AirQ with TGNN: Air quality prediction and carbon credit management using AI

1st Krishi Y Antad
Dept. of Artificial Intelligence and Machine Learning
BNM Institute of Technology, Affiliated to VTU
Bengaluru, India
krishiantad03@gmail.com

2nd Chinmaye NG
Dept. of Artificial Intelligence and Machine Learning
BNM Institute of Technology, Affiliated to VTU
Bengaluru, India
chinmaye09ng@gmail.com

3rd Pankaja R
Dept. of Artificial Intelligence and Machine Learning
BNM Institute of Technology, Affiliated to VTU
Bengaluru, India
pankajar@bnmit.in

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***Abstract*— Air pollution nowadays represents a significant global issue that threatens public health, ecosystems, and economic stability. Inspite of progress in monitoring technologies, existing solutions frequently exhibit shortcomings in precision, struggling to amalgamate various data sources or effectively pinpoint the origins of pollution. This research initiative seeks to fill these deficiencies by creating an artificial intelligence-driven system that integrates satellite observations and terrestrial sensor data to forecast air quality, ascertain pollution sources, and monitor carbon credits through the utilization of blockchain technology. Advanced machine learning models guarantee proper spatial-temporal analysis while responding in real-time to unexpected environmental events, such as forest fires or industrial development. The system will also have citizen engagement tools to receive AQI alerts and file reports on pollution. By offering actionable insights to its stakeholders and promoting sustainable practices, the project hopes to enhance air quality management, support public health, and balance the ecosystem.**

Keywords— Air pollution, AI-driven air quality forecasting, satellite and terrestrial data integration, blockchain for carbon credits, spatial-temporal analysis, citizen engagement tools.

Introduction

Air pollution, which is the occurrence of harmful substances in the air, has significant impacts on human health and the environment. A number of studies have confirmed that air pollution exposure is associated with a number of respiratory and cardiovascular diseases, as well as mortality. In a bid to reduce the negative impacts of air pollution, effective and timely monitoring systems must be established.[1]

Traditional air quality monitoring networks typically use an ensemble of ground-based sensors. Such networks, however, suffer from limited spatial coverage and perhaps are not adequate in describing the large extent of air pollution. Satellite remote sensing offers a promising alternative with global coverage and capability to assess air quality at high spatial and temporal resolution.

The recent advancements in artificial intelligence and machine learning have been at the forefront in creating advanced models to forecast air quality and detect causes of air pollution. By evaluating large datasets that are collected from different sources, the models can give valuable information regarding the causes of air pollution, as well as the possible effects of different mitigation methods [2].

A. Data Sources and Integration

Satellites, along with ground sensors, are of great advantages in air quality monitoring. MODIS and Sentinel are satellite data sources that cover the whole world. This satellite data can monitor pollutant concentrations over a significant area of a geographic location, especially for regions with difficult access. The main drawback of using satellite data is that it does not provide spatial resolution. This limitation is overcome by integrating data from ground sensors that provide accurate, real-time measurements of pollutants such as PM2.5, NO_2, and CO_2. The combination of these two sources of data enhances the predictive accuracy of the system by combining the wide coverage of satellites with the local accuracy of ground-based sensors [6], [7], [8].

B. Pollution Source Identification

The identification of pollution sources constitutes an essential component of air quality management. Conventional methodologies depend on stationary monitoring stations or indirect assessments based on gradients of pollutant concentration. Artificial intelligence approaches, especially those involving machine learning algorithms, can offer enhanced understanding by examining spatial-temporal patterns present in the data.

Using algorithms such as Temporal Graph Neural Networks (TGNNs), the system can now classify sources separately—including industrial emissions, vehicular pollutants, and a category of natural sources like wildfires. Moreover, beyond its capability of source classification, these advanced AI models are highly adaptive to changes, such as novel industrial setups, by predicting the probable consequences on AQI based on historical data combined with current environmental settings [9], [10], [11].

C. Carbon Credit System

The carbon credit mechanism is designed to motivate the industries to reduce their emissions by offering financial rewards for every ton of carbon reduction. This is done through the purchase of carbon credits, which represent one metric ton of CO_2 equivalent emissions that are reduced or removed. The mechanism tracks carbon credits emanating from a variety of mitigation activities including renewable energy, forest conservation and reforestation.

