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An Intelligent Wastewater Pollution Detection Framework Using Deep Learning and Sensor-Based Environmental Monitoring

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Abstract- — Water pollution has become a major environmental concern due to the increasing discharge of industrial and domestic contaminants into wastewater systems. Continuous monitoring of wastewater quality is essential to detect harmful pollutants and prevent environmental damage. This study proposes an intelligent wastewater pollution detection system that integrates low-cost multisensor technology with deep learning techniques. The system collects environmental data using multiple sensors capable of measuring chemical characteristics present in wastewater. The acquired sensor data is pre-processed and transformed into structured textual representations, enabling advanced machine learning models to analyse patterns associated with different pollutants. A deep learning model based on transformer architecture is then employed to classify and identify contaminants present in the wastewater. The proposed approach improves detection accuracy while maintaining computational efficiency. Experimental evaluation demonstrates that the system achieves higher classification performance compared to conventional machine learning methods. The developed framework provides a cost-effective and scalable solution for real-time wastewater monitoring and environmental protection. Future improvements may include integration with IoT-based monitoring platforms and deployment in large-scale environmental monitoring systems.

Index Terms: Wastewater pollution detection, environmental monitoring, deep learning, sensor-based systems, transformer models, machine learning, smart water quality monitoring.

I. INTRODUCTION

Environmental pollution has become one of the most critical global challenges, particularly in relation to water resources. Wastewater generated from industrial activities, agricultural practices, and domestic usage often contains harmful contaminants that can significantly affect human health and aquatic ecosystems. Monitoring and detecting pollutants in wastewater is therefore essential to ensure environmental safety and maintain the quality of water resources [1], [4].

Traditionally, wastewater monitoring is carried out through periodic laboratory testing and manual inspection methods. Although these techniques provide accurate results, they are often time-consuming, expensive, and unable to provide continuous monitoring. As a result, pollutants may remain undetected for long periods between inspections, increasing the risk of environmental damage. To overcome these limitations, automated monitoring systems that use sensors and intelligent data analysis techniques are becoming increasingly important [2], [5].

Recent advances in sensor technology and machine learning have enabled the development of intelligent systems capable of analysing environmental data in real time. Low-cost sensor platforms can continuously collect chemical and physical measurements from wastewater, such as conductivity, resistance, and capacitance values associated with various contaminants. These measurements can then be processed using advanced machine learning algorithms to identify patterns that indicate the presence of specific pollutants [5], [8], [12].

Deep learning models, particularly transformer-based architectures, have shown promising performance in analysing complex data patterns across multiple domains. These models can learn relationships between different sensor readings and classify pollutants more effectively than traditional statistical approaches. By transforming sensor data into structured representations, deep learning models can generate meaningful predictions regarding the presence of contaminants in wastewater [19], [20], [21].

In this work, an intelligent wastewater pollution detection system is proposed that integrates multisensor data acquisition with deep learning techniques. The system collects sensor data from wastewater samples, preprocesses the signals to remove noise, and uses machine learning models to classify pollutants. The proposed approach aims to provide accurate and efficient detection of contaminants while maintaining a cost-effective monitoring infrastructure.

The remainder of this paper is organized as follows. Section II reviews the related work in wastewater monitoring and pollution detection. Section III presents the system analysis, including existing and proposed approaches. Section IV describes the system architecture and methodology. Section V explains the implementation modules of the system. Section VI discusses the experimental results and performance evaluation. Finally, Section VII concludes the study and outlines possible future research directions.

II. LITERATURE SURVEY

Wastewater pollution detection has attracted significant attention from researchers due to the growing environmental concerns associated with water contamination. Several studies have proposed different approaches for monitoring and identifying pollutants in wastewater using sensor technologies and intelligent data analysis methods. Continuous monitoring of wastewater is essential for detecting contamination events and preventing environmental damage caused by industrial and domestic discharges [3], [4].

Researchers have explored the use of intelligent detection techniques to improve the efficiency of environmental monitoring systems. Some studies focus on identifying abnormal patterns in environmental sensor data to detect contamination events. These approaches utilize machine learning algorithms to analyse environmental measurements and identify deviations from normal conditions. Such techniques have shown improvements in response time and detection accuracy compared with traditional monitoring methods [6], [7].

