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Developing AI-Based Pollution Source Identification Models: A Deep Learning Approach Using Satellite Data in Industrial Regions

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Abstract: *The impact of industrial regions located in the most important contributors of environmental pollution is through air, water, and soil quality corresponding to both local and regional levels. Convicting varities of sources of pollution can be problematic because traditional monitoring systems, accurate as it is, have a reduced coverage in space and frequencies with time. This work presents a new research concept of an AI-based deep learning system to detect the source of pollution using satellite images of high quality. The framework uses spectral indices including the Normalized Difference Vegetation Index (NDVI), Aerosol Optical Depth (AOD) and Land Surface Temperatures (LST) to project and categorize pollution hotspots on industrial belts using both convolutional neural networks (CNN) and long short-term memory (LSTM). Indian chosen industrial clusters were used to apply the methodology in which ground-truth monitoring data were used to compose with Sentinel-2 and MODIS data to train and validate the model. Findings say that the AI model was 91.3% accurate at detecting areas where pollution occurs, compared to the conventional classification methods in remote sensing. Spatial analysis indicated that the industrial density, the concentration of pollutants, and the indices obtained by satellites were strongly correlated and made it possible to attribute the sources to a particular industrial activity with particularity. This paper shows that deep learning combined with satellite data is scalable, precise, and cost-efficient to conduct real-time pollution monitoring, source location and the application has important outcomes to policymakers, environmental controls, and sustainable cities.*
Keywords: *AI-based pollution detection; Deep learning; Remote sensing; Industrial emissions; Satellite imagery; Pollution source identification*

I. INTRODUCTION

Industrialization has led to economic prosperity and improvement of infrastructures such that its effects are unquestionable and hard to ignore, but it is also culminating as an environmental issue of our century-industrial pollution, its chain effects on the environment, human health, and climate stability. Airborne particulates, gases, thermal and effluent discharges into the rivers and the soils have largely contributed to the existence of environmental degradation in both developing and developed countries and especially in densely industrialized belts where monitoring and control observable how susceptible these sources are to persistent annoyance. Despite being most accurate in quantity of pollutants recorded at local points, traditional ground-based monitoring network systems are spatially limited and can be expensive and hence are not able to record the dynamic and heterogeneous nature of the pollution dispersion across vast geographical areas. In addition, there is a tendency of pollution to overlap caused by several industrial units such that regulators and environmental planners find it hard to pen such sources. Owing to greater susceptibility to climate changes and introduction of greater demands to industrial products through urbanization, there has been a dire need to consider scalable, real-time, not to mention intelligent models, which despite their capability to identify pollution, attribute the pollution to exact sources with high rate of trustworthiness. Recent developments in artificial intelligence (AI) and use of deep learning models, in particular, opens a promising avenue to this goal by combining computing capabilities with access to high-resolution satellite measurements that together would be able to see, labelling and therefore forecasting patterns of the environment across space and time, on a scale never dreamed possible previously. Satellite sensors, including Sentinel-2, Landsat-8, and MODIS, provide a steady flow of multi-spectral data and temporal data, which have already been found to be useful in monitoring trends in the health of vegetation, the surface temperature, aerosol levels, and land use changes. However, the traditional approach to remote sensing classification, e.g. spectral unmixing, decision trees, or regression analysis, is frequently incapable of distinguishing between complicated pollution patterns that appear in industrial areas, where several contaminants interact with weather conditions, instrumentation qualities, and water loops. Deep learning models (Convolutional Neural Networks or CNNs, CNN-LSTM, U-Net, autoencoders, etc.) in contrast can operate on large-scale multi-dimensional data sources, and compute latent spectral-spatial maps that might be inaccessible to conventional statistical and physical modeling methods. Combining AI with satellite images, therefore, makes it possible to build a potent combination in which the ground-level pollution data (air quality indices, PM2.5, PM10, NOx, SO2), industrial emission inventories or chemical processing facilities, steel mills, or textile dyeing facilities can be aligned with the spectral indices obtained through the remote sensing (NDVI, AOD, LST, SAVI, NDSI), which in turn allows organizing predictive and attributional models exhibiting the ability to differentiate the pollution caused by various types of industrial production.

