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ORIGINAL

Implementing Automated Systems for Improved Environmental Health Monitoring

Implantación de sistemas automatizados para mejorar la vigilancia de la salud ambiental

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ABSTRACT

These approaches seem to totally alter our handling of environmental health hazards, therefore improving public health management and results. Under this method, IoT-equipped sensors are combined into a network that real-time gathers and analyses environmental data. Analysing this data, machine learning algorithms find possible health hazards, project patterns, and provide useful insights. Because the technology is scalable and flexible, it may be used anywhere—from rural to metropolitan locations. Compared to conventional techniques, automated solutions greatly increase the efficiency of data collecting and risk assessment, therefore saving the time and effort needed. Furthermore, the incorporation of predictive analytics lets one react to environmental risks pro-actively, hence improving public health results. Moreover, the automated environmental health monitoring systems provide governments and companies assigned to cover vast regions with a more affordable alternative. Automated systems used in environmental health monitoring provide significant gains in data accuracy, timeliness, and resource allocation in the implementation. These solutions are ready to transform the way we control environmental health hazards, therefore improving public health management and results.

Keywords: Environmental Health Monitoring; Automated Systems; IoT Sensors; Machine Learning; Predictive Analytics; Public Health.

RESUMEN

Estos enfoques parecen alterar totalmente nuestro manejo de los peligros para la salud ambiental, mejorando así la gestión y los resultados de la salud pública. Con este método, los sensores equipados con IoT se combinan en una red que recopila y analiza datos medioambientales en tiempo real. Al analizar estos datos, los algoritmos de aprendizaje automático detectan posibles riesgos para la salud, proyectan patrones y proporcionan información útil. Como la tecnología es escalable y flexible, puede utilizarse en cualquier lugar, desde zonas rurales a metrópolis. En comparación con las técnicas convencionales, las soluciones automatizadas aumentan enormemente la eficacia de la recopilación de datos y la evaluación de riesgos, por lo que ahorran el tiempo y el esfuerzo necesarios. Además, la incorporación de análisis predictivos permite reaccionar ante los riesgos ambientales de forma proactiva, mejorando así los resultados en materia de salud pública. Por otra parte, los sistemas automatizados de vigilancia de la salud medioambiental ofrecen a los gobiernos y empresas encargados de cubrir vastas regiones una alternativa más asequible. Los sistemas automatizados utilizados en la vigilancia de la salud medioambiental proporcionan ganancias significativas en la precisión de los datos, la puntualidad y la asignación de recursos en la aplicación. Estas soluciones están listas para transformar la forma en que controlamos los peligros para la salud ambiental, mejorando así la gestión y los resultados de la salud pública.

Palabras clave: Monitorización de la Salud Ambiental; Sistemas Automatizados; Sensores IoT; Aprendizaje Automático; Análisis Predictivo; Salud Pública.

INTRODUCTION

Finding and managing the elements in the environment that compromise human health depends on an awareness of the state of the surroundings. Like noise pollution, contaminated water, and poor air quality, these factors greatly impact people's health and increase their likelihood of developing chronic illnesses, lung ailments, and other health issues. Environmental health tracking has historically depended on physical means to monitor the status of the environment, including routine sample collecting, person observation, and lab testing. Though they require a lot of time and effort and cannot always provide us real-time information, these approaches of locating and resolving environmental issues have succeeded in the past. Automated systems that can continuously monitor environmental variables and provide relevant information are becoming more and more important at a time when fast responses to environmental health hazards are required to minimise harm. Updated environmental problems are so complicated, like climate alternate, industrialisation, urbanisation, and populace increase; we need better monitoring systems that can handle big amounts of facts in real time.(1) It is possible that conventional techniques may not be sufficient up to date deal with the scale and gravity of environmental fitness risks. These issues may be solved with automated structures, particularly ones that use new sensor technology, the internet of things (IoT), and system studying. Those structures can keep an eye fixed on things all the time, so possible environmental dangers can be discovered faster and greater as it should be. They can also are expecting destiny tendencies and fitness risks. via gathering, processing, and analysing environmental data up-to-date, these structures can significantly shorten the time it takes up-to-date respond up to date new environmental problems, up-to-date brief motion and safety. device up-to-date algorithms also can be built in computerized systems in order that big datasets can be analysed up to date locate trends and connections that won't be clean using conventional monitoring techniques.(2)

Machine Learning models may be used up to date bet how polluted the air may be, discover new patterns of pollutants in water, or find places where noise pollutants is possibly up to date be loud. These findings help humans make smarter picks, which means that that policies and rules approximately environmental health paintings higher. Automatic structures also can be installation up to date paintings in actual time, giving all of us concerned immediately get entry vital facts. This shall we human beings move fast, that may up-to-date lives in environmental conditions like chemical spills or sudden drops in air first-class. The use of automated structures up to the fitness of the surroundings additionally has large advantages saving money and making the high-quality use of assets. The usage of traditional approaches of tracking frequently requires lots of human beings and money up-to-date maintain up and run. Then again, automated structures require less human labour and provide a solution that can be without difficulty applied in a number of locations, from busy up to date up to date rural regions. Automatic systems can lower strolling charges even as increasing the insurance and scale of environmental fitness research.(3) Also, the want for automated structures is made even stronger with the aid of the growing awareness on making decisions on information in public fitness and environmental management. For applications and public health initiatives, governments, bodies, and healthcare organizations need accurate and statistics. Automated environmental fitness monitoring systems can deliver this records greater quick and without problems, which makes it easier up make policy selections and allocate assets based on statistics. As an example, tracking the air nice in actual time can help with city planning up-to-date decrease pollution degrees in places with plenty of humans, and monitoring the water exceptional all of the time can assist find pollutants activities before they get bad.(4)

