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AI driven Environmental Monitoring: A Hybrid CNN- BiLSTM approach for Predicting Air Pollution

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Abstract

The systematic process of observing and analysing environmental parameters like air, water, soil, climate and biodiversity using sensors, satellite systems, and analytical techniques to assess environmental condition is referred to as Environmental Monitoring. It plays a crucial role in understanding, controlling, and mitigating the impacts of climate change, ecosystem degradation, and pollution. But the growing complexity and volume of environmental data have exposed the limitations of traditional monitoring methods, which often rely on manual data collection and conventional statistical analysis. Thus, the integration of Artificial Intelligence (AI) has significantly enhanced the scope and effectiveness of environmental monitoring by enabling real-time data processing, predictive modelling, and intelligent decision-making. This paper presents a comprehensive study that combines a general overview of environmental monitoring with the application of AI techniques for air pollution prediction. A hybrid deep learning model based on Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) is proposed and implemented using a five-year air pollution dataset from Delhi. The CNN component captures spatial patterns and noise characteristics in pollutant data, while the BiLSTM model effectively learns temporal dependencies to improve prediction accuracy. The results demonstrate the superiority of the proposed model in forecasting air quality compared to conventional approaches.

The paper also highlights the alignment of AI-based environmental monitoring with key Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being), SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land). By improving environmental prediction, resource management, and policy formulation, AI contributes significantly to sustainable development and climate resilience. Despite its advantages, challenges such as data availability, privacy concerns, and the need for skilled expertise remain critical considerations.

Keywords: Artificial Intelligence, Environmental Monitoring, Air Quality Monitoring, Sustainable Development Goals (SDGs)

1. Introduction

Environmental monitoring is the process of observing and analysing data related to air, water, soil, climate, biodiversity, and pollution levels through the use of sensors, satellites, and analysis to determine the status of the environment.

Environmental monitoring is an important activity in comprehending, controlling, and correcting the effects of climate change, degradation of ecosystems, and environmental pollution. It entails the systematic collection, analysis, and interpretation of environmental information such as air quality, water quality, land use, biodiversity, and climatic factors to facilitate informed decision-making and sustainable environmental management. With the increasing threats of climate change to ecosystems, economies, and human welfare, environmental monitoring has become imperative for forecasting environmental changes and facilitating early corrective measures for adaptation and mitigation.

One of the most important factors that make environmental monitoring a highly relevant topic in the current scenario is the growing complexity of environmental issues. The traditional methods of environmental monitoring involve the use of human resources for data collection and statistical analysis, which is not very effective in handling large amounts of data. Artificial Intelligence (AI) has proven to be a revolutionary tool that can process large amounts of environmental data and provide predictive insights that can make environmental monitoring more accurate and efficient. Environmental monitoring is a critical aspect of climate change analysis and prediction. AI-powered environmental monitoring tools have the ability to analyse past and current climate information to identify trends in atmospheric factors, ocean temperatures, greenhouse gas emissions, and land use changes. This is a critical aspect of improving the accuracy of climate models and the ability to predict future environmental trends such as global warming, weather-related disasters, and disruptions in ecosystems. This predictive ability enables climate researchers and policymakers to develop effective climate adaptation and mitigation strategies.

Another important area of environmental monitoring is the collection and analysis of real-time environmental data. Contemporary environmental monitoring systems combine data from satellite images, sensor networks, and Internet of Things (IoT) sensors to offer real-time and accurate environmental information. AI algorithms can analyse such data in real time and issue early warnings for environmental hazards such as pollution surges, deforestation, floods, and forest fires. The ability to monitor the environment in real time enables authorities to act promptly and prevent environmental damage.

