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Review paper

A narrative review of machine learning integrated electrochemical sensors for smart environmental monitoring

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Abstract

In the recent era, industrialization, urbanization, and unethical agricultural practices have caused environmental degradation and therefore, there is an utmost need for fast and efficient monitoring systems. The solution to the above is electrochemical sensors; these are one of the useful analytical tools used for environmental monitoring because of their high efficiency, sensitivity, less tedious, cost effective. However, these electrochemical sensors can experience signal noise, interference peaks from complex mixtures of analytes, and interpretation problems, especially with nonlinear electrochemical responses. In recent years, machine learning (ML) has become one of the most groundbreaking methods to improve the performance of electrochemical sensors by making it easy for complex signal processing, pattern recognition, and highly accurate modelling. Combining ML with electrochemical sensors enables advanced environmental monitoring with real-time analysis, simultaneous determination of multiple analytes, and improved selectivity and sensitivity. This review provides a detailed explanation of ML-based electrochemical sensors and their advantages and applications in environmental monitoring. This article also discusses the advantages of ML integration with nanomaterials and the Internet of Things for determining toxic dyes, pesticides, heavy metals, etc.

Keywords

Nanomaterial-based sensors, smart sensing systems; electrochemical data analysis; artificial intelligence; Internet of Things

Introduction

Toxic pollutants have increased due to fast industrialization, population growth, urbanization, deforestation, and unethical agricultural practices; this severely affects human health and the environment by contaminating soil, water, and air. Industries, agriculture, and urban activities add toxic pollutants such as pesticides, toxic dyes, heavy metals, and pharmaceutical wastes to the environment [1,2]. Most of these pollutants are non-degradable, highly stable, and can exert toxic effects for a very long time. These pollutants affect the environment, particularly water resources, and heavy metals such as mercury, lead, cadmium, and arsenic can cause serious health disorders in the kidneys, brain, and heart [3-10]. Figure 1 depicts global environmental pollution sources, major environmental contaminants, and their impact on humans [11]. Therefore, environmental monitoring research is now in the limelight, and many researchers are trying new methods to curb and control environmental pollution using advanced technologies. However, the world still has a strong demand for highly selective, sensitive, effective, and fast assessment techniques to detect pollutants at very low concentrations (nanomolar) [12-14]. Electrochemical sensors have emerged as promising analytical tools for environmental monitoring because of their high sensitivity, selectivity, rapid response, low detection limits, cost-effectiveness, and ease of miniaturization. These advantages facilitate their integration with portable electronic devices, making them highly suitable for real-time environmental monitoring applications [15-19].

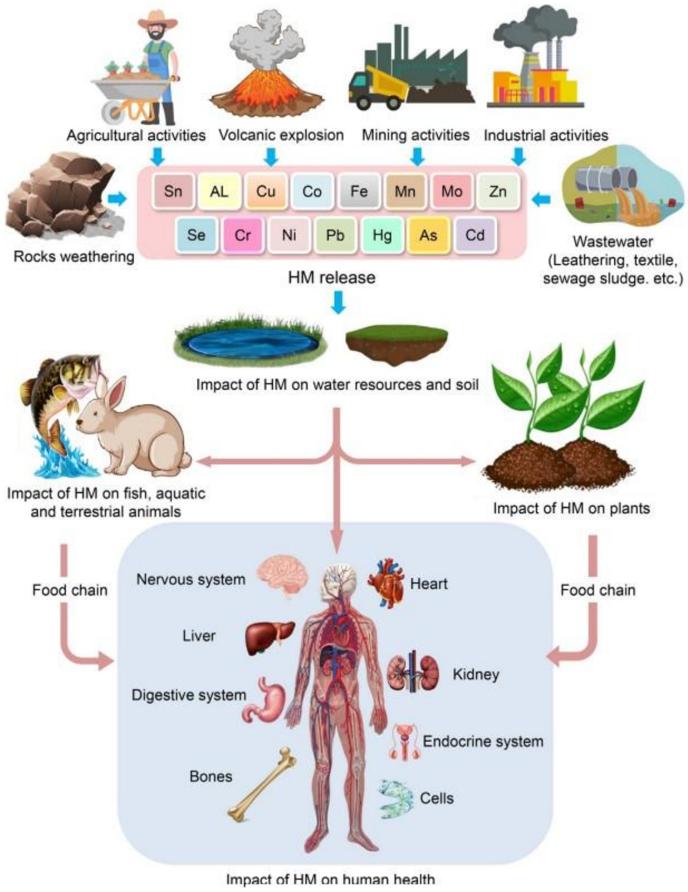

Figure 1. *Global environmental pollution sources and major environmental contaminants and their impact on humans [11], reproduced under CC BY 4.0 license*

Conventional spectroscopic, spectrophotometric, and chromatographic methods are fast, widely used, and accurate, but they are expensive, require skilled personnel to operate, involve complex operations, and are not suitable for real-time applications. On the other hand, advanced electrochemical sensors show great potential for environmental monitoring due to their excellent sensitivity, selectivity, low detection limit (LOD), fast response, ease of operation, and cost-effectiveness [20,21]. In addition, these sensors can be miniaturized and integrated with portable electronic devices to improve their efficiency [22-24]. Figure 2 represents the environmental monitoring applications of electrochemical sensors [25].