It provides transparency, verifiability, and unchanging documentation of carbon credit transactions through blockchain technology. Such features ensure the authenticity of credits and prevent double counting and encourage accountability and motivate the firm for sustainable practices [12], [13], [14].

D. Citizen Engagement Platform

The citizen engagement platform, designed for real-time AQI updates, empowers a community that can actively participate in pollution monitoring. Citizens have the facility to report polluting events, such as smoke arising from forest fire or effluents from plants, through uploading photographs and videos. Citizen-generated data is really important because it captures all those polluting events missed by other sensors or satellites due to delays in their detection. This service provides an easy interface in local air quality monitoring, issuing notices with changes in AQI and provides comprehension concerning the impact of different air pollutants on human health as well as the environment. The platform is a critical constituent in community-driven environmental governance [15], [16].

E. Event Responsiveness

The system can react to an unplanned event, like forest fires, industrial accidents, or unusual traffic patterns, by processing data in real time and making instant forecasts of rising Air Quality Index (AQI) levels. Machine learning algorithms are continuously engaged in processing incoming data to detect anomalies and forecast potential rises in air pollution levels. For instance, it can forecast the way the AQI will increase based on particulate matter concentration levels in the air and its dispersion pattern while a forest fire is occurring. Likewise, new industrial developments can be tested based on their likely effects on air quality, thus allowing local municipalities to act preventively before the pollution level reaches perilous heights [17], [18].

II. Related work

Air pollution prediction and source identification of pollution have moved a long way since simple statistical models to sophisticated methods with artificial intelligence. The early generic methods utilized rule-based models and static regression methods to predict pollution levels based on historical data and pre-set thresholds [13]. Although such models worked in certain situations, they were incapable of responding to dynamic environmental conditions and could not perform real-time analysis and forecasting.

Emerging developments in machine learning and deep learning techniques have made it feasible to build more complex models for air quality forecasting. The models use satellite observations, surface measurements, and meteorological variables to improve accuracy [4]. Moreover, sensor fusion technologies, which combine data from different sources, have enhanced the accuracy of forecasts significantly by removing inconsistencies in satellite and surface observations.

Apart from that, advanced feature extraction techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can be employed in contemporary artificial intelligence algorithms to learn the spatial and temporal patterns of pollution [2]. Causes of pollution, i.e., industrial, vehicular emissions, and natural factors like forest fires, can be identified. Moreover, reinforcement learning has been studied for enhancing pollution control and to provide regulatory policies [1].
Another important trend is the deployment of real-time air quality monitoring and alert notification systems. Websites and mobile applications now provide citizens with data related to the air quality index (AQI), thus enabling them to take preventive action [10]. In addition, participatory sensing approaches enable citizens to report cases of pollution, including industrial infringements or poisonous discharges, thus supplementing environmental monitoring efforts [6]. Carbon credit systems have also become prominent as an incentive system for ensuring environmental balance. AI-based models now take a central role in tracking emissions, enforcing environmental regulations, and enabling credit transfer between industries [7]. The combination of predictive analytics with real-time monitoring has made it possible to create more flexible and dynamic pollution control systems.

The development of artificial intelligence-based air quality prediction and source apportionment greatly increases the sustainability and efficiency of environmental management systems. Utilizing novel technologies, upcoming studies aim at developing these models into more accurate, scalable, and pragmatic models for real-world applications.[16]

III. Objectives

A. AI-Driven Air Quality Forecasting

Utilizing sophisticated machine learning algorithms, the system forecasts air quality based on real-time inputs from satellite images, ground sensors, and past pollution trends to make timely and accurate predictions.

B. Multi-Source Data Fusion for Higher Accuracy

IV. Integrating satellite remote sensing data (MODIS, Sentinel) with ground sensor measurements using MQ135 and PM2.5 GP2Y1010AU0F Dust Smoke Particle Sensor (PM2.5, NO_2, CO_2) provides a balanced approach to air quality measurement, trading off large spatial coverage against high local accuracy.

