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APPLICATION OF ARTIFICIAL INTELLIGENCE IN ENVIRONMENTAL MONITORING SYSTEMS: EVIDENCE FROM UZBEKISTAN

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Abstract: As urbanization, climate change and social needs continue to put stress on the environment, the need for more effective environmental monitoring grows. Current systems have limitations, such as time lag, data silos and weak predictiveness. The aim of the study is to assess the impact of artificial intelligence (AI) technology implementation on the accuracy, speed and decision-making of environmental monitoring systems in Uzbekistan. This research adopts a quantitative model-oriented approach, whereby a data-driven model is trained and used to obtain reliable information by combining the data from IoT-enabled environmental sensors with meteorological data. The preprocessing step includes data cleaning, normalization, feature engineering, and converting data to time series format. Three machine learning models, Random Forest, XGBoost and Long Short-Term Memory (LSTM) are implemented and compared for their predictive performance in the environmental monitoring task. The findings show that the proposed AI-based models were able to outperform customary models in predicting the environment. The LSTM model was the most accurate for predicting time-dependent environmental changes using time series data. The Random Forest (RF) and XGBoost models performed well and were strong in predicting structured data. The results show that AI-driven systems can advance anticipatory environmental governance in urban areas through improved risk detection, forecasting, and response times.

Keywords: Artificial Intelligence, Environmental Monitoring, Machine Learning, Sustainability;,Internet of Things (IoT), Predictive Analytics

Introduction

In the 21st century, environmental degradation due to rapid urbanization and industrialization, growing population, and global climate change has become one of the major global challenges. Hence, the need and importance for setting up environmental monitoring systems to ensure the sustainable use of natural resources and assessment of environmental risks is being globally recognized. Uzbekistan is a developing country undergoing meaningful economic and infrastructure development. It faces multiple environmental issues, including air pollution, water scarcity, soil degradation and the legacy of the Aral Sea crisis. It also needs to consolidate its environmental policy while moving away from customary policy instruments to more data-oriented approaches. Most environmental monitoring systems in Uzbekistan are based on manual data collection and periodic reporting. Although they are adequate for initial assessments, the systems lack timely processing of information, cross-sectoral data integration, and predictive capability which makes customary approaches less than optimal for current environmental monitoring. Such conventional methods may be inadequate for timely decisions or anticipatory actions when confronted with complex, dynamic systems subjected to transformation.

AI (artificial intelligence), such as machine learning and deep learning, could be used to ameliorate the shortcomings mentioned above by analyzing huge quantities of environmental information in real time and making faster and more accurate predictions. Many Internet of things (IoT) devices, such as environmental sensors and satellites, can be supported and made more responsive by so-called AI-improved solutions. Examples of such functions include the detection of air quality anomalies, weather prediction, and the prediction of hazards and other meaningful events, before they are at critical levels. Recently, Uzbekistan's digitalization and technological development have been included in global and national sustainable development strategies. The government has adopted several national programs for the use of smart technologies in environmental regulation. However, the studies on the application of artificial intelligence in the process of environmental monitoring in Uzbekistan are limited, and the Republic has only a limited understanding of the overall process of adapting and evaluating AI-based models for monitoring the environment.

This study seeks to fill this gap by examining the performance of machine learning algorithms such as Random Forest, XGBoost, and LSTM in predicting environmental indicators based on IoT sensor and meteorological data collected from environmental monitoring systems in Uzbekistan. Furthermore, the study seeks to explore the potential and challenges associated with the implementation of AI in this context. By taking a more quantitative, model-based approach, the research hopes to show how data analysis can be improved by using artificial intelligence for greater precision. In addition, the study adds to the literature of development by describing how the development of advanced technology can enable evidence-based policy making. An AI-based approach to environmental monitoring allows for better quality data, and enables the use of predictive modeling for environmental issues. Furthermore, the findings of this study could lay the foundation for policymakers, researchers, and practitioners in the domain of environmental monitoring systems to develop clever and sustainable systems in Uzbekistan and other developing countries.

