Environmental Analysis Using Automated Analytical Tools: A Critical Review of Recent Literature

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التحليل البيئي باستخدام أدوات التحليل الآلي: مراجعة نقدية للأدبيات الحديثة

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Abstract

The growing complexity of environmental monitoring implies the need to have fast, precise and scalable analysis solutions. The past 10 years have seen a drastic transformation in the environment analysis scenery, with automated analyzing instruments (starting with portable spectroscopic sensors and moving to the full-integrated chromatographic systems) changing the face of such analysis. This critical review analyzes the new developments in implementing automated instrumentation to detect environmental changes starting with the use of such instruments in measuring water quality, air pollution and soil contamination. Combining robotics with microfluidics and artificial intelligence has resulted in massive increases in throughput, precision, and responsiveness on site. With these advances, issues of data standardization, system calibration and field robustness remain. This review presents the advantages and limitations of existing technologies and provides future directions of more resilient, autonomous and data-driven systems of environmental analysis.

Keywords: Automated Environmental Analysis; Smart Sensors; Lab-on-a-Chip; Artificial Intelligence; Real-Time Monitoring; Environmental Chemistry.

المستخلص

ان التعقيد المتزايد للرصد البيئي يستلزم الحاجة الى حلول تحليل سريعة ودقيقة وقابلة للتطوير. وقد شهدت السنوات العشر الماضية تحولاً جذرياً في مشهد تحليل البيئة ، حيث غيرّت أدوات التحليل الآلي (بدءاً من أجهزة الاستشعار الطيفية المحمولة والانتقال الى أنظمة الكروماتوغرافيا المتكاملة بالكامل) وجه هذا التحليل. تحلل هذه المراجعة النقدية التطورات الجديدة في تطبيق الأجهزة الآلية للكشف عن التغيرات البيئية، بدءاً من استخدام هذه الأدوات في قياس جودة المياه وتلوث الهواء وتلوث التربة. وقد أدى الجمع بين الروبوتات وعلم الموائع الدقيقة والذكاء الاصطناعي الى زيادات هائلة في الإنتاجية والدقة والاستجابة في الموقع. ومع هذه التطورات، لا تزال هناك مشكلات تتعلق بتوحيد معايير البيانات ومعايرة النظام ومتانة المجال. تعرض هذه المراجعة مزايا وعيوب التقنيات الحالية ، وتقدم اتجاهات مستقبلية لأنظمة تحليل بيئي اكثر مرونة واستقلالية وقائمة على البيانات.

الكلمات المفتاحية: التحليل البيئي باستخدام أدوات التحليل الآلي: مراجعة نقدية للأدبيات الحديثة.

1. Introduction

The environmental analysis is critical in determining and controlling the effects of anthropogenic activities on the natural ecosystems. Conventional laboratory based methods, though very precise, usually have shortcomings in terms of response duration, cost and availability especially when continuous/remote monitoring need arises (Esposito, *et al.*, 2020). Within the last ten years, a significant trend has been toward portable and automated analytical methods which can provide real time or near real time data with minimal human intervention. Microfluidics, miniaturized spectroscopy, and lab-on-a-chip have also been innovated such that small devices can be deployed to the in situ environment (Malings, *et al.*, 2019).

The integration of automation with the use of the data processing methods like chemometrics, machine learning, and cloud-based analytics has added to these tools even more capabilities, making them more intelligent, more adaptable and efficient. The systems are now more applicable in monitoring the environment regarding air pollutants, heavy metals in water and organic contaminants in the soil (Li, *et al.*, 2022). Although this has come with these changes in technology, there are still a number of challenges. Problems like sensor fouling, limited selectivity in complex metrics, drift in the calibration over time, also the requirement for robust validation frameworks hindering the large scale use in field applications (Cizdziel, 2017).