Environmental monitoring is also an important aspect of biodiversity protection and ecosystem management. Based on ecological data, AI-powered environmental monitoring systems can monitor species distribution, habitat, and ecosystem health. This helps ecologists detect threatened species, measure ecological imbalance, and take appropriate biodiversity conservation measures. Environmental monitoring is vital for maintaining ecological balance and preserving biodiversity under environmental conditions

Environmental monitoring also facilitates pollution control and resource management. Environmental monitoring of air quality, water quality, and industrial emissions can detect pollution sources and measure environmental hazards. AI-powered models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have shown remarkable accuracy in predicting air quality and levels of environmental pollution, allowing for preventive measures for environmental protection. These predictive models improve environmental governance and facilitate the sustainable utilization of resources

The application of environmental monitoring has been greatly enhanced with the integration of modern technologies like remote sensing, AI, machine learning, and sensor networks. These technologies allow for large-scale monitoring in various environmental sectors, including climate, land use, water, and atmospheric environments. AI-powered environmental monitoring systems can provide high-resolution real-time information to improve decision-making and facilitate environmental policy formulation and sustainable development objectives.

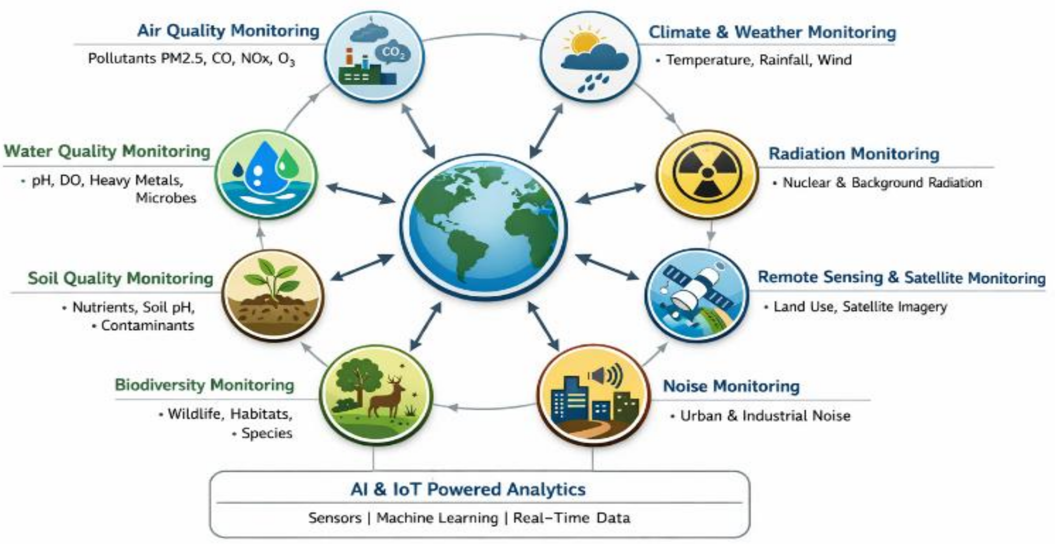

Fig1: Key areas of Environmental Monitoring

Fig 1. shows a general map of essential environmental monitoring areas in smart cities which include air, water, and soil quality, weather and climatic conditions, biodiversity, radiations, noise and remote sensors. These spheres are becoming more interconnected with each other in the age of Artificial Intelligence, which provides tools of the IoT and certain sensors as well as data-driven analytics to collect and process environmental data in real-time. The prediction, detection of anomalies and effective management of resources within interdependent ecological systems should be predicted correctly, using AI and machine learning methods. This combined monitoring system does not only boost environmental awareness and decision making, but it also promotes sustainable urban development by resolving issues like pollution control, climate resilience and ecosystem conservation.

Furthermore, environmental monitoring contributes to climate change mitigation efforts by enabling emission tracking, renewable energy optimization, and carbon management. AI-based systems can detect emission hotspots, monitor carbon levels, and optimize renewable energy production, thereby reducing environmental impact and supporting global climate goals. These capabilities highlight the critical role of environmental monitoring in achieving sustainable development and environmental protection

In summary, environmental monitoring is highly relevant for addressing global environmental challenges, improving climate prediction, protecting ecosystems, managing pollution, and supporting sustainable development. The integration of AI has significantly expanded the scope and effectiveness of environmental monitoring by enabling real-time data analysis, predictive modelling, and intelligent decision-making. As environmental challenges continue to grow, AI-enabled environmental monitoring will play a vital role in ensuring environmental sustainability and climate resilience.

