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A Comprehensive Review of Ensemble and Hybrid Air Pollution Forecasting Models

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***Abstract*— Modern research increasingly employs deep learning architectures to capture spatial-temporal pollutant patterns. The study has examined deep learning and hybrid modelling methods for the prediction and management of air pollution. The identified models, such as CNN-LSTM, GCN-LSTM and ensemble frame-works, are able to capture spatial-temporal dependencies more effectively com-pared to higher forecasting accuracies using traditional means. The IoT and satellite technologies closely capture monitoring urban and industrial areas in real-time and high resolution. Multi-output and ensemble learning methods are used to improve the simultaneous prediction of multiple pollutants. It boosts forecast accuracy as well as meteorological, traffic, and remote sensing data. This works aims at a comprehensive study of AI/ ML models used in air pollution detection.**

***Keywords*— Air Pollution, Deep learning, Air Quality Index, WHO, TB.**

I. INTRODUCTION

Increase in exposure to pollutants was said to have resulted in a variety of negative health effects, including respiratory and cardiovascular diseases, psychological effects, or even Covid-19 infection and mortality. Providing city-wide in-formation on air pollutants is of great implication for healthy living and the quality of life for the citizens [1]. Air Pollution refers to the discharge or release of hazardous pollutants into the air, which endangers human life as well as the global environment. The World Health Organization (WHO) states that almost seven million deaths are caused each year by air pollution worldwide. The worrying trend is seen for about nine out of 10 people breathing air that exceeds WHO pollutant levels. Those who suffer the worst consequences are low- and middle-income country residents. Air pollution has a negative effect on climate change and is further worsened by it. Global warming temperature flares due to air pollution by carbon dioxide and methane as forms of pollution. An intensified form of air pollution known as smog is aggravated under such conditions. These play out in conditions when the temperature is warmer, and ultraviolet radiation is more prevalent. Moreover, climate change increases Mold hazards, allergenic air pollutants, enhanced humidity level because of more calamities, increased floods triggering an extended pollen season through shifting climatic patterns [2]. IoT finds used in almost every environment from smart buildings, through health to energy management and even agriculture. Air quality, for instance, is one of the most interesting applications of IoT because it has a substantial impact on human health and ecosystems through air pollution. The major air pollution control system is a static measurement station that is operated by local regulatory institutions [3]. The U.S.

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Environmental Protection Agency and the WHO [2][4] have defined and identified several air pollutants including nitrogen dioxide (NO2), Sulphur dioxide (SO2), carbon monoxide (CO), ozone (O3), particulate matter (PM), and lead, which are linked with health and environmental problems over a defined time [4]. The human respiratory system, particularly of children and old people, is affected when high concentrations of NO2 and SO2 are breathed in. Short terms of NO2 might induce asthma attacks and result in emergency department visits and hospitalizations, while long exposure may cause respiratory infection. NO2 leads to acid rain in interaction with other atmospheric constitu-ents, whereas SO2 yields particulate matter both injurious to human health and ecological well-being. High O3 concentrations adversely affect children, the elderly, outdoors-active individuals, and asthmatic persons [4][5].
High levels of O_3 may induce lung inflammation and whereas CO hampers ox-ygen supply to the heart and brain The burden of Tuberculosis (TB) is shared by 56% in countries such as India, Indonesia, China, the Philippines, and Pakistan, where worsening air pollution is compounding TB risks. Barriers to TB elimina-tion by 2030 via SDG Goal 3 include delayed TB detection and low population awareness levels [6].
The different sources of information used to predict air quality are: ground monitoring stations, meteorological satellites, and monitoring aircraft. The pri-mary challenge to predict the air pollution is that even when some areas success-fully set up numerous regional air quality monitoring stations, and even inter-connecting micro air quality monitoring stations along the streets, many areas do not have comprehensive air quality monitoring systems. Another aspect of the problem is formed by the fact that air pollutants are produced by complex chemi-cal processes, which are subject to significant spatial and temporal variation [7].