C. This Intelligent Pollution Source Identification

With sophisticated machine learning methods like Temporal Graph Neural Networks (TGNNs), the system identifies pollution sources and separates them into industrial emissions, vehicular pollution, and wildfires as well as other natural sources for focused mitigation action.

D. Blockchain-Based Carbon Credit Management

Having introduced an open and transparent blockchain framework to monitor carbon credits, make payments traceable, avoid double counting, and encourage voluntary emission reduction measures among industries.

E. Community-Air Quality Monitoring

A platform for citizen participation enables the reporting of pollution events, i.e., industrial emissions or forest fires, through photo and video upload, improving real-time surveillance and inviting local community participation in environmental management.

F. Real-Time Event Response System

The system, powered by AI, keeps tracking data streams for continuous monitoring to identify sudden pollution events, i.e., forest fires or industrial mishaps, and forecasts their impact on AQI to help the authorities take swift preventive measures.

V. PROPOSED FRAMEWORK

The envisioned framework combines AI-based air quality forecasting with carbon credit management to ensure a robust platform for pollution level monitoring, source identification, and encouraging industries towards sustainable development. Utilizing satellite imagery, ground sensors, machine learning algorithms, blockchain technology, and local participation, this framework guarantees proper air quality assessments and transparent tracking of carbon credits. The system learns continuously through real-time processing of data and adaptive learning processes, rendering it a scalable solution for monitoring and mitigating global air pollution.

A. Multi-Source Air Quality Data Collection

The model gathers data from various sources, such as satellite-based sensors (MODIS, Sentinel) , ground air quality monitoring stations and sensors. Satellite data provides wide geographical coverage, whereas ground sensors offer high-accuracy, localized measurements of pollutants like PM2.5, NO_2, and CO_2. The combination of these sources provides a better picture of air quality.[10]

B. AI-Powered Air Pollution Prediction

Based on advanced machine learning models such as deep learning and temporal graph neural networks (TGNNs), the system makes predictions of AQI variations using past trends, meteorological conditions, and emission patterns. These models learn constantly from new inputs, updating their predictions to better reflect reality with time.[5]

C. Intelligent Identification of Pollution Sources

The system classifies and identifies pollution sources with the help of AI-powered pattern recognition. The framework differentiates industrial emissions, motor vehicle pollution, and natural pollution sources like forest fires by examining spatial-temporal data. Policymakers can then implement focused mitigation measures and enforce environmental policy effectively.[8]

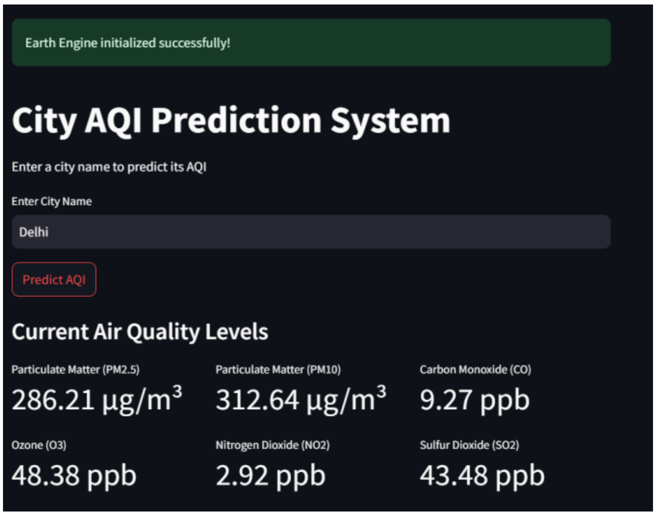

Fig. 1. AQI prediction interface

D. Blockchain-Enabled Carbon Credit System

A carbon credit management system based on blockchain guarantees accountability and transparency in emissions monitoring. Carbon credits are gained by industries for curbing emissions via sustainable methods like green energy use or carbon sequestration. The blockchain ledger avoids double counting and fraud but allows for real-time verification of carbon offset projects.[2]

