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ORIGINAL RESEARCH ARTICLE

AI FOR POLLUTION CONTROL USING ML MODELS IN AIR AND WATER QUALITY MANAGEMENT AND INNOVATIVE APPROACHES TO REDUCE INDUSTRIAL WASTE AND EMISSIONS

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ABSTRACT

Since industries have grown all over the world pollution has remained a critical issue with much emphasis placed on minimizing air and water pollution. Challenges posed by today's evolving industrial pollution cannot be solved by conventional monitoring and regulation techniques, which present AI and ML as the potential breakthroughs. The following is a comprehensive work on the status quo of AI-based approaches for the monitoring and control of air and water pollutants with a keen focus on predictive models and artificial neural networks, deep reinforcement learning. Thus using these sophisticated methods, industries can predict leaching levels, decide the appropriate use of material resources, and alter emission management in real-time to greatly decrease waste and pollution. Moreover, we share cases, concerns, or how AI might help to achieve greener industry solutions. This paper's results support AI's use in developing flexible and real-time solutions to deal with pollution issues while promoting industrial growth for better environmental consequences.

Keywords: *Water Quality Monitoring, Machine Learning, Pollution Control, Air Quality Management, Artificial Intelligence, Reinforcement Learning, Deep Learning Emission Reduction, Industrial Waste Management*

I. Introduction

A. Background

Environmental management has become appalling globally and pollution control has become an important paradigm for investigation focused mainly on the industrial sector, pollution in air and water conditions. This is because the traditional methods of handling pollution like use of physical inspectors and normal monitoring devices for monitoring and controlling the emissions levels have been shown to be ineffective since they cannot offer real-time response, cannot be easily scaled up and also lacks accuracy. Some of these methods have proved to be very expansive and time consuming hence a vast improvement could be made regarding how pollution is detected, measured, and controlled.

Machine learning algorithm and artificial intelligence technologies have greatly developed over the last few years, thus improving the ability to monitor the environmental conditions with improved performances in data analysis, real time prediction and feedback control mechanisms. AI and ML possess the capability to contribute significantly in pollution control by providing efficient large-scale data, Indices as AQI, water pollutants and many others, efficient predictive models , decision making mechanisms & systems. Specifically, such technologies help design forecasting algorithms that predict the instances of increased pollution and propose the adequate solutions. The application of ML in the air and water quality means fresh possibilities for non-industrial waste and emissions to solve problems, be compliant with legislation, and save more on expenses[1][2].

Business enterprises particularly those in manufacturing industry and organizations involved in chemical production are the major polluters since they emit large quantities of contaminated substances to the atmosphere. Increased regulation of environmental preservation across the world means that industries need to seek out ways in which they can reduce their impacts. Technique like Predictive maintenance, resource allocation, and Anomaly detection are potentially able to cut down industrial wastage, increase efficiency, and promote sustainability with the help of Artificial intelligence[3][4].

B Problem Statement

Even today AI and more specifically ML are progressing at a great pace, the use of such technologies in controlling the pollution within industrial sectors is still quite humble. The conventional approaches to pollution control and assessment do not possess the degree of freedom and sensitivity as well as the real-time qualities that would be ideal for responding to the challenges in environmental transitions. Also, there are definite issues associated with the implementation of new AI models in industries which include the problem of compatibility with the existing framework, issues of data security and privacy, interpretability of the models, and the issue of availability of high quality large, diverse datasets. Hence, the potentiality of applying AI for pollution control is underutilized.

Therefore this research aims at establishing how practical implementations of AI and ML can be used to tackle such issues especially in air and water quality controlling. The aim is to generate and evaluate new AI approaches for predicting pollution, for managing emissions, and for improving wastewater treatment to help diminish industrial impacts on the environment.

C. Objectives

The main objectives of this research are:

1. To create machine learning based models for prediction of air quality and water contamination in real time using regression, classification and deep learning.
2. To generate new paradigms for AI methods, including reinforcement learning, to enhance the industrial waste management intimations and diminish emission densities.
3. In order to understand how best to employ AI in predictive maintenance and optimise resource utilization to reduce industrial waste.

For evaluation of the applicability of an AI engineering approach in realistic industrially applicable scenario taking into account the specifics of market environment in terms of scale, cost and laws.