***Figure 2**. Environmental monitoring applications of electrochemical sensors [25], reproduced under CC BY 4.0 license*

Electrochemical sensors are based on electrochemical (redox) reactions at the electrode-electrolyte interface, which convert chemical data into quantifiable electrical signals. Electrochemical reactions occur when the electrode surface contacts the analyte and produce electrical signals such as changes in potential and current [26-31]. Electrochemical methods such as cyclic voltammetry (CV), differential pulse voltammetry (DPV), amperometry, and electrochemical impedance spectroscopy (EIS) are popular and commonly used for environmental assessment. These techniques are important for the sensitive determination of various pollutants and for studying electron-transfer mechanisms [32-34]. Figure 3 shows the overview of common electrochemical techniques used in environmental monitoring [25].

The fundamental principles of electrochemical sensors are well known from classical electrochemistry. In classical electrochemistry, the connection between electrode potential and analyte concentration is mostly based on the Nernst equation, while the kinetics of electron-transfer reactions are explained through the Butler-Volmer equations. Diffusion-controlled electrochemical processes are often described by the Randles-Ševčik equation in cyclic voltammetry. These principles provide a theoretical basis for electrochemical sensors and remain important in designing high-quality sensors.

Even though these sensors have shown significant selectivity, sensitivity and LOD for various environmental contaminants, they will always come across some drawbacks like low precision, significant noise in electrochemical signals, frequent electrode fouling, overlapping of redox peaks, *etc*. [35,36]. These electrochemical sensors also exhibit low repeatability, sensor drift, and difficulty in converting complex electrochemical data.

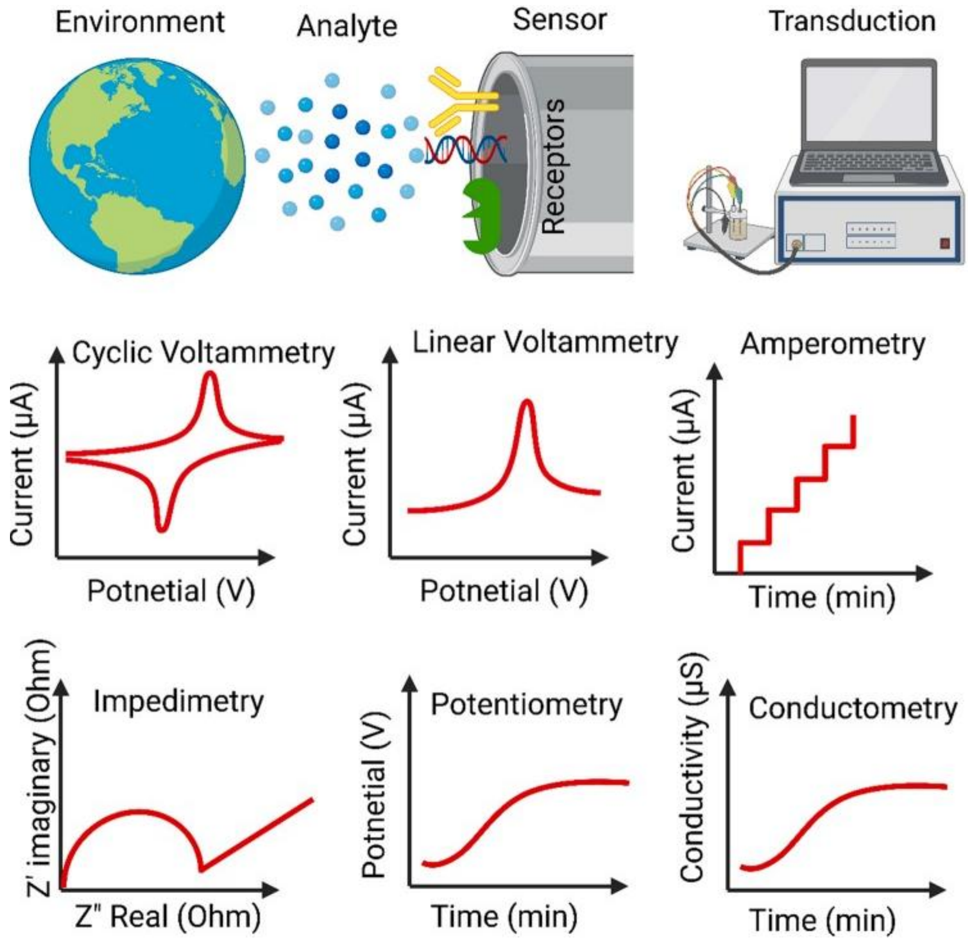

Figure 3. *Overview of common electrochemical techniques used in environmental [25], reproduced under CC BY 4.0 license*

Furthermore, CV and EIS often produce large datasets with nonlinear, multidimensional electrochemical signals that are challenging to evaluate using conventional statistical techniques.

However, artificial intelligence (AI) techniques, like machine learning (ML), have recently caught the attention of electrochemists and they are blending ML with electrochemical sensors to get rid of the above drawbacks [37-39]. ML allows computers to identify electrochemical patterns in data and make judgments and predictions without explicit programming. These predictions from ML-integrated electrochemical sensors can be further improved by using advanced algorithms such as artificial neural networks (ANN), support vector machines, decision trees, random forests, and deep learning models [40,41].