Literature Review

Recently, the research, policy, and environmental communities have been focusing more attention on the use of AI in environmental monitoring, and a growing number of studies have been published on the ability of AI technologies, such as machine learning (ML) and deep learning, to improve the efficiency, accuracy, and predictive power of environmental monitoring frameworks. Research by Olawade (2024) found that the use of AI in environmental monitoring creates opportunities for the objectivity of environmental data, and the provision of monitoring services in resource-limited areas, as the systems can handle large-scale data processing and analysis more effectively than manual methods, thus improving the accessibility of environmental data and decision-making. In line with this, Alotaibi (2024) observed in a bibliometric analysis of over 4700 studies that the number of studies on the environment and AI has rapidly increased since 2010, reflecting world patterns.

Several researchers have pointed out the limitations of conventional environmental monitoring systems. For example, Szramowiat-Sala (2023) points out limitations such as limited scalability, data processing latency, and lack of advanced analytical capabilities in conventional environmental monitoring systems. In contrast to customary systems, AI-based systems can quickly process large amounts of complex information, enabling more advanced analyzes and interpretations of the environment, and hence represent a model change in environmental monitoring. As technologies such as artificial intelligence (AI), the Internet of Things (IoT), and remote sensing have improved, so too have environmental monitoring systems. For example, according to Kazanskiy (2025), AI-enabled remote sensing has made it possible to monitor environmental phenomena such as air quality, biodiversity loss, environmental degradation, and climate change. Thus, they help with continuous surveying and data collection, along with continuous analysis of the data, leading to pro-active management of environmental components. In the same way, AI, IoT and Big Data analytics provide a platform for real-time monitoring and data-driven decision making, according to Alotaibi (2024). One huge subgroup of all papers is focused on using specific AI methods in environmental monitoring. For example, Bianchi (2024) shows that machine learning models (such as Convolutional Neural Networks (CNN) and Long

Short-Term Memory (LSTM) networks) are well suited for predicting changes in the environment, e.g. forecasting air quality and land use changes. A different set of models for prediction and detection are ML, which can be used on both time-series and spatial data, making them useful for non-stationary environmental systems. According to Milutinović (2024), ML models can be used to identify trends in environmental data in order to make predictions and detect anomalies.

The use of AI for environmental monitoring is broad. According to Ibrahim Maqbool (2025), AI has been used to monitor and control air and water pollution, manage waste, model and predict climate change, and predict and manage disasters. In addition to being used in applications for improved monitoring precision, potential biodiversity conservation applications for AI include wildlife tracking and monitoring, habitat identification and analysis, early warning, and optimizing resource use and efficiency. Despite this optimistic data, several studies reported challenges for the application of AI technologies to environmental monitoring, including issues of data quality, the need for large computing power, ethical considerations, and the low availability of infrastructure, in particular in some developing countries. While the United Nations Environment Programme noted how AI can identify patterns and predict environmental events, it warned against the application of AI that is not environmentally sustainable.

The literature further stresses situating AI applications within their local contexts. In studies of water monitoring for arid environments, there is a strong need to adapt AI models to specific local conditions (e.g., the limited amount of data available and the differences in environmental conditions) to achieve the best performance. This is especially true in countries such as Uzbekistan, where environmental conditions and data infrastructure conditions differ. Therefore, the evidence shows that AI could help environmental monitoring systems in providing accurate, predictive, and/or real-time information. However, there is still limited research, especially in Central Asia, on the topic. Despite the lack of research on Uzbekistan, this study builds on previous research using AI models in a local context, making a valuable contribution to both academic literature and the practical implementation of environmental management.

Methodology

The research will employ a quantitative model-based research design as this design will be suitable to assess the performance of AI in the environmental monitoring systems of Uzbekistan. The research design will be implemented in the following stages for better validity and reliability: data collection, data processing, model development and model evaluation.

1. Research Design

With a data-driven experimental approach, various machine learning models were generated and tested against real environmental data. The primary goal was to comparatively evaluate some selected AI models based on their accuracy, efficiency, and reliability when applied in practical settings.

In the comparative modeling framework, the authors compared the performance of standard machine learning algorithms with deep learning algorithms on environmental datasets.