II. Role of AI/ML

Innovation in today's field of air quality (AQ) forecasting, environmental monitoring, and pollutant decontamination, has also been fast by finding the hybrid deep learning and data-driven frameworks. These architectures implement some sort of spatio-temporal learning structures, like CNN–LSTM, GCNs, and Transformer-based structures, to capture space-dependent behaviour of the mon-itoring stations and temporal variations of the pollutants [1]. Usually, data pipe-lines integrated using heterogeneous sources, such as traffic, AQI, meteorologi-cal, noise, and IoT sensors, usually undergo preprocessing imputation, calibra-tion, and spatial scale. CNN layers capture spatial relationships; LSTM or GRU layers find sequential and long-term trends; and dense or multitask prediction layers for pollutants such as PM10, NO_2, and AQI usually, and sometimes noise, process outputs based on user engagement or other dimensions [3].
Some of the architectures contain some meta-heuristic optimizers such as ge-netic algorithms and PSOs so that feature selection and hyperparameters settings could be robust. It goes beyond forecasting and would, in fact, connect sustaina-bility and health, tracing the pathways of pollutants from sources of emission through atmospheric transport and exposure to health outcomes. Examples of sustainable pollutant removal and bioresource utilization are methods based on microalgae bioremediation.

III. Literature Study

Table.1 refers to study that covers several domains in air-quality research: me-teorological-AQI fusion studies, multimodal traffic-pollution sensing, mobile IoT measurements, satellite-based observations, and CFD-simulated data. Applica-tions include environmental monitoring, smart-city AQI estimation, health-exposure analysis, deep learning prediction, and environmental image classifica-tion. Major limitations include constraints of coverage either in geographical areas or in rural settings, issues in calibration, low temporal resolutions of satel-lite systems, region specifications of datasets, very little validation in the real world, and no data recorded for large deployments.

TABLE I. DATASETS FOR SUPPORTING AIR QUALITY MODELLING AND ENVIRONMENTAL ANALYTICS

Title and Author	Data Type	Domain	Capacity	Accuracy / BER	Limitations
(Binbusayyis et al., 2024)[1]	Tabular (time-series)	Environmental Monitoring	High (multi-source integration)	High correlation for PM prediction	Limited rural coverage
(Kostadinov et al., 2024)[2]	Multimodal (tabular + sensor)	Smart City AQI Estimation	High	RMSE < 12 μg/m³	Limited cross-city validation
(Do et al., 2020)[3]	Spatiotemporal	IoT Sensing	Variable	±5 μg/m³	Battery & calibration challenges
(Omokpariola et al.,2024) [4]	Satellite (Raster)	Remote Sensing	High (Global coverage)	Validated vs CPCB	Low temporal resolution

(Rakholia et al., 2023) [5]	Tabular (Hourly)	Urban AQI Analysis	Moderate	High R^2 in LSTM	Limited geographic scope
(Sharma & Mauzerall, 2022) [8]	Tabular (Official)	Urban AQI	Large-scale	Validated by CPCB	no rural data
(Ravishankara et al., 2020)[12]	Tabular + Satellite	Exposure–Health Linkage	Large-scale	-	limits coarse spatial resolution
(Yenkikar et al., 2025) [13]	Simulated + Measured	Air Quality Forecasting	Medium	High ($R^2 > 0.9$)	limited real-world data
(Sciannameo et al.,2022)[14]	Tabular + Mobility	Health Informatics	Medium	-	limited to specific regions
(Yin et al., 2023) [15]	Image (Augmented)	Environmental Image Classification	Moderate	Acc > 90%	limited real-world validation
(Macatangay & Hernandez, 2020) [16]	Tabular	Government AQI	Moderate	-	limited open access
(El-Sheekh et al., 2025)[18]	Experimental	Environmental Biotechnology	Moderate	80%removal efficiency	Lacks large-scale deployment data

IV. METHODOLOGIES

A. Machine Learning Methods

- ARIMA/SARIMA: Modelling trends and seasonal behaviour for a pollutant's time-series (hourly/daily PM2.5, NO2). → Short-term forecasting
- Random Forest/XGBoost: Input features: past pollutant levels, temperature, humidity, wind speed, traffic counts. Train models to learn the nonlinear rela-tionships between features and pollutant concentrations. Use them for feature importance analysis to understand pollutant drivers.
- SVM/SVR: Learn optimal margins for pollutant prediction. Used in small-sized datasets, where relationships are moderately nonlinear.
- Ensemble: Combining predictions from multiple models can reduce variance and increase bias. Used for more stable predictions across time and city.
- Statistical analysis (EDA, correlation): Interaction between different pollu-tants (e.g. PM2.5 vs humidity).