Moreover, environmental monitoring also helps in mitigating climate change by allowing the tracking of emissions, optimization of renewable energy, and carbon management. AI-based systems are capable of identifying hotspots of emissions, tracking carbon, and optimizing renewable energy, thus minimizing environmental effects and helping in meeting global climate objectives. The above points emphasize the importance of environmental monitoring in achieving sustainable development and environmental protection.

In conclusion, environmental monitoring is very much relevant to global environmental challenges, climate prediction, environmental protection, pollution management, and sustainable development. The inclusion of AI has greatly increased the importance and efficiency of environmental monitoring by allowing real-time analysis and intelligent decision-making. With increasing environmental challenges, AI-based environmental monitoring will play a very important role in ensuring environmental sustainability and climate resilience.

2. Literature Review

Environmental monitoring is an important aspect in the study of the effects of climate change, pollution trends, and the sustainability of ecosystems. Traditional methods of environmental monitoring involve human observation and statistical analysis, which are not scalable and predictive. Artificial Intelligence (AI) improves environmental monitoring by providing an opportunity for automated analysis and prediction. Machine learning and deep learning algorithms analyse large-scale environmental data obtained from satellite images, sensors, and IoT devices, making predictions more accurate and contributing to sustainable environmental management [1], [2].

AI greatly improves air quality monitoring by predicting the levels of air pollution and pinpointing the sources of pollution. Machine learning algorithms such as Random Forest and Support Vector Machines analyse environmental data to predict air pollution levels. Deep learning algorithms, specifically Convolutional Neural Networks (CNN), provide accurate environmental mapping and pollution detection from satellite images. AI improves environmental risk analysis and provides an opportunity for anticipatory environmental protection [2], [7]. Long Short-Term Memory (LSTM) networks improve time-series predictions of environmental factors such as temperature, air quality, and climate change.

AI-based environmental monitoring systems also enhance the analysis of climate change and disaster prediction. Conventional weather forecasting systems use physical modelling simulations that demand high computational power. AI-based models enhance the accuracy of predictions by detecting hidden patterns in environmental data and facilitating early warning systems for severe weather-related disasters like floods, droughts, and cyclones. These systems enhance climate change resilience and help in adapting to climate change [1], [5].

AI helps in sustainability by facilitating environmental protection and Sustainable Development Goals (SDGs). AI-based water quality monitoring systems facilitate real-time detection of pollutants, helping in SDG 6 (Clean Water and Sanitation). AI-based air quality monitoring systems improve public health, helping in SDG 3 (Good Health and Well-being). AI helps in biodiversity conservation, land monitoring, and environmental protection, contributing to SDG 15 (Life on Land). AI also helps in renewable energy optimization and reduction of emissions, contributing to SDG 13 (Climate Action) [3], [6].

The integration of AI with IoT, remote sensing, and cloud computing makes intelligent environmental sensing and continuous monitoring possible. AI-based systems offer real-time environmental analysis, anomaly detection, and predictive capabilities. These systems help in environmental governance, climate mitigation, and sustainability planning. AI-based environmental monitoring systems improve environmental protection and resource management [2], [7].

However, there are challenges in the implementation of AI for environmental monitoring. Data quality, availability, and accessibility are important factors that influence model performance. Deep learning models are not interpretable, which raises difficulties in transparency and trustworthiness. Ethical issues associated with data privacy, governance, and infrastructure constraints also need to be addressed. Researchers have stressed the need for sustainable and interpretable AI models, referred to as Green AI, for environmentally responsible AI deployment [4].

In conclusion, AI has revolutionized environmental monitoring with improvements in prediction accuracy, automation, and sustainability performance. AI-based environmental monitoring systems help in climate change adaptation, pollution management, and sustainable development. Further research and development will improve AI applications in environmental monitoring and sustainability.