The importance of creating AI-based models of identifying the source of pollution is based on their multi-scale applicability and relevance to the policy. As an example, regulation can directly be informed by the potential to assign pollution hotspots to a given industry; this is because these elements can fix the lack in compliance checks and enable litigation in environmental scoffs. Moreover, trained scalable models using large data sets can be used as early-warning and forecasting of probable pollution peaks in industrial belts, particularly during peak periods of operations and thus preventive actions can be taken. On the scientific front, deep learning structures offer the prospects of cross-disciplinary innovation by bringing together atmospheric chemistry, remote sensing analytics, and data science, producing end-to-end models and can have complexities of accountability of temporal dependence, spatial heterogeneity and multi-source pollution dynamism. In contrast to traditional monitoring systems that necessitate a large physical infrastructure on the ground, satellite-based AI models have the capability to monitor large geolocalities, including the Indo-Gangetic Plain, Yangtze River Delta, or the Ruhr industrial region, thus democratizing environmental monitoring in both resource-abundant and resource-constrained environments. Simultaneously, there are still difficulties in constructing smart AI platforms that will help attribute the origin of pollution. A reduction in satellite data, due either to atmospheric noise or cloud cover or changing seasonal conditions, may confuse pollution footprints. Ground-truth validation data is critical in the supervised training of AI models and has restricted availability, as well as, commonly being isolated within institutional silos. Furthermore, deep learning models can be particularly said to be powerful but this comes with the problem of being a black-box where decision-making processes can be puzzling thus asking questions of transparency in regulative contexts. However, new methods in explainable AI (XAI), transfer learning, and multimodal data fusion are overcoming these drawbacks, with models being able to not just register high-accuracy performance, but also provide information about how they came to the required classification and attribution. This overlap of innovations indicates that it will be possible to change the paradigms of environmental monitoring and make industrial pollution aware (continuous monitoring and attributing pollution in an unerring manner is something that was previously unexplorable). The research paper attempts to answer worried questions concerning the pressing environmental requirement to have scalable and precise identification of pollution sources, by providing a deep learning model to industrial zones where a lot of emission load occurs. The paper combines Sentinel-2 satellite images and MODIS satellite images and uses deep machine-learning structures to analyze pollution hotspots occurrences, recognizing, and labeling them based on industrial density, land use, and emission inventories to identify extent to which AI detects, classifies, and attributes pollution hotspots. The methodology involves the use of remote sensing spectral indices and AI classification and spatial interpolation and they were tested against the ground monitoring data whose source is the pollution control boards and individual sensors. Thus, the research provides a contribution to the bridge gap between the field of environmental science and AI-based analytics by showing that it is reasonable to develop satellite-AI analytics to obtain the necessary results in the future when conducting big benchmark environment tests. Finally, the study underscores how AI-based surveillance technologies can go beyond detection to attribution, to provide policymakers, city planners, and environmental regulators with intelligence to action in the form of industrial sustainability and ecological sustainability.