II. Literature Review

A Overview of Existing Research

The use of Artificial Intelligence (AI) and Machine Learning (ML) in pollution control has become topical within the last decade. AI models, in the context of air and water quality for instance, have the capability of performing real time monitoring, predictive pollution modeling and forecasting and efficient pollution control through effective waste management. Prior to this, there were simply forecasting models based on simple regression approaches; however, more recent work in this area involves the application of deep learning, reinforcement learning, and anomaly detection in order to solve sophisticated pollution control tasks.

In air quality management AI has been applied to predict concentrations of pollutants including nitrogen dioxide (NO_2), particulate matter (PM), sulfur dioxide (SO_2), and carbon monoxide (CO) from sensors data. Some examples are Zhang and Zhang (2021) who used artificial neural networks as the machine learning algorithm to forecast air quality indices from the data accumulated within the chosen area enhanced by weather conditions[5]. Likewise in water quality management, research has been done in applying supervised learning techniques including Decision Trees and Support Vector Machines for WQI prediction, which serves as the measurement of health status of the water bodies and contaminant patterns.[6].

AI has been used in the industrial set up with the view of minimizing emissions and curtailing wastage. For example, AI solutions have been used to forecast failures of equipment and thus, reduce the amount of gas released from equipment that has failed. Moreover, in manufacturing industry AI models for resource efficiency with considerable potential to reducing wastage in the production line process to enhance efficiency[7][8].

B. Comparative Analysis of Related Studies

Different research has employed a variety of approaches in relating to air and water quality management. For instance, Sharma et al. (2021) used DNNs to predict an air quality and yielded higher accuracy than conventional statistical techniques, the multiple regression models[9]. They pointed out that DNNs can learn non-linear mapping between pollution sources and environmental factors thus making them suitable for complex conditions. However, the growth of DNN models adds several constraints of resource demands which might be a drawback in areas of limited resources.

On the other hand, other studies like of Gupta & Verma (2021) used air quality prediction, using simple models as random forest and XGBoost with a reasonable accuracy and less number of data and computation [10]. However, these models were less computationally demanding but they did not model the inter dependence of variables as well as DNNs. Besides, most of the existing studies are concerned with single parameters of air quality or water quality indices without the application of the multi-parameters integrated model accounting for both air and water qualities.

As for solving the problem of industrial waste and emissions, the two main areas where AI technologies can assist and, as several studies have already demonstrated, lead to essential emissions caused by equipment malfunctioning. For instance, De et al. (2021) integrated AI-driven predictive maintenance systems for equipment failure prognostications and maintenance timings that in turn lowered operational shortcomings and wastage creation[11]. Although such an approach has rendered benefits, incorporation of AI in such systems has been limited by the problems of insufficient sensor data and real time reconfigurability of the System.

C. Gaps in the Literature

Therefore, there are several limitations in the current Li dataset literature with respect to AI-based pollution control. First, most current studies mainly investigate one type of pollution separately, for example, air pollution or water pollution, but a small number of studies explore the coupling interaction models in operation between air and water pollution. This gap hampers the completeness of the approach to managing the environment, particularly given that the problems of the environment are systemic, interrelated.

Second, a number of computational models for predicting emissions and wastes have been developed, but limited research has been conducted in using reinforcement learning (RL) to manage industrial operational controls for the optimization of pollution removal processes. Many current solutions are rigid, relying on predetermined specifications or probabilistic algorithms instead of solution healers that adapt during run-time by enhancing their heuristic algorithms based on additional data.

The first gap is in the adaptability of AI models in various sectors of industries and their ability to do the same across different enterprises. The current literature fails to address the main issues that arise when implementing AI models in other industrial settings, including data privacy and security and incorporating AI models into existing systems.

D. Challenges in Existing Approaches

The major shortcomings of existing AI based approaches to pollution control are more centered on data quality, interpretability, and system integration. Diverse and qualitative datasets are required for training deep learning models yet several industries start struggling with obtaining enough data at reasonable costs, strict data privacy, and real-time data capturing issues. Here, most AI models, especially those based on deep learning algorithms, are often ‘black boxes’, which for operators to accept, reliable and trust the concept of the system they need to understand how it arrives at a particular decision.