The dream of developing advanced computational electrochemical sensing systems has come true through the integration of ML techniques with electrochemical sensors. The main advantage of integrating ML with sensors is the ability of ML algorithms to process complex electrochemical signals easily and effectively. This also improves the identification of useful features from multidimensional data, noise filtering, and compensation for sensor drift [42]. This, in turn, further increases the selectivity, sensitivity, anti-fouling, and repeatability of the electrochemical sensors. ML algorithms also enable automatic sensor calibration, simultaneous multi-analyte determination, predictive analysis of environmental contamination trends, *etc*. These ML-based features reduce the disadvantages of traditional data analysis techniques and significantly improve the analytical performance of electrochemical sensors [43,44].

The integration of electrochemical sensors with Internet of Things (IoT) technology is another important and substantial development in environmental monitoring. IoT-based electrochemical sensing systems make data collection easy and continuous; they also enable wireless connection and remote environmental monitoring [45,46]. Integrating IoT and ML algorithms with electrochemical sensors can further improve real-time data collection, pollutant determination, and automated decision-making.

These ML-based electrochemical sensors have already shown potential for determining environmental contaminants such as pesticides, heavy metals, toxic dyes, and pharmaceutical wastes, with high accuracy and precision. These integrated sensors can reduce the dependency on conventional sensors for environmental assessment, which has some drawbacks as we discussed earlier. These are considered next-generation electrochemical sensors with improved accuracy, selectivity, sensitivity, repeatability, robustness, and reproducibility. These electrochemical sensors are expected to play an important role in solving global environmental problems due to advances in AI and electrochemical sensor technology, and they could be sustainable for environmental management.

This narrative review provides a detailed overview of the basic concepts of electrochemical sensing platforms and electrochemical sensors integrated with ML and IoT for smart environmental monitoring. The drawbacks, advantages, and the future of these next-generation electrochemical sensors are also discussed in this review article.

Fundamentals of electrochemical sensors

Electrochemical sensors play a crucial role in determining various bioactive and electroactive species and therefore, they are useful for environmental and healthcare monitoring [47,48]. The key advantage of these sensors is their ability to convert chemical information into detectable electrical signals, enabling the determination of a wide variety of analytes. The electrochemical redox reaction takes place at the interface between the electrode and the target analyte and produces electrical signals proportional to analyte concentration, based on electron-transfer mechanisms such as current and potential difference. During oxidation, analytes lose electrons, and during reduction, they regain them; this is the basic redox reaction mechanism. Variables such as the concentration of the target analyte, pH, electrode surface area, and electron-transfer kinetics can significantly affect the electrochemical signal during redox reactions [49-51]. During environmental monitoring, analyte molecules diffuse to the working electrode surface, making the electrochemical process diffusion-controlled. These diffusion-controlled reactions and electron-transfer kinetics are more often explained by the relationship between the redox peak and analyte concentration. The Randles-Ševčik Equation (1) [52,53], can be useful in determining the diffusion coefficient, analyte concentrations, and active surface area of the electrodes.

$$I_p = 2.69\times10^5 n^{2/3} A D^{1/2} C v^{1/2} \tag{1}$$

where I_p / A is the peak current, n is the number of electrons transferred, A / cm^2 is the electroactive surface area of the electrode, D / cm^2 s^{-1} is the diffusion coefficient of the electroactive species, C / mol cm^{-3} is the bulk concentration of the electroactive species, and v / V s^{-1} is the scan rate. The Randles-Ševčik equation applies only to electrochemically reversible, diffusion-controlled systems at 298 K and should not be directly applied to quasi-reversible, irreversible, or adsorption-controlled electrochemical processes. Under these conditions, the equation can be used to estimate parameters such as the diffusion coefficient, electroactive surface area, or analyte concentration. The electrode's surface area, electrode type, pH, and electrochemical method can affect the selectivity, sensitivity, and reproducibility of electrochemical sensors. Further, the efficiency of electrochemical sensors can be improved by integrating the ML algorithm and IoT.

Machine learning techniques for electrochemical data analysis

Nowadays, a huge volume of experimental data can be generated because of fast advancements in electrochemical sensor research [54,55]. Powerful electrochemical tools like CV, DPV and EIS are very useful in yielding multidimensional datasets like the type of electrochemical reaction, interfacial phenomena, electrode kinetics, analyte concentration, *etc*. However, high signal noise, nonlinear correlations, overlapping peaks during multi-analyte measurements, and interference from other chemical species in environmental samples can make it difficult to determine electrochemical reactions using traditional electrochemical techniques [56-58].

Therefore, electrochemical sensors integrated with ML algorithms can address these deficiencies and significantly improve sensor efficiency. ML algorithms use relationships between variables to identify hidden patterns and make accurate predictions based on observed data [59]. Researchers can significantly improve the accuracy of the electrochemical sensors by integrating them with AI tools and providing a huge volume of data [43,60]. Most limitations in conventional electrochemical sensing systems can be addressed by integrating ML algorithms. The ML-integrated electrochemical sensors can generate electrochemical signals in various ways, such as anomaly detection, signal categorization, feature extraction, regression analysis, and predictive modelling. These sensors can perform real-time environmental monitoring and simultaneously determine multiple analytes with ease [44].