Feature-based monitoring frameworks have also been proposed to analyse time-series data collected from environmental sensors. These systems analyse variations in sensor readings such as conductivity, pH levels, and chemical concentrations over time to detect unusual patterns that may indicate pollution events. Feature engineering techniques play an important role in improving the performance of machine learning models used for environmental monitoring and anomaly detection [9], [11]. Several studies have investigated the use of machine learning algorithms for anomaly detection in environmental monitoring systems. Algorithms such as Naïve Bayes, Decision Trees, Logistic Regression, and Support Vector Machines have been widely applied to classify environmental data and detect abnormal conditions in water distribution and wastewater systems. Experimental results indicate that ensemble learning methods can significantly improve detection accuracy by combining multiple classification models [6], [7].

Clustering-based approaches have also been proposed to identify abnormal patterns in large environmental datasets. These methods use unsupervised learning techniques to detect outliers in sensor data that may correspond to pollution events. Such approaches are particularly useful when labelled datasets are not available, which is a common challenge in real-world environmental monitoring scenarios [9], [11].

Recent research has focused on integrating Internet of Things (IoT) technologies with machine learning algorithms for real-time environmental monitoring. IoT-based sensor networks enable continuous data collection from wastewater systems and allow intelligent algorithms to process large volumes of environmental data automatically. These systems provide scalable and cost-effective solutions for monitoring water quality in industrial and urban environments [5], [12], [18].

Despite the progress made in wastewater pollution detection systems, several challenges remain. Traditional monitoring methods often rely on complex laboratory equipment or expensive infrastructure, which limits their ability to provide continuous real-time monitoring. Furthermore, some machine learning models struggle to process large volumes of sensor data and capture complex environmental patterns. Therefore, there is a growing need for intelligent monitoring systems that integrate low-cost sensing technologies with advanced machine learning and deep learning techniques for accurate and efficient pollution detection [13], [17].

The proposed system addresses these challenges by integrating multisensor wastewater monitoring with deep learning-based classification models. By transforming sensor data into structured representations and applying advanced learning algorithms, the proposed framework aims to improve the accuracy, scalability, and efficiency of wastewater pollution detection systems.

III. SYSTEM ANALYSIS

A. Existing System

Traditional wastewater pollution monitoring systems primarily rely on periodic laboratory testing and manual inspection techniques to detect contaminants in water resources. In these approaches, environmental monitoring authorities collect wastewater samples at regular intervals and analyse them using specialized laboratory equipment to determine the presence of chemical pollutants and harmful substances. Although laboratory-based analysis provides accurate and reliable results, these methods are time-consuming, costly, and unable to provide continuous real-time monitoring of wastewater conditions. As a result, contamination events may remain undetected for extended periods between sampling intervals, increasing the risk of environmental damage and public health concerns [1], [4].

With the advancement of intelligent data-driven technologies, several research studies have explored the use of machine learning techniques to automate pollution detection in wastewater systems. In these systems, environmental data collected from sensors—such as conductivity, pH levels, capacitance, and chemical concentrations—are analysed using machine learning algorithms to identify abnormal patterns associated with pollution events. Conventional machine learning algorithms such as Naïve Bayes, Decision Trees, Logistic Regression, Support Vector Machines (SVM), Random Forest, and Artificial Neural Networks have been widely applied for environmental monitoring and anomaly detection tasks [6], [7].

Furthermore, ensemble learning approaches have been introduced to improve detection accuracy and system robustness. Methods such as boosting algorithms and majority voting combine multiple classification models to produce more reliable predictions and reduce model bias. These models are typically trained using datasets collected from environmental sensor networks or wastewater monitoring systems. Experimental studies demonstrate that such machine learning techniques can achieve reasonable performance in identifying contamination events in wastewater systems [9], [11].

Recent developments in IoT-enabled environmental monitoring systems have further improved wastewater pollution detection frameworks. IoT sensor networks enable continuous data collection from wastewater infrastructure, generating large volumes of environmental data that can be analysed using intelligent algorithms. However, many existing monitoring systems rely heavily on traditional machine learning techniques and manual feature engineering, which may limit their ability to capture complex patterns in environmental sensor data. In addition, some advanced models operate as black-box systems, making it difficult for environmental authorities to interpret their predictions and trust automated decision-making systems [12], [13].