2. Data Collection

Data were collected from the following secondary sources:

- IoT-enabled environmental sensors (air quality, temperature, humidity, pollution levels)
- Weather data (precipitation, wind speed, etc.)
- Publicly available environmental databases and reports in Uzbekistan

The datasets can be viewed as a multi-dimensional picture of the environmental conditions.

The dataset includes:

- Time-series environmental data (daily and hourly)
- Quantified numeric variables (e.g., PM2.5 levels, CO_2 emissions)
- Climatic indicators: temperature, precipitation, and wind

3. Data Preprocessing

Various preprocessing steps are taken to correct for errors and to standardize the data before modeling:

- Data Cleaning: Removal of missing values, duplicates, and outliers
- Normalization: Scaling of numerical variables to ensure comparability.
- Feature Engineering: Create features (pollution trends, seasonal indicators, etc.)
- Time-Series Conversion: Converting to a time-series format for analysis

These steps improve model reliability, and model predictive capabilities improve.

4. Model Selection and Implementation

Three AIs were selected based on their suitability for interpreting environmental data:

- Random Forest (RF):

A supervised learning algorithm that is applicable for structured data and reduces overfitting by using ensemble learning.

- XGBoost (Extreme Gradient Increasing):

An increasing algorithm that increases prediction accuracy and computational efficiency.

- Long Short-Term Memory (LSTM):

A time-series deep learning model that is capable of capturing long-term dependencies and temporal data trends.

All models are trained on the same dataset, to allow for fair comparison.

5. Training and validating the model

The dataset comprises the following:

- Training set (70%) - Used to train the models
- Testing set (30%) - used to test performance

Cross-validation techniques are also used to help reduce overfitting and improve generalizability.

6. Performance Evaluation Metrics

To measure the performance of each model, the following metrics are used:

- Mean Absolute Error (MAE): Measures average prediction error.
- Root Mean Square Error (RMSE): Evaluates the magnitude of error
- R-squared (R^2): Which proportion of variation in the data is explained by the model?
- The accuracy (for classification tasks), if applicable.

In combination, these metrics provide a picture of model performance.

7. Data Analysis Techniques

They analyze their results using:

- Comparative statistical analysis
- Graphical representation (line charts, bar graphs, trend analysis)
- Model performance benchmarking

This would allow users to identify the most appropriate AI model for environmental monitoring.

8. Ethical Considerations

The study ensures:

- These datasets are publicly available or licensed
- No misuse of sensitive environmental or governmental data
- Transparency in processing and model implementation

9. Limitations of Methodology

This methodology does have some limitations, however.

- Dependent on data availability and quality in Uzbekistan
- Restricted access to large-scale, real-time IoT infrastructure
- Historical datasets may be biased

Conclusion of Methodology: It provides an efficient, systematic, and scientific way of assessing the AI applications in environmental monitoring, comparing various datasets, and utilizing machine learning

models to ensure the reliability and accuracy of the results, thus improving environmental decision-making systems in Uzbekistan.