The use of machine learning algorithms depends, to some extent, on whether labels are available and is divided into four main categories: supervised, unsupervised, semi-supervised, and reinforcement learning. Electrochemical sensing requires supervised machine learning algorithms in most cases because quantitative measurements in this area are always made using calibrated data sets. Supervised algorithms are particularly effective for predicting and classifying electrochemical signals, while unsupervised algorithms help reveal hidden patterns in datasets, cluster new data, and detect anomalies. Semi-supervised and reinforcement learning algorithms represent recent developments in machine learning that combine both the advantages of labelled and unlabelled data, respectively. Thus, the choice of a particular machine learning algorithm depends on several criteria.

Data acquisition and preprocessing of electrochemical signals

As we discussed, noise signals, baseline drift, and fluctuations are very common in raw electrochemical signals. Therefore, we need to collect data carefully, and preprocessing is essential for effectively integrating ML algorithms into electrochemical sensors [61]. If all processing goes smoothly as planned, integrating ML with sensors can achieve excellent accuracy. For every measurement of CV and EIS, one has to collect thousands of raw data, and many tests will be carried out frequently at various analyte concentrations and at various parameters, especially for environmental monitoring. This will produce a large dataset suitable for ML analysis. Figure 4 depicts the ML workflow for electrochemical data analysis, including raw data acquisition, preprocessing, feature extraction, model training, and analytical data prediction [2].

Savitzky-Golay filtering is commonly employed to reduce high-frequency noise and improve the quality of electrochemical signals. However, careful optimization of the smoothing parameters, including the window size and polynomial order, is essential because excessive smoothing may distort peak characteristics and influence the accuracy of subsequent electrochemical data analysis [62,63].

Similarly, baseline correction can remove background currents. Another important data-processing step is feature extraction; electrochemical peak characteristics such as peak width, peak potential, peak current, and charge transfer resistance can be extracted from electrochemical measurements rather than using raw data directly. By reducing high-dimensional data while retaining crucial information, this approach can greatly improve model performance and forms the basis of ML methods.

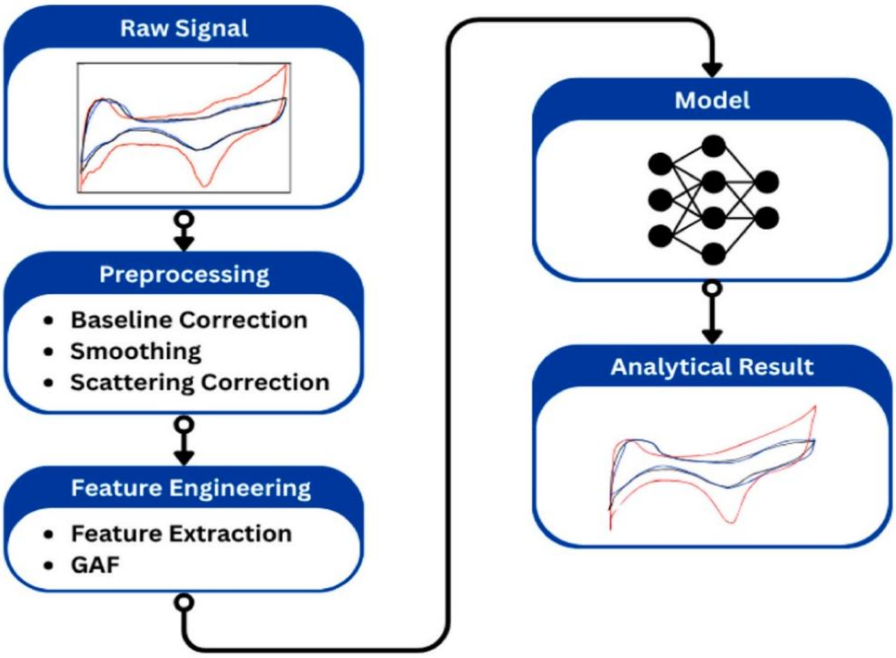

Figure 4. *ML workflow for electrochemical data analysis, including raw data acquisition, preprocessing, feature extraction, model training, and analytical data prediction [2], reproduced under CC BY 4.0 license*

Supervised learning is considered one of the more efficient ML techniques used in electrochemical sensing applications. This ML technique uses labelled datasets, where the input data, like electrochemical signals, are linked to standard output data, like the known concentration of analyte. Then, the supervised learning model calculates results for fresh and unknown data. Recently, support vector machines (SVM) and artificial neural networks (ANN) have been frequently used in environmental monitoring to classify different contaminants according to their electrochemical properties [64-66]. SVM models are very efficient at determining voltammetry signals from mixtures of organic contaminants and show excellent selectivity. On the other hand, ANN models are very effective for analysing nonlinear electrochemical datasets. They are also used to simulate the correlation between analyte concentration and the corresponding electrochemical signals [67,68]. ANN models can be employed for environmental monitoring to detect and quantify the contaminants and their concentrations. Figure 5 represents the relationship in AI components and a schematic of an ANN-based analytical technique [37]. ML models like ANN and their connection to AI data treatment used for environmental monitoring are shown in Figure 6 [37].

Another important ML technique is deep learning (DL), one of the promising models used for voltammetry analysis. This model exhibits excellent selectivity, even when electrochemical signals overlap, and can resolve them successfully [69,70]. DL models can manage the huge datasets produced by sensor networks and can be continuously employed for environmental monitoring [71-73]. They are also integrated with cloud computing and IoT to improve real-time environmental monitoring. The main disadvantage of DL models is that they require significant computer resources and huge training datasets. However, this disadvantage can be mitigated by improving data processing and accessibility for electrochemical sensing applications.

