-LSTM model (DLBL-WQA)	*Khullar and Singh, 2022*

c. Anomaly detection

The process of identifying unexpected problems in water supply data, such as missing values, unusual patterns, or inconsistent specifications, is called anomaly detection. Anomaly detection is done by applying ML models that may or may not require model calibration against a labeled data set, like the SupVL ML model in the first and the unSupVL ML model in the second case. Given that the SupVL model requires large datasets, the unSupVL models can be used as the alternative (*Russo et al., 2021*). In **Table 4**, a few ML *algo.* used for anomaly detection, within reviewed articles are presented.

Table 4 Common ML *algo.* used for anomaly detection

Domain of application:	**Type of algorithm:**	**References**
Water quality Anomaly detection	Logistic Regression	*Muharemi et al., 2019*
	SVM (Support vector machine)	*Muharemi et al., 2019*
	LSTM (Long Short-Term Memory)	*Miau and Hung 2020, Muharemi et al., 2019*
	ANN (Artificial Neural Network)	*Miau and Hung, 2020, Muharemi et al., 2019*
	DNN (Deep Neural Network)	*Muharemi et al., 2019*
	RNN (Recurrent Neural Network)	*Muharemi et al., 2019*
	LDA (Linear Discriminant Analysis)	*Muharemi et al., 2019*
	CNN with an extreme learning machine (ELM) (CNN-ELM)	*Miau and Hung, 2020*
	Sec2Sec	*Miau and Hung, 2020*
	Conv-GRU (CNN and GRU model)	*Miau and Hung, 2020*
	BAR (Bayesian autoregressive) model and IF (Isolation forest) *algo.*	*Liu et al., 2020*

Muharemi et al., 2019, in their article, attended to check whether ML models give more accurate results than logistic regression and which model performs best for WQ data. To identify anomalies in WQ data authors applied ML *algo.* SVM, ANN, DNN, RNN, LSTM, and LDA and they all were compared to the logistic regression *algo*. used for data classification. Experiment results were ranked based on the F1 value (as a measure of accuracy) and the SVM model performed the best with 0.9891, followed by DNN (0.9485), LSTM (0.9023), RNN (0.8345), logistic regression (0.6027), ANN (0.5768) and LDA (0.0820). All models show vulnerability in the case of unbalanced data sets giving worse results, except for SVM, logistic regression, and ANN which were less vulnerable. This is pointing out the clear laxity of the ML model when using unbalanced WQ data. But the results also revealed logistic regression's ability to explain the relationship between one dependent variable and one or more independent variables and SVM's ability to accurately predict data series in the case of non-linear and non-stationary underlying systems. NN *algo.* can stimulate the structure of the human brain and include a network of many interconnected neurons (ANN), they are effective and reliable models with many hidden layers (DNN) and can use previous time series information and use recurrent loops where the output state is fed back to the input state of the cell (RNN). Considering LSTM, it has long-term benefits for making accurate predictions, and learning useful information while forgetting useless information, while LDA gives excellent results for independent measurements, but classical recognition techniques pose a problem for this model. Research conducted by *Miau and Hung, 2020*, focused on the comparison of ANN, CNN, LSTM, Sec2sec, and Conv-GRU models while dealing with water level prediction in the Danshui River basin in Taiwan. Achieved performance expressed through Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) was as follows Conv-GRU (RMSE - 0.774, MAE - 0.567, MAPE - 30.684), LSTM (RMSE - 1.032, MAE - 0.620, MAPE - 31.035), CNN (RMSE - 1.144, MAE - 0.745, MAPE - 37.154), LSTM (RMSE - 1.032, MAE - 0.620, MAPE - 31.035) and CNN (RMSE - 1.144, MAE - 0.745, MAPE - 37.154). The error between actual and predicted values by the Conv-GRU model was minimal and it had the best results when predicting the river level, LSTM and CNN had slightly higher errors when predicting the river level, but smaller than ANN and Sec2sec. CNN achieved good predicting results since it could pick out local trends and observe the same patterns repeating themselves in different places. Only integrated, the CNN and GRU model outperformed the other four models in prediction performances, by being a time series modeler, which provides an early indication of anomalous behavior. Sek2sek provided sequence-by-sequence forecasting, based on multi-step time series forecasting, and LSTM and ANN confirmed its abilities as mentioned in *Muharemi et al., 2019.* Anomaly detection performed by *Liu et al., 2019*, implied appl. of Potomac River in West Virginia, USA data, by integrating the BAR model and the IF *algo.* The evaluation index was represented by error indicators RMSE, MAE, and MSE (Mean Square Error), while turbidity (TURB), specific conductivity (SC), and DO were used as quality parameters. Error indicator values were RMSE (TURB - 0.1694, SC - 0.0831 and DO - 0.0332), MAE (TURB - 0.1086, SC - 0.0453, DO - 0.0282), and for MSE (TURB - 0.0287, SC - 0.0069, DO - 0.0011). Both models showed excellent results in anomaly detection. The developed integration model showed accuracy in the detection of water quality anomalies and revealed the ability to provide effective early warning for emergency operations.

5. Future perspective

Application of ML in surface/river water management has many opportunities. However, all the opportunities face different challenges. Although many authors already recognized importance of comparative analysis and include several ML models in order to determine the most suitable one, it is important to highlight that prediction accuracy depend also on input parameters. Hence, careful selection of available water qulity parameters is of key importance. Several ML *algo.* struggle with generalization aspect, which is important for real applications within different areas. Inclusion of other variables (hydrological, morhological, geological etc.) in model development and assesment of the model presented in one study should be considered for other rivers with diverse climate and hydrology (*Asadollah et al., 2021*). Quantification of the uncertainty of regression model caused by missing input data is highly challenging. In order to compansate missing data concerning WQ parameters, hydrometeorology data could can be used (*Zhi et al., 2021*). In order to achieve higher prediction accuracies, future studies should be strategically planned. Besides choice of ML *algo.*, their comparison and parameter selection, this includes covering critical sampling points and sampling periods, when higher oscilations of input parameter concentrations are expected (*Zhi et al., 2021*). Utilization of hybrid ML models has, generally, been an attractive solution as they can overcome limitations of single models and achieve higher performance and accuracy than single ML models (*Khullar et al., 2021*). This trend has been observed for all three application domains, to certain extend. Accordingly, researchers should consider this aspect in the future studies.

6. Conclusion

Machine learning has relatively recently found its purpose within EE including river water management. Various ML *algo.* have proved its applicability for monitoring, classifying and predicting river WQ and detecting anomalies. Among most common *algo.* that proved its efficiency within mentioned research were DT, ANN, DNN and SVM and DNN based *algo.* for classification, prediction and anomaly detection purposes, respectively. Limitations of single models are found to be overcomed by hybrid approach. Application of AI for mentioned purposes is beneficial from economycal, ecologycal and strategical aspects. However, full potential and real *appl.* of these systems is yet to be investigated and implemented.

Acknowledgements

This research was supported by the Science Fund of the Republic of Serbia, grant number 6707, REmote WAter quality monitoRing anD IntelliGence – REWARDING and by the Ministry of Science, European Union's Horizon Europe Marie Sklodowska-Curie Actions (MSCA) under Grant Agreement number 101086387 and Technological Development and Innovation through project no. 451-03-47/2023-01/200156 "Innovative scientific and artistic research from the FTS (activity) domain".

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