3. Methodology

3.1 Data Collection

The data that is being used in the current research is the high-resolution data of the environmental monitoring of 23 different air quality monitoring sites in the National Capital Region (NCR) of India, which encompasses Delhi, Noida, Gurugram, Faridabad, and Ghaziabad. The data is within the period of six years (2020-2026) and has a total of 201,664 observations on an individual basis. Each record has one complete set of environmental indicators, divided into the major pollutants, namely Particulate Matter, Nitrogen Dioxide, Sulphur Dioxide, Carbon Monoxide, and Ozone and the key meteorological parameters, such as temperature, relative humidity, wind speed, and visibility. The predictive model focus on the target variable of the hourly Air Quality Index (AQI) which is further broken down into categorical indices of health-risk (e.g., Moderate, Poor, Severe).

Attribute	**Details**
Geographic Coverage	Delhi-NCR (Delhi, Noida, Gurugram, Faridabad, Ghaziabad)
Time Period	January 2020 – December 2025
Total Observations	201,664 records
Monitoring Stations	23 stations
Key Features	6 Pollutants (PM2.5, PM10, NO2, SO2, CO, O3) + 4 Weather metrics
Target Variable	Air Quality Index (AQI)

Table 1: Attributes in the dataset along with the details

```
Data columns (total 25 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   datetime      201664 non-null  object
 1   date          201664 non-null  object
 2   year          201664 non-null  int64
 3   month         201664 non-null  int64
 4   day           201664 non-null  int64
 5   hour          201664 non-null  int64
 6   day_of_week   201664 non-null  object
 7   is_weekend    201664 non-null  int64
 8   season        201664 non-null  object
 9   city          201664 non-null  object
 10  station       201664 non-null  object
 11  latitude      201664 non-null  float64
 12  longitude     201664 non-null  float64
 13  pm25          201664 non-null  float64
 14  pm10          201664 non-null  float64
 15  no2           201664 non-null  float64
 16  so2           201664 non-null  float64
 17  co            201664 non-null  float64
 18  o3            201664 non-null  float64
 19  temperature   201664 non-null  float64
```

Fig 2: Sample data set (Column name and details available in the dataset)

3.2 Model Development

The hybrid CNN + BiLSTM model is used to predict AQI levels using its methodology. The initial stage is the raw time-series data, which is initially normalized during the preprocessing stage to enhance the convergence of the model. The data is then passed in the sequence into the 1D-CNN layer that detects the essential local spatial features and eliminates ambient noise. These characteristics are subsequently on fed to the BiLSTM layer that extracts both forward and backward temporal relationship to model the past and future contextual relationship in the air quality trends. Lastly, mapped data using a dense layer is used to produce the overall AQI prediction.

Step	Component	Role
1	Input & Preprocessing	Normalization and cleaning of AQI data.
2	CNN Layer	Extraction of local feature patterns.
3	BiLSTM Layer	Modeling of long-term bidirectional temporal dependencies.
4	Output Layer	Regression output for predicted AQI value.

Table 2: Components available in the model and their role

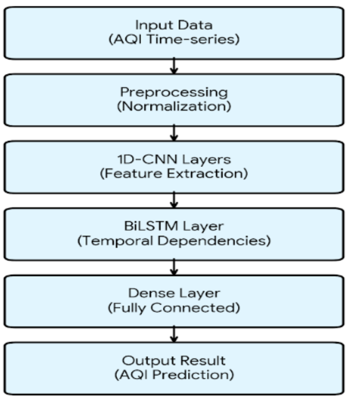

Fig3: Hybrid CNN-BiLSTM architecture for AQI Prediction

4. Results and Interpretations

The AQI of the hybrid CNN-BiLSTM model was tested with the Delhi-NCR AQI data. The outcome shows that the model is very competent in the short-term variation and long-term seasonal patterns in the quality of the air.