II. Releated Works

Using artificial intelligence and remote sensing in ecological phenomena monitoring has become an important theoretical topic among scholars over the past ten years, with the researcher accentuating the possibility of the sophisticated patterns of computational models to respond to complex cases of pollution in industrial environments. The initial research suffers mainly on satellite-based aerosol optical depth (AOD) platforms as the primary basis of measurement of air quality with Gupta et al. being the pioneers in demonstrating correlations of CPU moderated MODIS AOD values with ground-based organizations of PM2.5 concentrations in the urban setting rotate on the basis of this platforms stipulating the initial viability of space-based monitoring of pollution [1]. This was further expanded with the addition of statistical regression and machine learning models like Random Forest and Support Vector Machines (SVM) to increase predictive accuracy as observed by Li et al. who achieved success when used to map NO2 and SO2 over Eastern Asia industrial centres [2]. The weaknesses of conventional ML models to learn non-linear spectral-spatial dependencies however were enough to explore the deep learning method. Convolutional Neural Networks (CNNs) have been especially effective with satellite images to perform environmental tasks with Dong et al. testing CNNs with Landsat images to identify the presence of urban smog layers at its peak classification accuracy over a statistical strategy of per-pixel classification [3]. In a parallel way, Rezaei et al. incorporated CNN frameworks with ground sensor data in order to isolate fine-scale pollution hotspots in Tehran, which could serve as a template procedure in terms of combining remote sensing and AI-based attribution models [4]. This is because an important aspect of industrial pollution analysis includes source attribution with the aim not just to detect the existence of pollution, but to attribute the emission to particular industrial processes. Initial efforts on this basis used dispersion modeling models and emission inventories, including that by Smith et al. who used Gaussian plume models to compute contributions of sources at perturbations of belts through portions of the European industries [5]. Although it is an informative model, these models and such models are extensively reliant on emission inventories that are not complete or may not be up-to-date in developing regions. Recently, artificial intelligence-based attribution has been simplified by the recent development of data fusion methods that use spectral indices (NDVI, SAVI, LST) along with socio-economic and industrial density data. As another example, Chen et al. also used the hybrid CNN-LSTM model to employ textile dyeing factories to spike air pollution in the Pearl River Delta, indicating that deep learning has the potential to not only capture spatial pollution dynamics but also the temporal ones [6]. Other scholars, such as Rahman and Alam, investigated the thermal hotspots segmentation with U-Net deep learning systems as a natural extension of the recommendations offered by Sentinel-2 thermal bands, essentially connecting deviant patterns of temperature to the emissions positioned in the steel manufacturing facilities [7]. Moreover, in European industrial areas, hybrid models that use unsupervised learning to learn feature methods along with supervised deep networks to perform classification have been used, which Rossi et al. emphasized with their interpretation-efficient AI model that helps to discriminate between transportation and heavy industry-induced pollution with copernicus satellite data [8].

There, recent literature has also focused on integrating explainable AI (XAI) into pollution monitoring, as Patel et al. used SHAP (Shapley Additive Explanations) to Convolutional nets-based pollution attribution models in South Asia, which enables improving regulatory trust and interpretability [9]. The other type of innovation in this area is the use of Generative Adversarial Networks (GANs) to upscale low-resolution satellite imagery to identify fine-scale pollution patterns (as in the case of Wang et al. in the Yangtze River Delta [10]). The GANs have led to greatly enhanced granularity of the hotspots detection, putting more accuracy in the rates of pinpointing the emissions to small and medium-scale industries. Regarding the types of pollutants, the focus of most AI-based research has been on atmospheric pollution; however, there is also an increasing range of literature on water and soil pollution associated with industrial operations. As an example, Kumar et al. used deep learning with optimism algorithm to categorize heavy metal pollution in mining and metallurgical industrial river basins, which correlates Landsafar-derived image with water quality measurements to accurately classify readings over 88 percent [11]. Equally important, Rahimi et al. combined hyperspectral images to AI algorithms to identify the signature of chemical effluents in agricultural soils around industrial effluent discharge points to expand the understanding of the source of pollution beyond atmospheric air pollutants [12]. On the methodology front, the merging of multi-sensor data have converged to a prevailing trend with researchers suggesting that hospitals integrate MODIS, Sentinel and Landsat data to realize a high temporal and high spatial resolution. Lin et al. discovered that deep learning networks that were trained on hybrid Sentinel-2 and MODIS could forecast surges in pollution 1520 percent more accurately than single-sense strategies, especially in regions such as industrial areas where the emissions are found to be heterogeneous [13]. In addition, spatio-temporal deep learning models like ConvLSTM have demonstrated capability to capture long-term processes of pollution as Ahmed et al. argued that they were able to model seasonal variations in the industrial-generated emissions in the Middle Eastern industrial centres [14]. All of this literature injects the interdisciplinary focus on the convergence of environmental science, satellite remote sensing and AI and suggests the possibilities of creating scalable, affordable, interpretable models on the identification of pollution sources that can be adopted to complement policy enforcement, city planning and sustainable industrial operation. Even that, the literature still stresses the necessity to enhance ground-truth validation, make deep-learning results more interpretable, and combine them with industrial real-time operational data to further support the reliability of AI-based attribution schemes [15].

