

PAPER

Prediction of Atmospheric Pollution Using Hybrid Machine Learning Algorithms: A Review

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ABSTRACT

Accurate prediction of atmospheric pollution is critical for public health, guiding environmental policies, and mitigating the adverse effects of air pollution. Traditional statistical models and standalone machine learning algorithms, while useful, often fail to capture the complex, nonlinear interactions between multiple factors influencing air quality, such as meteorological conditions, traffic emissions, and industrial activities. This paper presents a comprehensive review of machine learning techniques applied to air pollution prediction, with a special focus on the growing trend of hybrid models (HM). In addition, this paper highlights future research directions centered on developing adaptive HM capable of integrating diverse data streams, addressing gaps in data availability, and dynamically responding to changing pollution patterns. Furthermore, the paper presents a strategy on how combining machine learning algorithms can enhance predictive accuracy and robustness by leveraging the unique capabilities of each model. The findings from this study aim to provide a foundation for future research and practical applications in air quality management, ultimately contributing to more effective pollution forecasting and control strategies.

KEYWORDS

atmospheric pollution prediction, machine learning, hybrid models (HM), air quality forecasting, data preprocessing

1 INTRODUCTION

According to the World Health Organization (WHO), air pollution is the presence of one or more contaminants in the atmosphere, such as dust, fumes, gas, or smoke, in quantities and durations that can be injurious to human health. The sources of air pollution are the excess use of transport with fossil fuels, household fuels for cooking, lighting and heating; coal-fired power plants, agriculture and waste burning. Exposure to high levels of air pollution can cause significant issues such as respiratory infections, heart disease, lung cancer, chronic obstructive pulmonary disease (COPD), cardiovascular problems stroke and cataract. There are

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many toxins that have adverse impacts on health, such as particulate matter (PM), carbon monoxide (CO), OZONE (O_3), nitrogen dioxide (NO_2) and Sulphur dioxide (SO_2). Particulate matter ($PM_{2.5}$) is severely harmful as it can penetrate deep into the lungs and enter the bloodstream, causing systemic inflammation and damage to vital organs [1]. In addition, air pollution not only degrades the air quality but also has significant impact on Climate change as greenhouse gas emissions, including CO_2 , N_2O , CH_4 , O_3 and various fine particles, contribute to the heat generation of the planet [2]. In 2019, air pollution caused about 6.7 million deaths, where almost 85% are attributable to non-communicable diseases (NCDs), including ischemic heart disease, stroke, lung cancer, asthma, COPD, and diabetes. Considering the above, air pollution is the second leading cause of NCDs globally [3]. Traditional statistical models, while useful, often fall short in capturing the complex, nonlinear interactions between various factors influencing air quality, such as meteorological conditions, traffic emissions, and industrial activities. Single machine learning models have shown promise in this domain; however, their performance can be limited by specific assumptions or constraints inherent to each method. The latest developments in the area of prediction of atmospheric pollution using machine learning algorithms suggest the combination of machine learning algorithms in order to overcome individual limitations by leveraging the strengths of different models. This paper presents a survey of machine learning model combinations to provide more reliable and actionable air quality predictions. Unlike previous surveys, which primarily focus on standalone machine learning models, our paper is one of the first dedicated reviews specifically examining hybrid machine learning approaches for atmospheric pollution prediction. We comprehensively analyze how different machine learning techniques are combined to enhance predictive accuracy, model robustness, and interpretability, providing a structured comparison that is currently lacking in published literature.

The remainder of this paper is organized as follows: Section 2 delves into the data sources and methodologies for implementing machine learning, describing key algorithms and evaluation metrics. Section 3 presents a comprehensive literature survey, reviewing existing studies on machine learning applications in atmospheric pollution prediction, with a focus on the emerging trend of hybrid and ensemble models. Section 4 outlines the main research directions, detailing the motivation behind using hybrid machine learning approaches and proposing methodologies for the implementation of hybrid machine learning models in atmospheric pollution prediction. Finally, Section 5 concludes this paper and presents our future work.