	precision	recall	f1-score	support
0	0.93	1.00	0.96	2905
1	0.99	0.96	0.98	9083
2	0.93	0.96	0.94	3764
3	0.98	0.95	0.97	6438
4	0.99	1.00	0.99	12165
5	0.97	0.98	0.98	5978
accuracy			0.98	40333
macro avg	0.97	0.97	0.97	40333
weighted avg	0.98	0.98	0.98	40333

Fig 4: Classification Report of the proposed model

With a high overall accuracy of 98% on the Delhi NCR AQI dataset, the classification report shows that the suggested CNN–BiLSTM model performs well in all classes. While recall values between 0.95 and 1.00 demonstrate the model's efficacy in correctly identifying the majority of true instances, precision values between 0.93 and 0.99 show that the model generates very few false positives. For every AQI category, the F1-scores, which are continuously above 0.94, demonstrate a fair trade-off between recall and precision. Furthermore, the weighted-average (0.98) and macro-average (0.97) scores attest to the model's consistent performance even in the face of class imbalance, demonstrating its dependability for practical environmental monitoring applications.

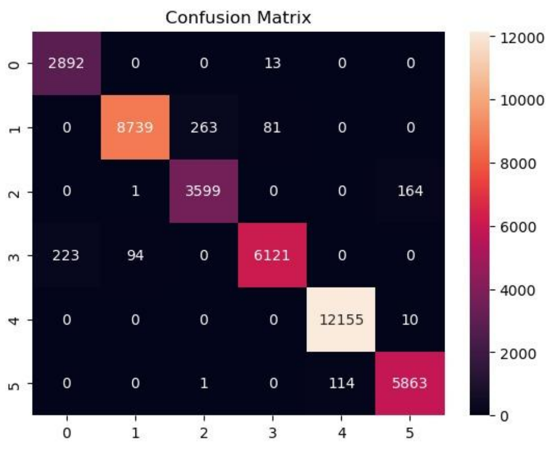

Fig 5: Confusion Matrix of CNN- BiLSTM Model

These conclusions are further supported by the confusion matrix's strong diagonal dominance, which shows that the majority of the predictions fall along the main diagonal, indicating accurate classification. Confusion between classes 1, 2, and 3, or between classes 4 and 5, are examples of the few misclassifications that have been found. The gradual transition and overlapping characteristics of air quality levels make this pattern expected. Crucially, the lack of notable misclassification between distant classes indicates that the model has effectively acquired significant feature representations and is capable of differentiating between clearly different levels of pollution.

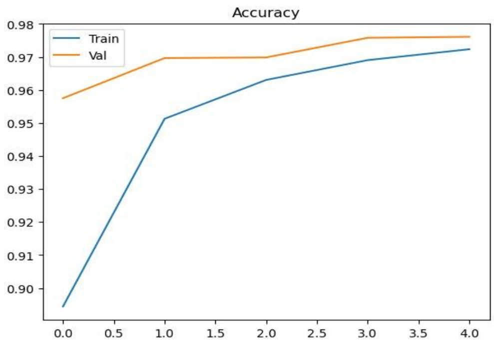

Fig 6: Validation accuracy of CNN- BiLSTM Model

The training and validation accuracy obtained shows a steady increase and converge around 97–98%, which indicates consistent learning. Since there is close alignment between the two curves it suggests good generalization with no signs of overfitting.

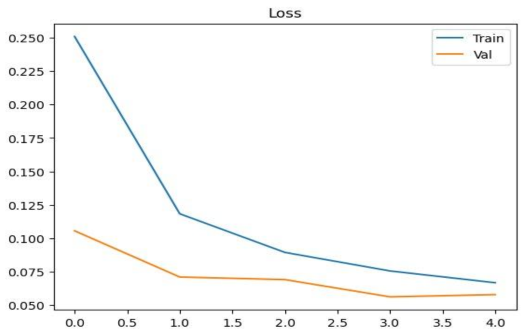

Fig 7: Validation Loss Graph

Insights into the models learning behaviour can be obtained by training and validation loss curves. Both losses decrease steadily over successive epochs, with training loss dropping from approximately 0.25 to 0.07 and validation loss from around 0.10 to 0.06. The close alignment between the two curves indicates minimal generalization gap, suggesting that the model does not suffer from overfitting or underfitting. The stabilization of validation loss after a few epochs reflects convergence, demonstrating that the model has effectively learned the underlying data patterns. Overall, these results confirm the robustness, stability, and generalization capability of the CNN–BiLSTM model for AQI classification.