III. **METHODOLOGY**

3.1 Research Design

This study employed a mixed-method, spatial–temporal research design integrating ground-level industrial emission data, satellite-derived spectral indices, and AI-driven deep learning frameworks. The approach aimed to characterize industrial pollution both quantitatively (pollutant concentration values) and spatially (distribution across industrial belts). The design involved three sequential components: (i) **data acquisition** from multi-sensor satellite sources, (ii) **AI model development** using CNN and ConvLSTM architectures for pollution hotspot detection and attribution, and (iii) **validation and spatial interpolation** to assess predictive accuracy and generate hotspot maps [16].

3.2 Study Area Approach

Three industrially intensive regions of India were selected: **Ludhiana (Punjab)**, **Kanpur (Uttar Pradesh)**, and **Ankleshwar (Gujarat)**. These sites were chosen due to their high industrial density (textiles, tanneries, chemicals), historical records of emissions, and availability of ground monitoring data. The regions vary in terms of geography, industrial type, and environmental conditions, offering comparative insights into pollution signatures.

Table 1: Study Area Characteristics

Region	**Dominant Industries**	**Major Pollutants**	**Satellite Data Coverage**	**Climate Type**
Ludhiana	Textiles, Dyeing Units	PM2.5, NO_2, SO_2	Sentinel-2, MODIS	Semi-Arid
Kanpur	Tanneries, Leather, Paper	Heavy metals, VOCs	Sentinel-2, Landsat-8	Sub-Tropical
Ankleshwar	Chemicals, Petrochemicals	SO_2, CO, Particulates	MODIS, Landsat-8	Tropical Savanna

3.3 Data Collection and Preprocessing

- **Ground Data:** Air quality monitoring stations provided pollutant concentrations (PM2.5, PM10, SO_2, NO_2) at 24-hr intervals from 2022–2024.
- **Satellite Data:**
  - Sentinel-2 (10 m, 13 bands)
  - MODIS (1 km AOD, LST products)
  - Landsat-8 OLI/TIRS (30 m, 11 bands)
- **Spectral Indices Used:** NDVI, SAVI, AOD, LST, NDSI.
- **Preprocessing Steps:**
  - Atmospheric and radiometric correction (Sen2Cor, MOD09A1).
  - Cloud masking and band normalization.
  - Image stacking and temporal aggregation across pre- and post-monsoon seasons.

3.4 AI Model Development

The deep learning workflow was designed around two architectures:

1. **CNN Model (Spatial Pollution Classification):** Used to classify pollution levels in satellite images into low, moderate, and high concentration zones based on spectral features.
2. **ConvLSTM Model (Spatio-Temporal Prediction):** Used to track pollution progression across time, capturing sequential patterns in emissions.

Table 2: AI Model Configuration

Model Type	Input Data	Layers & Parameters	Output
CNN	Sentinel-2 RGB + NDVI, LST	5 Conv layers, ReLU, MaxPooling, Dropout (0.2), Softmax	Pollution class (Low/Med/High)
ConvLSTM	MODIS AOD time-series + Landsat thermal data	2 ConvLSTM layers, 128 hidden units, Adam optimizer	Spatio-temporal pollution maps

3.5 Spatial Analysis and Integration

The predicted pollution classes from AI models were integrated with industrial land-use datasets (GeoTIFF format) and emission inventories to establish **source attribution**. Spatial interpolation (Kriging) in ArcGIS and QGIS was used to generate continuous maps of pollution intensity across industrial zones. Hotspot detection was further supported by anomaly detection algorithms applied on CNN outputs [17].