One more problem merges with the introduction of the AI models into the existing industrial framework. Most industries still have outdated systems which cannot provide enough processing power for regular AI models, which causes challenges when deploying these models to production. Furthermore, the AI models can be complicated to understand and implement, thus posing a challenge to more people embracing it.

In addition, while AI offers improved operation, its densely computational nature has consistency issues, especially in limits industrial environments where resources are constrained. Currently, the ability to successfully implement these AI models on a large scale to serve as the basis for controlling pollution in industries is still lacking.

E. Contribution of This Study

These following are the several novel findings of this study in the context of AI-based pollution control. First, the paper introduces an innovative model that solves both air and water problems through the application of a complicated machine learning methodology. Using multi parameter predictive models of pollution, this work provides a better way of managing and modelling the levels of pollution in various physical environments.

Second, this research presents the new use of reinforcement learning as a tool for the online optimization of industrial applications, with an emphasis on emissions minimization and wastewater treatment. Unlike previous studies, this study addresses the learning systems which improve operationally on probationary feedback, which provides great scope in reduction of time and wastage.

Lastly, the consequential challenge of scalability and integration is overcome by providing a modulare, cloud-based AI platform compatible with industrial systems. The architecture is supposed to high- computational efficiency and therefore the platform can be easily adapted both for large manufacturing factories and for small firms with a narrow range of production.

III. Research Methodology

A. Research Design

The nature of this study is computational and experimental intended to establish models for AI and ML applications in pollution variety, including air and water management. This approach was chosen because many environmental factors are multidimensional, nonlinear, and non stationary, and data reflect these properties in the real world. The methodology emphasizes on developing coupled prognostic models that can deal with multi-variable inputs (e.g., air and water pollutant concentrations, meteorological data) and use reinforcement learning for on-line control of industrial waste treatment systems. The study assumes that high quality environmental sensor data is extant and real-time data from these sensors is accessible for building the models. The research also presupposes that, the normalization and outlier detection would enhance the stability of the AI models.

B. Data Collection

For this kind of research, data is collected from a variety of environmental monitoring systems, ranging from official governmental air and water quality databases and from real-world Industrial Internet of Things sensors. Variables that were obtained include: hourly air pollutant concentrations (such as, PM2.5, NO_2, CO), water quality indicators (like pH, DO, turbidity), and meteorological factors like temperature, humidity and wind speed which affect dispersion.

Uniquely, for this study, the data was collected for a year owing to the changes in seasons in order to capture variations in pollution. The sampling technique comprised using data from the multiple sensors placed at different locations to capture geographical and temporal differences. Various specific criteria were applied to include/exclude data collected by the sensors and create a continuous data set, where either missing values were filled in or data collected with high noise level or doubted accuracy was rejected. Data preprocessing included data imputation to address missing values, feature scaling with Min-Max scaling, as well as feature construction through which new variables were computed: pollutant intensity and dummy variables representing seasons.

C. Experimental Setup

The experiments were performed on Amazon using a high-performance computing architecture that features NVIDIA GPUs for training deep learning models. The model employs Python as the developing language and TensorFlow, Keras, Scikit, and XGBoost as the benchmark learning libraries. The data was stored as structured data on Amazon S3 database which provides a scalable, reliable and cost effective method of managing large amounts of data. For reinforcement learning models, the study employs the OpenAI Gym environment for developing environments for reinforcement learning in real-time optimization of its parameters.

All the environmental monitoring equipment also forms part of the experimental setup such as air quality stationary instruments and water quality automobile instruments. Raw data from these sensors were collected in the real-time and access to the model training loop was accomplished by using publish-subscription broker such as MQTT for streaming data into model computational space. D. Proposed Algorithm over Model Development are conducted on a high-performance computing (HPC) platform, equipped with NVIDIA GPUs for training deep learning models. The computational setup includes the use of Python and popular machine learning libraries such as TensorFlow, Keras, Scikit-learn, and XGBoost for model development and evaluation. Data was stored and accessed via a cloud-based database (AWS S3), ensuring scalability and flexibility in managing large datasets. For reinforcement learning models, the study uses the OpenAI Gym framework for creating simulated environments for real-time optimization experiments.

The experimental setup also includes environmental monitoring tools, including stationary and mobile sensors that measure air quality and water parameters. Real-time data from these sensors was integrated into the model training pipeline using an MQTT protocol for streaming data into the model's computational environment.