B. Deep Learning Methods

- LSTM/GRU: Input: time-series pollutant values + meteorology. Learn long-term pollutant dependencies (e.g., weekly cycles). → Used for temporal fore-casting.
- CNN: Input: spatial maps, satellite images, dust images. Extract spatial pat-terns (hotspots, pollution plumes). → Used for dust classification or spatial AQI mapping.
- ConvLSTM: Combines CNN + LSTM for learning the spatio-temporal patterns. Used when spread of pollution occurs across areas (e.g., in city grids).
- Graph Convolutional Networks (GCN): This method has been applied to IoT sensor networks (sensors represented as nodes). To persist in and keep pollu-tant flow between connected areas.
- Transformers: Forecasting at long distances due to self-attention. Handles long sequences (seasonal effects, long-range dependencies).
- Autoencoders: Missing data of AQI to be reconstructed from the incomplete stations

C. Hybrid/Multimodal/Fusion Methods

- CNN-LSTM (DL + DL): The CNN extracts spatial features from the grid maps of pollution. The LSTM predicts the future pollution using time-sequence learning. → Used in metropolitan cities where the pollution spreads spatially.
- GCN-LSTM: The GCN captures relationships between sensors (road net-works, neighborhoods). The LSTM models temporal evolution. → Used for mobile sensor and IoT-based networks.
- ARIMA-RF/ML-DL hybrids: ARIMA would deal with the linear temporal trend. The nonlinear residuals are managed with the use of RF/XGBoost. →Compared to either of them used independently, these are expected to be more accurate.
- Multi-tailed Deep Learning: Combine all possible inputs: Traffic flow, Me-teorological factors, Noise levels, Satellite AOD, IoT sensor streams→ Models learn to understand interactions between environment factors.
- Optimization-enhanced DL (PSO/GA) : PSO/GA optimize, Number of layers, Neurons in LSTM, Learning rate, Activation functions →Results: the best per-formance accompanied by reduced manual tuning.

➢ IoT + Cloud + DL: Real-time data are sent from the IoT sensors. The cloud servers process the CNN/LSTM models. Mobile apps show live AQI. →Used for smart cities and real-time alerts.

Satellite with Ground Fusion: Fuse the Sentinel-5P with ground data from CPCB.

Fig. 1 represents the Workflow of air pollutants which involves (a) data acqui-sition from ground stations, IoT, meteorological feeds, and satellites (such as Sentinel-5P/3A/B), (b) preprocessing and feature engineering (lag variables, rolling statistics), (c) hybrid deep architectures (CNN-LSTM, ConvLSTM, GCN-LSTM, Transformers) with cross-validation-based model training, (d) evaluation via rolling-window validation, and (e) explainability using SHAP values or atten-tion mechanisms. As such, deployment frequently targets real-time, cloud-based dashboards or mobile systems for decision support.

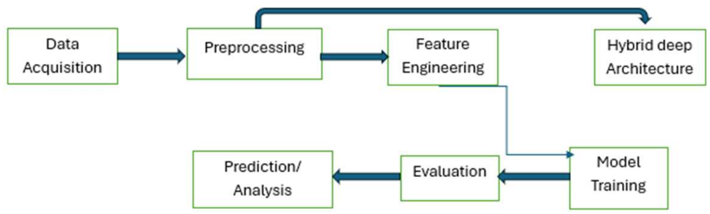

Fig.1 Workflow of Air pollutants analysis using Hybrid models

Data acquisition

Robust forecasting begins with diverse, high-quality data. Studies exploit fixed stations, mobile IoT sensors, satellite products, and domain-specific sources

Preprocessing

Preprocessing takes care of noise, missing values, temporal alignment, and spatial interpolation. Calibrating and geoprofiting are necessary for satellite and mobile sensor streams, and traffic and weather feeds need to be resampled and synchronized. These works include pipelines for gap filling and bias correction in documents such as the satellite analysis and the local integrated meteorology forecasts.

Feature Engineering

The feature engineering entails turning the input signals into forms that are usable for prediction. Engineering traffic-aware forecasting (PM10 and noise) and CFD-based studies have created domain-specific engineered features, while image-based mining studies extract visual dust indicators. Most of these hybrid approaches do usually create multi-scale features as temporal lags for sequence models and spatial grids for convolutional components.