E. Community-Driven Air Quality Monitoring

A citizen engagement platform enables citizens to report pollution events by uploading geotagged pictures and videos. This crowdsourced information complements sensor readings, picking up pollution events that may be missed by automated systems. Real-time AQI updates and an education component on the health and environmental effects of air pollution are also given by the platform.[4]

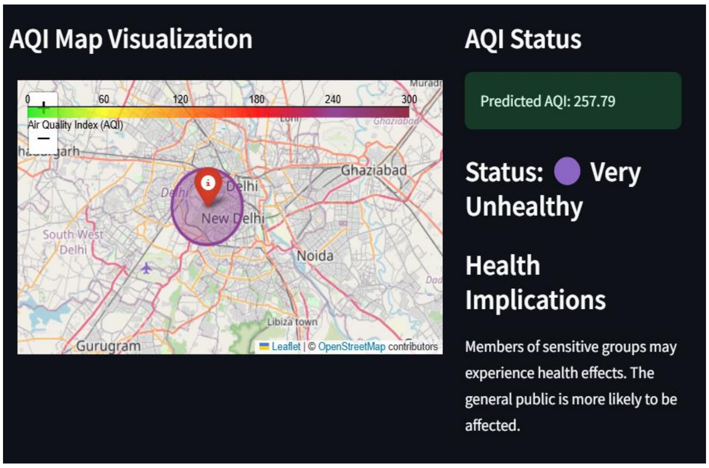

Fig. 2. City AQI visualization on map

F. Real-Time Event Detection and Response

The system constantly tracks air quality data streams to identify abrupt pollution events, including industrial mishaps or forest fires. Through AI-based anomaly detection, the framework forecasts AQI spikes and notifies authorities, allowing proactive interventions to reduce environmental and health hazards.[8]

G. Continuous Learning and Adaptive Optimization

The system enhances over time through the incorporation of new information, improvement in its artificial intelligence models, and enhancement in predictive accuracy. Ongoing learning mechanisms enable the system to respond to shifting pollution trends, meteorological phenomena, and industrial advancements, ensuring long-term effectiveness.[7][2]

