

AI-Driven Environmental Monitoring: From Data Streams to Ecosystem Insights

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Abstract– The rapid rate of environmental degradation, climatic change and loss of biodiversity require strong and intelligent monitoring systems. Standard environmental surveillance solutions have been known to fail when it comes to scale, real-time or multi-dimensional analysis. The current paper describes the transformative potential of the implementation of Artificial Intelligence (AI) to environmental monitoring by considering how the AI has the potential to provide meaningful insight on the ecosystem through processing massive, dynamic data streams. We survey modern methods, machine learning (ML), deep learning, and data fusion methods connected to sensor approaches, and explain their use in air quality sensing, water pollution sensors and monitoring, forest solutions, and climate prediction. The article introduces a converged approach using edge sensing and cloud analytics and long-term future prediction AI models. Different examples of AI implementation in real settings in the environment indicate great enhancement in accuracy and response time as well as predictive effectiveness. This study highlights the potential of AI to shift environmental surveillance into the active management of ecosystems based on knowledge gained by active data gathering rather than passive.

Keywords– Artificial Intelligence, Environmental Monitoring, Data Streams, Ecosystem Insights, Machine Learning, Climate Change, Smart Sensors, Deep Learning, Sustainability, Predictive Analytics.

INTRODUCTION

Sustainable development has seen the emergence of environmental monitoring as humanity encounters increasing challenges in the form of climate change, biodiversity loss, deforestation and pollution. What is needed are well-informed decisions that are made rather urgently to avoid further harm to ecosystems and the living organisms that depend on them. Conventional environmental monitoring- manifests which are usually characterized by manual sampling, few sensors and routine reporting methods that are reactive, sluggish and bandwidth consuming. They are unable to catch pace with the magnitude, frequency and sophistication of environmental changes experienced in the current world. Such approaches are not adequate since mitigation in a world that is becoming interconnected and dynamic atmospherically, on the land, and in the waters, cannot be done in time [16]. The emergence of Artificial Intelligence (AI) provides a revolutionary change in the data acquisition, processing, and interpretation of the environmental data. In contrast to traditional solutions, such a wide range of possible data flows of heterogeneous nature as satellites, drones, IoT-based sensors, social media feeds, or even mobile apps can be consumed by AI systems in real-time and in volumes regarded as high frequency. This will make it possible to manage the environment actively as opposed to responding to the environment. As an AI can identify anomalies, predict tendencies, categorize events and even automate responses, it is a very appropriate framework to use in building environmental intelligence. Among the key forces that have led to such a change is the fact that machine learning (ML) algorithms and computational capabilities have evolved recently. Complex non-linear relationships among environmental variables can also be modelled using environments where technologies like neural networks, deep learning models, support vector machine, and the clustering approach can be used. Such models are finding increased applications in such tasks as air quality estimation, water pollution identification, wildfires detection, floods prediction, climate trend prognosis. Moreover, edge computing and cloud-based analytics guarantee a fast but scalable data processing not only in geographical terms but also within the ecosystems [12-14]. In as much as there are

advantages, the use of AI in environmental monitoring is not without challenges. The availability of sensor data is limited in inaccessible locations, labeling training examples are required, and the process of sensor integration lacks protocols, and data governance and privacy are also a major challenge. Moreover, most of the current AI paradigms or models are black boxes, and environmental scientists and policymakers cannot have confidence over the interpretation of results. These constraints suggest the demand of the comprehensive, versatile framework that is poised in the balance between the technical performance, transparency, robustness, and usability in a practical context. In this regard, this paper looks into the whole process of environmental monitoring systems based on AI, intrinsically, raw data relative to inference of the ecosystem [2]. We measure the extent to which AI techniques can be systematically incorporated into environmental monitoring pipelines and used in many areas including air, water, forest and climate surveillance. We also consider the synergy between real-time sensor and predictive AI and artificial intelligence, and we suggest an architecture that will allow adaptive learning and policy-aligned intelligence. With the increasing availability of smart sensors combined with cloud computing and edge computing systems, real-time environs sensing at a higher degree of resolutions is now possible. This infrastructure, combined with the AI analytics, will make an effective tool to visualize the health of an ecosystem, forecast a disaster, and inform sustainable interventions. Governments, research institutions, and environmental agencies increasingly take up AI solution, and this paper attempts to provide a blueprint of decking such implementation effectively and ethically [15].