Hybrid deep architectures

A hybrid tends to be a highly spatial-temporal modelling trend: CNN-LSTM frameworks, GNNs, ensembles of statistical models (ARIMA) combining tree-based learners (Random Forest), and metaheuristic-augmented LSTMs. Deep-AIR: A Hybrid CNN-LSTM Framework and numbers of CNN+LSTM studies are examples of architectures generally employing whitespace in the first capture of spatial patterns and then modelling temporal developments. Graph-based infer-ence from mobile sensors and ensemble/hybrid RF-ARIMA methods illustrate alternative ways of blending physics, statistics, and deep learning.

Model training

Emphasis on hyperparameter search, regularization, and transfer across sites are some of the themes emphasized in studies on LSTM with metaheuristics and ensemble learning. A few studies work on synthesizing pollutant scenarios using simulators-they're conducting case studies in the Philippines-while some do training across multiple outputs for simultaneous predictions of different pollu-tants.

Evaluation

Evaluation metrics span RMSE, MAE, classification accuracy for AQI catego-ries, and more specialized measures for spatio-temporal fidelity, which can be compared across deep learning versus statistical models and city-specific stud-ies. Ground-to-satellite comparison papers against CFD evaluations explore fur-ther not purely metric physical plausibility.

Prediction/ Analysis

Explainability is an emerging but fast-growing priority. Explicit targets for in-terpretability have studies combining RF+ARIMA; while some CNN-LSTM and graph models with attention mechanisms or learned spatial patterns result in ex-planation, bibliometric and policy-focused papers would link explainable out-comes to the need for decision-making.

V. Performance Evaluation

According to Table 2, Statistical based air quality predictions range from tra-ditional, simple ARIMA/SARIMA to hybrid, advanced deep learning. Among them ARIMA/SARIMA is a very simple model with accuracy between 70% to 80%, but they cannot account for nonlinear data. SVR and RF accounted for the nonlinear handling and thereby increased the accuracy levels averaging around 88% though these two are limited in learning the temporal features. CNN cap-tures spatial dependency (≈95%) and LSTM/GRU captures the trends of time series data (≈92%). A hybrid combination of CNN and LSTM achieves the best results RMSE < 12 m g3, R2 > 0.9. Hybrid Transformer and GA/PSO would in-crease long-term forecasting and tuning efficiency (≈96%).

TABLE II. Comparison of Air Pollution Forecasting Models and Their Perfor-mance

Ref	Algo-rithm / Model Type	Typical Accuracy Range (%)	Advantages	Limita-tions	Results
(Zhang et al., 2022) [1]	ARIMA / SARIMA	70–80	Simple, easy to understand, good for sta-tionary time series	Poor at nonlinear & multivariate modelling	Baseline for RMSE/MAE com-parison; typically, higher RMSE (>15 μg/m³)
(Bin-busayyis et al., 2024) [19]	SVR (Support Vector Re-gression)	75–85	Handles nonlinear rela-tionships; ro-bust	Sensitive to kernel choice, slow-er training	RMSE im-proves ARIMA by about 10–15%, with R^2 (~0.8) near statistics
(Mu-nandar et al., 2025) [6]	Hybrid ARIMA–RF /ML Hy-brids	82–90	ML Hybrid Combine linear & nonlinear modelling	Increased complexity; loss of inter-pretability special	RMSE reduc-tion ≈ 10–12%; others often cap-ture trend error
(Jurado et al., 2022) [23]	CFD-Supported Deep Learn-ing (Regres-sion/ANN)	85–90%	Combines physical simu-lation and DL; robust under variable air-flow	Computa-tionally ex-pensive; needs CFD expertise	Enhanced ac-curacy under mi-cro-environmental scenarios
(Do et al., 2020) [3]	GCN / ConvLSTM (Graph-Based)	88–94	Spacetime learning; can-didate to de-velop IoT sen-sor networks	Relies on structured graph data	Cross-city val-idation R^2 > 0.85, robustness with missing data
(Yin et al., 2023) [15]	CNN (Convolu-tional Neu-ral Net-work)	88–95	Learns spa-tial dependen-cies effectively	Weak in long-term temporal modelling	CNN, with 95% precision (image-based AQ/classification of dust)
(Naz et al., 2023) [26]	Hybrid Deep Mod-els (Opti-mized with GA/PSO)	92–96	Automated hyperparame-ter tuning; improved con-vergence	Costly op-timization	RMSE reduced ~18%; enhanced accuracy +10–15%

A. RMSE – Root Mean Squared Error

The RMSE assesses the average severity of prediction errors with a large weight devoted to the squaring of errors.

$$RMSE = \sqrt{\frac{1}{n}\sum(yi - \hat{y}i)2} \quad (1)$$

Interpretation

Lower RMSE → model predictions are closer to actual pollutant values.