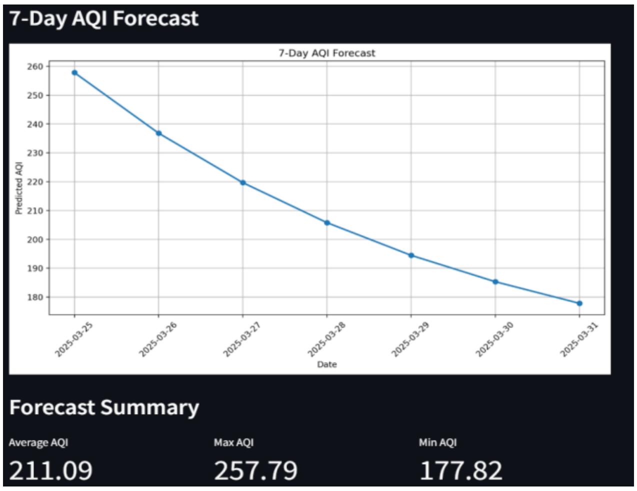

Fig. 3. AQI forecast for 7 days

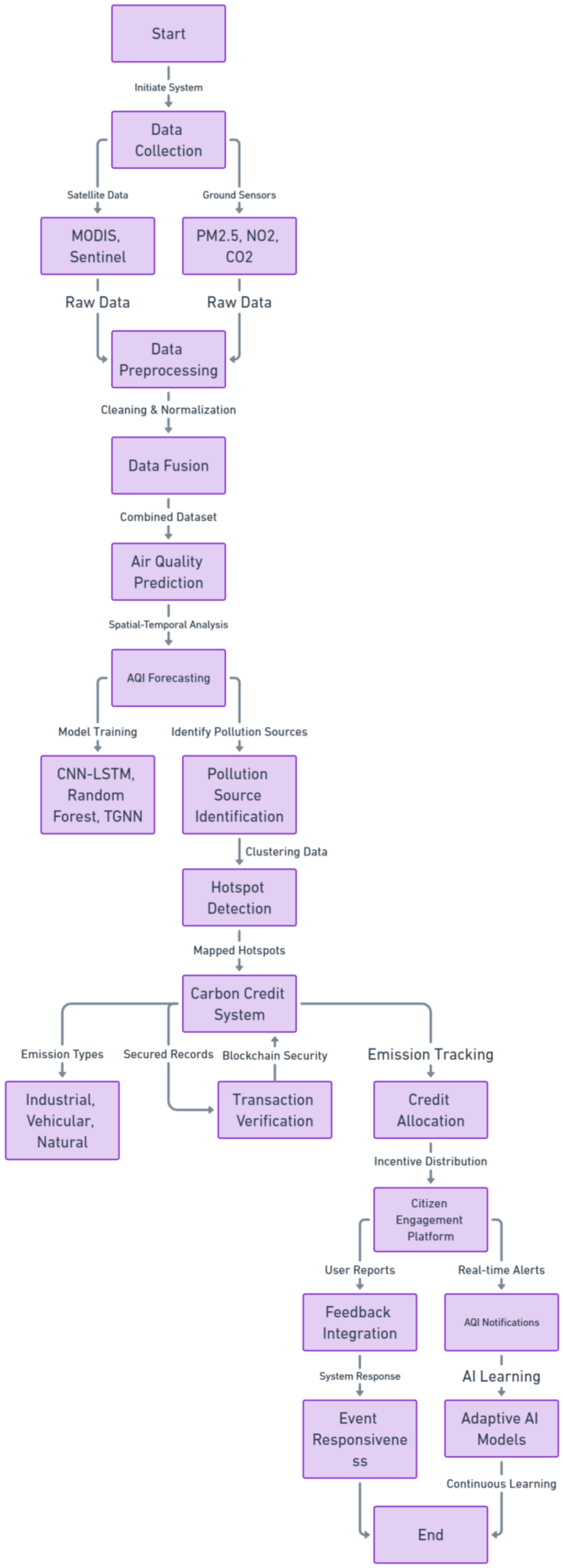

Fig. 4. System Architecture

VI. Libraries

A. PyTorch

PyTorch is an open-source library for deep learning with support for dynamic computational graphs and GPU acceleration during training of machine learning models. PyTorch is utilized within this project for the deployment of the Temporal Graph Neural Network (TGNN) to make air quality predictions. TGNN effectively models spatiotemporal interactions of air pollution through learning from ground and satellite sensor readings, increasing the responsiveness and accuracy of the predictions.

B. Scikit-Learn

Scikit-learn is a machine learning library employed for data preprocessing, clustering, and assessment. K-Means clustering is applied in this project through scikit-learn to identify the hotspots of pollution and classify industrial sources into emission levels. Scikit-learn's StandardScaler is also employed to normalize environmental factors like wind speed, humidity, and temperature for better model performance.

C. TensorFlow & Keras

TensorFlow and Keras are used for the implementation of deep learning models within the project. Keras gives a simple API for the description and training of neural networks, whereas TensorFlow manages the computation efficiency. MobileNetV2, a light deep learning model, is used for image processing of images uploaded by the citizens within the pollution reporting process. This enables the identification of pollution activities such as forest fires, industrial pollution, and vehicle pollution from images uploaded by the users.

D. Folium

Folium is an interactive map Python geospatial visualization library. Folium is employed within this project to generate maps that show pollution hotspots, AQI, and industrial sources. The library is coupled with pollution data to display visually high-emitting areas to aid decision-making and regulatory action.