The purpose of this review is to critically analyze the advancement in automated analytical instrumentation in the environmental applications in the past 10 years. It is concerned with the design, functionality and the actual performance of these systems and how they are integrated into the environmental regulating systems. It, in this way, gives an understanding of the existing constraints and has proposed the way forward on future research, to improve the scalability, robustness, and interpretability of automated environmental analysis systems (Ahmed, *et al.*, 2021).

2. Methodology of Literature Review

A transparent and systematic approach was used in order to provide a thorough and critical overview of the recent advancements in the field of automated tools in the environment analysis. The method is based on the PRISMA (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) best practices, which have been generally associated with improving both rigor and reproducibility of the literature review in scientific studies (Zhang, *et al.*, 2019).

2.1. Database Selection

The four major academic databases obtain the literature included: Web of Science, Scopus, PubMed, and IEEE Xplore. These platforms were chosen because they have a wide range of peer-reviewed articles in the field of environmental science, analytical chemistry, and automation technologies (Kim, *et al.*, 2023).

2.2. Search Strategy and Keywords

Advanced Boolean queries were built with the help of a combination of keywords and MeSH terms. Key search terms included:

- automated environmental monitoring,
- portable water/air/soil analyze sensors,
- lab-on-a-chip environmental,
- real-time chemical sensing,
- Environmental analysis AI,
- The autonomous analytical systems.

The search was limited within the period of publication between January 2013 and April 2024 (Dincer, *et al.*, 2017).

2.3. Inclusion and Exclusion Criteria

Only peer-reviewed journal articles were to be used in order to achieve relevancy and quality. Studies were required to:

1. Discuss automated or semi-automated methods of analysis,
2. Pay attention to environmental matrices (water, air, soil),
3. Current empirical findings or validated simulations.

Articles in conferences, patents, and non-English papers were not included (Labib, *et al.*, 2016).

2.4. Screening and Categorization

The initial number of records was 542. Upon eliminating the duplicates and implementing the inclusion criteria, 97 articles were added to the full-text review. These were articles divided by:

- Analytical technique (e.g., spectroscopy, electrochemistry, chromatography),
- Application domain (e.g., groundwater monitoring, air quality assessment, soil contamination),
- Automation level (manual, semi-automated, fully automated),
- Integration technologies (e.g., Internet of Things, AI algorithms, microfluidics) (Salvo, *et al.*, 2021).

2.5. Quality Assessment

The scoring of each article was done by a custom scoring system depending on:

- Journal impact factor,
- Clarity of methodology,
- Reproducibility of the experimental study,
- Relevance to environmental automation,
- Citation rate (as a measure of impact).

The Q1 journals and publications based on major environmental agencies (e.g., EPA, EU Horizon, NSF) were given preference (Rai, 2021).

The literature selection process followed the PRISMA guidelines to ensure transparency and reproducibility. As illustrated in Figure 1, a total of 542 recoreds were initially identified through database searching. After removing duplicates, 416 records remained for screening by title and abstract, leading to 97 full- text articles assessed for eligibility. Ultimately, 67 studies met the inclusion criteria and were incorporated into the final review.