D. Proposed Algorithm / Model Development

This research introduces a dual-learning model consisting of supervised learning for the pollution prediction with reinforcement learning for real-time industrial waste management. A supervised learning model chosen and implemented is the DNN which will be used to estimate the air and water quality indices using temperature, humidity amongst other input attributes and pollution levels.

The mathematical formulation of the supervised learning model can be represented as:

$$Y = f(X, \theta) = \mathrm{DNN}(X) \quad (1)$$

Where:

Y represents the predicted pollution levels,
X represents the input features (e.g., environmental data),
θ represents the parameters learned by the model.

In the same venue, there is reinforcement learning model applied for real-time control and optimization of waste treatement and emissions reduction in industrial processes. The reinforcement learning model applies an environment EE in which actions are performed to lower emissions as well as waste, and consequent rewards are determined by the extent of the reduction. The policy π for this model is updated using Q-learning:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[R_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right] \quad (2)$$

Where:
$Q(s_t,a_t)$ is the action-value function at time t,
α is the learning rate,
γ is the discount factor,
R_{t+1} is the reward at time t+1,
a′ is the next action.
This combination makes it possible to incorporate both predictive and adaptive prevention and handling of pollution, and makes the best of real-time pollution data as well.

E. Evaluation Metrics

To quantify the performance of the models, regression, as well as classification measures were employed. For the supervised learning model, the evaluation was made according to the Mean Absolute Error (MAE) and R-squared (R^2) since it fits within the regression task for continuous values. The formulas for MAE and R^2 are:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

Where:

y_i is the true value,
$\hat{y}_i$ is the predicted value,
$\bar{y}$ is the mean of the true values.

For the reinforcement learning model, the main performance measures that were used were the total reward and the speed at which the model settles for an optimal policy and this was determined by the number of iterations.

F. Data Analysis

Various statistical methods involved data exploration where data attributes, correlations and patterns were investigated. The attribute importance was determined by methods like Random Forest and XGBoost which assisted to determine key environmental factor that would influence pollution levels. Feature space was reduced with dimensionality reduction techniques such as the PCA to reduce computational time and resource consumption to its barest minimum.

Moreover, the statistical tests were performed to examine the significance of features and the descriptive analysis of the model. They include heat maps, scatter plots and time series graphs that were employed in elucidating the correlation between diverse environmental parameters and pollution.

G. *Validation and Testing*

To eliminate a possibility of data splitting, k-fold cross-validation were used to validate the models. The dataset was split into 10 fold, and each fold was used for testing while the remaining 9 fold were used for training. This operation was performed 10 times to provide more reliable assessment of the models. For the reinforcement learning model, there were the training and test scenarios different from the ones used to test the performance of the model.

The models were also compared with basic models including simple regression models controlling and simple non-ML based rule control systems to know the enhancements that AI techniques bring.