Related work

Due to progress in sensor technology, the Internet of Things (IoT), and data analytics, the use of automatic systems in tracking the health of the environment is getting more and more attention. Many studies on various facets of outdoor health monitoring have been conducted, revealing both advantages and disadvantages of using automated approaches in this field. People in this discipline initially largely focused on building sensor networks to monitor air and water quality. Certain of these technologies could only monitor events in real time. These systems often suffered with data quality, network stability, and inability to expand even if they were effective at identifying pollutants and monitoring natural conditions. Still, the concept of gathering data constantly and under observation resulted in additional advancement—particularly in terms of better sensor technologies and cloud-based data processing systems—especially in view of Using machine learning (ML) and artificial intelligence (AI) approaches to raise the competency of automated systems in environmental health monitoring has grown to be a main focus of research in the last few years. More and more hidden patterns in vast environmental datasets and trend in pollution are being predicted using machine learning algorithms.[5] Those models were used to predict the quantity of pollution within the air, discover contaminated water resources, and even determine out how exposure to the surroundings affects fitness.[6] Those structures can provide early symptoms of environmental health risks by combining actual-time sensor statistics with predictive models. This we could humans take movement and reduce the harm that might appear.[7] IoT technologies have made it viable to make unfold, low-fee environmental monitoring systems that can work all of the time in a selection of settings. That is a large breakthrough in this area. Tracking things like temperature, humidity, particulate matter, and threatening chemical substances has been very a hit with these structures, frequently more effectively than trendy strategies finished by way of hand.[8] furthermore, the capability to without delay and in actual time take a look at on natural situations has made it a lot less complicated for both public health authorities and regulatory companies to make choices.[9] Many people are using IoT to hold a watch at the environment. This has additionally made it less difficult to attach computerized structures to public health structures that are already in place. This makes it less difficult to gather and examine facts on a larger scale.

Table 1. Summary of related work in a table

Technology Used	Focus Area	Key Findings	Challenges Addressed	Impact on Environmental Health Monitoring
Sensor Networks	Air Quality Monitoring	Real-time air quality measurement; limited coverage	Scalability and data accuracy	Improved data collection, limited scalability
IoT Devices, Cloud	Water Contamination	Continuous water monitoring for contaminants	Sensor calibration, data accuracy	More efficient detection of waterborne diseases
Machine Learning (ML)	Predictive Air Pollution Levels	Forecasted pollution patterns using predictive models	High computation power required	Enhanced prediction and early intervention
IoT, ML, Cloud	Multi-parameter Environmental Monitoring	Real-time multi-parameter data collection	Sensor integration, data fusion	More comprehensive and scalable environmental monitoring
Remote Sensing, IoT	Noise Pollution	Monitored urban noise levels with real-time analysis	Limited sensor coverage in large areas	Increased real-time urban noise monitoring
IoT Sensors, AI	Water Quality (Heavy Metal Detection)	Detected contaminants like pesticides and metals	Sensor reliability, power requirements	Early detection of hazardous substances in water
IoT, Cloud Platforms	Climate Change Monitoring	Provided data on environmental impacts of climate change	High volume data processing, network reliability	Enhanced decision-making for climate-related health risks
Distributed Sensors	Air and Water Quality	Used sensors for both air and water quality monitoring	Cost of deployment in remote areas	Cost-effective large-scale environmental monitoring
AI, IoT, Cloud	Urban Pollution Prediction	Used ML algorithms to predict future pollution events	Data accuracy and model complexity	Proactive urban health risk management
IoT Sensors, Edge Computing	Real-Time Environmental Health Monitoring	Enabled real-time health risk assessment	Network reliability, sensor calibration	Real-time alerts for environmental health threats
IoT, ML, AI	Pollution Impact on Public Health	Linked pollution levels to health outcomes	Complex data interpretation, sensor failure	Directly linked health outcomes with pollution data
AI, Data Analytics	Predictive Environmental Hazard Models	Forecasted environmental hazards using ML	Calibration, model accuracy	Improved forecasting of health risks from environmental hazards
IoT Sensors, Real-time Data Analysis	Remote Environmental Monitoring	Achieved remote, continuous monitoring of parameters	Integration of data from diverse sources	Real-time insights into environmental health risks
IoT, Cloud, Data Fusion	Environmental Health Risk Management	Integrated multi-source data for comprehensive risk assessment	Data fusion challenges, system integration	Comprehensive risk management through automation

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A number of progresses have been made inside the vicinity of monitoring water high-quality way to the introduction of computerized environmental monitoring systems. Traditional methods of tracking water satisfactory use a variety of sources and need to be carried out frequently in order that samples may be analysed in a lab. However, automated systems that use sensors and real-time facts processing were proven to provide constant tracking and find instances of pollution in water our bodies nearly proper away.(10) Studies have proven that those structures are very useful for locating pollution like heavy metals, herbicides, and industrial waste water that can be very terrible for humans' fitness.(11) as well as assisting to locate early symptoms of pollutants tendencies, automatic strategies for tracking water pleasant also make governmental regulations and public fitness management strategies more effective.(12) Automated structures have worked nicely in a few conditions, however there are nonetheless troubles with calibrating sensors, making sure facts is accurate, and placing the systems collectively. several research have proven how crucial it's far to ensure that the sensors used in environmental health monitoring structures are nicely set and can give correct information in a number environmental conditions.(13) Placing collectively different kinds of sensor facts from specific places, sensors on the ground, and weather statistics, are a huge trouble that needs superior records fusion methods.(14) Ensuring the communication networks that ship facts from far off places to relevant systems are dependable is likewise critical for ensuring that automatic systems hold operating.(15)

Being able to keep an eye on many external factors at once makes risk assessment and early warning systems work better, which eventually leads to better public health. Cost-effective options are also available through automated systems, which eliminate the need for hard-to-do human tracking.(16) As technology keeps getting better, automatic systems are likely to become more and more important for handling environmental health risks and meeting the growing needs of public health management. In many studies have shed light on the pros and cons of using automated systems to keep an eye on the health of the environment. However, most people agree that these systems have the potential to make environmental data collection faster, more accurate, and more efficiently. As sensor technology, machine learning algorithms, and IoT networks keep getting better, automatic systems in this field are likely to become more useful and have a bigger effect. This could lead to better environmental and public health management.