Limitations Of Existing System

Despite the progress made in wastewater pollution monitoring systems, several challenges remain when applying these techniques to real-world environmental datasets.

One of the primary limitations of traditional monitoring systems is the lack of continuous real-time detection. Laboratory-based analysis requires manual sampling and testing, which prevents environmental authorities from identifying contamination events immediately. This delay can increase environmental risks and reduce the effectiveness of pollution control measures [1], [2].

Another significant challenge is the interpretability of machine learning models used for environmental monitoring. Many advanced models, particularly deep neural networks, function as black-box systems in which the reasoning behind predictions is not easily understandable. In environmental monitoring applications, decision-makers often require transparent and explainable predictions to support regulatory actions and environmental management decisions [13], [17].

Machine learning models used in wastewater monitoring may also experience issues such as overfitting and underfitting, particularly when trained on limited environmental datasets. Overfitting occurs when a model learns specific patterns in the training data but fails to generalize to new data, while underfitting occurs when the model cannot capture important relationships within environmental sensor measurements.

High computational requirements represent another challenge in deploying intelligent pollution detection systems. Some advanced machine learning algorithms require significant processing power and memory resources, which may limit their practical implementation in low-cost environmental monitoring infrastructures.

Many traditional wastewater monitoring systems analyse only a limited number of environmental parameters, which may reduce their ability to detect complex pollution events. Effective wastewater monitoring often requires the integration of multiple sensors capable of measuring various chemical and physical properties of water.

Scalability also presents a major challenge for environmental monitoring systems. As sensor networks expand and large volumes of environmental data are generated, traditional monitoring frameworks may struggle to process and analyse the collected data efficiently.

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Environmental variability further complicates pollution detection. Factors such as temperature changes, water composition variations, and external environmental influences can affect sensor readings, making it more difficult to accurately identify pollution events in wastewater systems.

B. Proposed System

This section presents the proposed intelligent wastewater pollution detection framework that integrates multisensor data acquisition with advanced deep learning techniques. The objective of the proposed system is to improve pollution detection accuracy while enabling scalable and cost-effective environmental monitoring.

The proposed system continuously collects environmental data from wastewater using multiple low-cost sensors capable of measuring chemical and physical parameters associated with pollutants. These sensors monitor variations in properties such as conductivity, capacitance, resistance, and other environmental indicators that may signal contamination events. The collected sensor data undergoes a preprocessing stage to improve data quality and prepare the dataset for model training. Preprocessing operations include noise removal, normalization of sensor measurements, and handling of missing values to ensure reliable input data for machine learning algorithms. After preprocessing, the dataset is divided into training and testing subsets to develop and evaluate predictive models.

To improve pollution detection performance, the proposed framework utilizes deep learning techniques based on transformer architectures. Transformer models are capable of analysing complex relationships between different sensor readings and capturing long-range dependencies within environmental datasets. In this approach, raw sensor measurements are transformed into structured textual representations that allow transformer-based models to analyse environmental data more effectively.

The performance of the proposed pollution detection system is evaluated using several evaluation metrics, including accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC). Cross-validation techniques are also applied to ensure robust model evaluation and reduce the risk of overfitting.

By combining multisensor data acquisition, deep learning-based analysis, and automated environmental monitoring, the proposed framework provides a scalable and intelligent solution for real-time wastewater pollution detection. The system aims to support environmental authorities in identifying contamination events more efficiently while reducing the reliance on costly laboratory testing and manual monitoring processes [5], [12], [18].