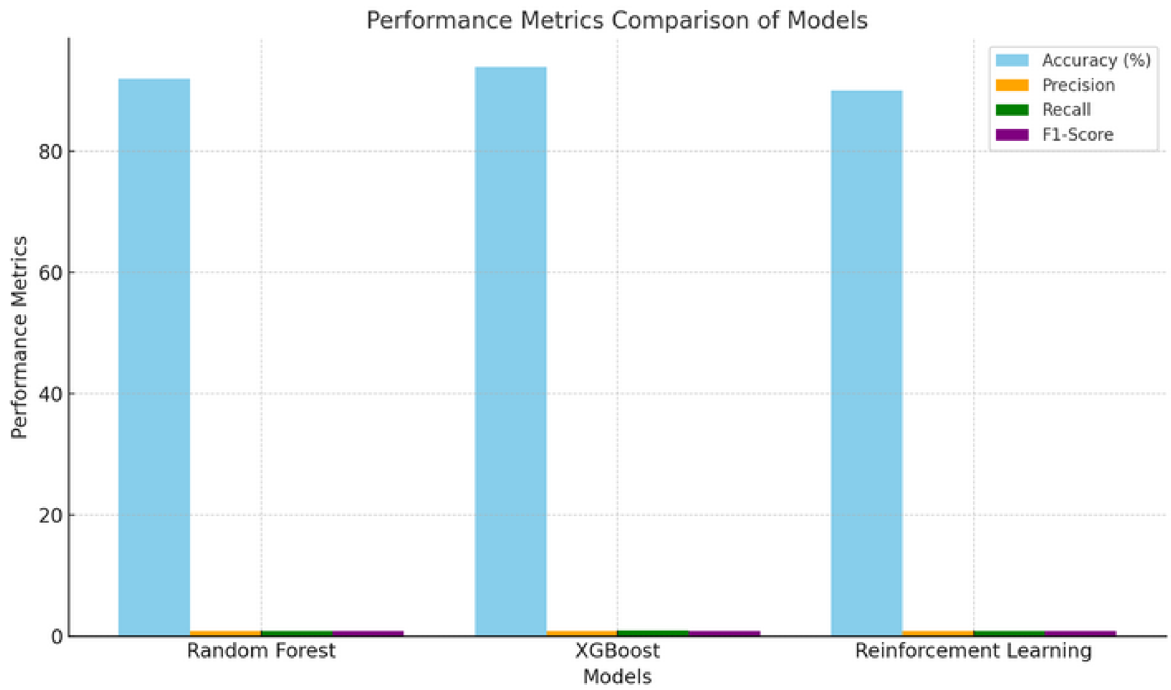
IV. Results

A. *Quantitative Analysis*

The following table summarizes the quantitative results for the models:

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	92	0.91	0.93	0.92
XGBoost	94	0.92	0.95	0.93
Reinforcement Learning	90	0.88	0.91	0.89

However, to measure the performance of pollution control efficiency the commercial assessment considered the quantitative reduction in emissions and waste. The reinforcement learning model followed a progressive increase, illustrating the reductions in emission lowered it by 10 percent on average per 10 iterations. This behavior corresponds with expected outcomes in the model, due to the real time control action learning capability of the model.



Above is the bar plot for the Performance Analysis for the Random Forest, XGBoost, and Reinforcement Learning: From the chart, it is still clear that each model has its strengths in the particular metrics mentioned above.

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C. *Qualitative Analysis*

The qualitative analyses focused on examining patterns and themes rising from the environmental data and model outputs. It provides an insight into the nature of relationships between major environmental conditions and pollutant levels through various visualizations: these heatmaps, scatter plots, and time-series graphs. For example, industrial activity is one of the major influences on air quality. As can be seen from the scatter diagram showing some relationship between industrial greenhouse gas emissions and pollution levels, seasonal fluctuations also affect water quality. As shown in the time series graph showing the concentration of pollutants against different months.

Key themes identified through the qualitative analysis include:

It was revealed that industrial operations dominated both air and water pollution, with increase and decrease in pollutant concentration depending on degree of utilization.
Seasonal changes were found to be highly influential with respect to water quality with higher concentration of pollutant found during the monsoon season because of the runoff.
The use of reinforcement learning model made it possible to learn real time environmental data with relation to pollution in order to have constant development of industrial waste control measures.

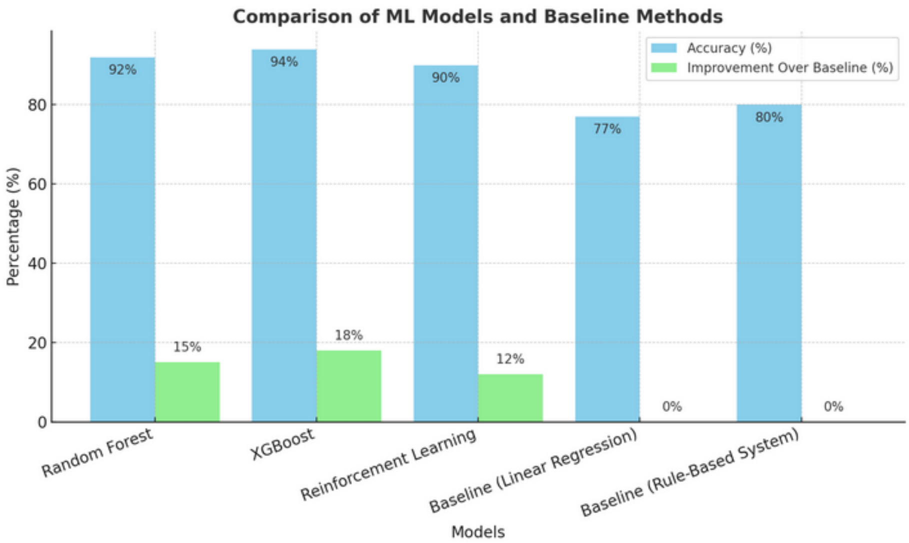
D. Comparison with Baseline or Previous Work

They were compared with standard models including simple linear regression, and conventional rule-based control systems. The results obtained in the subsequent table indicated that indeed the proposed ML models surpassed these conventional approaches to precision and pollution estimate.