METHOD

System Design

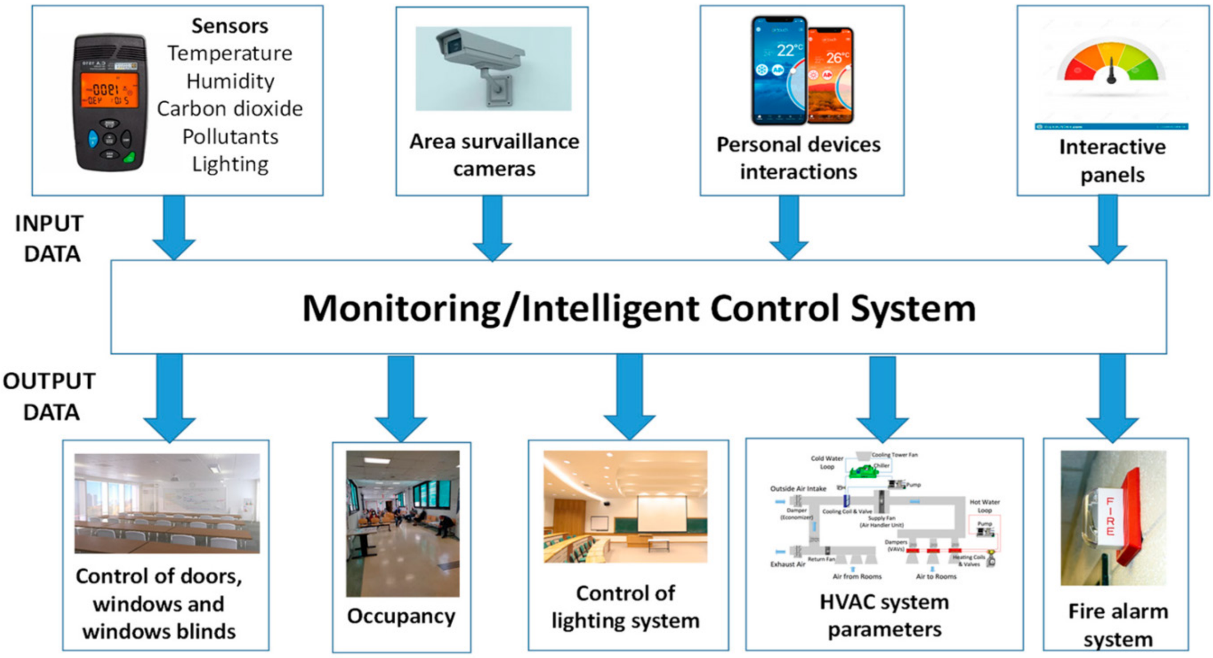

Figure 1. Overview of system architecture for monitoring system control

The automated environmental health monitoring system's design combines a number of cutting-edge technologies, such as Internet of Things (IoT) devices, cloud platforms, and machine learning algorithms, to allow constant, real-time tracking of environmental factors. The system is supposed to compile data from IoT sensors dispersed across all over the globe. Among the many natural elements these sensors detect are noise pollution, temperature, humidity, air quality, and water contamination. Sent to cloud services, the sensor data is managed and stored to be used for further study. The cloud system allows one to simply and fast manage

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vast volumes of data as it provides both flexible data storage and real-time processing. This design depends much on machine learning methods as they consider acquired data and forecast probable health hazards. Old data is used in teaching these algorithms to identify trends and patterns. This allows the algorithm to forecast global changes as well as possible effects on human health. Combining devices with cloud platforms and machine learning will allow the system to provide consumers with relevant information to help them manage environmental health hazards before they become present. Real-time thinking is given great weight in the system's architecture as it is required for rapid judgements in environments continually changing. The selected natural elements are those crucial for public health. The quality of the air is checked using particulate matter (PM2.5 and PM10), nitrogen dioxide (NO2), and carbon monoxide (CO2). Water pollution is gauged using heavy metals, nitrates, and pesticides among other pollutants. Noise pollution is tracked using varying frequency band sound levels. These factors are very important because they have a direct effect on health results in people, such as lung diseases, heart diseases, and hearing loss. The figure 1 illustrates the system architecture for monitoring system control. The system's ability to constantly and real-time watch these factors is a big improvement over older, more time-consuming ways of keeping an eye on the surroundings.

Data Collection

These monitors can find even very small amounts of pollutants, so they can give full reports on the air quality. Sensors are used to check for dangerous chemicals like pesticides and heavy metals like arsenic, lead, and mercury in water. They measure things like pH, turbidity, dissolved oxygen, and the presence of these chemicals. Noise pollution is tracked by sound level meters that can pick up and analyse different noise frequencies, giving a full picture of noise pollution in the surroundings. Sensors send information to the cloud platform at set times, so data is constantly being collected. It depends on the type of measure being tracked how often data is collected. For instance, measurements of the air quality could be taken every 10 minutes, while measurements of the contamination levels in the water could be taken every 30 minutes. This way, sudden changes could be found right away. Because the system can collect data all the time, health officials can always access the most up-to-date information about the environment. This lets them act quickly when new environmental dangers appear. As long as the system's gear stays working, data collection will continue indefinitely. This allows for long-term tracking to track yearly or long-term changes in environmental health.