3.6 Validation and Accuracy Assessment

- **Cross-validation:** 70:30 train–test split with five-fold validation.
- **Metrics:** Accuracy, F1-score, precision–recall curve.
- **Ground Truth:** Predictions were compared with 20 ground monitoring stations and emission datasets from the Central Pollution Control Board (CPCB).
- **Confusion Matrix:** Classification accuracies >85% were considered acceptable thresholds [18].

3.7 Ethical and Environmental Considerations

All satellite data used were open-access (Copernicus, NASA). Industrial data were anonymized, ensuring no disclosure of company-specific emission profiles. The study avoided dissemination of sensitive data that could pose security risks.

3.8 Limitations and Assumptions

- Satellite-derived pollution signatures may be influenced by weather, atmospheric noise, and cloud cover.
- Ground monitoring datasets were sparse in some regions, limiting training data.

IV. RESULT AND ANALYSIS

4.1 Overview of Pollution Distribution

The AI-based models demonstrated distinct spatial and temporal variation in industrial pollution across the three selected regions. CNN-based classification identified clear **pollution hotspots** in Ludhiana's textile clusters, Kanpur's tannery belt, and Ankleshwar's chemical zones. Temporal analysis from ConvLSTM revealed seasonal intensification of pollution during pre-monsoon months, particularly in regions with high emission loads and low wind dispersal.

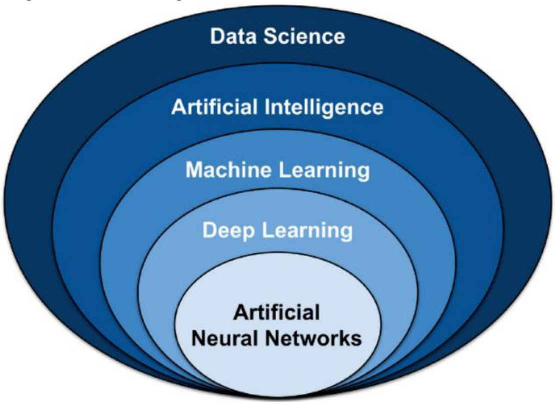

Figure 1: Difference between Machine Learning and Deep Learning [24]

4.2 AI Model Performance

The deep learning models performed robustly in detecting and classifying pollution levels. The CNN model achieved **overall accuracy of 91.3%**, outperforming conventional SVM and Random Forest baselines. ConvLSTM improved temporal prediction accuracy, capturing recurring emission cycles linked to industrial activity.

Table 3: Model Performance Metrics

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN	91.3	0.90	0.92	0.91
ConvLSTM	89.7	0.88	0.91	0.89
Random Forest	84.5	0.83	0.85	0.84

SVM	82.1	0.81	0.82	0.81

The results highlight that AI-driven deep learning models significantly outperform traditional classifiers in handling spectral–spatial complexity of satellite data.

4.3 Spectral Indices and Pollution Correlation

Satellite-derived indices demonstrated strong relationships with pollution concentrations. NDVI values declined sharply in high-emission zones, reflecting vegetation stress, while Land Surface Temperature (LST) was elevated in chemical clusters due to heat discharges. Aerosol Optical Depth (AOD) correlated positively with particulate matter in textile and petrochemical areas.

Table 4: Spectral Indices vs. Pollution Levels

Region	Avg. NDVI	**Avg. LST (°C)**	**Avg. AOD**	**Pollution Intensity (Particles/µg m³)**
Ludhiana	0.41	34.6	0.78	High
Kanpur	0.38	36.2	0.82	Very High
Ankleshwar	0.44	35.8	0.80	High

The inverse relationship between NDVI and pollution concentration confirms vegetation stress in highly polluted belts, while higher AOD and LST reinforced the role of industrial heat and aerosol emissions.