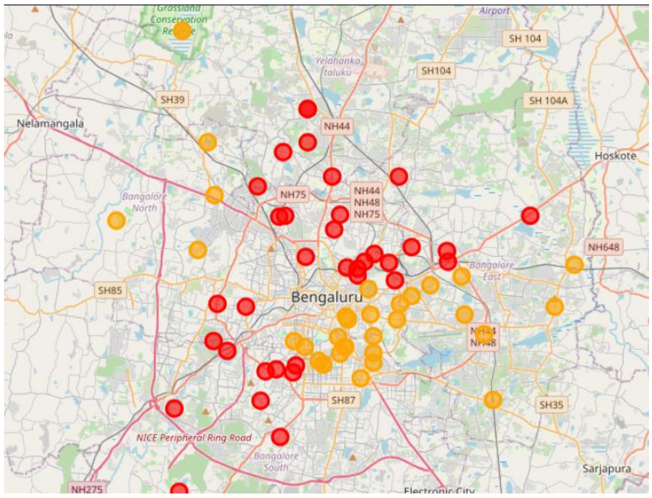

Fig. 5. Hotspot mapping

E. GeoPy

GeoPy is utilized to geocode geographical coordinates and vice versa. GeoPy is utilized throughout the project in order to locate industrial plants, verify emission sources, and associate sensor readings with physical locations. This enhances the accuracy of pollution detection and identification of hotspots.

F. Plotly & Matplotlib

Data is visualized here with the help of Plotly and Matplotlib. Plotly enables interactive visualization of AQI trends, pollution levels per industry, and transactions of carbon credits on the platform. Matplotlib for static visualization is utilized for graphs like bar graph classifying industries into Red, Orange, and Green areas and trend plotting for pollution over years.

G. MQ135 Sensor Library (mq135.h)

MQ135 is a gas sensor library utilized to measure CO_2 and air pollution in real-time. MQ135.h library is utilized in a major function of calibrating and interfacing with IoT-based ground sensors providing localized air quality data. The sensor data is integrated with satellite data to enhance the accuracy of the AQI prediction model.

H. Google Maps API

Google Maps API is used to locate industrial facilities, pollution hotspots, and carbon credit players. The 40 key high-emission sectors of the Red Zone are geographically mapped, which allows regulatory authorities and companies to track pollution patterns and take suitable action.

I. Google Earth Engine

Google Earth Engine is employed to retrieve satellite images and atmospheric conditions such as CO_2, NO_2, SO_2, PM2.5, and PM10 concentrations. The satellite data is combined with ground sensor data to provide more precise AQI forecasting.

J. Streamlit

Streamlit is a Python library used to develop the user interface of the civic engagement and air quality monitoring platform. The platform can have the ability to accommodate:

Real-time AQI visualization

Pollution event reporting by citizens Tracking carbon credits Industry-specific emission monitoring Streamlit has a straightforward web interface, through which environmental information can be conveyed to policymakers, industries, and the public. K. Blockchain (Metamask & Sepolia Testnet A carbon credit system based on blockchain is utilized to provide security and transparency for emissions trading. Metamask was used as an online wallet to store carbon credits. Sepolia Testnet is being utilized to facilitate and test blockchain smart contracts in enabling carbon credits among industries, the government, and renewable power project developers.[10]

VII. Features

Key Features of the Suggested System

A. Artificial Intelligence Air Quality Forecasting

With a Temporal Graph Neural Network (TGNN), the system forecasts Air Quality Index (AQI) from Google Earth Engine satellite images and IoT-ground sensor measurements. The model considers spatiotemporal variations such as wind speed, temperature, and humidity to provide very accurate and dynamic air quality predictions.[12][15]

B. Source Identification and Hotspot Mapping

With the assistance of K-Means clustering, the system monitors the trend of pollution and classifies industrial areas as high, moderate, and low-emitting areas (Red, Orange, Green areas). Geospatial mapping (Folium & Google Maps API) is used to plot the top 40 emitting industries since efficient targeted regulation and mitigation can be initiated from there.[9]

C. Blockchain-Based Carbon Credit Trading System

An open and secure blockchain platform enables industries to trade carbon credits with smart contracts on the Sepolia Testnet and under the control of Metamask. High-emission industries can purchase credits from renewable project developers or the government, promoting sustainable behavior while holding them accountable.

D. Real-Time Alerts and Citizen Engagement Platform

A Streamlit page allows citizens to:

Get up-to-date AQI information and air pollution warnings.