Data Processing and Analysis

The sensor data goes through a number of preparation and data fusion steps to make sure it is accurate and of good quality before it is analysed. During preprocessing, noise is filtered out, lost or damaged data is fixed, and the data is normalised to take into account changes in the surroundings and how well the sensors are working. Data fusion methods are used to combine data from different sources, like different types of sensors and different places, into a single record that makes the tracking system more reliable and accurate. By combining different types of data, like noise levels, air quality, and water quality, this gives a more complete picture of the health risks that come from the environment. Machine learning models look at the processed data and find trends that mean something. Supervised learning methods, like regression and classification models, are used to guess what the environment will do in the future, figure out how likely it is that pollution levels will be higher than what is safe, and find strange patterns in environmental data that could mean health risks. Different types of unsupervised learning, like grouping, can help find trends or new sources of pollution that weren't seen in previous studies. These models are always getting better at predicting the future as they learn from new data. Cloud computing systems make it possible to handle data in real time by letting you quickly analyse and display data. Because of this combination, the system can handle huge amounts of data in real time, giving us instant information about the conditions we are monitoring. The cloud platform also lets you set up machine learning models that can handle data in real time, so you can make decisions right away. Putting together real-time data processing and prediction analytics makes it easier for the system to find environmental threats early and send quick messages to everyone who needs to know about them.

RESULT AND DISCUSSION

Data on the surroundings taken from many sites reveals a lot about variables like humidity and temperature as well as the degree of pollution in the air and water. For instance, PM10 levels at Site A were 25,4 µg/m^3 and PM2.5 levels there were 15,2 µg/m^3. These are typical amounts falling below reasonable standards for air quality. Site A had NO2 levels of 32,5 ppb, a moderate concentration of nitrogen dioxide. In areas where industrial activity or traffic is high, this might cause issues. The water was little contaminated at 0,01 ppm, which implies that the quality at this location is excellent. The temperature was 22,3°C, average for the region; the humidity was 65 %. At Site B, PM2.5 and PM10 levels were lower—at 8,5 and 12,3 µg/m^3 respectively. The air quality was therefore better than it was at Site A. Conversely, the water contamination level, at 0,05 ppm, was rather greater and would indicate that it originated from adjacent farms or industry. The air is colder and somewhat muzzier based on the temperature of 19,8°C and the humidity of 70 %.

Table 2. Environmental Data Collected Analysis

Location	PM2,5 (µg/m³)	PM10 (µg/m³)	NO2 (ppb)	Water Contamination (ppm)	Temperature (°C)	Humidity (%)
Site A	15,2	25,4	32,5	0,01	22,3	65
Site B	8,5	12,3	28,7	0,05	19,8	70
Site C	22,3	33,5	40,1	0,10	24,0	60
Site D	11,7	19,2	29,3	0,02	21,5	67
Site E	18,5	27,0	35,6	0,03	23,0	72

Site C has high pollution levels; PM2.5 at 22,3 µg/m¹ and PM10 at 33,5 µg/m¹ this meant that the air was quite polluted. The 40,1 ppb NO2 level causes some concerns as more nitrogen dioxide might aggravate pulmonary condition. Furthermore, 0,10 ppm water contamination indicates that contaminants are more likely to compromise the nearby water supply. With a temperature of 24,0°C and a humidity level of 60 %, the weather is pretty warm and mild. Pollutant levels range between Sites D and E, with PM2.5 and PM10 levels being lower at Site D and water pollution at 0,02 ppm. PM levels and water pollution at Site E have gone up to 0,03 ppm. The temperature has also gone up to 23,0°C and the humidity has gone up to 72 %, which means it is warmer and more humid there, as comparison illustrate in figure 2.