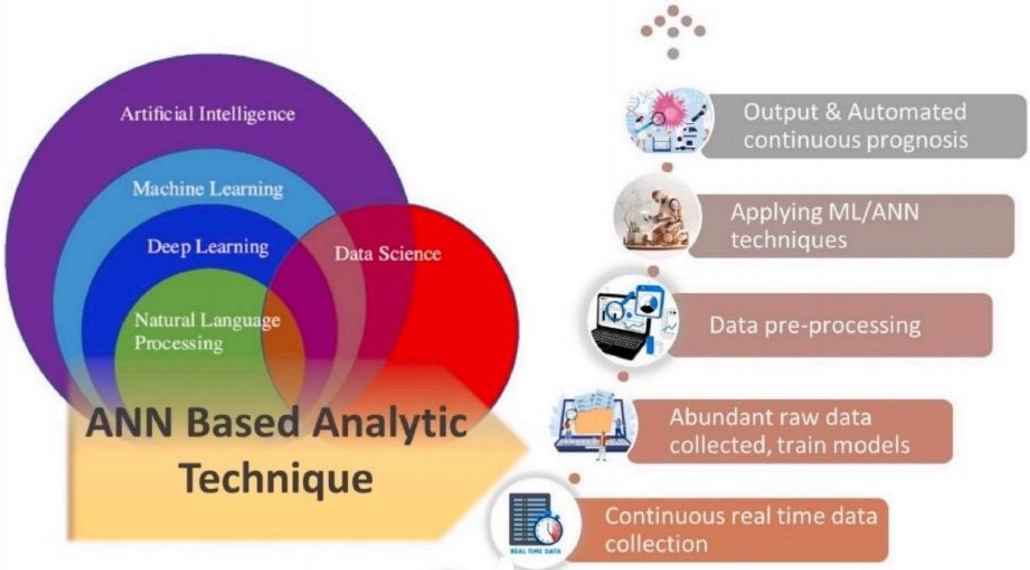

***Figure 5**. Relationship in AI component and schematic of an ANN-based analytical technique [37], reproduced under CC BY 4.0 license*

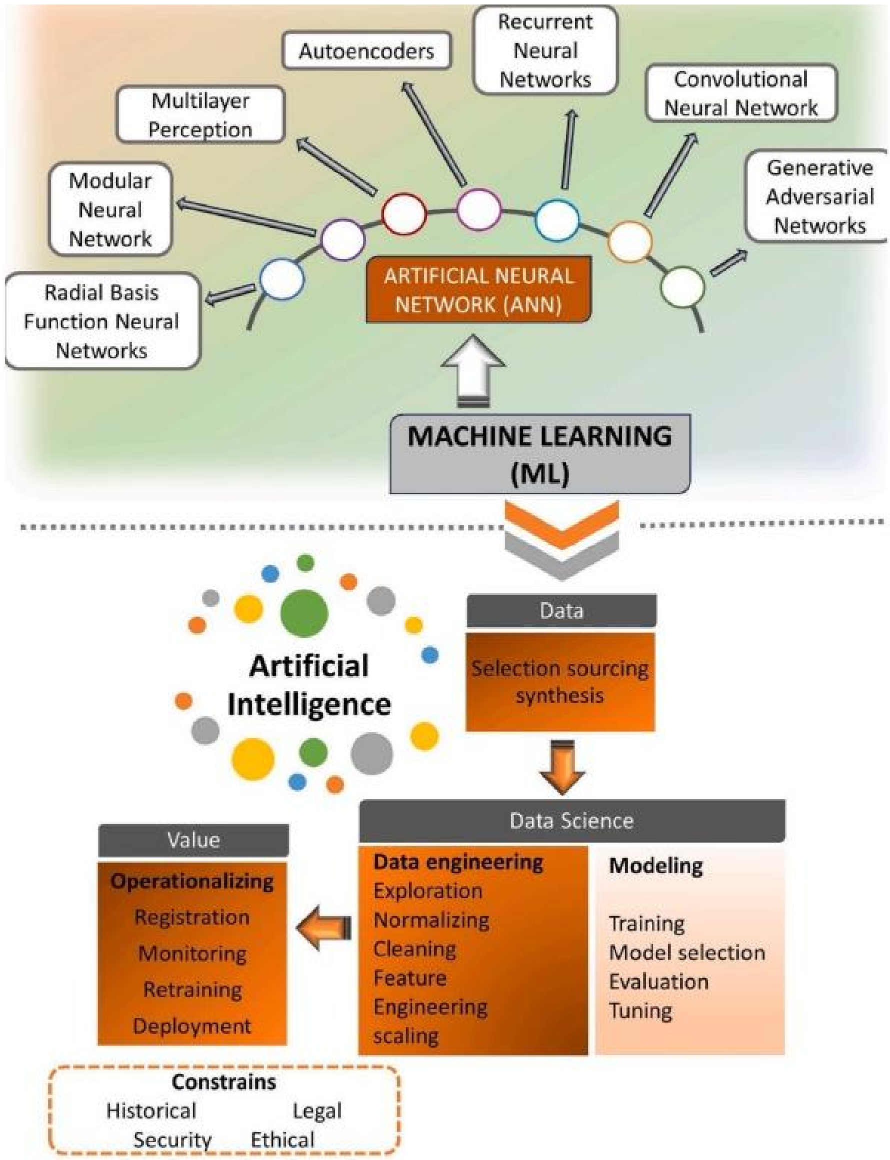

***Figure 6**. ML models like ANN and their connection to artificial intelligence data treatment used for environmental monitoring [37], reproduced under CC BY 4.0 license*