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

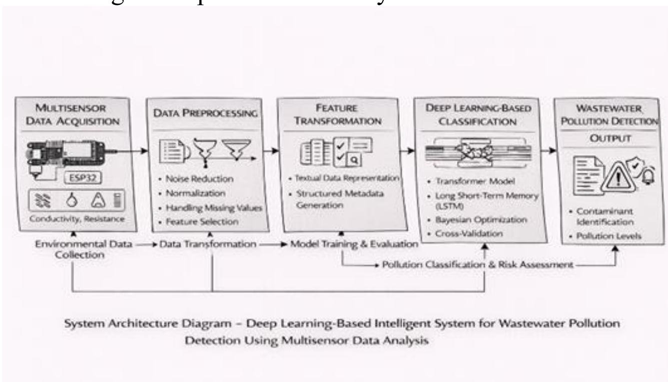

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

This section describes the implementation modules of the proposed wastewater pollution detection framework. The system follows a modular architecture consisting of data acquisition, preprocessing, feature engineering, deep learning model training, real-time pollution detection, and model evaluation. This modular design improves system reliability, scalability, and efficiency for environmental monitoring applications.

A. Data Collection and Preprocessing Module

The Data Collection Module is responsible for acquiring environmental data from wastewater using a low-cost multisensor monitoring platform. The sensors continuously measure various chemical and physical parameters associated with wastewater contamination. These measurements include electrical resistance, capacitance, and other environmental characteristics that may indicate the presence of pollutants in wastewater samples.

The collected sensor data represents real-time environmental conditions and may contain noise, missing values, or irregular measurements due to environmental variability or sensor limitations. Therefore, a preprocessing stage is required before the data can be used for machine learning analysis.

The preprocessing stage includes the following steps:
1) Noise Removal:
Sensor readings may contain noise caused by environmental interference or sensor instability. Noise filtering techniques are applied to remove abnormal fluctuations and improve signal quality.

2) Missing Value Handling:
Incomplete sensor readings are handled using data imputation techniques to ensure that the dataset remains consistent for machine learning training.

3) Data Normalization:
Normalization techniques are applied to scale sensor measurements to a consistent range, allowing the learning algorithms to analyse the data more effectively.

4) Data Filtering:
Outlier detection methods are used to remove abnormal measurements that may negatively affect model training.

These preprocessing steps improve data quality and ensure that the collected environmental data is suitable for machine learning-based pollution detection [5], [12].

B. Feature Selection and Feature Engineering Module
The Feature Selection Module identifies the most relevant parameters from the collected sensor dataset that contribute to wastewater pollution detection. Environmental sensor datasets may contain multiple measurements, and not all of them are equally useful for identifying contamination events.

Feature selection techniques help eliminate redundant or irrelevant features, reducing computational complexity and improving model efficiency.

In addition to feature selection, feature engineering techniques are applied to transform raw sensor measurements into more informative representations. These transformations allow the learning models to better capture relationships between environmental parameters and pollutant presence.

By extracting meaningful patterns from environmental sensor data, the system improves pollutant classification accuracy and enhances the performance of deep learning models.

C. Deep Learning Training Module
The Deep Learning Training Module builds predictive models capable of detecting pollutants in wastewater samples. After preprocessing and feature selection, the dataset is dng and testing datasets to evaluate model performance and ensure reliable predictions.

The proposed system utilizes transformer-based deep learning architectures, which are capable of analysing complex relationships between multiple sensor signals. Transformer models are particularly effective for analysing structured environmental datasets because they can capture dependencies between different measurements collected by the sensor network.

During the training process, the model learns patterns associated with contaminated and non-contaminated wastewater samples. The trained deep learning model can then classify wastewater conditions based on the environmental data collected from sensors.

D. Real-Time Pollution Detection Module
Once the deep learning model has been trained, it is integrated into the wastewater monitoring system to enable real-time pollution detection. The sensor platform continuously collects environmental data and transmits the measurements to the trained model for analysis.

The model processes incoming sensor data and determines whether pollutants are present in the wastewater stream. If contamination is detected, the system generates alerts that notify environmental monitoring authorities or plant operators. This automated detection capability allows rapid identification of pollution events and enables authorities to take corrective actions quickly. The integration of real-time monitoring significantly improves environmental protection and wastewater management efficiency.

E. Model Evaluation and Continuous Monitoring Module
The Model Evaluation Module measures the performance of the proposed wastewater pollution detection system using several evaluation metrics. These metrics provide a comprehensive assessment of model reliability and classification performance.