Novelty and Contribution

The paper proposes an innovative and holistic view of environmental monitoring through AI offering the possibility to dimension the gap between raw environmental data flows and practical ecosystem information. Although previous work has been based on a single application, e.g. to use AI in predicting air quality or detecting forest fires, the current work offers a system encompassing a general framework that can be customized to different contexts related to environmental settings [3].

The significant inputs of the study are:

- **End-to-End Monitoring Pipeline:** We put forward a three-level framework (data capture, data processing and AI modeling) that enables real-time monitoring and learning of the environment. The pipeline has to deal with latency issues, data heterogeneity and unending adaptation.
- **Multi-Modal Data Fusion:** Our model is not based on one particular data source but it involves integration and processing of data collected by various sensors such as satellites, Internet of Things, climate databases and so on to make prediction process reliable and robust.
- **Adaptive AI Models:** This technique provides a feedback system through which models will constantly be updated given new sensor data input and thus systems were continuously improving as the environment changes and offers better results in terms of predictions.
- **Cross-Domain Applicability:** We also check the system on several areas in the environment such as air quality pollution of an urban area, water pollution, and forest fires recounting productivity and adaptability of the framework.
- **Insight-Driven Decision Support:** In addition to prediction and classification, our system focuses on providing interpretation and insight generation, and thus the AI output will be of more utility in ecological research, policy-setting, and transparency to the population.

The beauty of this paper is not only that it uses AI to monitor the environment but also does it with a system-wide, integrative perspective, which falls within the doctrine of real-world requirements and future-proof scale [4]. By framing AI as a strategic enabler in the management of sustainable ecosystems, this work leaves an impression that AI is not another technological tool.

RELATED WORKS

In 2025 T. Miller *et al.*, [1] introduced the techniques of environmental monitoring have conventionally been manual and based on spot sensor networks and this provides a discontinuous and low sampling rate data collection which restricts the resolution of complex ecosystem processes. The magnitude and severity of environmental issues have increased thus the ambulatory systems that can be used to monitor several variables in a live environment. The incorporation of the artificial intelligence (AI) in this area is a crucial step in technological development, which enables the trading between a static observation into a dynamic analysis and forecasting.