2 DATA PREPARATION AND MACHINE LEARNING ALGORITHMS FOR ATMOSPHERIC POLLUTION PREDICTION

The process of implementing machine learning in pollution prediction begins with data collection and preprocessing. This stage involves gathering data from a range of data sources, such as weather stations, air quality sensors, satellite data, and historical pollution records. Typical pollutants monitored include $PM_{2.5}$, PM_{10} , CO, NO_2 , SO_2 , and O_3 . Preprocessing steps are essential for ensuring data quality and may include handling missing values, addressing outliers, normalizing or scaling data, encoding categorical variables, and applying time-series decomposition if needed. Next step is the feature selection, where relevant features are identified, such as meteorological factors (temperature, humidity, and wind speed),

terrestrial information, and traffic patterns. Once features are selected, algorithm selection follows. After selecting an algorithm, the dataset is split into training, validation, and test sets in the training and testing phase. Cross-validation techniques, such as k-fold cross-validation, are used to improve model robustness and to help with tuning hyper-parameters. Hyper-parameter tuning is the next step, where model parameters are optimized to enhance accuracy and efficiency. The model evaluation stage involves measuring performance using relevant metrics. Finally, once a model performs well, it can be moved into model deployment and maintenance.

2.1 Data sources

Air pollution prediction relies on diverse datasets, capturing both pollutant concentration levels and factors influencing air quality. Key data sources include the following: *Air quality monitoring stations* [9]: Air quality data is often collected from governmental and private monitoring stations. These stations measure pollutant levels such as $PM_{2.5}$, PM_{10} , CO, NO_2 , SO_2 , and O_3 at regular intervals. *Meteorological data* [10]: Weather conditions play a critical role in pollution levels. Meteorological data sources, such as public agencies, meteorological agencies, and global databases, offer data on temperature, humidity, wind speed, wind direction, precipitation, and solar radiation. *Satellite data* [11]: Satellite sources provide continuous, large-scale information on pollutants such as aerosols and NO_2 . *Traffic and transportation data* [12]: Road traffic emissions are a significant source of urban pollution, especially for pollutants such as $PM_{2.5}$, PM_{10} , CO, and NO_2 . *Land use and topographical data* [13]: Land use data helps quantify pollution sources (e.g., industrial zones, residential areas, green spaces) and geographical features that affect pollution dispersion. *Socioeconomic and population data* [14]: Demographic and socioeconomic factors, including population density, urbanization levels, and industrial activity, can impact local pollution levels. *Historical pollution and event data*: Historical records, including previous pollution episodes, wildfires, or seasonal events, help models account for recurring pollution patterns or extreme events that influence air quality.

2.2 Data preprocessing

To ensure that data from various sources is ready for modeling, several preprocessing steps are applied to handle inconsistencies, enhance quality, and standardize features across datasets. These steps typically include data cleaning, where missing values are addressed through techniques such as interpolation, mean imputation, or forward filling, depending on the nature of the data. For datasets that combine information from multiple sources, data normalization and scaling ensure that features measured on different scales are standardized. Min-max scaling or z-score standardization are commonly used techniques, particularly when working with models sensitive to feature magnitude, such as neural networks (NN) and distance-based algorithms.

Finally, data integration and alignment are crucial for combining datasets from different temporal and spatial resolutions. Techniques such as time interpolation or spatial resampling are applied to align data points consistently across sources, ensuring that all features are synchronized before they enter the modeling stage.

Together, these preprocessing techniques transform raw, multi-source data into a cohesive and high-quality dataset, setting a solid foundation for accurate pollution prediction.

Table 1. Strengths and the weaknesses of machine learning algorithms

ML Algorithm	Strengths – Pros	Weaknesses – Cons
Linear Regression (LR) [19]	Simple to implement and interpret; computationally efficient; provides a clear understanding of relationships between variables.	Assumes linear relationships; sensitive to outliers; may underperform with complex, nonlinear data.
Decision Trees (DT) [20]	Easy to understand and visualize; handles both numerical and categorical data; requires little data preprocessing.	Prone to overfitting; can be unstable with small changes in data; lacks predictive power on its own for complex datasets.
Random Forest (RF) [5]	Reduces overfitting compared to single decision trees; robust against noise and outliers; provides feature importance metrics.	More complex and less interpretable; longer training times with large datasets; can be computationally intensive.
Support Vector Machines (SVM) [6]	Effective in high-dimensional spaces; robust to overfitting, especially with high-dimensional data; can handle nonlinear relationships using kernels.	Memory-intensive; sensitive to the choice of parameters; less effective on exceptionally large datasets.
Neural Networks [21]	Capable of modelling complex nonlinear relationships; flexible architecture allows for various applications; excels in large datasets with rich features.	Requires large amounts of data for effective training; often seen as a “black box,” making interpretation difficult; longer training times.
K-Nearest Neighbors (KNN) [22]	Simple to understand and implement; no training phase; effective for small datasets with clear clusters.	Computationally expensive during prediction; performance degrades with high-dimensional data; sensitive to irrelevant features and distance metrics.