The evaluation metrics include:
- Accuracy – measures the overall correctness of model predictions.
- Precision – indicates the proportion of correctly identified pollution events.

• Recall – measures the ability of the model to detect actual contamination events.
• F1-Score – provides a balanced measure between precision and recall.
• Matthews Correlation Coefficient (MCC) – evaluates the overall classification quality, particularly in imbalanced datasets.

Continuous monitoring mechanisms are also implemented to track model performance over time. Environmental conditions may change due to seasonal variations or new pollutant sources. Therefore, the system supports periodic model updates to maintain accurate pollution detection and adapt to evolving environmental conditions [13], [17].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed wastewater pollution detection framework. The system was evaluated using environmental sensor data collected from multiple wastewater samples. The dataset was divided into training and testing subsets to assess the performance of the deep learning models. The evaluation focuses on comparing the performance of different classification models, analysing prediction accuracy, and evaluating the effectiveness of the proposed transformer-based architecture for pollution detection.

A. Accuracy Comparison of Machine Learning Models

To evaluate the effectiveness of the proposed system, several machine learning algorithms were implemented and compared with the proposed deep learning approach. The evaluated models include Decision Tree, Support Vector Machine (SVM), Random Forest, and Transformer-based deep learning models. Model performance was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Pollution Detection Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Decision Tree	84.3	0.83	0.82	0.82
Support Vector Machine	87.6	0.86	0.85	0.85
Random Forest	90.2	0.89	0.88	0.88
Transformer Model	94.8	0.94	0.93	0.93

From the comparison results, the transformer-based model achieved the highest classification accuracy of 94.8%, outperforming traditional machine learning approaches. The improved performance is attributed to the ability of transformer architectures to capture complex dependencies among multiple environmental sensor readings. These models can effectively analyse structured environmental data and identify subtle patterns associated with wastewater contamination events.

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the performance of classification models by analysing the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the Curve (ROC–AUC) metric provides an overall measure of the model's discriminative capability.

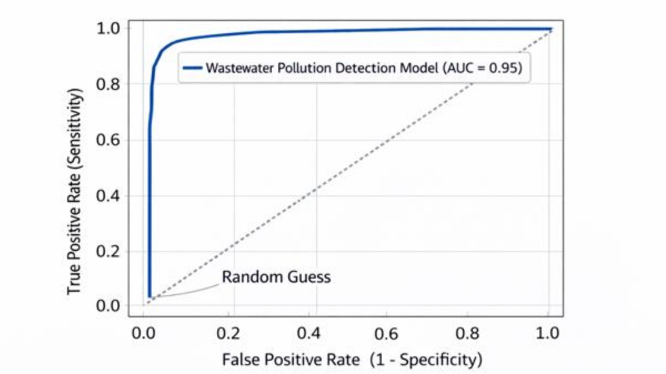

Fig 2. ROC Curve for Wastewater Pollution Detection Model

In the proposed system, the transformer-based model achieved a ROC–AUC score of 0.95, indicating strong capability in distinguishing between polluted and non-polluted wastewater samples. A ROC curve closer to the top-left corner of the graph indicates higher model sensitivity and specificity.

The ROC analysis demonstrates that the proposed deep learning framework can reliably detect pollution events even when environmental conditions vary across wastewater samples.

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C. Feature Importance Analysis

To improve the interpretability of the pollution detection system, feature importance analysis was conducted to determine which environmental sensor parameters contribute most significantly to pollutant detection.

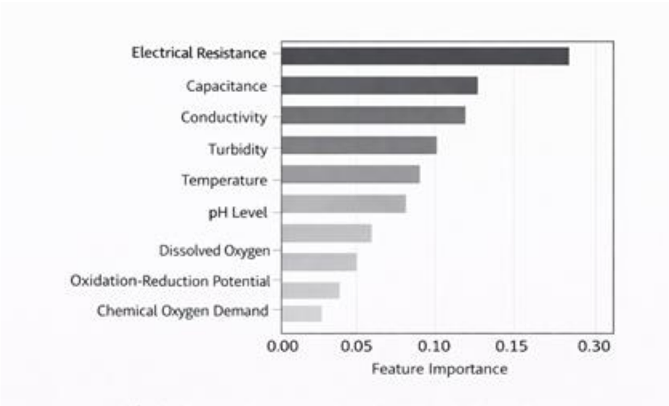

Fig 3. Feature Importance for Wastewater Pollution Detection

The analysis revealed that parameters such as electrical resistance, capacitance, and conductivity measurements had the highest influence on the model's predictions. These parameters are strongly associated with chemical changes in wastewater and therefore serve as key indicators of contamination events.