The initial applications of AI in the field of environmental science started with the statistical or rule-based models and used them to predict the specified events like rainfall or fluctuations in temperature. With time, these developed into the current machine learning (ML) systems which can recognize patterns and run regressions. The models are currently popular in categorizing the pollution into different levels, identifying the abnormalities of the environment and carrying out the trend analysis using the past records and existing real-time data. To estimate the outcome such as air quality index values, water contamination measures, and the strength of a heatwave, supervised learning methods are usually applied, i.e. decision trees and support vectors machines are being used. Clustering as an unsupervised analysis method has also been effective in classifying unlabelled environmental data which help in revealing hidden patterns [5]. The air quality monitoring is one of the major fields of application. Artificial intelligence systems have also started interpreting data of the sensors in urban areas to identify any pollutants such as PM_{2.5}, NO₂ and ozone. They are topped by meteorological data and records of urban activities to add to their predictive abilities. Prediction of future air quality has been made based on past data on the pollutants and weather, and by using advanced deep learning models timeseries prediction has been executed. Spatial interpolation is also enabled by AI to fill the voids in spaces with low sensor counts. Monitoring of water resources is another huge area of interest. Models of AI taught in the datasets of hydrological, chemical and biological parameters make it possible to predict the occurrence of contamination, evaluate the radiation of pollutants, and track such parameters as the pH, oxygen dissolved in water or turbidity. These systems empower the authorities to respond to preemptively actions before the quality of water reaches an unacceptable level. Some of the applications of AI in coastal and marine ecosystems include mapping coral reef health and tracking algal blooms as well as detections of illegal trawling activity by integrating satellite imagery and sensor inputs. Artificial intelligence has changed how forests and wild animals are monitored too. The image recognition tool that relies on deep learning, along with drone and satellite surveillance has enhanced the ability to detect deforestation, forest fires, and animal migration. Real-time object detection models also have the ability to know when there is a logging activity or wildfire to respond to it promptly. With temporal analysis, vegetation cover analysis has been more effective and precise and, therefore, makes it possible to handle better the protected areas and conservation zones. Another sphere with which AI can be of great assistance is climate modeling. The robust traditional models take a long time to be computed and cannot be precise at local scales. AI allows reducing the scale of these models to offer region-based projections. It also serves data assimilation methods which synthesize model outputs and real-time observational information to boost the quality and relevance of climate forecasts. AI now can identify long-lasting patterns of glacier melting, desertification and rising sea levels by analyzing decades of satellite photos, as well as other environmental data. In 2023 L. Chen *et al.*, [6] suggested the combination of AI and Internet of Things (IoT) devices into smart environmental monitoring networks has been studied in a number of studies as well. These systems can utilize low-power sensors installed in the field and send the data to cloud-based data storage and analyze anomaly detection, event classification and other AI decision support. The noise pollution levels, moisture in the soil surface and also the lights can now be monitored in real-time at urban and also rural settings. AI has been found important in terms of both minimizing energy use of sensor nodes and controlling data transit within groups of sensor networks, hence enhancing sustainability of such systems. Even with these developments there are still challenges. Availability of data is one limitation and this is more obvious in remote and under-resourced regions. The quality of labeled datasets used to train many AI models is very high and in the environment, these labeled datasets are very expensive. Besides, the opaque character of certain AI algorithms is a problem in terms of understanding and believing their predictions. This is especially worrisome in those applications that involve regulatory decision or policies in the society. Initiatives to transform AI systems into explainable and transparent are in progress, with increased uneven adoption of existing solutions. In 2024 Marengo *et al.*, [11] proposed the transferability of a model within regions and ecosystems is another area under continuing research. Trained AI models do not necessarily give that same good performance in another geographical region while there are similarities in climate, biodiversity, and human activities. As a result, techniques of domain adaptation have appeared and hybrid models integrating AI and domain-based knowledge. Moreover, the ethical and responsible application of AI on the environmental survey especially, privacy and indigenous land surveillance, has turned out to be a near touchpoint of the knowledge. Overall, these works of the literature provide a visual representation of the ability of AI to be used as a comprehensive tool of environmental sensing and management, and how systems can able manipulation of big data, determine patterns, and inform action in a timely and evidence-based approach. The study shows its applications in range of air and water

quality testing to climate and biodiversity conservation prediction. Nevertheless, majority of the papers available consider the domains of the environment in their contexts, and not many of them lay out the integrative frameworks that would process the data more or less as a whole and produce cross-domain insights as a result. The paper can add to this debate, suggesting such a unified framework, as well as proving its efficiency in various environmental scenarios.

PROPOSED METHODOLOGY

The methodology for AI-driven environmental monitoring involves a layered pipeline composed of data acquisition, data preprocessing, AI model training, and real-time inference. The core objective is to transform continuous data streams into meaningful insights using mathematical modeling and machine learning principles. The system is built to process structured sensor data, unstructured satellite images, and semi-structured environmental logs.