2.3 Machine learning algorithms

Several machine learning algorithms have been used for atmospheric pollution prediction, and each algorithm has distinct characteristics and applications that cater to varying data types and modeling needs: *Linear regression (LR)* [7]: This algorithm models the relationship between dependent and independent variables by fitting a linear equation to the observed data. *Decision trees (DT)* [15]: DT are intuitive models that partition data into subsets based on feature values, creating a tree-such as structure of decisions. Each node represents a feature, and branches represent decision outcomes, leading to terminal nodes that provide predictions. *Random forest (RF)* [16]: RF is an extension of DT. RF deploy an ensemble approach, constructing multiple trees from bootstrapped subsets of data and averaging their predictions. This method enhances robustness and accuracy by reducing variance, making it less susceptible to overfitting compared to individual DT. *Support vector machines (SVM)* [17]: SVMs are powerful classifiers that operate by finding the optimal hyperplane that separates different classes in high-dimensional space. *NNs* [8]: Deep learning models, especially feedforward NN and recurrent neural networks (RNNs), have revolutionized prediction capabilities. Feedforward neural networks consist of interconnected layers of nodes that learn to identify complex patterns in data through backpropagation. *K-nearest neighbors (KNN)* [18]: KNN is an algorithm that classifies data points based on the majority class of their nearest neighbors. Table 1 shows the strengths and the weaknesses of the above algorithms.

2.4 Algorithms evaluation metrics

The most important metrics used to evaluate the performance of machine learning algorithms [23] for pollution prediction are the following: *Mean absolute error (MAE)*: MAE is the average of the absolute differences between the predicted and actual values.

MAE formula is the following: $MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$. MAE provides a direct measure of how far predictions are from actual values, making it easy to interpret.

Mean squared error (MSE): MSE calculates the average of the squared differences between predicted and actual values. The MSE formula is the following: $MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$.

MSE is sensitive to large errors due to the squaring process, which makes it useful for models where large deviations from actual values should be penalized.

Root mean squared error (RMSE): RMSE is the square root of the MSE and is expressed in the same units as the target variable. RMSE formula is the following: $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$.

RMSE is often used in pollution prediction as it emphasizes larger errors while remaining on the same scale as the target variable, making it easier to interpret than MSE.

R-squared (R^2) coefficient of determination: Definition: R^2 measures the proportion of the variance in the dependent variable that is predictable from the independent variables. R^2 formula is the following: $R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$. R^2 ranges from 0

to 1, where values closer to 1 indicate that the model explains a high proportion of the variance in the target variable.

Mean absolute percentage error (MAPE): MAPE calculates the average of the absolute percentage errors between predicted and actual values. MAPE formula is the following: $MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$. MAPE is

useful for interpreting errors as percentages, which can provide context on the relative magnitude of errors, especially when comparing different datasets or prediction models in pollution forecasting.

Confusion matrix: A confusion matrix is a table that summarizes the performance of a classification model by showing the counts of true positives, true negatives, false positives, and false negatives. *Accuracy*: Accuracy is the proportion of correct predictions out of all predictions made. Accuracy formula is the following: $Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$. Although accuracy is a commonly used metric for classification tasks, it can be misleading if the data is imbalanced (e.g., with many "low pollution" and few "high pollution" cases).

Precision, recall, and F1 score: Precision measures the proportion of true positive predictions out of all positive predictions. Precision formula is the following: $Precision = \frac{TP}{TP + FP}$.

Recall measures the proportion of true positive predictions out of all actual positives. Recall formula is the following: $Recall = \frac{TP}{TP + FN}$.

F1 score is the harmonic means of precision and recall, providing a balanced measure when classes are imbalanced. F1 Score formula is the following: $F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$.

Precision, recall, and F1 score are used to evaluate the performance of classification models in pollution forecasting.

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and F1 score are particularly important in imbalanced classification tasks, such as detecting high pollution levels, where accurately identifying rare cases is crucial. Selecting the appropriate metrics is essential for ensuring reliable predictions and ultimately guiding effective pollution management strategies.

3 LITERATURE SURVEY

The application of machine learning in atmospheric pollution prediction has evolved rapidly, offering new methods to provide accurate, real-time forecasts for complex environmental systems. While traditional machine learning models, such as LR, DT, and SVM, have been widely explored, recent research highlights the growing interest in hybrid machine learning approaches.