Despite the tremendous improvements machine learning algorithms have made in analysing electrochemical data, no single algorithm applies to all electrochemical sensing cases. SVM algorithms can provide high classification accuracy and work effectively with relatively small, high-dimensional datasets; however, their computational cost increases substantially as dataset size grows. ANN algorithms can successfully model non-linear electrochemical signals; nevertheless, proper optimization and sufficiently large training sets are needed to prevent overfitting. Deep learning algorithms allow automatic feature extraction from complex electrochemical signals, but they are resource-intensive and can be considered black-box due to their low interpretability.

While machine learning has tremendously enhanced electrochemical sensors' analytical potential, the efficiency of each algorithm is highly dependent on the nature of electrochemical signals, the characteristics of the dataset being analysed, and the required analytical task. SVM algorithms deliver highly accurate classifications of relatively small, high-dimensional datasets and are therefore useful for electrochemical signal classification and analyte identification. ANNs, on the other hand, are quite efficient in modelling nonlinear electrochemical responses as well as quantitative predictions. However, ANNs require thorough optimization and large enough datasets to prevent overfitting. Deep learning techniques advance electrochemical data analysis by automatically extracting features from complex voltammetric and impedance signals without extensive manual feature selection. Deep learning models, however, have huge requirements for computing power and amount of labelled data and tend to lack interpretability because of the black-box character. Therefore, the decision about which machine learning algorithm is best for the particular electrochemical problem at hand should not be based on a one-size-fits-all approach. Moreover, as research on machine learning-based electrochemical sensing grows, comparing studies becomes difficult because they use different sensing materials, analytes, methods, validation approaches, and evaluation criteria. Thus, standard benchmark datasets and common evaluation criteria should be developed to allow for proper comparison of the discussed machine learning algorithms.

Integration of nanomaterials and machine learning

Integrating nanomaterials with ML models is a novel approach to developing a smart environmental monitoring electrochemical sensing system. ML techniques help interpret complex datasets effectively, while nanomaterials increase sensitivity and reactivity. This synergistic integration will enhance the selectivity, sensitivity, repeatability, reproducibility, detection accuracy, and automated data interpretation of the electrochemical sensing systems [16,17,26-28]. It will also reduce the need for frequent sensor calibration, improve the long-term stability of electrochemical systems, and increase the ability to compensate for sensor drift. This integration can improve real-time environmental monitoring and system stability. These types of integrated models can detect pollutants very quickly and effectively by gathering environmental data continuously and analyse them accurately. Therefore, integrating nanomaterials and ML techniques plays an important role in developing next-generation smart environmental monitoring systems. Figure 7 represents the different types of nanomaterials used in electrochemical sensors for environmental monitoring [1].

Internet of Things-enabled smart electrochemical sensing platforms

In recent years, intelligent environmental monitoring models have emerged as popular and effective electrochemical sensing platforms due to advances in sensor technology, real-time monitoring, and data collection [74].

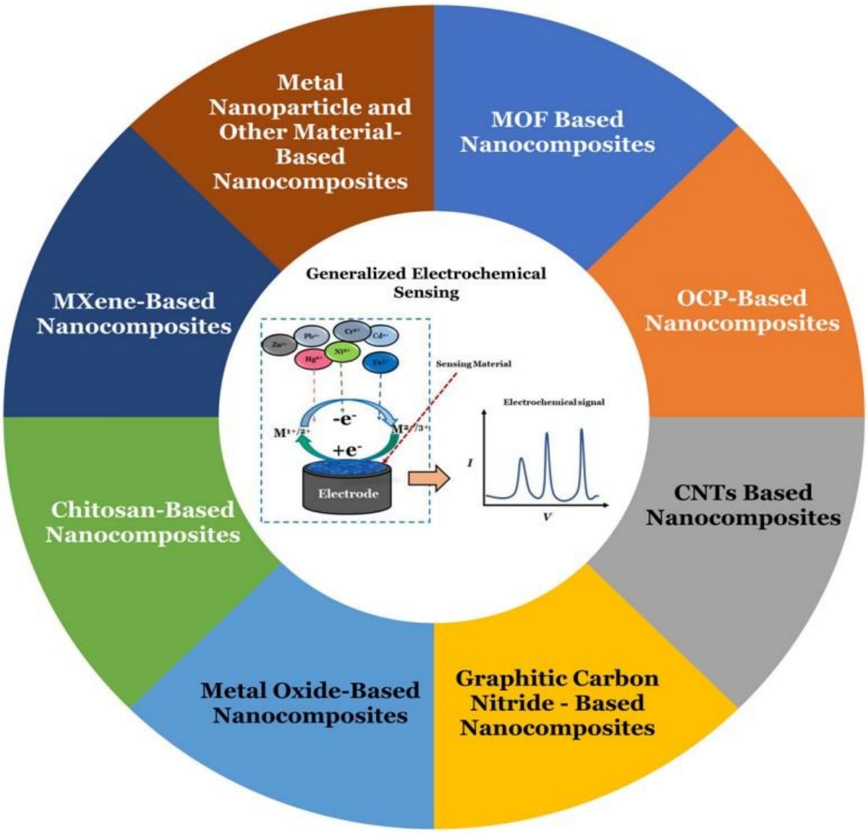

Figure 7. *Different types of nanomaterials used in electrochemical sensors for environmental monitoring [1], reproduced under CC BY 4.0 license*