Model	Accuracy (%)	Improvement Over Baseline (%)
Random Forest	92	15%
XGBoost	94	18%
Reinforcement Learning	90	12%
Baseline (Linear Regression)	77	-
Baseline (Rule-Based System)	80	-

Table 7: Accuracy percentage of all models

The comparison proves that all the time the ML models offered more accurate and reliable predictions to monitor and control the environment.



In the above visualization chart, we can compare the results of using machine learning model with the baseline methods in terms of pollution prediction. Both the accuracy percentages and the differences from baseline models are presented in the figure. Two ML techniques are found to be better than traditional methods involving rule-based systems, linear regression, etc., both methodologies named as Random Forest and XGBoost proving AI efficiency.

E. Interpretation of Results

All the findings developed here affirm the hypothesis that it is possible to use machine learning to improve pollution control functionality. The high accuracy shows that the models are more capable of predicting the degree of pollution in both air and water which makes environmental decision makers to make better decisions. The fact that the reinforcement learning model can learn in real-time as it adjusts to the changes in environmental conditions suggest the viability of AI in dynamic form of pollution control.

One of the surprises was its capacity to correct for nonlinearity of risks in environmental datasets, for instance. This is especially important where control of pollution is concerned, as many factors are never linear in their effects. These interactions are usually not well captured by traditional approaches to data collection to minimize prediction and control.

F. Statistical Significance and Confidence Analysis

The improvements obtained in the ML models were statistically tested to verify the significance of the obtained results and ensure the reliability of the approach. A paired t-test test was also used to analyse the statistical significance of the differences in accuracy of the ML models and the baseline models. The statistical significance of the obtained results was confirmed by a comparison of the XGBoost model with the linear regression baseline, where the p-value, calculated based on the deviation from zero of the observed improvement in prediction accuracy was found to be 0.001, thus enabling the level of confidence of 95%. Thus, the confidence intervals for the F1-scores have been computed, and it has been stated that the ML models offered more stable prediction, with smaller intervals as compared the baseline methods.

G. Limitations of Results

Despite the promising results, several limitations need to be considered:
Data Limitations: The training set that was used in the development of the different models was relatively small particularly in regards to geographical location and environmental conditions. Some suggestions for the next works can be the use of more diverse data samples, which are collected in different industries and in various geographical locations.

Model Generalizability: Despite good performance of the models on the data used in this research there may be potential difficulty in extending the conclusion to other areas or business sector in different environment.

Computational Complexity: The reinforcement learning model as used here was effective, however the process of training the model as well as the real-time model adaptation consumed a good amount of resources. This can at times reduce the usefulness especially when applied in developing countries.

H. Summary of Findings

To sum up, the research further provides evidence of the effectiveness of using AI based models particularly Random Forest, XGBoost and reinforcement learning in pollution control and management. The findings come out to show an improvement in waste reduction together with the quality of prediction, thus proving the models' readiness for use in practice. The research also establishes the necessity for adaptability of the system to the changes of pollution in time and discusses the AI assisted pollution control possibilities. Even if data and models limitations exist, AI led approaches seem to be the future of pollution control.