The research of Harishkumar, K. et al. [34], conducted in Pingtung station, Newport city in Taiwan. According to the paper, fifty percent of the kids have unhealthy conditions due to air pollution. The prediction of PM_{2.5} concentration is an imperative need as it plays a vital role in public health. The researchers deployed RF algorithm, gradient boosting regression algorithm (XG Boost), DT Regression algorithm and multilayer perception algorithm (MLP regression). On the contrary, the research of Xiao et al. [4] propose a dual-path dynamic directed graph convolutional network (DP-DDGCN), where spatial and temporal correlations are included, for prediction of air quality in China. With this algorithm, researchers deploy the static distance relationships of stations and the dynamic data generated by the wind speed and direction. Furthermore, researchers deployed the long short-term memory (LSTM) algorithm, graph convolutional networks and long short-term memory networks (GC-LSTM) algorithm, and spatio-temporal graph convolutional networks (STGCN) algorithm. The LSTM algorithm can capture temporal data but not spatial ones, whereas GC-LSTM and STGCN algorithms can capture both temporal and spatial data. Afterwards, the outcome of each of the above algorithms is compared with the ground truth data values. Researchers derived data from government sources and ERA5 [24].

Another research carried out by Gaganjot Kaur Kang et al. [25] points out that researchers have carried out air quality forecasting using big-data analysis and machine learning techniques. Researchers deployed the former technique to forecast the air quality in various cities worldwide. Data is being provided by sensors, and they are concentrations of PM, O₃, dust, smoke, and haze. There are no reports of the researchers' results expect the research carried out in a laboratory, which produced a coefficient of $R^2 = 0.7567$. In the same research, authors deployed machine learning technics to forecast air quality, as well. Data is being provided by sensors, as well, and, in this technique, data are NO₂, SO₂, CO₂ and PM_{2.5}. The models deployed were artificial neural networks algorithm (ANN), genetic algorithm ANN (GA-ANN), deep belief network algorithm (DBN), DT, RF and SVR. Based on [25], the DPN algorithm has the lowest error. There are some forms of ensemble the data provided, such as bagging, boosting and stacking [26]. In the bagging form, each model is trained, using the training data, and the results are average. By averaging the results, overfitting is eliminated. On the other hand, in Boosting form, a sequence of models is built and the output of the residuals of one model is the input of the next one. The purpose of Boosting form is to reduce bias. Finally, in Stacking form, the outputs from individual models are provided to another estimator, called the meta-model, to obtain the final output. An implementation of the above ensemble is described in Samad et al. [26] where researchers modelled the pollutants PM_{2.5}, PM₁₀, and NO₂ at two locations in Stuttgart, Germany, from January the 1st 2018 to 31st of March 2022. The scope of

this study was to replace monitoring stations with machine learning models to avoid the high cost of establishing a monitoring station.

Another implementation of hybrid algorithms (HA) described in Ling Xiao Zhao et al. [27]. The scope of this study was to predict the $PM_{2.5}$ concentration in Beijing and Dalian Liaoning. Back propagation neural network (BPNN), RF, AR, DT algorithms were deployed, however, in all cases the results were inaccurate. In [27], researchers deployed hybrid integration (HIG) algorithm that combines data pre-processing, time-series decomposition, signal decomposition, a prediction module, a matching strategy, and hybrid integrated optimization. Implementing the HIG algorithm in RNN and LSTM algorithms, four hybrid models (HM) were produced, namely, adaptive moment estimation-RNN (Adam-RNN), adaptive gradient-RNN (Adagrad-RNN), Adam-LSTM, AdaGrad-LSTM. In Zhendong Zhang et al. [28], a hybrid deep learning technology deployed to forecast the $PM_{2.5}$ concentrations in various cities in China. In this study, data collected from the US Embassy and various stations, in Beijing, from 2013 to 2017, and as a result, there were 35,064 samples. In this experiment, the first 24,000 data were selected for training in the algorithms, and 2,400 individuals were selected for evaluation. Initially, data were standardized by deploying the zero-mean standardization method. Because of the non-linearity and the volatility of the samples, data were decomposed deploying VMD and EMD decomposition algorithms. The decomposition accounted for signal stability. After pre-processing the data mentioned, eight compositions have been created. At each composition, conventional machine learning algorithms deployed, namely, DT, RF, SVR, MLP, and long short-term memory.