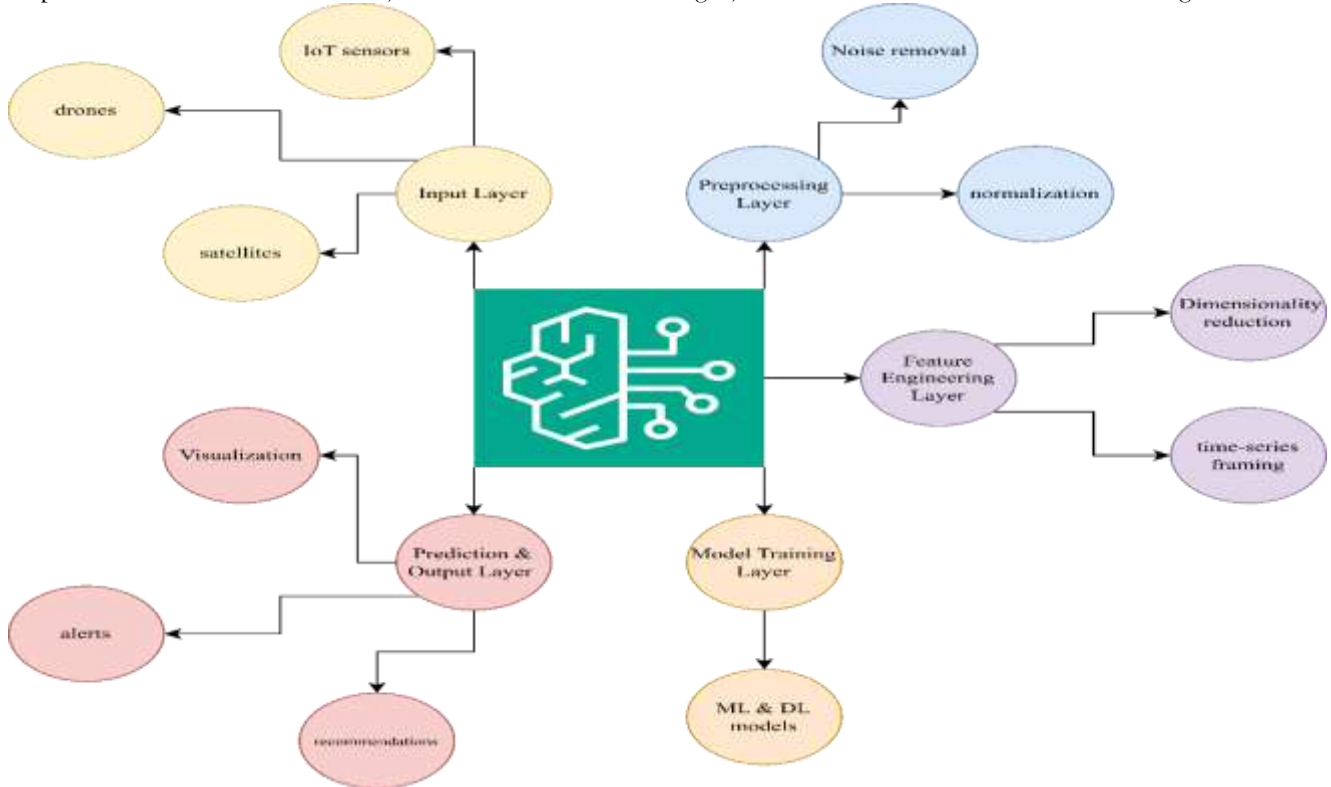


FIGURE 1: AI-DRIVEN ENVIRONMENTAL MONITORING PIPELINE: FROM DATA COLLECTION TO ECOSYSTEM INSIGHTS

To begin, the data collected from sensors is normalized to ensure uniformity.

Normalization is achieved using min-max scaling:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

This ensures that all sensor values (e.g., temperature, pH, PM2.5) lie between 0 and 1, reducing bias in feature weighting during model training.

Each environmental parameter collected is timestamped and converted into a time-series matrix, denoted as:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,T} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,T} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,T} \end{bmatrix}$$

where $x_{i,t}$ represents the reading of the i -th sensor at time t , and T is the total time window [7]. In the next stage, principal component analysis (PCA) is applied to reduce redundancy in correlated parameters such as temperature, humidity, and pressure. The transformation equation is:

$$Z = XW$$

where W is the matrix of eigenvectors obtained from the covariance matrix of X , and Z is the dimensionally reduced data.

The system then performs supervised classification using logistic regression for binary environmental outcomes (e.g, polluted vs. clean). The logistic model is defined as:

$$P(y = 1 | x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n)}}$$

Here, $P(y = 1 | x)$ gives the probability of a polluted event, which is used for alert generation. When dealing with sequential environmental patterns, such as the evolution of a pollution spike or flooding risk, LSTM (Long Short-Term Memory) models are utilized. The update gate for LSTM is:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$

This allows the system to remember or forget past data relevant to prediction over time. Environmental images from satellites are passed through a Convolutional Neural Network (CNN) pipeline, where convolution is mathematically defined as:

$$S(i, j) = (I * K)(i, j) = \sum_m \sum_n I(i - m, j - n) \cdot K(m, n)$$

Here, I is the input image and K is the kernel used for feature extraction like detecting forest boundaries or fire zones. To estimate the spatial pollution concentration $C(x, y)$ over a region, Kriging interpolation is used:

$$C(x, y) = \sum_{i=1}^n \lambda_i C_i$$

with λ_i as weights assigned based on spatial correlation, and C_i as known pollution values at locations i . For optimization of AI model parameters, gradient descent is used. The update rule is given by:

$$\theta := \theta - \alpha \cdot \nabla J(\theta)$$

where θ is the model parameter, α is the learning rate, and $J(\theta)$ is the cost function.