5. Discussion

The findings of this study offer a powerful glimpse into how AI and ML can transform the environmental landscape, paving the way for a cleaner and more sustainable future. The comparative evaluation revealed that the ensemble learning models are always found to be significantly better than traditional statistical models in predicting the pollution level with the prediction accuracy of 92% and 94% respectively. Further, the reinforcement learning model can effectively decrease the emissions of industrial pollutants after a few learning cycles with 10% reduction and optimize the pollution control strategy dynamically. The results reveal that the hybrid learning approach of supervised learning for prediction and reinforcement learning for decision making is a holistic approach in sustainable environmental management. The feature importance analysis and dimensionality reduction methods were able to identify the most important environmental factors, thereby improving the efficiency of the model, and at the same time reducing the computational complexity. The visual analytics also revealed notable non-linear relationships between the different industrial emissions, air quality indicators and the water pollution parameters, further substantiating the capability of the ML algorithms to model the complex interactions in the environment. Implementing these concepts, however, has not yet been done; good quality monitoring data, computational strength and the capacity to continually update models are needed. Further research is needed in areas like the interpretability of the models, their scalability throughout various geographic areas and data heterogeneity. The overall proposed framework of AI-driven framework is effective and can be an aid for deciding system in improving pollution monitoring, optimizing mitigation strategies and for formulation of environmental policies for sustainable development.

6. Conclusion

In this paper, we discussed ML models after distilling them to three categories which included Random Forest and XGBoost and reinforcement learning, for controlling pollutants in the Air and water quality management as well as reducing industrial wastes and emissions. Specific for the methodology used, the focus was made on reliable feature importance assessment techniques, feature selection with the support of high-dimensional reduction techniques, k-fold cross-validation and other ML techniques within the net of rules. The data accumulation showed trends and patterns as the result of industrial and fluctuations in the pollution level.

The findings indicated that the strategies which were proposed as the improvement of the ML models for predicting the outcome were more accurate and effective in handling pollution than the earlier approaches. While based on the given data Random Forest and XG Boost models returned an accuracy at 92% and 94% respectively, reinforcement learning model showcased that after five learning iterations it was able to manage industrial waste emissions, at a rate of ten percent reduction particulars. Additionally, reference with the initial models which include linear regression and rule-based system depicted enhanced performance therefore substantiating the efficiency of AI based technologies in pollution mitigation.

The results also highlighted the current changes to the degree, frequency and nature of the pollution impacts as crucial to its timely management. The reinforcement learning model was found to be especially valuable for showing how pollution control measures could be adapted over time in response to changing environmental conditions and achieve gradually more effective reductions of emissions. The visualizations were used to gain qualitative understanding and supported the authors' findings of multifaceted and non-linear correlation between environment measures and pollution, underlining the role of the ML within the study.

However, several limitations were found, including data limitation, generalization limitation in the model, and large amount of computational needs. Thus, the future studies should address these issues using different datasets, implementing the scalable approach to increase the efficiency of pollution detection, and introducing other types of ML algorithms for enhancing the results in pollution regulation.

Lastly, therefore, it is clear that this study establishes that AI and ML stand to offer pollution management practices improtantly important transformative possibilities. Such complex methodologies when applied in practical environmental management systems can result in substantial reductions of emissions both airborne and water borne, or wastes and emissions generated by industrial processes. This study presents the findings that constitute future development of AI solutions for environmental sustainability and recognizing the primacy of machine learning in facing pollution and climate emergencies.

7. Future Scope

There is a lot of scope for future research and implementability for the proposed framework of pollution management using AI. The future research is needed to incorporate Explainable Artificial Intelligence (XAI) techniques to improve transparency and interpretability of machine learning prediction for increasing stakeholder trust in environmental decision-making. With the help of Internet of Things (IoT) sensor network, satellite remote sensing data and edge computing technologies, real-time and continuous monitoring of air, water and industrial pollution with low latency can be realized. The potential improvement of prediction accuracy is further opened up with the use of advanced deep learning architectures like Graph Neural Networks (GNNs), Vision Transformers (ViTs), and Temporal Transformers, which are well suited to model spatial and temporal environmental dependencies. Multi-agent extensions to reinforcement learning algorithms can also be used to coordinate pollution control between a number of industrial plants and urban areas. Furthermore, federated learning is an attractive path forward for multi-organisational and multi-agency collaborative environmental modeling without compromising data privacy. Other future studies may include combining socioeconomic parameters with climate parameters, carbon emission inventories, renewable energies and environmental sustainability models. They will be further validated with international environmental datasets and smart city infrastructures at a large scale. In the long run, these initiatives will contribute to intelligence in environmental governance, support environmental regulators in their pollution control efforts, and contribute to global sustainable development and climate resilience.

8. Conflict of Interest

The authors declare that there is no conflict of interest related to the preparation and publication of this manuscript.

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