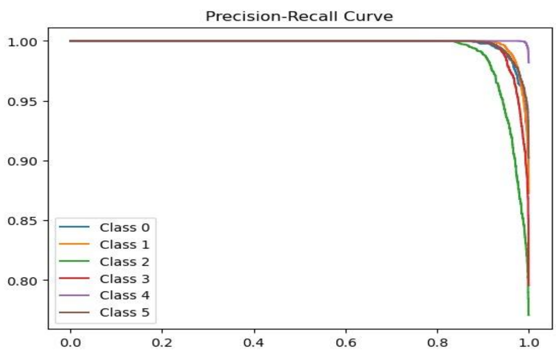

Fig 8: Precision Recall Curve of hybrid Model

High precision and recall across various thresholds are indicated by the concentration of the curves for all classes near the upper-right corner. The obtained results show how well the model can identify AQI categories with few false positives and false negatives.

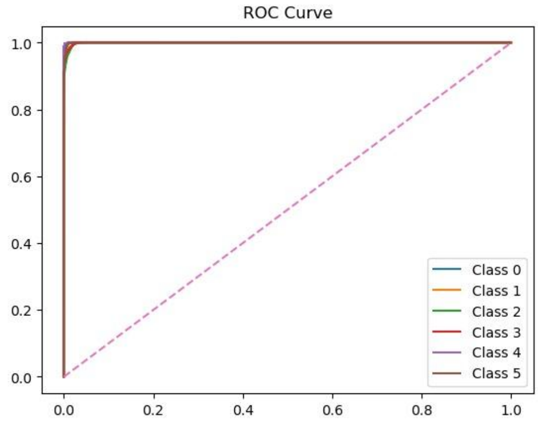

Fig 9: ROC curve obtained after application of model

The ROC curves obtained for all classes closely follow the top-left boundary, demonstrating excellent class separability and near-perfect performance which indicates a high true positive rate with a very low false positive rate across all categories.

Discussion

The performance of this model is due to the two-stage data processing framework. The CNN layer present effectively filters the sensor noise and captures meaningful patterns. The second layer i.e. BiLSTM layer influences temporal dependencies and helping to achieve more accurate interpretation of the data.

5. Environmental Monitoring and Sustainable Development

Sustainable development is based on satisfying the current needs without jeopardizing the future generations capacity to satisfy their own needs with a great emphasis on the environment, efficiency of resources to meet their needs and society in general. The adoption of artificial intelligence (AI) within recent years is a disruptive solution to these objectives, which will allow us to make decisions and monitor the environment in real time, using the data.

AI plays a crucial role in supporting Sustainable Development Goals (SDG). Table 3 cites how various AI Applications are helping to achieve certain SDGs, such as SDG 13 (Climate Action), SDG 3 (Good Health and Well-Being), SDG 6 (Clean Water and Sanitation), and SDG 15 (Life on Land).