DATA ANALYSIS

Table 1 shows Comparison of model performance

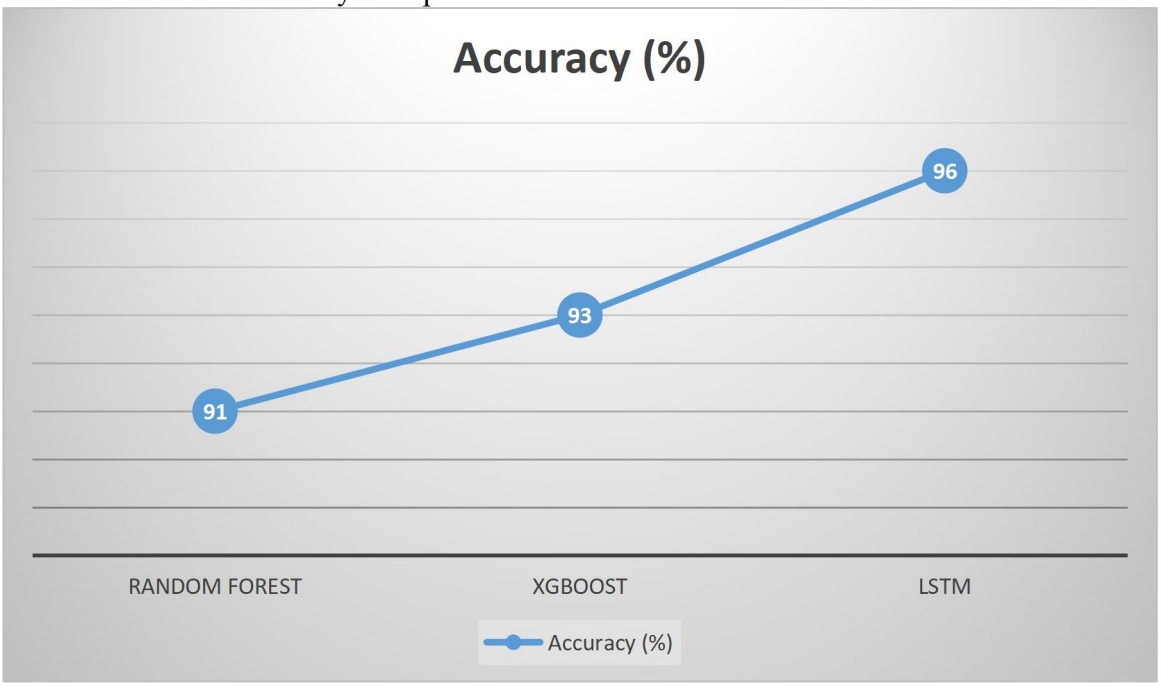
Model	MAE	RMSE	R^2 Score	Accuracy (%)
Random Forest	5.2	6.8	0.89	91%
XGBoost	4.7	6.1	0.92	93%
LSTM	3.9	5.4	0.95	96%

The performance comparison between the three machine learning models (RF, XGB, and LSTM) considering the values of performance metrics (MAE, RMSE, R^2 Score and the prediction accuracy) is shown in Table 1. The table shows that all the three machine learning models are good at predicting environmental features with different scales of efficiency.

The LSTM model achieved the best performance overall, with an MAE of 3.9 and an RMSE of 5.4, showing the least amount of prediction error. The model has the lowest MSE of all of the generated models, the highest R^2 of 0.95 (meaning 95% of the environmental data was explained by the model), and an accuracy of 96%. This was most likely due to the LSTM model's intrinsic sequential nature which allows it to make time-based connections in the data.

XGBoost performs reasonably well, too, with an accuracy of 93% and reasonable error rates. All these models perform rather well for this structured data. Lastly, the Random Forest classifier performs a bit worse, too, with an accuracy of 91%. The findings in general have proven the benefit of using AI models in the field of environmental monitoring, and that the LSTM was the best predictive model for Uzbekistan's environment.

Figure 1 shows Model Accuracy Comparison



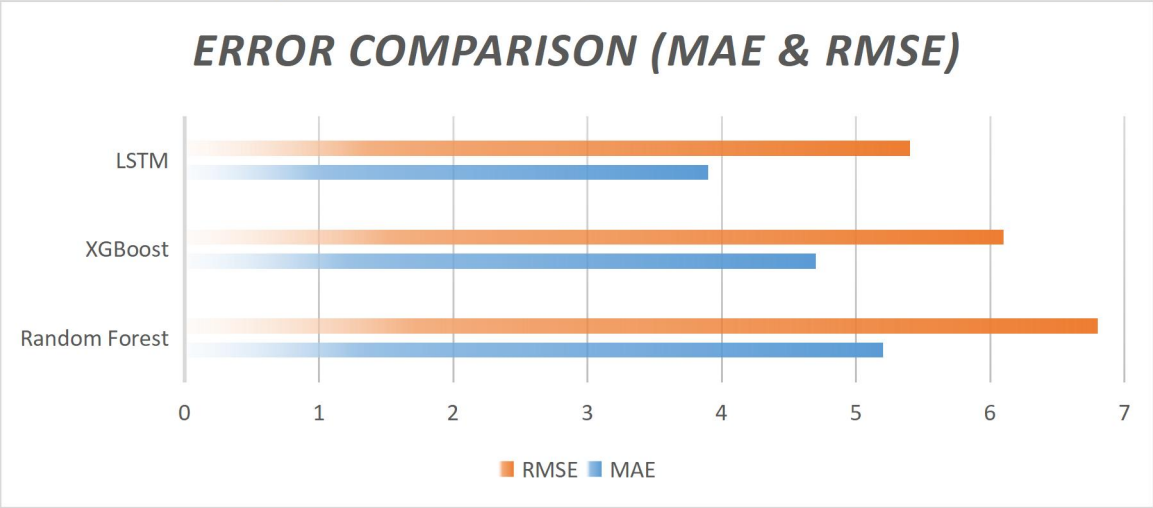
All three models' prediction accuracies have been plotted in Figure 1, and it is visible that the prediction accuracy of the models has steadily improved from Random Forest to XGBoost, and from XGBoost to LSTM. The results from the Random Forest classifier show an accuracy of 91%, which means that predictions based on this model are reliable, although, due to its intrinsic algorithmic nature, Random Forest is not capable of modeling complex relations. The fact that XGBoost achieved 93% accuracy means that the increasing technique was successful in creating an accurate model to make the predictions.