Integrating with different computational models will further improve the electrochemical sensing systems. One of them is integrating IoT with an electrochemical sensing system. IoT-enabled electrochemical sensing platforms can help in sending data to centralized servers for further processing and analysis [74]. This integration can also improve the stability and efficiency of the sensing system with increased automation and accuracy. Integrating IoT-enabled electrochemical sensors with ML algorithms and nanomaterials can further improve their selectivity, sensitivity, and stability. Figure 8 shows the IoT system models [45].

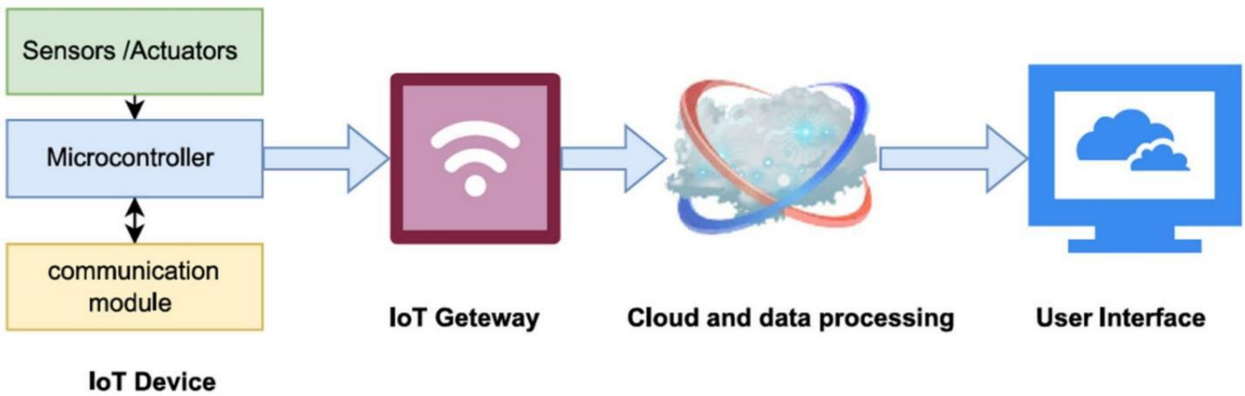

Figure 8. *The IoT system models [45], reproduced under CC BY 4.0 license*

Traditional environmental assessment platforms usually depend on laboratory-based analysis and recurring sampling, which make them expensive, tedious, and complex. As a result, these conventional methods are not adaptable to rapid changes in the surrounding environment and are difficult to use to assess contaminants accurately.

IoT-enabled electrochemical sensing systems allow real-time, continuous environmental monitoring by setting up a network of sensors. These integrated sensors can collect real-time data on many environmental features, such as pH, temperature, conductivity, humidity, and contaminant concentration. Electrochemical sensors are small, energy-efficient, highly sensitive, and selective for analyte detection, making them a popular and practical choice to integrate with IoT for portable, remote sensing.

Architecture of Internet of Things-based electrochemical sensor systems

The IoT-enabled electrochemical sensing system is generally composed of sensing units, a number of interconnected components, data processing units, and communication modules, to transmit, collect, process, and analyse the environmental data [75]. The electronic units required for signal collection and the electrochemical sensing platform form the sensing unit, the system's central component. Electrochemical redox reactions at the electrode interface change the current or potential, and the sensor detects this variation. Signal-conditioning circuits and analog-to-digital converters will transform these electrical signals to readable digital data. The communication module then transmits these data to external devices through Wi-Fi, cellular networks, Zigbee, and LoRaWAN. Data management platforms may run on cloud-based systems, local servers, or edge computing devices and process the received electrochemical sensor data. During this stage, ML algorithms evaluate the data received by the data management platforms, which may run on local servers, edge computing devices, or cloud-based systems, and process it after transfer. At this point, machine learning algorithms examine electrochemical data by measuring trends and identifying contaminants present in the environment [76-78]. After this, the results are displayed using user interfaces such as web dashboards, mobile apps, monitoring stations, *etc*.

Real-time environmental monitoring

One significant advantage of IoT-enabled electrochemical sensors is real-time environmental monitoring. Contaminant concentrations in the environment vary over time, especially in industrial, agricultural, and biomedical waste. Therefore, researchers are now using IoT-based sensors because of their high selectivity and continuous data-collection capabilities. When pollutant levels exceed the permissible limit, IoT-integrated sensors detect the change and send a warning notification [79,80]. These warnings can be sent early and may respond quickly to abrupt variations in pollutant concentrations, helping prevent ecological and environmental disasters and protect human health.

IoT-based electrochemical sensors can continuously monitor environmental factors such as pH, dissolved oxygen levels, and heavy metal concentrations in rivers, lakes, and wastewater sources. Toxic gases such as CO and SO_2 can also be detected by integrating gas sensors with IoT modules. The accuracy and efficiency of the IoT-enabled electrochemical sensors for environmental monitoring can be further improved by integrating with ML algorithms [81-83]. The integration of ML models can improve the prediction of pollution patterns by evaluating past data. Therefore, integration of electrochemical sensors with IoT and ML algorithms is more advantageous.