The combination of two machine learning algorithms for predicting PM10 concentration is, without the need for data decomposition, is described in Ekta Sharma et al. [29]. The scope of this paper was to predict PM10 concentrations in the atmosphere, in four states of Australia, especially Queensland (Mount Isa), New South Wales (Hunter Valley), South Australia (Port Pirie Smelter) and Victoria (La Trobe Valley). In order for the researchers to achieve greatest accuracy, deployed both machine learning conventional algorithms and HA, as well. All deployed had 12 inputs, namely, dust scattering, total aerosol extinction, cloud top pressure, cloud top temperature, etc. [29]. The conventional algorithms deployed were CNN, GRU, LSTM, BiLSTM. The HA deployed were CNN-GRU, CNN-LSTM and CNN-BiLSTM, namely, the output of the former (CNN e.g.) algorithm turned into the input of the latter one (GRU e.g.). The researchers of Yue-Shan Chang et al. [30], deployed HA to predict PM2.5, however, with a different approach. The aim of their research was to make an 8h prediction for PM2.5 concentration in cities of Daliao, Linyuan, Pingtung, Zhushan, Xiaogang, Dongshan and Nanzi, in Taiwan state. Data were retrieved from Environmental Protection Administration of Executive Yuan, R.O.C from 2012 to 2017 for training and from 2018 were selected for testing. To begin with, researchers split the 8h prediction into 1h intervals. For each hourly interval and for each one city, researchers deployed GBT, SVR, LSTM and LSTM2 machine algorithm algorithms in order to predict the PM2.5 concentration. Afterwards, data produced from the previous predictions, Pearson's correlation deployed in order to find whether there is correlation between the real values of PM2.5 concentration, and the predicted ones from the previous machine algorithm models. Researchers of Yali Hou et al. [31] deployed DT, AdaBoost, CatBoost, XGBoost, GBDT and RF to predict PM2.5 concentration across 297 cities in China between 2000 and 2021. The PM2.5 data was retrieved from the Atmospheric Composition Analysis Group at Washington University, meteorological data retrieved from Zhongli data network and the individual ones from mark data network. The study conducted under an innovative approach, namely,

not only considered meteorological data but also human-controlled factors. The former factors include wind speed, rainwater, sunshine, and humidity. Another study deploying hybrid algorithm referred to Alan Domínguez et al. [32]. The aim of this study is to assess air pollution to evaluate the health effects. Researchers deployed land use regression (LUR), dispersion (DM), and HM to estimate the concentrations of NO_2 , $\text{PM}_{2.5}$, black carbon (BC), and $\text{PM}_{2.5}$ -constituents (Fe, Cu, Zn) in Barcelona. Data was retrieved by monitoring stations and two independent campaigns, namely, «BiSC-home» where took place at 984 home addresses, and «BiSCAPE» where measurements retrieved from 34 locations across Barcelona.

The aim of study conducted by Youness El Mghouchi et al. [33] was to predict PM_{10} , $\text{PM}_{2.5}$, and PM_{10} concentrations in Craiova city, in Romania deploying HA. Data provided from twelve sensors established across Craiova city, from 22 September 2021–17 February 2022. Each sensor transmitted data every minute. Eleven sensors provide PM concentrations, temperature, relative humidity, and pressure. The twelfth sensor provides volatile organic compounds (VOC), Ozone, CO_2 and noise level. Prior to deployment of ML algorithms for pollutants prediction, researchers implemented autonomous anomaly detection method, during data processing, to exclude outliers. The HA deployed were ANN, SVM, Gaussian process regression (GPR), LR where implemented feature selection – machine learning (FS-ML) methods to identify the most relevant predictor variables and enhance prediction accuracy. Chelhaoui et al. [35] present a novel hybrid modelling approach that integrates chemical transport models (CTM) with ML techniques to improve the prediction of PM_{10} concentrations. The study addresses the limitations of CTMs, such as bias due to input precision, by enhancing their forecasts with ML-based corrections. The hybrid approach utilizes predictions from the WRF-CHIMERE model in combination with five machine learning algorithms: Multiple linear regression (MLR), RF, extreme gradient boosting (XGB), SVR, and artificial neural networks (ANN). The HM were trained on hourly data from September to December 2020 across seven Moroccan monitoring sites, incorporating nine meteorological, chemical, and spatiotemporal variables.

Zaheer et al. [36] present a hybrid machine learning approach for predicting aerosol optical depth (AOD) over Pakistan, addressing the challenges of nonlinear relationships, uncertainties, and temporal variability in aerosol concentration data. The study introduces a novel SVR- gray wolf optimizer (GWO) model, which integrates SVR with the GWO, to enhance predictive accuracy by optimizing SVR hyper-parameters using a meta-heuristic algorithm. The proposed model is compared against standard SVR and MLR models, utilizing satellite-based AOD data on a monthly basis. Petrić et al. [37] explore ensemble machine learning, deep learning, and time-series forecasting to enhance the generalization capabilities of predictive models for hourly air pollutant concentrations, particularly in scenarios with limited access to high-quality data. The study implements multiple machine learning techniques, including Prophet, RF, and three deep learning architectures—LSTM networks, CNNs, and multilayer perceptron's (MLPs). Additionally, the authors introduce a hybrid model combining RF and Prophet, leveraging Prophet's time-series forecasting strengths alongside RF's predictive power to capture complex temporal patterns more effectively. Shen et al. [38] propose a novel deep learning blending ensemble model for the accurate prediction of hourly $\text{PM}_{2.5}$ concentrations in dry bulk port clusters, addressing the spatiotemporal correlations between neighboring ports and surrounding urban pollution sources. The study highlights the challenges of $\text{PM}_{2.5}$ prediction in port clusters, where unique meteorological conditions, the interdependence of $\text{PM}_{2.5}$ levels across ports, and the influence of urban background pollutants complicate forecasting. To tackle these issues, the authors