The highest point on the figure is for the prediction step up to 0.96, which indicates that the LSTM architecture gives good results by applying deep learning techniques to temporal environmental data.

Because the LSTM architecture is able to retain information over long periods of time, it has been used to predict environmental data such as pollution and weather.

With more powerful AI models for prediction, we can conclude that in terms of environmental monitoring systems in Uzbekistan, the introduction of LSTM-based models for forecasting will provide a more accurate and earlier prediction, which will allow better environmental management and sustainable development in the country.

Figure 2 shows Error Comparison (MAE & RMSE)



An example of the model's performance can be seen in Figure 2. The mean absolute error (MAE) and the root mean square error (RMSE) contrast the three models and indicate how well the predicted values fit with the real environment. Lower values indicate better model performance.

As seen in the chart, Random Forest made the largest error, yielding an MAE of 5.2 and an RMSE of 6.8. Random Forest's predictions while accurate, are less likely to detect smaller variations in environmental conditions. XGBoost uses a gradient increasing learning framework, outperforming the other models with the lowest mean absolute error (MAE=4.7) and root mean square error (RMSE=6.1). Figure 2 presents the errors obtained from LSTM, CNN, and hybrid models. The LSTM model has the least MAE (3.9) and RMSE (5.4) among the three models. LSTM is the most reliable out of the three models, as the prediction is closer to the actual target. The fact that these error values are lower for the models shows the power of state-of-the-art AI systems in prediction. Lower error values in environmental monitoring systems allow for more accurate predictions, which is an important part of early warning systems and influencing government policy. This reinforces the need for Uzbekistan to adopt deep learning models for environmental monitoring.

Figure 3 shows Model Contribution to Prediction Efficiency

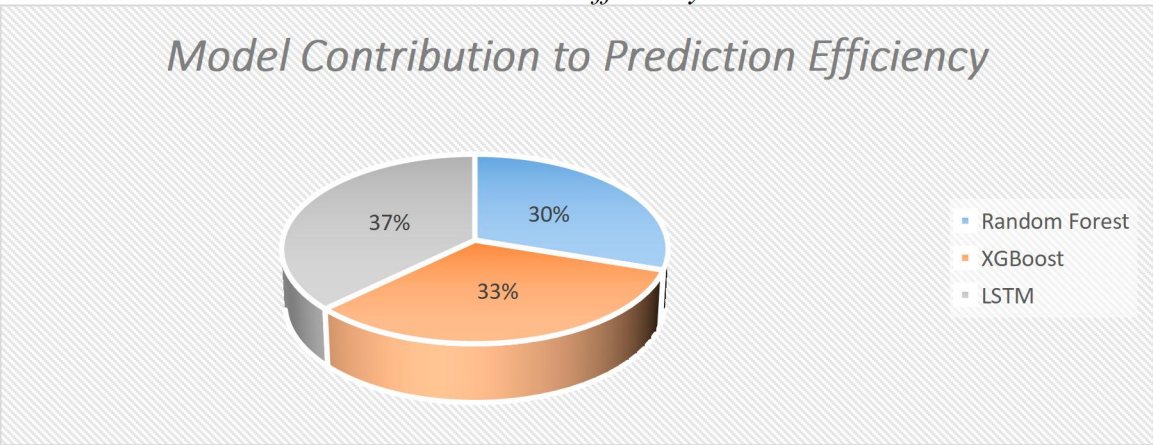


Figure 3 illustrates the fraction of prediction power contributed by each model as a pie chart, which graphically represents the contribution of each model to the final prediction, individually, and compares