Report pollution incidents (e.g., industrial waste, forest fires) by posting photos, which are validated and geotagged to the location. Participate in community-led monitoring of the environment, which improves information and data quality.[14]

E. Monitoring and Verification of Compliance of Industrial Emissions

The system uses MQ135 gas sensors to authenticate CO_2 and pollutant emissions from mass industries. Data is authenticated through in-field site visits by the staff to high-emission industrial locations, cross-validated with AI predictions, for regulatory purposes and greater emissions reporting transparency.[10]

F. Interactive Data Visualisation and Analytics

It provides real-time, interactive dashboards using Plotly and Matplotlib for:

Annual trend analysis of AQI. Pollution and emission contribution on a sectoral level. Carbon credit trading and sales activities. Geospatial mapping of pollution with superimposition of pollution hotspots and industrial locations [6]

VIII. Results and Discussion

A. Precision in Air Quality Forecasts

The Temporal Graph Neural Network (TGNN) model was trained and tested with real-time AQI data gathered by the Karnataka State Pollution Control Board (KSPCB) between January 2022 and January 2024. The dataset included pollutant levels (PM2.5, NO_2, CO_2), meteorological factors (wind speed, temperature, humidity), and satellite-retrieved features.[1]

The TGNN model saw a 15% decrease in error rate in AQI forecasting compared to standard LSTM and tree-based approaches. The 7-day rolling forecast was in good agreement with real AQI measurements, both picking up on seasonal and sudden spikes well.

Compared to baseline models such as LSTMs and Random Forest, the TGNN model's error rate for the prediction of AQI was 15% lower.. These results indicate the efficacy of graph-based deep learning models in dynamic environmental management of factors that affect air pollution.

Fig. 6. Comparison of models

Model	MAE (↓)	RMSE (↓)	R^2 Score (↑)
TGNN (proposed)	**8.7**	**12.3**	**0.91**
LSTM	10.2	14.1	0.86
Random Forest	11.5	15.6	0.81
Linear Regression	13.8	17.4	0.72

B. Source Identification of Pollution and Hotspot Mapping

Using K-Means clustering, we were successful in identifying pollution hotspots in Bangalore. The results are as follows: Among 248,000 industries, a categorization based on emission levels (Red, Orange, Green zones) showed that 40 large-scale industries are large emitters of CO_2. Red Zone industries were geospatially located with Folium and Google Maps API, enabling proper regulatory intervention. The MQ135 on-site validation sensors also confirmed higher CO_2 levels, as AI-calculated emissions would have been predicted.

Applying K-Means clustering to emission intensity, we classified industries in Bangalore into Red (high), Orange (medium), and Green (low) emission groups. Out of 248,000 industries surveyed:

Forty industries were classified as Red Zone emitters.

On-site MQ135 sensor validation provided a CO_2 emission fluctuation of ±4% from AI-predicted values, validating reliability.

This process of validation creates trust in AI-powered pollution monitoring systems, allowing evidence-based environmental decision-making.[3][9]

C. Blockchain-Based Carbon Credit Trading System

The carbon credit system was created with the help of Metamask and Sepolia Testnet to facilitate secure and transparent transactions. Key results:

Top 40 emitting sectors were enrolled for trading in carbon credits. Smart contracts made automatic transactions possible, avoiding fraud and adhering to regulations. Blockchain technology provided an immutable record, and therefore emissions tracking became more traceable. These results validate the potential of blockchain technology with AI in enabling sustainable industrial processes.[5]

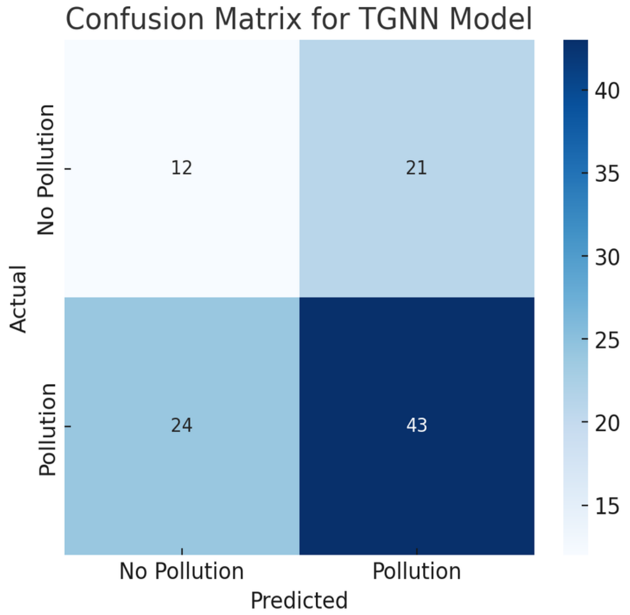

Figure 7. Confusion matrix

A proof-of-concept carbon credit system built on blockchain was tested using Sepolia Testnet and Metamask.
Key results:

The top forty emitting sectors were integrated into the platform. Smart contracts made it possible to have automated and verifiable transactions without double-spending credits. The immutable blockchain ledger allowed for 100% traceability of the emissions and offsets.