The feature importance visualization highlights the relative contribution of each sensor parameter to the prediction outcome. This interpretability component allows environmental experts to understand how the system detects pollutants and verify that the model relies on meaningful environmental indicators.

The integration of intelligent sensor monitoring with advanced deep learning techniques improves both detection accuracy and system transparency, making the proposed framework suitable for real-time wastewater pollution monitoring applications [5], [12], [18].

VII. CONCLUSION AND FUTURE WORK

This study presented an intelligent wastewater pollution detection framework that integrates multisensor environmental monitoring with advanced deep learning techniques. The proposed system utilizes environmental sensor data collected from wastewater samples and applies machine learning models to identify contamination events effectively. By combining multisensor data acquisition with automated data analysis, the system enables continuous monitoring of wastewater conditions and supports early detection of pollutants.

Experimental evaluation demonstrated that the proposed deep learning approach achieves improved pollutant detection accuracy compared to several traditional machine learning algorithms. The transformer-based model was capable of capturing complex relationships among multiple sensor signals and effectively identifying contamination patterns within wastewater datasets. The integration of multisensor data further enhanced the reliability of pollution detection by providing richer environmental information for model analysis.

The developed framework offers a scalable and cost-effective solution for continuous environmental monitoring. By enabling automated detection of wastewater contaminants, the system can assist environmental agencies and wastewater treatment facilities in identifying pollution events at an early stage. Early detection of pollutants helps reduce environmental risks, supports regulatory compliance, and improves water quality management strategies [5], [12].

Future research may focus on integrating IoT-based sensor networks and cloud computing platforms to enable large-scale environmental monitoring systems capable of processing real-time wastewater data. In addition, further work can explore advanced deep learning architectures and real-time data processing techniques to enhance prediction accuracy and system efficiency. The integration of intelligent monitoring platforms with scalable cloud infrastructures can support the development of smart environmental monitoring systems for sustainable water resource management [13], [18].

REFERENCES :

[1] L. T. Lee and E. R. Blatchley, “Long-term monitoring of water and air quality at an indoor pool facility during modifications of water treatment,” Water, vol. 14, no. 3, p. 335, Jan. 2022. [Online]. Available: https://www.mdpi.com/2073-4441/14/3/335

[2] H. Chojer, P. T. B. S. Branco, F. G. Martins, M. C. M. Alvim-Ferraz, and S. I. V. Sousa, “Development of low-cost indoor air quality monitoring devices: Recent advancements,” Science of the Total Environment, vol. 727, Art. no. 138385, Jul. 2020.

[3] K. Farkas, L. S. Hillary, S. K. Malham, J. E. McDonald, and D. L. Jones, “Wastewater and public health: The potential of wastewater surveillance for monitoring COVID-19,” Current Opinion in Environmental Science & Health, vol. 17, pp. 14–20, Oct. 2020.