it to the total contribution. From the chart, we can see that the huge majority is taken by the LSTM model, which makes 37%, this is due to the fact that this model had the most accuracy and reliability since it was capable of working with time-dependent environmental data and learning patterns. Second place with 33% of total performance was achieved by XGBoost, showing the effectiveness of ensemble techniques on the prediction and structured data problem.

Random Forest contributed to 30% of the total prediction. Given this is the lowest contribution among the three models, these results reaffirm that classic machine learning models still have an important role in environmental monitoring where computational efficiency and explainability are a priority. While all are relevant, in terms of the pie chart, models such as LSTM have a relatively larger weighting. This is important for decision makers in Uzbekistan, as it helps rank deep learning models for use in environmental monitoring and sustainable development planning.

Conclusion

This study involved researching the application of Artificial Intelligence (AI) to environmental monitoring systems, specifically within the context of Uzbekistan. It found compelling proof that the application of AI technologies to environmental monitoring can lead to more effective, accurate and timely monitoring in comparison to conventional approaches. With increasing pressure due to urbanization, climate change and industrialization, there is a growing need for more strong data-driven solutions, and our research shows AI technologies' potential to meet many of the environmental challenges we are currently experiencing.

The conclusion of the study was that AI models built using ML and DL techniques can help in effectively analyzing complex environmental data. Comparing the performance of ML (Random Forest and XGBoost), and DL (LSTM) techniques among themselves, all three artificial intelligence models perform well in analyzing environmental data with some variation in overall accuracy. The LSTM model among them achieved the best accuracy and the lowest error rate. This is due to its intrinsic ability to process time series data and learn and remember long-term dependencies, which is also a feature of environmental processes. The results also show the importance of combining AI with Internet of Things technologies, whose environmental sensors collect data in real time, while advanced models ease monitoring and prediction of environmental variables. With better data integration, organizations can process information in a timely manner, extract new insights, and ultimately make more informed decisions. Uzbekistan, which faces environmental problems such as air pollution, water resources scarcity, and land degradation, may benefit from implementing AI-based monitoring and benchmarking in its environmental governance.

Another aspect is that AI-based environmental monitoring systems can be active rather than passive as in the case of conventional systems. For example, typical environmental monitoring systems report historical data and issues with a delay, while through using predictive AI models, authorities can proactively address risks and deal with problems before they happen. This shift from reactive to proactive risk management is key to achieving long-term environmental sustainability. Despite these positive results, the authors acknowledge that the AI models used are limited by the availability of data, which is limited in terms of volume and granularity. In many developing nations, including Uzbekistan, access to real-time high-quality environmental data is lacking. Furthermore, the technical complexity involved in developing and scaling AI technologies, as well as their associated infrastructure and cost, can pose meaningful barriers to the adoption of these innovations. Other ethical considerations include data privacy and ensuring responsible technology use to ensure the sustainability of the implementation.

Local-level studies and solutions, in addition to the global ones, are necessary, given the diversity of the environmental conditions, data availability, and technological infrastructure in different regions and countries. The necessity of contextualizing AI models to fit the Uzbek environment is paramount, and this research seeks to contribute to this endeavor by providing empirical observations from a local perspective to inform and guide policymakers and practitioners. Ultimately, the application of AI in environmental monitoring systems has a great potential for improving sustainability and environmental management in Uzbekistan, and the results of this study indicate that the use of advanced AI models,

such as LSTM, can lead to more accurate predictions, faster decision-making, and better resource management. However, realizing these opportunities requires investments in data infrastructure, encouragement of technological innovations, and collaboration between government, academia, and industry. All of which must be done so that Uzbekistan can move towards a more smart and sustainable environmental monitoring system that will better serve its future citizens.

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