Big errors are severely penalized.

B. MAE – Mean Absolute Error

MAE measures the average magnitude of errors, all of which are weighted equally.

$$MAE = \frac{1}{n}\sum \mid yi - \hat{y}i \mid \quad (2)$$

Interpretation
Easily understandable: "The model is off, on average, by X units."
Less influenced by outliers than RMSE.

C. MAPE - Mean Absolute Percentage Error

MAPE gives the average percent error: i.e., how far predictions are in percent terms.

$$MAPE = \frac{100}{n} \sum | \frac{yi - y\^{}i}{yi} | \quad (3)$$

Interpretation
Communication is easy with MAPE%.
However, errors explode when actual values get closer to zero.

D. R^2 - Coefficients of Determination

R^2 is the part of variance in pollutant concentration that the model accounts for.

$$R^2 = 1 - \frac{SSres}{SStot} \quad (4)$$

Interpretation
$R^2=1 \rightarrow$perfect prediction
$R^2=0 \rightarrow$no better than predicting mean
$R^2<0 \rightarrow$worse than naïve mean prediction

VI. Challenges

- Air pollution models are continuously challenged by the almost perennial presence of incomplete and heterogeneous data. Cloud cover, the irregular pass timings of satellites over particular areas, and poor representation by ground reality limit the present-day data collection through satellites.
- The cross-regional and multi-city studies have challenges arising from varia-tions in sensor calibration as well as non-uniform preprocessing standards. Bibliometric and meta-analysis studies are severely constrained by incon-sistent nomenclature, duplicates in journal names, and poor keyword indexing.
- Deep learning models like CNN-LSTM, GCN-LSTM, and hybrids act like black boxes, making it difficult to interpret them with regard to policy and health decisions. Main hindrances to scalability and generalization of deep models are computation-expensiveness and hyperparameter sensitivity.
- The inference latency and sudden emissions-exposure changes due to season-ality or policy actions make real-time forecasting challenging.
- Some of the unresolved operational constraints are related to sensor mainte-nance, model drift, re-training requirements after regular intervals, and re-strictions imposed on real-time alleviation.

VII. Applications

- Smart city air monitoring systems continuously and in real time monitor pol-lution, while IoT- and AI-based real-time alert systems generate workings warnings to the public against any sudden pollution spikes. Dust-level moni-toring technologies add to the safety of the environment of mining activity.
- Urban health risk assessments can be further refined through air quality pre-diction integration framework. Air quality forecasts guide planning and effec-tiveness evaluation of nonpharmaceutical interventions (NPIs). Public adviso-ries on regional AQI forecasts provide an evidence-based policymaking basis. ~10% RMSE reduction over the baseline models is achieved with hybrid deep-learning models, thus improving the reliability of forecasting.
- The real-time feedback from sensors and predictive models forms on the basis of traffic emission control. Microalgae research-culture method serves the in-novative remediation of industrial effluents and wastewater. Pollution-driven digital twins are a way to smart city planning and dynamic congestion man-agement.

VIII. Conclusion

With hybrid deep-learning architectures such as CNN-LSTM and Transform-ers, high performance has been demonstrated in fine-tuning and near-term air-quality forecasting. The other approaches, including microalgal remediation, IoT-AI convergence, blending satellite and ground observations, widen the sphere of influence and sustainability in poorly reported areas such as rural India and Africa. Multi-output graph-based frameworks and ensemble-type prediction techniques like RF-ARIMA and hybrid CNN-LSTM-type models continue ensur-ing predictive robustness, interpretability, and policy relevance. Although there is rapid methodological advancement with increasing generalizability and scala-bility of models, there are still considerable gaps in large-scale optimization, standardized benchmarking, uncertainty quantification, and explainability.

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