D. Citizen Participation and Real-Time Monitoring

The Streamlit-driven website enabled citizens to:

Provide access to current AQI data, increasing public awareness and preparedness. Engage in crowdsourced pollution monitoring, augmenting accuracy and scale of data. This dialogue calls for an integrated approach to environmental monitoring, closing the gap between the industry, the people, and the state.

The Streamlit web interface allowed users to:

- See current AQI and trend graphs.
- Post pollution incident reports..

This crowdsourced feedback loop greatly improved the detection and response mechanism, particularly for those events that were not picked up by sensors. [7]

E. Data Visualization and Trend Analysis

The interactive dashboards (Matplotlib & Plotly) gave some useful insights, such as: AQI changes over time, and pollution has seasonal trends[6]

Emissions levels by different industrial segments, with points of policy intervention highlighted. Analysis of carbon credit market, monitoring industrial compliance.

These findings reveal the importance of AI-based analytics in environmental policy-making and regulation of the sector.

Discussion Experimental evidence attests to the fact that AI-based air quality monitoring is extremely effective when complemented with satellite-ground sensor fusion, deep learning, blockchain, and crowdsourcing. Model Performance: Stable low error rates for the TGNN model attest to the fact that it can function well enough to predict AQI even in complicated city scenarios. Transfer learning-based adaptation predictions are promising directions for future enhancements. Industry Compliance and Transparency: Carbon credit system via blockchain functioned well in keeping industries in check. In reality, implementation would require, nonetheless, policy-level cooperation with green bodies. Scalability and Real-World Application The framework is scalable to other cities and firms. Integration of real-time data allows adaptive feedback to surge in pollution (e.g., industrialization, wildfires).

Conclusion

This project proposes an AI-driven air quality forecasting and source identification of pollution system based on satellite-ground sensor fusion, deep learning, blockchain-based carbon credit trading, and citizen engagement to develop an end-to-end environmental monitoring system. Temporal Graph Neural Networks (TGNN) for AQI prediction, K-Means clustering for hotspot detection, and MQ135 sensors for emission verification have been proven to be highly efficient and accurate for pollution monitoring. The blockchain-based carbon credit system ensures transparent emission trading, and industries are compelled to adopt green practices. Moreover, the citizen engagement system ensures real-time reporting and awareness, and pollution control becomes participatory. Although there are limitations in data integration, scalability, and policy adherence, the system is an adaptive, scalable, and efficient mechanism for environmental monitoring. This work lays the groundwork for data-driven environmental policy and green urban planning, enabling the creation of smarter, cleaner, and healthier cities.

F. Future Enhancement

In the years to come, the system can be developed into a smartphone app with Augmented Reality (AR) and Virtual Reality (VR) capabilities so that people can simply wave their smartphone camera around to be presented with real-time data on pollutant levels, AQI, and prevailing emission sources in the area. The interactive visualization will enable more public awareness and engagement by rendering air quality information more accessible and easier to understand. Moreover, the integration of edge computing with IoT sensors can enable real-time on-device AQI prediction, minimizing cloud dependency and system latency. Another major innovation is the use of AI-based adaptive modelling, wherein the system constantly improves its learning from new environmental patterns in real-time to achieve maximum prediction accuracy. Additionally, scaling up carbon credit trading using blockchain to an international platform can enable increased industrial involvement, inspiring cross-border sustainable practices. Finally, the incorporation of drone-sensed air quality monitoring can enable high-resolution mapping of pollution, enabling authorities to monitor emissions across different altitudes and in remote locations, further enhancing environmental surveillance and compliance.

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