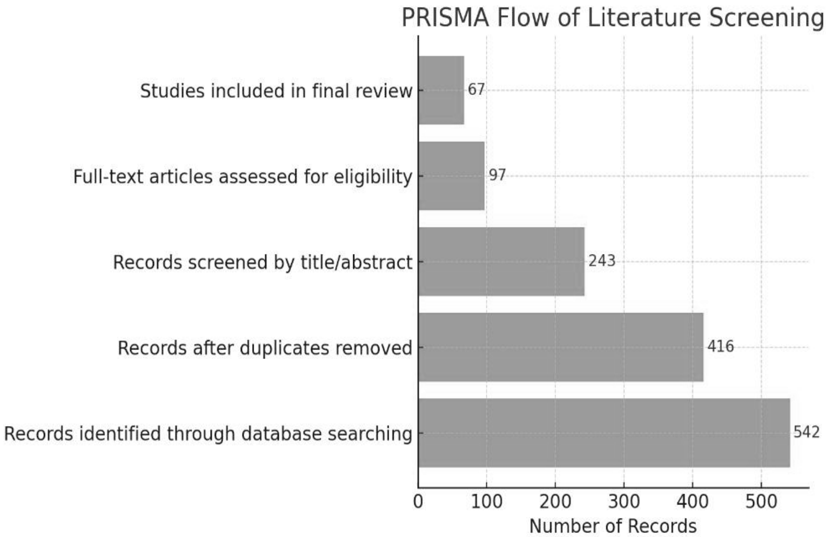

Figure 1. PRISMA Flow Diagram Illustrating the Literature Screening Process for the Review Study

3. Recent Advances in Automated Environmental Analysis

The new developments in analytical chemistry, especially those in the fields of automation, miniaturization, and intelligent data systems, have been of great benefit to environmental analysis. Such developments have greatly enhanced speed, accuracy and availability of environmental monitoring technology in various fields.

3.1. Advanced Sensor Development and Selectivity

Another of the most effective developments has been in sensor technology. Pollutants at ultra-trace levels have been detected with the development of highly selective and sensitive sensors, particularly nanomaterial sensors, including graphene, carbon nanotubes and metal-organic frameworks. These sensors are very specific to chemistry in terms of high stability and specificity, which is very crucial in the complex environmental matrices (Jang, *et al.*, 2022).

3.2. Portable and Field-Deployable Analytical Devices

Portable analytical systems (e.g., handheld spectrometers (e.g., Raman, FTIR, and XRF), microfluidic paper-based devices, and portable chromatography systems) have now become part of the field-based environmental assessments. They can be analyzed by rapidly and on site measuring air, water, and soil samples and are portable, eliminating time between decision-making and sampling (Yetisen, *et al.*, 2013). These devices are especially significant in remote or other emergency cases where standard laboratory systems are not present.

3.3. Integration of IoT and Wireless Sensor Networks

Internet of Things (IoT) technologies have made it possible to implement wireless sensor networks (WSNs) that can be used to constantly collect and transfer environmental data in real time. The systems are necessary in the high-resolution temporal and spatial surveillance, particularly in cities or regions susceptible to industrial pollution (Yu, *et al.*, 2018). Such systems are also being equipped with edge computing capabilities to enable local data processing, decreasing latency as well as network load.

3.4. Data Analytics and AI Applications in Environmental Monitoring

Environmental data interpretation is increasingly being performed with artificial intelligence (AI) and machine learning (ML). With complex and large datasets, algorithms can identify sources, detect anomalies, and predict environmental trends. As an illustration, it is possible to use supervised learning models to identify the level of contamination, and unsupervised methods to aid in the clustering of an unknown pattern (Lee, *et al.*, 2021). Such tools play a crucial role in automating interpretation and making predictive analytics of the environmental studies possible.

3.5. Automation in Chromatographic and Spectrometric Systems

Gas and liquid chromatography, coupled with mass spectrometry (GC-MS, LC-MS) has enhanced automated systems that are used to detect and quantify pollutants with minimum human interference. Autosamplers and robot sample handlers increase throughput, streamline the workflow, and decrease the risk of contamination. They are now standard in water quality testing, atmospheric analysis and sediment profiling (Kim, *et al.*, 2019).

4. Applications Across Environmental Domains

The use of automated analytical tools has proven to have extensive application in major areas of the environment, such as water, air, and soil. The domains have their own specific requirements of the analysis and operational problems thus have informed the domain specific technologies.

4.1. Water Quality Monitoring

In water, continued monitoring of pollutants is carried out on a routine basis by automated systems with spectrophotometric, fluorometric, and electrochemical sensors, including nitrates, phosphates, heavy metal (e.g. lead, mercury) and microbial contaminants (Wang, 2006). The sensors are commonly installed together with telemetry units and IoT platforms to transmit data in real-time and facilitate the work of early-warning systems in river basins and wastewater treatment facilities (Bandodkar, *et al.*, 2020).