AI Application	**Description / Use**	**Related SDG**	**How it Supports the SDG**
Climate prediction using LSTM and RNN models	Forecasting temperature trends, extreme weather events, and long-term climate patterns	SDG 13: Climate Action	Enhances climate resilience, supports mitigation strategies, and improves disaster preparedness
Disaster prediction and early warning systems	Predicting floods, wildfires, hurricanes, and droughts using real-time sensor data	SDG 13: Climate Action	Reduces vulnerability to climate-related hazards and strengthens adaptive capacity
Air quality monitoring using AI models	Real-time analysis and forecasting of pollution levels (AQI, PM2.5, CO_2)	SDG 3: Good Health and Well-Being	Helps prevent health risks by enabling early interventions and pollution control
Water quality assessment with AI	Monitoring contamination, predicting water quality changes	SDG 6: Clean Water and Sanitation	Ensures safe water availability and supports sustainable water resource management

AI Application	Description / Use	Related SDG	How it Supports the SDG
Land cover classification using CNN	Detecting deforestation, land-use changes via satellite imagery	SDG 15: Life on Land	Supports ecosystem conservation, forest management, and biodiversity protection
Wildlife tracking and ecosystem monitoring	AI-driven analysis of species movement and habitat changes	SDG 15: Life on Land	Aids in biodiversity conservation and restoration of terrestrial ecosystems
Integrated environmental sensing systems	Combining satellite, sensor, and IoT data for holistic monitoring	SDG 13 & SDG 6	Enables informed policy decisions for climate action and sustainable water management

Table3: AI application and related SDG

The introduction of AI into the sphere of environmental control enhances the achievement of a sustainable development greatly because such a solution allows making correct judgments and managing resources as well as predetermining decisions. The applications described reveal the ways in which technology can be directly used in meeting some of the major SDGs as well as solving practical environmental issues. Therefore, AI-based solutions are vast in terms of creating resilient, sustainable, and environmentally responsible societies.

6. Conclusion

The study demonstrates the transformative role of Artificial Intelligence in advancing environmental monitoring by overcoming the limitations of conventional methods. The proposed CNN–BiLSTM hybrid model, applied to a five-year Delhi NCR air pollution dataset, achieves high classification performance with 98% accuracy and strong precision, recall, and F1-scores. The macro and weighted averages also affirm that there is balanced performance despite the difference in class distribution. The confusion matrix analysis indicates that there was high diagonal dominance, which means that most of the samples were correctly classified, and few cases of misclassification were only between the neighbouring AQI levels, due to its natural similarity and gradual change of the pollution levels. Moreover, the training curve and the validation curve show a continuous decrease and finally converge, and the difference between the two is small, which means that the model learns and generalises successfully without overfitting. The findings indicate that the hybrid architecture is very effective in using CNN to extract spatial features and BiLSTM to learn temporal relationships and is, therefore, very applicable in systems of smart environmental monitoring and air quality prediction.

The findings also highlight the contribution of AI-driven environmental monitoring toward achieving key Sustainable Development Goals, particularly **SDG 3 (Good Health and Well-being)**, **SDG 6 (Clean Water and Sanitation)**, **SDG 11 (Sustainable Cities and Communities)**, **SDG 13 (Climate Action)**, and **SDG 15 (Life on Land)**. Overall, the study underscores the potential of AI-enabled systems for sustainable and intelligent environmental management.

References

1. Steven Dewitte, Jan P. Cornelis, Richard Müller and AdrianMunteanu, "Artificial Intelligence Revolutionises Weather Forecast, MDPI, 2021.
2. David et.al, "Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions", Hygiene and Environmental Health Advances, Elsevier, 2024.
3. Favour N. Eze, Adepeju Nafisat Sanusi, lsrael Jonathan Iheoma," Artificial Intelligence in Climate Change Mitigation and Adaptation: A Review of Emerging Technologies and Real-World Applications ", Global Journal of Engineering and Technology advances, 2025
4. Adedolapo Olujuwon Adegbite, Ibrahim Barrie et.al., "Artificial Intelligence in Climate Change Mitigation: A Review of Predictive Modeling and Data-Driven Solutions for Reducing Greenhouse Gas Emissions ", WJARR, 2024.