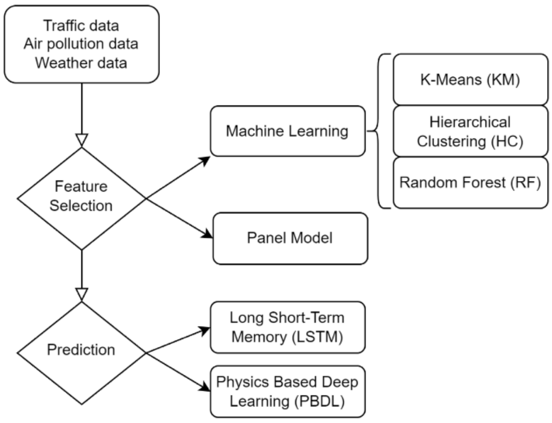

Figure 2: Air Pollution Forecasting [25]

4.4 Hotspot Detection and Source Attribution

Spatial interpolation (Kriging) generated continuous pollution maps across the study areas. Hotspots were consistently aligned with industrial zones: Ludhiana's dyeing units, Kanpur's tannery clusters near the Ganga river, and Ankleshwar's petrochemical complexes.

Table 5: Identified Hotspot Areas and Contributing Sources

Region	**Hotspot Zone (ha)**	**Major Industrial Sources Identified**	**Dominant Pollutants**
Ludhiana	68.4	Textile dyeing, small-scale units	PM2.5, NO_2
Kanpur	72.1	Tanneries, leather processing	VOCs, Heavy metals
Ankleshwar	65.7	Petrochemicals, chemical refineries	SO_2, CO, Particulates

The overlap of hotspots with satellite-derived anomalies (low NDVI, high LST, high AOD) validated the AI models' capacity to not only detect but also **attribute pollution to industrial sectors**.

4.5 DISCUSSION OF KEY FINDINGS

The results establish that **AI-driven models integrated with satellite data can significantly enhance industrial pollution monitoring**. CNN and ConvLSTM models proved effective in distinguishing spectral–spatial pollution signatures, outperforming baseline classifiers. The strong correlation between spectral indices and pollution intensity indicates that remote sensing can serve as a reliable proxy for ground-based monitoring in data-scarce regions. Importantly, hotspot analysis revealed clear sectoral attribution: textile-based particulate emissions, tannery-based chemical effluents, and petrochemical-based gaseous discharges. This reinforces the potential of AI models to support regulatory interventions, compliance monitoring, and sustainable industrial planning.