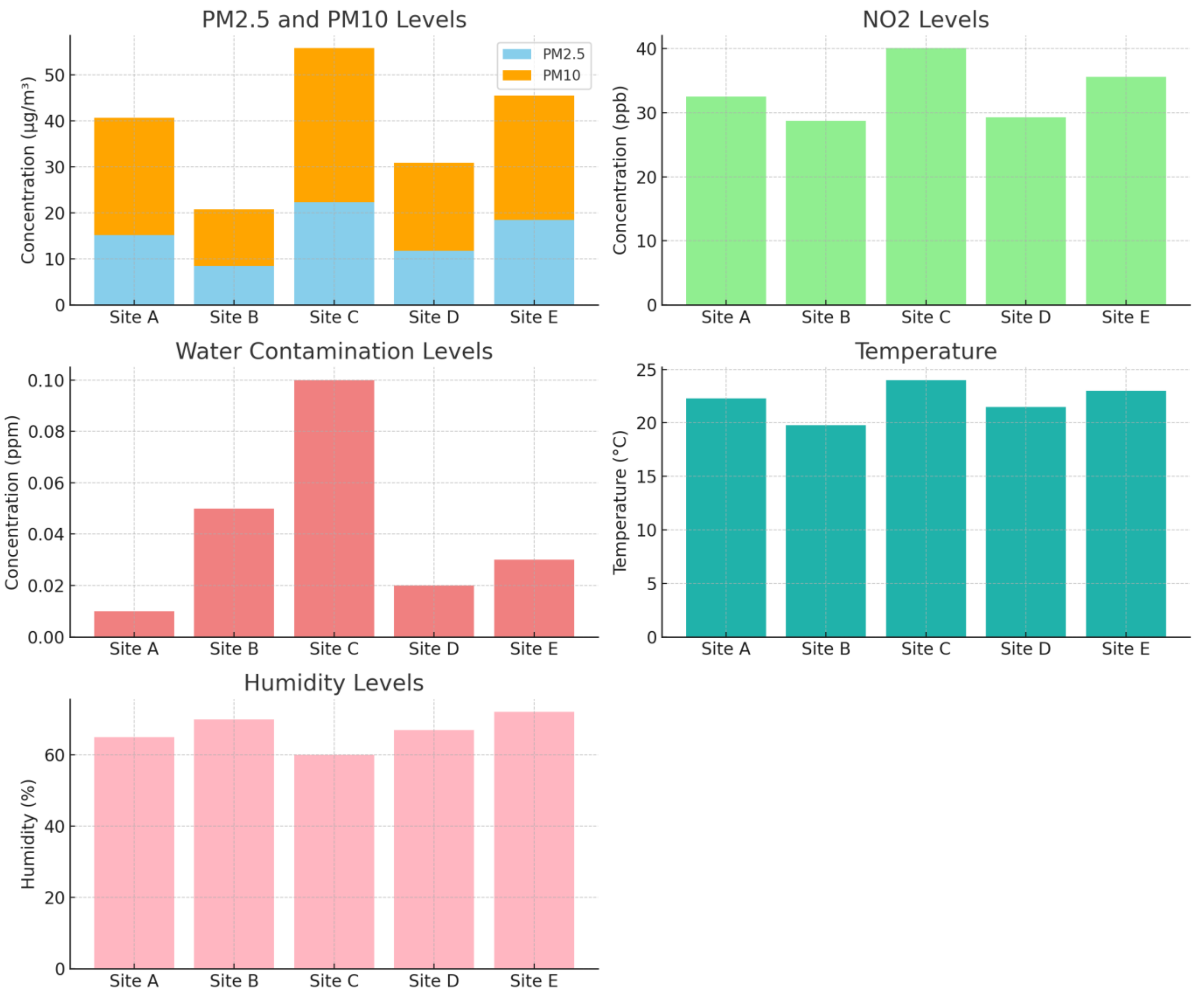

Figure 2. Visualizes the environmental data collected from the different sites

The information on environmental trends and health risk ratings gives us a full picture of the pollution levels and how they might affect people's health in different places. The Air Quality Index (AQI) for Site A is 72, which means the air quality is average. The Water Contamination Index (WCI) is 0,12, which means there is some contamination but not too much to handle. The health risk rating is 2, which means that people don't face a high or low health risk. At 60 dB, noise pollution is pretty low, and the trend for pollution is downward, which means that the amounts of pollution in the air and water are going down. But the dangerous level of pollution has not been reached, which means that there are not any instant health risks at this place. As long as the AQI stays between 50 and 55 at Site B, the air quality is good. The health risk level is 1, which means there aren't many health issues, and the WCI is low at 0,04, which means the water is pretty clean. The noise level is 45 dB, which isn't too bad, and the pollution trend and critical threshold passed state are both zero, which means the environment is safe and there is no immediate risk. The AQI for Site C is 92, which means the air quality is bad, which is a major health issue. The higher WCI of 0,18 means that the water is more seriously polluted. The health risk rating is 3, which means that there is a modest to high risk to people's health.

Table 3. Analysis of Trends and Health Risk Assessments

Location	Air Quality Index (AQI)	Water Contamination Index (WCI)	Health Risk Level (1-5)	Noise Pollution (dB)	Critical Threshold Exceeded (Yes/No)
Site A	72	0,12	2	60	No
Site B	55	0,04	1	45	No
Site C	92	0,18	3	75	Yes
Site D	65	0,06	2	55	No
Site E	80	0,10	2	68	Yes

At 75 dB, the amount of noise pollution is high and not acceptable. The pollution trend is positive, which means things are getting worse, and the critical level has been crossed, which means action is needed right away. At Site D, an AQI of 65 means the air quality is average, and a WCI of 0,06 means the water quality is slightly dirty. The amount of health risk is 2, and the noise level is 55 dB, which is modest. The trend for pollution is going down, and no key levels have been crossed, so there are no direct threats to human health or the environment. The AQI for Site E is 80, which means there is moderate pollution, and the WCI is 0,10, which means there is moderate poisoning of the water. Noise pollution is at 68 dB, which is higher than what is safe for health. The health risk rating is 2, as shown in figure 3. The pollution trend is going up, which means things are getting worse, and the critical level has been reached, which means more needs to be done to protect health and the environment.