5. Daisy Shah, Harnessing Artificial Intelligence for Climate Resilience: Advancements in Environmental Monitoring and Predictive Mitigation,n pj Digital Medicine,
6. Olivia Bianchi1*, Herman Purwoko Putro, Artificial Intelligence in Environmental Monitoring: Predicting and Managing Climate Change Impacts, International Transactions on Artificial Intelligence (ITALIC) Vol. 3, No. 1, November, 2024, pp. 85−96, 2024.
7. Artificial Intelligence in Environmental Monitoring: In-Depth Analysis, Research Paper, 2024.
8. M Rastogi, Goel N et.al, “Predicting Air Pollution: A Smart Step in Pollution Management”, Recent Advances in Aerospace Engineering, Springer ,2024
9. U. Rusilowati, H. R. Ngemba, R. W. Anugrah, A. Fitriani, and E. D. Astuti, “Leveraging ai for superior efficiency in energy use and development of renewable resources such as solar energy, wind, and bioenergy,” International Transactions on Artificial Intelligence, vol. 2.
10. V. Melinda, T. Williams, J. Anderson, J. G. Davies, and C. Davis, “Enhancing waste-to-energy conversion efficiency and sustainability through advanced artificial intelligence integration,” International Transac tions on Education Technology (ITEE), vol. 2, no. 2, pp. 183–192, 2024.
11. Y. J. Wong, Y. Shimizu, A. Kamiya, L. Maneechot, K. P. Bharambe, C. S. Fong, and N. M. Nik Sulaiman, “Application of artificial intelligence methods for monsoonal river classification in selangor river basin, malaysia,” Environmental Monitoring and assessment, vol. 193, no. 7, p. 438, 2021.
12. M. Pereira, I. Guvlor et al., “Implementation of artificial intelligence framework to enhance human resources competency in indonesia,” International Journal of Cyber and IT Service Management, vol. 4, no. 1, pp. 64–70, 2024.
13. Z. Fan, Z. Yan, and S. Wen, “Deep learning and artificial intelligence in sustainability: a review of sdgs, renewable energy, and environmental health,” Sustainability, vol. 15, no. 18, p. 13493, 2023.
14. N. Misra, Y. Dixit, A. Al-Mallahi, M. S. Bhullar, R. Upadhyay, and A. Martynenko, “Iot, big data, and artificial intelligence in agriculture and food industry,” IEEE Internet of things Journal, vol. 9, no. 9, pp. 6305–6324, 2020.
15. Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdalla, H., Mahfood, B., 2020. Artificial intelligence applications in solid waste management: a systematic research review. Waste Manage. 109, 231–246.
16. Abebe, W.T., Endalie, D., 2023. Artificial intelligence models for prediction of monthly rainfall without climatic data for meteorological stations in Ethiopia. J. Big Data 10
17. Ahmed, T., Zounemat-Kermani, M., Scholz, M., 2020a. Climate change, water quality and water-related challenges: a review with focus on Pakistan. Int. J. Environ. Res. Public Health 17 (22), 8518.
18. Kumar, S., & Hooda, S. . (2023). Healthcare and Hospital Promotions and Audience Reception. *MediaSpace: DME Media Journal of Communication*, *3*(01), 16–19. https://doi.org/10.53361/dmejc.v3i01.03
19. Chauhan, D., Bahad, P., Jain, J.K., 2024. Sustainable AI: environmental implications, challenges, and opportunities. Explain. AI (XAI) Sustain. Develop. 1–15.
20. Chen, Y., Song, L., Liu, Y., Yang, L., Li, D., 2020. A review of the artificial neural network models for water quality prediction. Appl. Sci. 10 (17), 5776.
21. Fan, Z., Yan, Z., Wen, S., 2023. Deep learning and artificial intelligence in sustainability: a review of SDGs, renewable energy, and environmental health. Sustainability 15 (18), 13493.
22. Kumar, S. ., & Hooda, S. (2023). An Analytical Review of Political Communication in India with Special Reference to the Social Media. *MediaSpace: DME Media Journal of Communication*, *3*(01), 8–15. https://doi.org/10.53361/dmejc.v3i01.02
23. Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environmental science and pollution research, 29(28), 42539-42559.