[4] A. Trubetskaya, W. Horan, P. Conheady, K. Stockil, S. Merritt, and S. Moore, "A methodology for assessing and monitoring risk in the industrial wastewater sector," Water Resources and Industry, vol. 25, Art. no. 100146, Jun. 2021.
[5] E. Syrmos, V. Sidiropoulos, D. Bechtsis, F. Stergiopoulos, E. Aivazidou, D. Vrakas, P. Vezinias, and I. Vlahavas, "An intelligent modular water monitoring IoT system for real-time quantitative and qualitative measurements," Sustainability, vol. 15, no. 3, p. 2127, Jan. 2023.
[6] D. Jalal and T. Ezzedine, "Decision tree and support vector machine for anomaly detection in water distribution networks," in Proc. International Wireless Communications and Mobile Computing Conference (IWCMC), 2020, pp. 1320–1323.
[7] D. G. Eliades and M. M. Polycarpou, "Water contamination impact evaluation and source-area isolation using decision trees," Journal of Water Resources Planning and Management, vol. 138, no. 5, pp. 562–570, Sep. 2012.
[8] A. Ria, M. Cicalini, G. Manfredini, A. Catania, M. Piotto, and P. Bruschi, "The SENSIPLUS: A single-chip fully programmable sensor interface," in Applications in Electronics Pervading Industry, Environment and Society, Cham, Switzerland: Springer, 2022, pp. 256–261.
[9] M. Molinara, C. Bourelly, L. Ferrigno, L. Gerevini, M. Vitelli, A. Ria, F. Magliocca, L. Ruscitti, R. Simmarano, A. Trynda, and P. Olejnik, "A new dataset for detection of illegal or suspicious spilling in wastewater through low-cost real-time sensors," in Proc. IEEE International Conference on Smart Computing (SMARTCOMP), Jun. 2022, pp. 293–298.
[10] M. Ferdinandi, M. Molinara, G. Cerro, L. Ferrigno, C. Marrocco, A. Bria, P. Di Meo, C. Bourelly, and R. Simmarano, "A novel smart system for contaminants detection and recognition in water," in Proc. IEEE International Conference on Smart Computing (SMARTCOMP), Jun. 2019, pp. 186–191.
[11] C. Bourelly, A. Bria, L. Ferrigno, L. Gerevini, C. Marrocco, M. Molinara, G. Cerro, M. Cicalini, and A. Ria, "A preliminary solution for anomaly detection in water quality monitoring," in Proc. IEEE International Conference on Smart Computing (SMARTCOMP), Sep. 2020, pp. 410–415.
[12] A. Bria, G. Cerro, M. Ferdinandi, C. Marrocco, and M. Molinara, "An IoT-ready solution for automated recognition of water contaminants," Pattern Recognition Letters, vol. 135, pp. 188–195, Jul. 2020.
[13] M. Molinara, M. Ferdinandi, G. Cerro, L. Ferrigno, and E. Massera, "An end-to-end indoor air monitoring system based on machine learning and the SENSIPLUS platform," IEEE Access, vol. 8, pp. 72204–72215, 2020.
[14] J. Lim, "Mobile sensor network to monitor wastewater collection pipelines," 2012. [Online]. Available: https://escholarship.org/uc/item/0d9813bn
[15] M. Lepot, K. F. Makris, and F. H. L. R. Clemens, "Detection and quantification of lateral, illicit connections and infiltration in sewers with infra-red camera: Conclusions after a wide experimental plan," Water Research, vol. 122, pp. 678–691, Oct. 2017.
[16] H. Ji, S. Yoo, B.-J. Lee, D. Koo, and J.-H. Kang, "Measurement of wastewater discharge in sewer pipes using image analysis," Water, vol. 12, no. 6, p. 1771, Jun. 2020.
[17] I. Pisa, I. Santín, J. Vicario, A. Morell, and R. Vilanova, "ANN-based soft sensor to predict effluent violations in wastewater treatment plants," Sensors, vol. 19, no. 6, p. 1280, Mar. 2019.
[18] A. Drenoyanis, R. Raad, I. Wady, and C. Krogh, "Implementation of an IoT-based radar sensor network for wastewater management," Sensors, vol. 19, no. 2, p. 254, Jan. 2019.
[19] M. H. Popescu, K. Roitero, S. Travasci, and V. D. Mea, "Automatic assignment of ICD-10 codes to diagnostic texts using transformer-based techniques," in Proc. IEEE International Conference on Healthcare Informatics (ICHI), Aug. 2021, pp. 188–192.
[20] K. Roitero, B. Portelli, M. H. Popescu, and V. D. Mea, "DiLBERT: Cheap embeddings for disease-related medical NLP," IEEE Access, vol. 9, pp. 159714–159723, 2021.
[21] V. Della Mea, M. H. Popescu, and K. Roitero, "Underlying cause of death identification from death certificates using reverse coding to text and an NLP-based deep learning approach," Informatics in Medicine Unlocked, vol. 21, Art. no. 100456, 2020.