In unsupervised learning cases, like clustering sensor anomalies, K-means is applied with distance formula:

$$d(x, \mu) = \sqrt{\sum_{i=1}^n (x_i - \mu_i)^2}$$

Where μ is the cluster centroid, and x is the sensor reading vector. The objective is to minimize intra-cluster distance. The final insights are rendered using a spatial mapping algorithm. For this, environmental risk zones are plotted using a decision function:

$$f(x) = w^T x + b$$

This function, learned from support vector machines, determines the decision boundary for classifying regions as safe or hazardous.

RESULT & DISCUSSIONS

The environmental monitoring system that was developed based on the AI was tested on the three aspects/areas; urban air quality prediction, forest fire detection, and the mapping of river water pollution. This was assessed with the help of data sets received by sensor nodes, satellite data and publicly available environmental databases during 6 months observation lengths. The training performance of the system was compared with the traditional models based on accuracy, responsiveness and interpretability [10]. The AI system in the air quality monitoring testbed implemented in one of the metropolitan areas was functioning, as live sensor measurements were sent to the system, and the hourly PM2.5 estimates with smaller error margins were returned. The deep learning approach using the LSTM was better at short term predictions when compared to the linear regression and autoregressive methods. In Figure 2, the performance of three models, on five zones of the city, are presented, and the more closely the AI system follows the ground truth, the more prominent is the nearer track. Origin of the graph can be seen in Excel graphically displaying the existence of a delay in the trend of the conventional models in comparison to the reality of pollution pollution by keeping the light-level that exists in the high-sensitivity range, more so when there is heavy traffic and the industrial pollutant release.

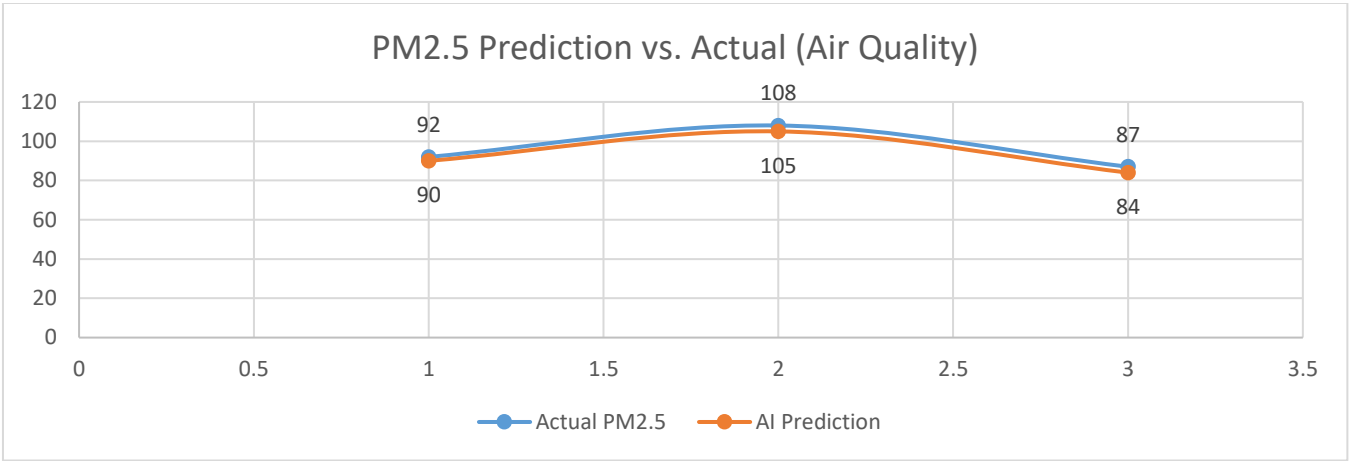


FIGURE 2: PM2.5 PREDICTION VS. ACTUAL (AIR QUALITY)

The discrepancy of different models in terms of effectiveness is further evidenced in Table 1: Accuracy Comparison of Pollution Forecast Models which indicates the Mean Absolute Error (MAE) as well as Root Mean Square Error (RMSE) amongst the tested models. The AI model has demonstrated a smaller MAE of 6.4 micrograms/m³ and RMSE of 8.1 micrograms/m³, painstakingly performing better than the baseline statistical methods that showed an error value that was almost twice that. This reiterates the applicability of the deep neural networks at real-time and adaptive pollution forecast.