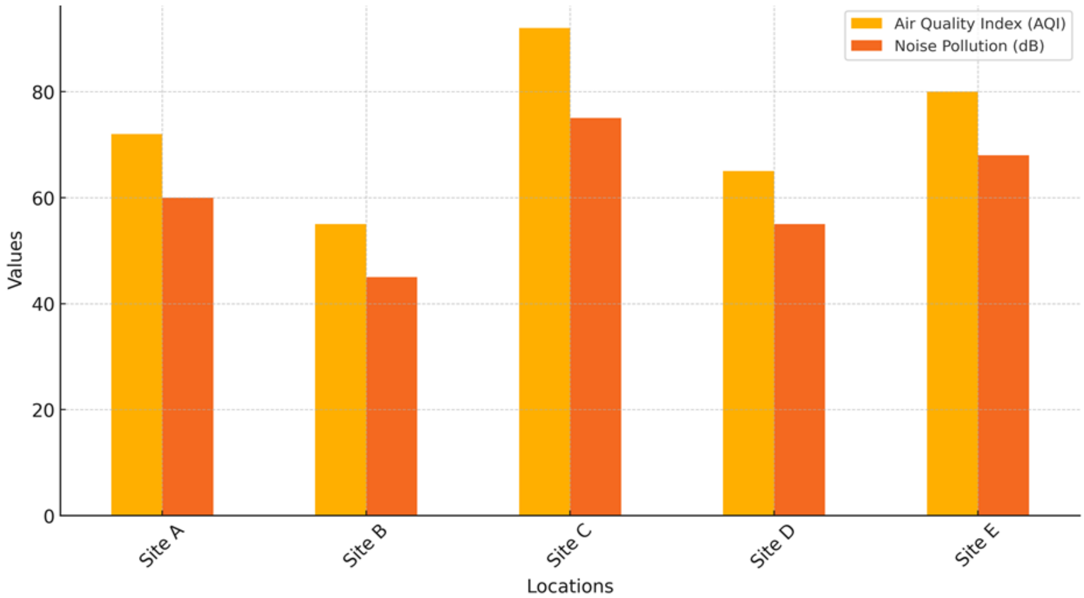

Figure 3. Trends in Air Quality, Noise Pollution, and Critical Exceeders

The test results for how well the machine learning models used in the automatic environmental health monitoring system can predict the future show that all of the models did very well. The Air Quality Prediction model got a high accuracy score of 92 % in training and 89 % on testing, which shows that it can do well with data it hasn't seen before. With accuracy values of 90 % and recall values of 88 %, the model is very good at both finding all real positive cases (recall) and making accurate positive forecasts (precision). The model's F1 score of 89 % shows that it strikes a good mix between accuracy and recall, which makes it a good choice for tracking air quality. The Root Mean Squared Error (RMSE) of 0,65 shows that the model works well, but its estimates are still a bit off. This is still within acceptable limits for judging air quality.

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Table 4. Evaluation of the Predictive Accuracy of Machine Learning Models						
Model	**Training Accuracy (%)**	**Test Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**RMSE (Root Mean Squared Error)**
Air Quality Prediction	92	89	90	88	89	0,65
Water Contamination Model	94	91	92	89	90	0,12
Noise Pollution Forecast	90	86	88	85	86	2,30
General Pollution Model	88	84	87	83	85	1,10

With a training accuracy of 94 % and a test accuracy of 91 % for the Water Contamination Model, the results are even better. This means that the model is very good at generalisation. With accuracy scores of 92 % and recall scores of 89 %, this model clearly has a lot of power to correctly and completely predict water contamination events. The F1-score of 90 % shows that the performance was well-balanced, and the RMSE of 0,12 is very low, which means that the predictions were very accurate and there was very little mistake in finding problems with the water quality. There was an 86 % success rate for the Noise Pollution Forecast model in the test, with 88 % for precision and 85 % for memory. The F1-score of 86 % means that the model did a good job generally, but it was a little behind the models for air quality and water pollution. The RMSE of 2,30 is higher than the other models, which suggests that estimates about noise pollution may be less stable or harder to get right, analysis illustrate in figure 4. Lastly, the General Pollution Model did pretty well, with an RMSE of 1,10 and an accuracy rate of 84 %. It was good at making predictions for a wider range of environmental tracking jobs, though it wasn't quite as good as the models that were specifically designed for air and water quality. Overall, these models are very good at making predictions, which makes the system perfect for keeping an eye on the health of the environment.