develop a hybrid deep learning model, integrating GCN, LSTM networks, residual neural networks (ResNet), and CNN. In this architecture, GCN captures spatial correlations in $PM_{2.5}$ levels among ports, LSTM models long-term temporal dependencies influenced by meteorological factors, and ResNet accounts for the impact of urban air pollutants.

The following paragraph presents a comparative overview of various research papers that explore machine learning models for atmospheric pollution prediction, with each paper highlighting different methodologies, datasets, and objectives. Harishkumar, K. S. et al. [34] evaluated models such as gradient boosting regressor, random forest regressor (RFR), and decision tree regressor across air quality monitoring stations in Taiwan, focusing on $PM_{2.5}$ prediction. Their results demonstrate that gradient boosting regressor outperforms other models with an R^2 of 0.8891, indicating high predictive accuracy, while simpler models such as ridge regression show significantly lower R^2 values of 0.1104, underlining their limitations. Xiao Xiao et al. [4] analyzed data from 184 cities in China and compared the performance of multiple models, including Lasso and Ridge regression. The study found that advanced models such as RFR yielded better predictive metrics ($R^2 = 0.8699$), whereas linear models such as ridge struggled with an R^2 of 0.1104, highlighting the challenges of capturing non-linear pollution patterns in large datasets. Lingxiao Zhao et al. [27] introduced HM such as VMD-AdaGrad-LSTM, which demonstrated remarkable performance with R^2 values approaching 1.0000 for $PM_{2.5}$ prediction, emphasizing the effectiveness of hybrid methodologies in handling complex pollution data. Similarly, in [31] explored boosting techniques such as CatBoost and XGBoost and observed significant improvements in accuracy, with CatBoost achieving an R^2 of 0.9407, surpassing traditional tree-based models such as AdaBoost ($R^2 = 0.2295$). Finally, in [25] implemented ANN, and genetic algorithm-enhanced ANN (GA-ANN) models are implemented to predict pollutants such as NO_2 and SO_2 . Their results show that GA-ANN models substantially improve prediction accuracy, achieving a mean absolute percentage error (MAPE) of 18.6%. These findings demonstrate the importance of tailoring model selection to specific datasets and prediction objectives for optimal performance. Chelhaoui et al. [35] enhance PM_{10} predictions by integrating the WRF-CHIMERE model with RF and XGB, achieving correlation coefficients of 0.756 and 0.747 and reducing MSE from 42.39 to 21.72 $\mu g/m^3$ for CHIMERE-RF, demonstrating a substantial reduction in bias and error. Zaheer et al. [36] optimize AOD predictions using the SVR-GWO hybrid model, which outperforms traditional SVR ($R^2 = 0.18$) and MLR ($R^2 = 0.03$) by achieving an R^2 of 0.60 and reducing RMSE and MAE by up to 30%. Petrić et al. [37] focus on hourly pollutant forecasting using ensemble (RF-Prophet) and deep learning models (LSTM, CNN, MLP), with their hybrid RF-Prophet model improving R^2 by up to 35% for PM_{10} and achieving R^2 values between 0.83 and 0.87 for O_3 . Shen et al. [38] introduce a blending ensemble deep learning model (GCN-LSTM-ResNet-CNN) for $PM_{2.5}$ forecasting in port clusters, outperforming six benchmark models and achieving MAE and RMSE reductions of 10.59%–20.00% and 13.22%–17.11%, respectively, while improving R^2 by up to 35.38%. Among these studies, in [38] achieve the highest predictive accuracy due to their ensemble deep learning framework, while in [35] and in [37] showcase strong results in integrating traditional models with machine learning. Zaheer et al. [36] highlight the benefits of meta-heuristic optimization, demonstrating how hybridization can improve model efficiency in various atmospheric pollution prediction tasks. The results indicate that advanced and HM, such as Gradient Boosting Regressor, VMD-AdaGrad-LSTM, and CatBoost, consistently outperform simpler models such as ridge and Lasso regression in atmospheric pollution prediction. Models incorporating

neural network architectures or ensemble techniques demonstrate superior performance, particularly for complex datasets and large-scale applications.