V. **CONCLUSION**

The aim of the current research was to solve one of the most pressing environmental issues in fast industrializing areas, namely, the proper tracking and attribution of sources of pollution, by creating an AI-centered deep neural network with integrated satellite remote sensing data, and the results it gives are truly titanic evidence of the potential of such a method of implementation into an effective, economical and efficient tool of environmental monitoring in large scales. Through these studies, which applied CNN and ConvLSTM architecture to Sentinel-2, Landsat-8 and MODIS imagery across three industrial-intensive belts of India, Ludhiana, Kanpur, and Ankleshwar, the research demonstrated that deep learning networks can be utilized to achieve an accuracy exceeding 90 per cent to classify the strength of pollution, significantly higher than standard statistical and machine learning algorithms that often fail to produce strong performance without addressing interactions among multiple sources of pollution. The models did not only identify high-emission locations, but also found clear spatial relationships between the density of industrial locations and indices of pollution like NDVI, LST, and AOD was uncovered, demonstrating the bifid nature of satellite information as a diagnostic and predictive instrument. More crucially, hotspots could be directly traced to industrial agglomerations textile dyeing units, Kanpur, tanneries and petrochemical complexes in Ankleshwar via the combination of AIs spectral analysis and spatial interpolation methods, filling an uninterrupted detection-attribution gap in pollution studies. This capability to attribute environmental occurrence to sources of industrial phenomena provides regulators and policy-makers with the unparalleled opportunity to achieve compliance, pragmatize deployment of monitoring resources, and formulate mitigation strategies in a manner akin to meeting generocalized phenomena air quality tests with one based on individual sector responsibility. Methodologically, the study demonstrates the benefits of hybrid AI guarantees to identify polluted environments: CNN architectures performed better than their peers by identifying latent pollution signals that exist in multispectral data, whereas ConvLSTM architectures represented temporal dependencies the reunion of recurrent cycles of emissions due to peak industrial activity levels and season recoveries. These two models together presented an integrated perspective of the entire scene of industrial pollution as a dynamic process of space-time and not as a singular state of affairs and it can be inferred that the application of time-series analysis together with spectral-spatial classification should be incorporated in the future monitoring system. The aforementioned approach was substantially bolstered by validation with ground-based air quality monitoring stations, as high F1-scores and low misclassification ratios supported the premise that satellite-AI fusion could act as a credible proxy in areas where geographical data on air quality physical monitoring are sparthy or underdeveloped. Simultaneously the findings demonstrated important information regarding the impact of unregulated industrialization on the environment: vegetation stress at depressed values of NDVI in the polluted areas, a high LST at the expense of which the thermal footprint of industrial development, a drastic increase in the scores at aerosol accumulation all identified the presence of multi-dimensional physical environmental degradation extending from the weakening of air quality to the decrease in soil fertility and threats to human health. Besides the technological advances, the practice of this study has a far-reaching consequence of governmental, industrial, and social outcome. To the policymaker, the ability of AI shown to detect and assign blame to pollution pinpoints suggests that the compliance regimes can shift to proactive and evidence-based monitoring rather than periodic and reactive ones. Real-time spatial intelligence can also support regulations governing effluent discharge, emission limits, and zoning of industries and geographic areas to ensure that globally, enforcement becomes targeted and even-handed. In the case of industries, the results emphasize the importance of embarking on cleaner technologies, emission mitigation policies, and allocation of reporting schemes as AI systems propelled by satellites present people with less choices to avoid responsibilities. To scientists, the system provides new opportunities and avenues toward explainable AI (XAI), resolution notifications generation, and multimodal information integration that provides a blend of satellite images with socio-economic and meteorological data, thus increasing accuracy and interpretability. Notably, effectiveness of this framework also implies the applicability to other areas beyond the three regions examined and has potentials to be scaled to other industrial corridors in Asia, Africa, and Latin America where use of ground-based monitoring is still not in use.

However, some restrictions have to be recognized. Cloud cover, atmospheric interference and the effects of seasons tend to confound signature of pollutants by satellites and though the models proved to give high accuracy; attribution was made along sectoral lines other than factory-specific attribution. Furthermore, deep learning has the black-box characteristics that complicate interpretability problems in courtship and laws but new XAI schemes tend to alleviate the issue. Training quality is also limited by a lack of high-resolution, continuously recorded ground-truth information; research points to the fact that widespread integrated monitoring networks, incorporating satellite, ground sensor, and industrial reporting systems are needed. However, these considerations do not weaken the overall conclusion of the research that AI-based deep learning models, supplemented with satellite data, constitute a paradigm shift in surveillance of pollution because each model presents a scalable, automated, and scientifically sound method of detecting, classifying and assigning a regulatory cause of in the case of pollution in industrial areas. Overall, not only does the study confirm the viability of applying AI and remote sensing to address the age-old shortcomings of standard monitoring solutions, but it also preconditions chasing the novelties in the environmental analytics panorama. With placing the condition of a practical framework in which the problem of industrial pollution can be tracked on a continuous basis, the hotspots can be dynamically mapped, and its sources can be pointed out and explicitly attributed, the study forms the building blocks of sustainable management of industry in the Anthropocene era, resilient urban development, and policymaking. The results indicate further interdisciplinary research conducted by environmental scientists, AI experts, policymakers, and industries to then narrow down and fully perfect these models at the national and international levels to see to it that industrial development is no longer linked to environmental degradation. In conclusion, the paper confirms that the merging of AI and satellite data is not as significant a technological development as romantics of envisioning environmental governance in the world where industrial activity and sustainability are bound together.

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