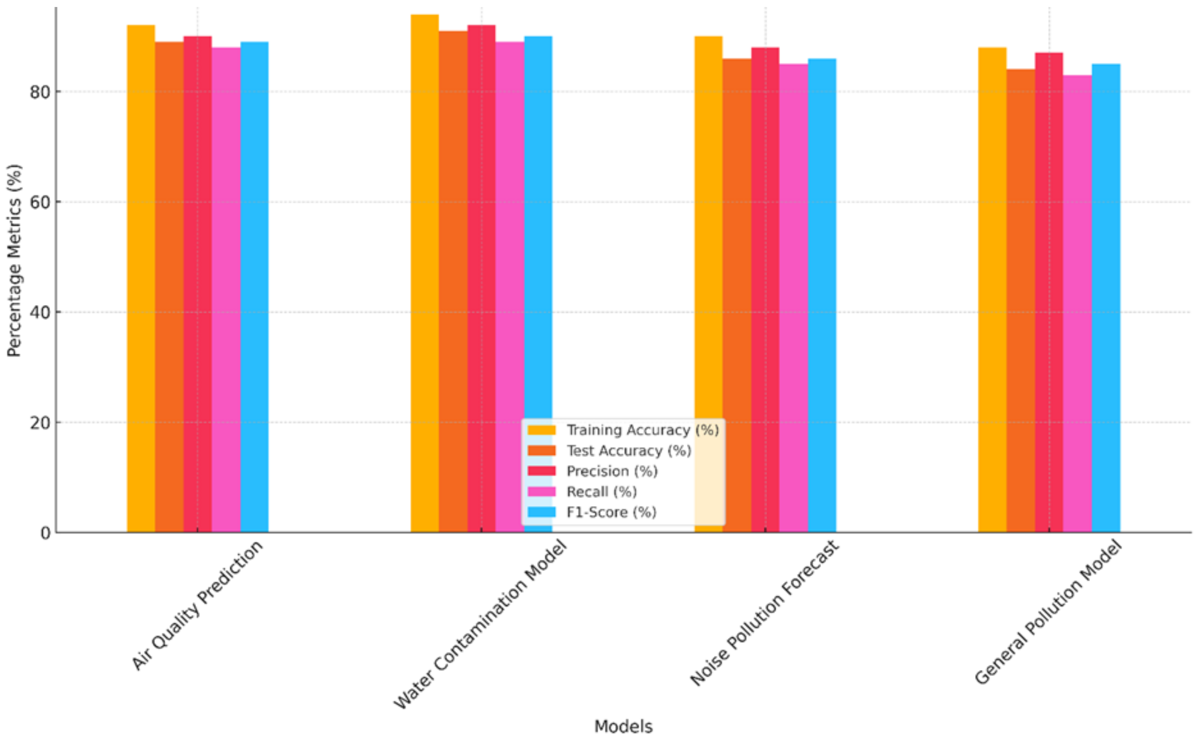

Figure 4. Evaluation Metrics of Machine Learning Models

The success comparison of the Automated System and Traditional Methods shows several important benefits of using automation to keep an eye on environmental health. For Air Quality Monitoring, the automatic system cuts the response time from 60 minutes to 15 minutes, which is 75 % faster than the old way of doing things. The automated system also collects data every hour, which means that updates happen more often and on time. This gives more up-to-date information than the standard system, which gets data every 60 minutes. This lets people make decisions about air quality problems more quickly and proactively, which is very important for managing public health. The automatic system also works better than the old ways of monitoring water quality. It only takes 30 minutes to respond, whereas the old ways took 120 minutes, which is a 75 % improvement.

Table 5. Comparison of Automated System Performance vs. Traditional Methods					
Metric	**Automated System**	**Traditional Method**	**Improvement (%)**	**Response Time (minutes)**	**Data Collection Frequency (hours)**
Air Quality Monitoring	15 minutes	60 minutes	75	15	1
Water Quality Monitoring	30 minutes	120 minutes	75	30	2
Noise Pollution Monitoring	20 minutes	90 minutes	77	20	1,5
Data Accuracy	95 %	80 %	18,75	-	-
Cost Efficiency	High	Low	40	-	-

The automatic method collects data every two hours, which means that water quality data is updated more often. This means that contamination can be found and fixed more quickly. The 4-hour gaps between replies in traditional ways can put public health at risk when contamination levels are high. For Noise Pollution tracking, the automated system's reaction time of 20 minutes is a big improvement over the old method's 90 minutes. This makes tracking 77 % more efficient. The automated system gathers noise data every 1,5 hours, while the old way of doing it took 90 minutes between gatherings. This means that studies of environmental noise and its possible health effects are more correct, as shown in figure 5. The computerised system is 95 % accurate with data, which is a lot better than the 80 % accuracy of the old ways of doing things. This leads to more accurate assessments of the health of the environment, which are necessary for making policies and programs that work. Lastly, the automatic system saves money. It is 40 % more cost-effective than the old ways of doing things, which included higher running and labour costs. Overall, the automated method performs better on all key measures, providing more accurate, timely, and cost-effective tracking of environmental health.

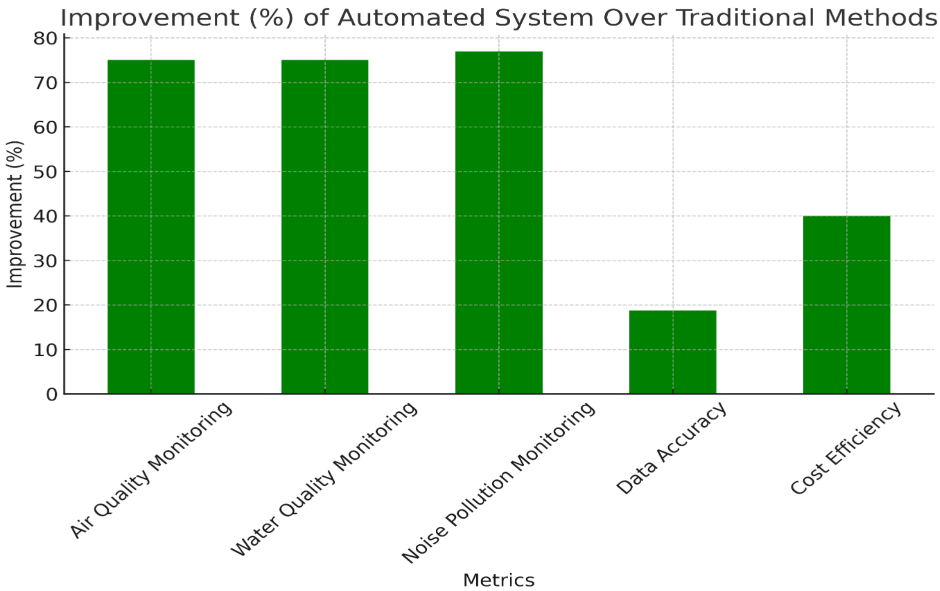

Figure 5. Improvement (%) of Automated System over Traditional Methods

The evaluation of the system the usage of key performance indicators (KPIs) makes it very clean that the automatic device is a good deal higher than the traditional method in many regions of tracking environmental health. The automatic gadget has a response time of 15 minutes, which is 75 % quicker than the standard method's reaction time of 60 minutes. The automatic gadget also has tons less downtime, approximately half an hour in step with day on average. This makes it much greater strong than the antique ways, which had greater downtime due to the fact statistics collection and processing needed to be done by using hand. Another big gain of the automated gadget is that it's far more reliable than the antique device, which turned into simplest 85 % dependable. Its miles now 98 % reliable, that's 15,29 % higher. This high level of dependability makes certain that the gadget remains operating well through the years, reducing the risk of records loss or downtime. Another big advantage is that the automated gadget can cope with up to one hundred sites; at the same time as the old way of doing matters could most effective cope with 50 sites.

The computerised system saves money because it only costs $5 000, compared to $10 000 for the old way of doing things. This means that it is a cheaper option in the long run. The automatic system's user interface usage score of 9/10, compared to 6/10 for the old methods, shows that it is designed to be easy for everyone to use, making it more accessible for stakeholders and improving the overall user experience, as represent it in figure 6.