Edge computing and data processing

As huge amounts of environmental data are continuously produced, we need more sensor networks to transfer all raw data to centralized servers; this causes high connection costs and increased latency. To solve these problems, we can use edge computing, which has become one of the easiest and most effective ways to process data closer to the sensor nodes. Edge computing processes and analyses the data directly on local devices close to the electrochemical sensors. Edge computing devices perform initial operations like signal filtering, anomaly identification and feature extraction prior to sending the condensed data to cloud servers [84]. This increases reliability and response times and reduces data transmission requirements, making edge computing devices enabled with IoT electrochemical sensors easier to use for real-time environmental monitoring and electrochemical signal interpretation. It is also possible to access the autonomous environmental monitoring systems remotely with the integration of edge computing, ML and IoT models.

Challenges and future perspectives

Although ML-enabled electrochemical sensors have made excellent progress in environmental assessment, a few drawbacks still limit their widespread use. Some drawbacks include sensor stability, data quality, and integration into real-world monitoring systems. Long-term stability of these electrochemical sensors is always a big problem because, in real environmental conditions, the electrochemical sensors will be in continuous contact with various types of toxic chemicals, particulate materials, and pollutants; these conditions will cause fouling of electrodes, degradation of the electrode surface, and also result in signal drift. Using nanomaterials and integrating them with ML and IoT systems could address these limitations, but not completely. Therefore, researchers must focus mainly on fabricating highly robust and possibly self-cleaning electrodes.

One more important limitation is the availability of high-quality data. Generally, the ML models need a large, well-labelled raw dataset for environmental monitoring. However, collecting this volume of raw data is challenging because changes in pH, temperature, and interfering materials can alter the electrochemical sensor response. As a result, ML and IoT models evaluated in the lab environment will fail in real-world environments. Therefore, we need to develop standardized datasets and models that can adapt instantaneously to the environment. Advanced models like deep learning act as black boxes, making sensor models difficult to predict. This affects the usability and integration of such models. On the other hand, their high computational requirements can limit their usage only to portable devices.

Integrating electrochemical sensors with IoT models increases energy consumption and raises concerns about data security and reliable communication. Therefore, lots of research must be carried out in low-power electronics and address these issues.

One of the main problems with implementing machine learning-integrated electrochemical sensors is the scarcity of high-quality training datasets. Electrochemical datasets are typically smaller than other types of datasets, increasing the risk of model overfitting and limiting the generalizability of models to new data samples. To address this problem, techniques such as data augmentation, cross-validation, regularization, transfer learning, and active learning have been suggested to improve model reliability while using less labelled training data.

A major challenge in the practical deployment of machine learning-integrated electrochemical sensors is the limited availability of high-quality training datasets. Electrochemical datasets are often relatively small, increasing the risk of model overfitting and reducing their ability to generalize to unseen samples. To address this issue, strategies such as data augmentation, cross-validation, regularization, transfer learning, and active learning have been proposed to improve model robustness while minimizing the dependence on large, labelled datasets. Furthermore, the development of collaborative data repositories and standardized datasets will enhance model reliability, improve reproducibility, and accelerate the practical implementation of intelligent electrochemical sensing systems [85]. Moving forward, this research should focus on explainable artificial intelligence (XAI), which could increase the transparency and interpretability of electrochemical decision-making. Moreover, transfer learning approaches can minimize the need for calibration by enabling trained models to adapt to new electrochemical platforms using limited experimental data. Physics-informed models that combine electrochemical reaction mechanisms with data-driven predictions are expected to provide more accurate and reliable models. Standardized benchmark datasets and evaluation protocols, along with accessible open databases, will facilitate comparison between machine learning methods and improve the implementation of intelligent electrochemical sensors. Finally, the integration of electrochemical sensors with nanotechnology, ML algorithms, and IoT models has a great future. These computational integrations will improve the selectivity, sensitivity, and real-time applications of electrochemical sensors in environmental monitoring.

Conclusion

Highly toxic contaminants such as pesticides, heavy metals, and organic dyes are increasing in the environment due to rapid industrialization, urbanization, and agricultural activities, and they severely affect human health and ecosystems. Therefore, the need for effective, selective, sensitive, and cost-effective monitoring technology is greater. Electrochemical sensors have proven to be a popular and effective technique for environmental monitoring. Further, integrating electrochemical sensors with ML models can improve their selectivity, stability, and reproducibility. This integration will improve pattern recognition, reduce noise, and increase accuracy in predictive modelling by overcoming the conventional electrochemical sensor challenges like signal interference, overlapping peaks, and sensor drift. In addition to ML integration, nanomaterials such as graphene, carbon nanotubes, metals, and metal oxide nanoparticles increase electrode surface area, sensitivity, reaction kinetics, and limit of detection. Integration of sensors with IoT technology can improve real-time environmental monitoring, continuous environmental assessment, remote data analysis, and predictive modelling of electrochemical sensors. Although challenges such as stability, data quality, and the huge volume of data required can hinder advanced applications, integrating nanomaterials, ML, IoT, and other AI with electrochemical sensors can significantly improve these properties. Overall, electrochemical sensors integrated with various computational models could be the next-generation environmental monitoring systems.

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