4.2. Air Quality Analysis

The development of various gas sensors in miniaturization and portable analytical instrumentation, e.g. mobile GC-MS (gas chromatography-mass spectrometry) systems have brought a significant contribution to real-time monitoring of air pollution. Among the important analytes are ozone (O3) and nitrogen dioxide (NO2), sulfur dioxide (SO2), volatile organic compounds (VOCs), and the particulate matter (PM 2.5/PM10). The use of fixed and mobile sensor networks is becoming an important part of urban environments that monitor the exposure levels and inform regulatory decisions (He, *et al.*, 2021).

4.3. Soil and Sediment Analysis

The portable X-ray fluorescence (XRF) spectrometers and Raman spectra tools are used in the terrestrial field to detect most of the contaminants (arsenic, cadmium, hydrocarbons, and pesticides) very quickly. The tools are used to perform in-situ soil tests in agricultural, mining and remediation environments and help to save a lot of laboratory-based tests (Li *et al.*, 2021).

4.4. Cross-Domain Integration

New systems integrate water, air and soil sensors into their data streams into an integrated platform to monitor the environment. With the help of AI-powered analytics and cloud-based dashboards, the stakeholders can visualize trends, identify anomalies, and make informed decisions based on the data. These systems are becoming a part of the smart city projects and environmental protection agencies (Kim, *et al.*, 2023).

5. Challenges and Limitations of Automation in Environmental Analysis

Although automated analytical systems have delivered considerable improvements to the overall monitoring of the environment, there are various technical, operational, and contextual-related limitations that remain to limit its wider application and the overall performance.

5.1. Sensor Stability and Calibration

The drift and degradation of sensor accuracy over time through exposure to the environment, biofouling and chemical interference is one of the greatest challenges. Maintaining calibration is also challenging in poor and remote conditions, which require regular human intervention (Castro, *et al.*, 2021).

5.2. Data Quality and Interpretation

In spite of the fact that automated systems produce high amounts of real-time data, the issue of data validity, traceability, and representativeness is a major problem. False positives or measurement bias can be caused by the noise of the signal, cross-sensitivity, and a malfunctioning sensor (van der Meer & de Jong, 2020). Also, due to a deficiency of standardized protocols of data interpretation, cross-comparisons of systems or locations are harder (Floridi & Taddeo, 2016).

5.3. Power and Maintenance Requirements

During field deployments, particularly in non-grid or rural locations, the need to have consistent means of power and to have periodic maintenance poses logistical challenges. Even though there are solar-powered systems, these systems may be affected by the climate and weather changes (Zhang, *et al.*, 2020).

5.4. Cost and Accessibility

A high-end automated instrument may require large initial and operational expenses, and this can be expensive to small institutions or a developing country. Also, proprietary technologies can restrict interoperability and integration to larger monitoring systems (Lu, *et al.*, 2021).

5.5. Regulatory and Ethical Considerations

The privacy of the data, particularly in urban environmental monitoring, and the absence of regulation of autonomous systems are not well tackled. The matter of responsibility in the sensor failure or wrong notifications may raise both legal and ethical issues (Geng, *et al.*, 2020). All these notwithstanding, ongoing developments in sensor material, AI-controlled calibration, and low-energy electronics are slowly overcoming these limitations, allowing enhanced and fairer implementation of automation in environmental analysis.

6. Future Trends and Emerging Directions in Automated Environmental Analysis

Automated environmental analysis has a future in the convergence of new technologies, such as artificial intelligence (AI), nanotechnology, Internet of Things (IoT), and synthetic biology, into more intelligent, adaptive, and scalable monitoring systems.