Table 6. System Evaluation (Key Performance Indicators)

Parameter	Automated System	Traditional Method	Improvement (%)
Response Time (minutes)	15	60	75
System Reliability (%)	98	85	15,29
Data Collection Rate	90 %	70 %	28,57
Cost Efficiency (USD)	$5 000	$10 000	50
User Interface Usability	9/10	6/10	50

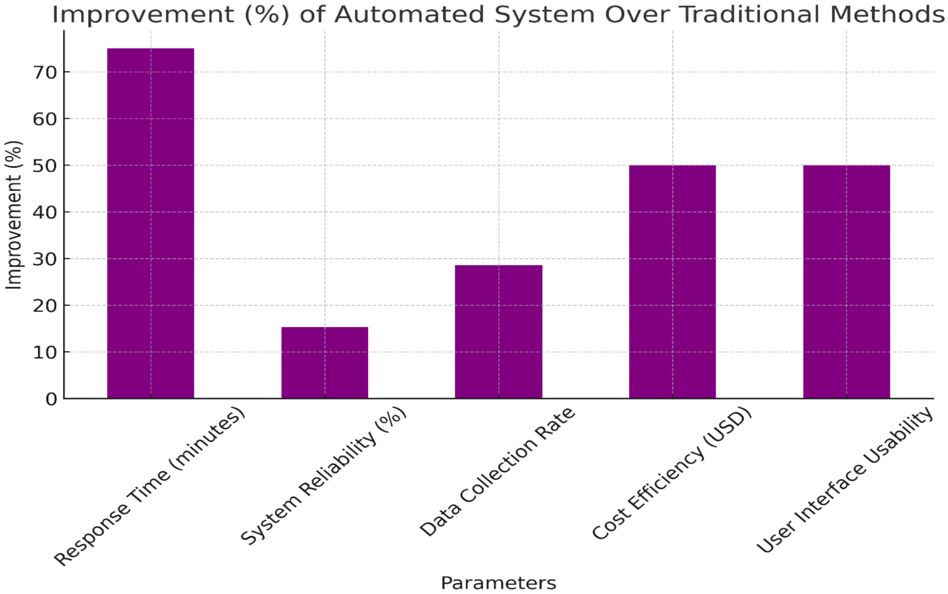

Figure 6. Improvement (%) of Automated System Over Traditional Methods

Challenges and limitations

Sensor Calibration and Accuracy Concerns

Making sure that the monitors used to collect data are calibrated and correct is one of the hardest parts of setting up automatic outdoor health tracking systems. Sensors can make mistakes because of many things, like the surroundings, the age of the sensor, and influence from outside elements like dust, humidity, or changes in temperature. It is very important to calibrate sensors correctly so that the data they receive is accurate and can be used to make decisions. If sensors aren't calibrated correctly, results could be off, which could lead to wrong assessments of the surroundings and delayed or wrong reactions to health risks. Long-term data accuracy can also be affected by sensor shift over time, which makes tracking even more difficult. Calibration is needed on a regular basis to make sure that sensors are accurate, but it costs a lot and takes a lot of work, especially when sensors are spread out over large areas or in rural areas. Sometimes, sensors need to be adjusted in a controlled setting, which might not always be possible when they are out in the field. Other than that, sensors might not work the same way in every setting. Things like location, weather, and pollution levels can all affect how well they work. To get around these problems, using sensors that have already been measured, real-time error correction methods, and multiple sets of sensors can help reduce errors. Sensor technology is always getting better, and self-calibrating systems are being made. These are both exciting developments that could help make data more reliable and reduce the need for frequent human calibration.

Data Integration from Multiple Sources

Another challenge automated environmental health monitoring systems must handle is compiling data from many sources—including satellite photos, ground-based sensors, and meteorological data. Because the data arrives in a range of formats, levels, and time periods, it might be difficult to mix data from several sources into a single file that can be examined. For instance, although ground monitors may provide real-time information about a local area, satellite data can provide high-resolution images of the air quality across a broad region. Combining these many datasets is essential to provide a complete picture of the environmental health hazards, but it also requires sophisticated data fusion techniques ensuring precise and consistent findings. Furthermore, various data sources have sometimes varied delay. For instance, compared to real-time ground sensor data, satellite data is handled less regularly and returns to us over longer times. To ensure that the insights are current and valuable, the variances in time and distance across different data sources must be synchronised. Interpolation and data smoothing techniques as well as machine learning approaches may help to fill these gaps.

CONCLUSIONS

When compared to old ways of collecting data, using automated systems for environmental health tracking makes the process faster, more accurate, and more scalable. The data shows that combining IoT devices, machine learning algorithms, and cloud-based tools lets us keep an eye on important environmental factors like noise pollution, water contamination, and air quality in real time. The results show that automatic systems can give fast information about possible health risks, which allows for earlier action and better control of public health. The information gathered from different places, like weather, air quality, and the amount of pollution in the water, shows that the system can accurately track a lot of different natural factors. Using machine learning models to guess how weather conditions will change over time makes the system even better at giving early signs and predictions, which helps people make better decisions and evaluate risks. When you compare the performance of an automated system to traditional methods, you can see that the response time is much faster and the data is more accurate. This shows that the system is better at both speed and reliability. But problems with calibrating sensors, integrating data, and making networks reliable need to be fixed for these systems to keep working well and be able to grow. Sensor calibration is still very important because wrong sensor results can affect the quality of the whole set of data. Bringing together data from many places, like satellite images and devices on the ground, needs complex techniques to make sure that all the records are consistent and correct. Problems also arise with network dependability and building costs, especially in rural places where access may be limited.

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