While this review provides an overview of the strengths and weaknesses of various machine learning algorithms used in atmospheric pollution prediction, it is important to note that the performance of these models is highly dependent on several factors, including dataset characteristics, feature complexity, and environmental variability. Models such as RF tend to perform well in capturing nonlinear relationships in high-dimensional datasets. Similarly, deep learning models such as LSTMs and CNNs have shown strong predictive capabilities for sequential and spatial data, respectively, but their performance can be constrained by computational requirements and data availability. Given the diversity of datasets and modeling approaches, it is difficult to generalize why a particular algorithm performs better under certain conditions without an extensive empirical and theoretical analysis across multiple case studies.

4 FUTURE RESEARCH DIRECTIONS

Based on the literature survey presented in the previous section, future research directions in the area of atmospheric pollution prediction will be mainly through the integration of hybrid machine learning methods. While traditional and stand-alone models have significant results for air quality forecasting, their limitations in capturing complex, dynamic interactions among environmental variables have prompted the need for more sophisticated approaches. By combining multiple machine learning algorithms, researchers will aim to leverage the unique strengths of different techniques, enhancing model accuracy, robustness, and interpretability. While machine learning has significantly advanced atmospheric pollution prediction, several key gaps and future directions remain. Among these, the combination of different machine learning methods to enhance predictive accuracy and robustness represents a promising area of research. Combining models such as DT, NN, and SVM [39], either in ensemble structures (e.g., stacking or boosting) or in sequential HM, could capture a wider array of pollution patterns and interactions. For example, ensemble methods such as RF or gradient boosting [40] have shown promise in handling high-dimensional datasets with nonlinear relationships, while recurrent NN are adept at handling time-series dependencies. Another aspect of combining machine learning methods involves integrating traditional statistical models with advanced machine learning techniques [41]. For example, LR or autoregressive models [42] could be used alongside NN to capture both linear and nonlinear components of pollution trends. This type of hybrid modeling could improve interpretability while benefiting from the flexibility of deep learning for complex patterns, thus addressing the “black box” issue that is often a drawback of purely neural network-based approaches.

A related challenge is the limited availability of high-resolution and real-time pollution data, particularly in underserved regions. To overcome this, researchers could explore data fusion techniques [43] that combine satellite data, mobile sensors, and crowdsourced data with traditional monitoring station data. Additionally, combining supervised learning (where labeled data is available) with semi-supervised or unsupervised learning techniques (useful in less-labeled environments) could enhance predictive capabilities in regions with limited data.

Lastly, adaptive modeling frameworks that continuously incorporate new data and evolving environmental factors are critical for maintaining model accuracy

over time. Integrating machine learning models that adapt to real-time data updates and learn continuously could help models adjust to shifting pollution patterns resulting from urbanization, industrial expansion, and climate change. Following, the necessary steps in order to implement hybrid machine learning models in atmospheric pollution prediction are presented. The first step is the base model algorithm selection, where a diverse set of algorithms is chosen to capture different aspects of the data. This selection typically includes linear models such as LR for identifying baseline trends, tree-based models such as DT and RF for handling non-linear relationships, SVM for robust classification in high-dimensional spaces, and NN for modeling complex, nonlinear patterns in time-series data.