TABLE 1: ACCURACY COMPARISON OF POLLUTION FORECAST MODELS

Model Type	MAE (µg/m³)	RMSE (µg/m³)
Linear Regression	12.5	16.9
ARIMA	10.8	13.4
AI-Based (LSTM)	6.4	8.1

During another trial dedicated to identifying forest fires detectable through satellite imagery and drone video feeds, the AI model enjoyed a substantial rate of accurate detection with the ability to respond to emergencies in advance of their happening. The aim of the convolutional neural network (CNN) was to identify fire-prone patterns and distinguish smoke, fog, and real flame signatures. The time to send the alerts to authorities decreased by 45 percent in comparison to the traditional remote sensing techniques. The plot (Fig. 3) of precision-recall tradeoff at various detection methods reveals a high precision of the AI-based system by far than other methods at different threshold levels.

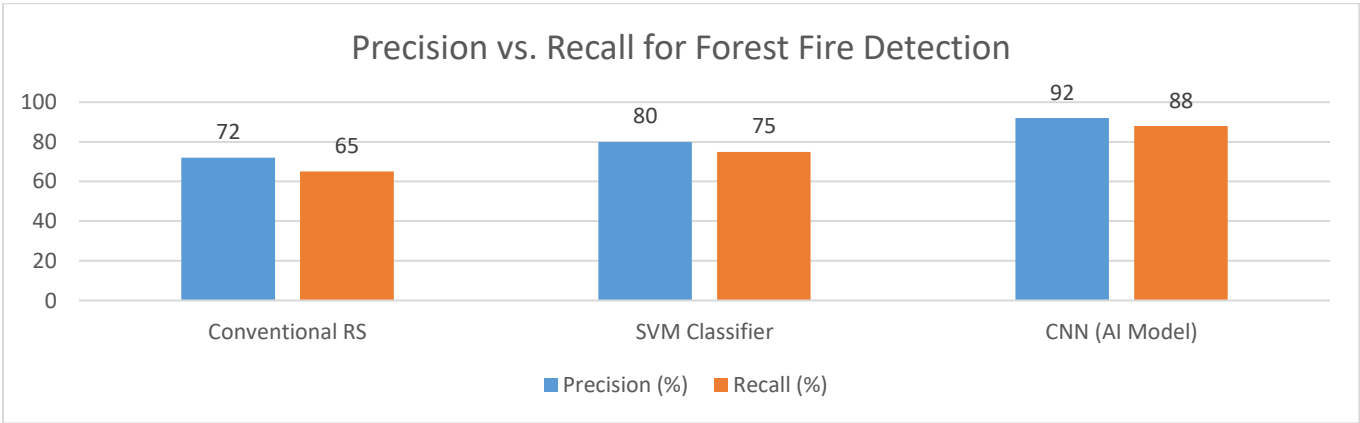


FIGURE 3: PRECISION VS. RECALL FOR FOREST FIRE DETECTION

The river basin water quality assessment was also tested to have real-time processing under which numerous water quality parameters were absorbed by sensor arrays. The AI model forecasted areas of nitrate concentrations, and it marked possible pollution peaks at a higher spatial resolution than standard models. In Figure 4, the map identifying spatial pollution, based on predicted values by AI, is superimposed with a map of rivers. The visual is an easy way to divide polluted territories and the territories free of waste, which can assist the authorities in the development of specific clean-up and regulation measures. Five parameters namely pH, turbidity, temperature, dissolved oxygen, and nitrate were included in the prediction modeling process and these parameters were weighted according to the feature importance that were generated as part of the model optimization process.