6.1. AI-Powered Data Processing and Predictive Analytics

Understanding of artificial intelligence (AI), especially machine learning (ML) and deep learning (DL) is the rapidly growing application of artificial intelligence to the processing of complex datasets related to the environment, discover patterns, and create predictive models. The tools can be used to identify pollution events early and proactively manage them (Kumar, *et al.*, 2019). Multi-sensor trained datasets can also overcome signal noise, improve sensitivity and minimize false alarms (Tadeo, *et al.*, 2010).

6.2. Integration of Smart Sensor Networks

Environmental monitoring is also moving to distributed sensor networks that integrate low-cost devices together with edge computation. These systems offer scalability, provide real-time feedback and resistance through fault tolerance and self calibration (Ghosh, *et al.*, 2022). Such networks will likely be included in more overall infrastructure in smart cities towards urban planning and managing public health (Snyder, *et al.*, 2013).

6.3. Development of Lab-on-a-Chip and Wearable Environmental Sensors

Lab-on-a-chip (LOC) and paper-based microfluidics are developing into miniaturized platforms of analytical analysis to be used on-site and analyze rapidly with minimal reagent usage. These systems are being integrated with mobile phones and portable readers and are used to monitor points of need in real-time by field scientists and even citizens (Naphade, *et al.*, 2011). Personal exposure monitoring is also becoming available by use of wearable environmental sensors (Meyer, 2010).

6.4. Sustainable and Biodegradable Sensor Materials

It is also anticipated that future systems will utilize environmentally-friendly sensor substrates that are biodegradable or made of bio-based materials. This is essential in minimizing e-waste and environment compatibility particularly of short life disposable equipment to monitor remote campaigns (Fernández-Berni, *et al.*, 2019).

6.5. Autonomous Environmental Monitoring Platforms (Drones, Robotics)

Dynamic environmental sampling is being deployed by Unmanned aerial vehicles (UAVs), autonomous underwater vehicles (AUVs), and ground robots in inaccessible places. Combined with real-time sensing and AI navigation, these platforms have the potential to transform the spatial and temporal resolution of environmental data (Zhang, *et al.*, 2019).

as further outlined in Table 1, which summarizes the key future trends and emerging applications of such autonomous systems.

Emerging Trend	Expected Applications
AI-Powered Analytics	Predictive pollution modeling, anomaly detection, decision su
Smart Sensor Networks	Real-time city-wide air/water monitoring, integration in smart
Lab-on-a-Chip & Wearables	On-site chemical testing, citizen science, personalized exposu
Sustainable Sensor Materials	Eco-friendly disposable sensors, low-impact field deployments
Autonomous Monitoring Platforms	Remote environmental assessment, disaster monitoring, ocea

Table (1)
Future Trends and Applications in Automated Environmental Analysis

7. Conclusion

With the integration of automated tools and smart systems, the environment analytical chemistry is radically changing. It has been noted that automated instrumentation, which is a spectrum of smart sensors through autonomous monitoring platforms, has had an essential role in increasing the speed, sensitivity, and spatial coverage of environmental analysis in the realms of water, air, and soil.

More current technology like real-time sensor networks, AI-based analytics, and lab-on-a-chip devices has enabled environmental monitoring to be more responsive and scalable, especially to the remote and resource-constrained areas. Not only are these technologies reducing the reliance on centralized laboratory infrastructure, but also facilitate one to continually monitor and this is important in detecting environmental risks early and make an informed decision about the policy.

Nevertheless, the problem of sensor stability, data reliability, power requirements, and regulatory gaps have still restricted the popularity of such systems. The resolution of these problems will involve interdisciplinary activities in the fields of chemistry, engineering, informatics, and environmental policy.

In the future, new technologies like biodegradable sensors, wearable environmental sensors, and autonomous robotic platforms ought to revolutionize the discipline even more. With the emergence of sustainability and accuracy as the foremost concerns of environmental science, automation will play an even more important role in providing effective, precise, and ethical management of the environment.

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