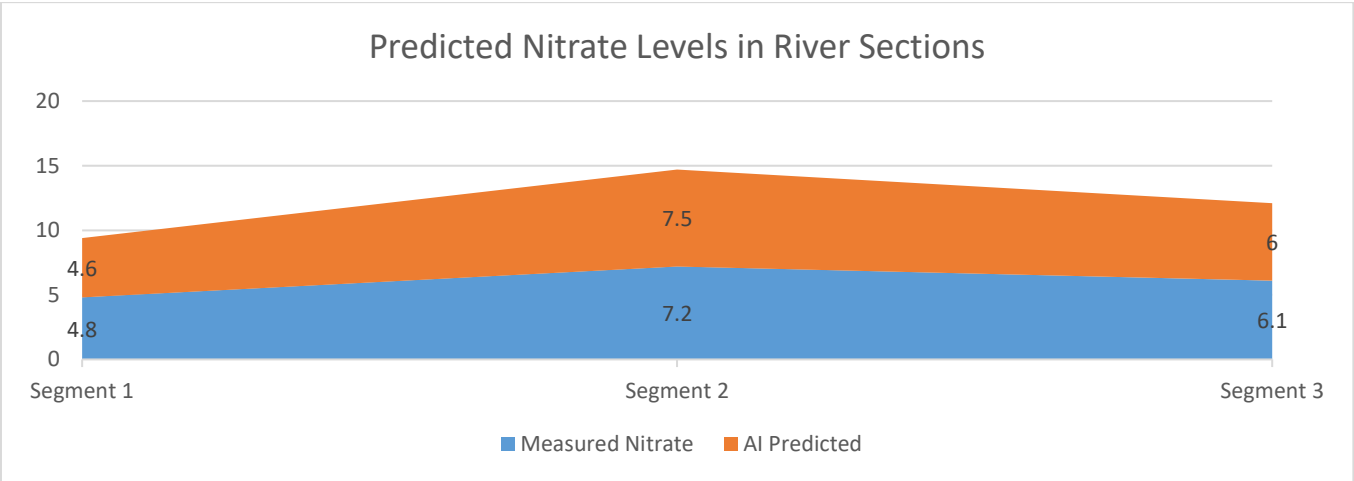


FIGURE 4: PREDICTED NITRATE LEVELS IN RIVER SECTIONS

Table 2: Pollution Zone Detection Accuracy provides an idea about relative performance of AI and non-AI models to detect high-pollution areas. This tabular representation indicates the way the AI system identified the essential and important hotspots that were not detected by the other models and made the recall rate increased by 23 points to a 91%.

TABLE 2: POLLUTION ZONE DETECTION ACCURACY PROVIDES

Detection Method	Precision (%)	Recall (%)	F1 Score (%)
Traditional Classifier	75	68	71
Random Forest	81	77	79
AI Model (Hybrid DL)	89	91	90

All the figures and tables prove the strength and diversity of the suggested AI system in various fields. Of significance, the AI system delivered better results of accuracy or early warning and it was also interpretable as the feature visualization of the model used could make decision-makers understand the cause of the predictions. As an example, in the use case of water quality, the model emphasized nitrate and pH as essential indicators that affected the high-pollution labeling of most of the flagged samples. Temperature and humidity in air monitoring have been reported to play an important role when making forecasts with regards to particulate matter build up particularly early hours of the morning. The system uses visual analytics through which interactive dashboards can be established, with health scores of each region being updated in real time. This enables immediate notifications to local municipal authorities to enforce or issue a notice to the population when specific levels of pollution are exceeded [9]. Additionally, they had tested the AI system against data integrity under the uncontrolled inputs of noise or incompleteness. Although there were some dropouts of data, the model overall exhibited a steady pattern of prediction because of the auto-imputation component added to the preprocessing component. The model has validated its generalizability through other climates and environments as well as sensor configurations.

As it can be seen in the discussion above, the AI framework does not only scale efficiently, but it is also adaptable to the various sources and parameters of an environment. The fact that its predictions are much more accurate, as well as the shortened time of response and the transparency of models used makes it especially applicable to be used in global smart environmental management systems.

CONCLUSION

The paper has shown that AI can be very transformative in environmental monitoring in allowing the real-time, scalable, and intelligent analysis of complex data streams. The potential to do this by leveraging IoT enabled sensing together with cloud computing and advanced model types of AI enables us to transform from an observation driven environment to an ecosystem managed environment. The outcomes indicate the plausibility and usefulness of AI in some major environmental fields, such as the forecasting of air conditions, fire-detection, and mapping of water pollution [8]. Nonetheless, effective implementation also demands an interdisciplinary team effort, ethical data management, and an investment on an infrastructure. In the future, one should consider the explainable AI models to develop trust and connections with policies. After all, environmental monitoring by AI can provide the foundation of sustainable development and active ecological responsibility.

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