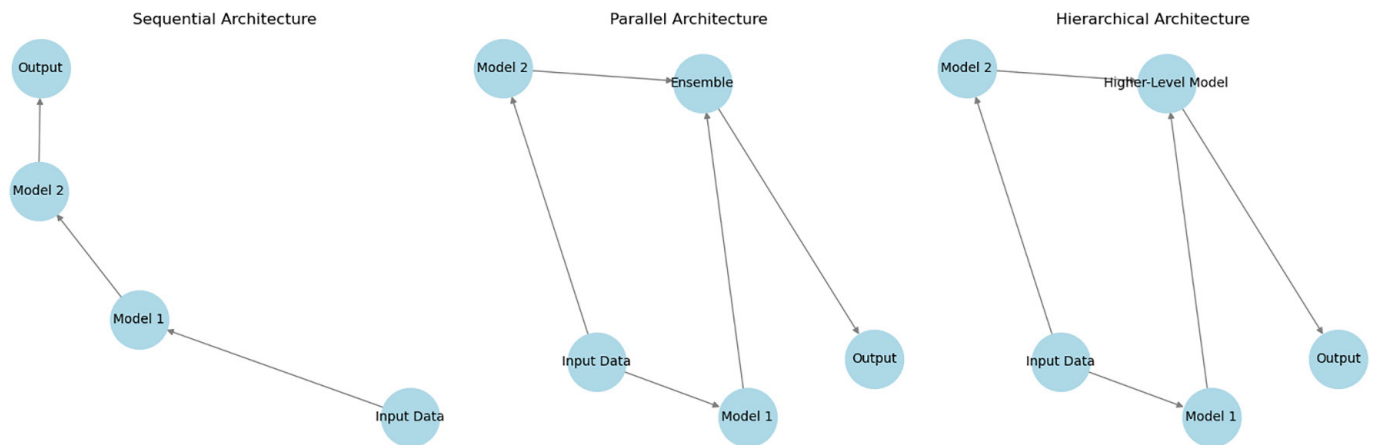


Fig. 1. Three hybrid model architectures: sequential, parallel, and hierarchical

In constructing a hybrid model, three main approaches are employed: sequential, parallel, and model for partial data. In the sequential approach, a simpler model such as LR is used first to capture basic trends and linear influences, followed by more complex models such as RF or NN to address residual errors and capture non-linear interactions. In sequential hybridization, models are applied in a layered manner where simpler algorithms are used initially to identify basic trends in the data. Residual errors from this initial model are then fed into more complex models, such as capturing additional nonlinear patterns and temporal dependencies. This cascading approach helps reduce prediction errors iteratively by learning from the shortcomings of each preceding model. In the parallel approach, different models are trained simultaneously on the same dataset. For instance, DT might capture feature interactions, while NN handle temporal dependencies. Here, each model independently generates its predictions, capturing different aspects of the data. The predictions from these diverse models are then combined using ensemble techniques such as stacking, blending, or weighted averaging. In stacking, a meta-model (often a simpler model such as logistic regression or a neural network) is trained to learn the optimal way to combine the predictions of the base models, improving overall performance. Alternatively, in weighted averaging, weights are assigned to each base model based on their performance during cross-validation, and the final prediction is a weighted sum of the individual outputs. An alternative hierarchical approach applies different models based on specific conditions or feature subsets, allowing for a tailored response depending on the characteristics of the data. The hybrid model is further fine-tuned by adjusting the weights in weighted averaging or refining the meta-model in stacking to achieve the best ensemble performance.

The performance of the hybrid model is then compared against individual base models and other standard approaches to verify its effectiveness.

To enhance the clarity of our proposed research directions, we introduce a visual representation of the three hybrid model architectures: sequential, parallel, and hierarchical, as shown in Figure 1. The hybrid approach's main benefit is the ability to combine the unique advantages of diverse machine learning models. By integrating these capabilities, the hybrid methodology mitigates the weaknesses of individual algorithms, resulting in a more robust and accurate prediction system. This is especially beneficial in atmospheric pollution prediction, where the data is complex and influenced by multiple interacting environmental factors. The combination of different models allows for adaptive learning, enabling the system to adjust dynamically based on varying pollution scenarios, thus enhancing its predictive capabilities across different geographical and temporal contexts. The hybrid implementation approach effectively mitigates the weaknesses of individual models. This synergy among various models helps in building a robust predictive framework, capable of adapting to the complex and dynamic nature of atmospheric pollution. By focusing on diverse base model selection and integrating them through a hybrid approach, the methodology aims to deliver improved prediction accuracy and generalizability, offering a powerful tool for real-time air quality forecasting and decision-making support. In conclusion, the combination of machine learning methods holds substantial promise for advancing air quality prediction. Hybrid, ensemble, and interdisciplinary approaches could provide more accurate, interpretable, and resilient models. Addressing this primary research direction alongside data fusion and adaptive modeling will be critical for the future of machine learning in pollution prediction and management.

5 CONCLUSION – FUTURE WORK

Accurate pollution forecasts can inform individuals about high-risk periods, enabling them to take precautionary measures, such as limiting outdoor activities. This paper presents a comprehensive review of machine learning techniques applied to air pollution prediction, with a special focus on HM. Our analysis highlights how combining algorithms can enhance predictive accuracy and robustness by leveraging the unique capabilities of each model. This study also highlights data sources, preprocessing techniques, and evaluation metrics commonly used in this domain. Furthermore, this paper proposes a novel research direction centered on developing adaptive HM capable of integrating diverse data streams, addressing gaps in data availability, and dynamically responding to changing pollution patterns. The findings from this study aim to provide a foundation for future research and practical applications in air quality management, ultimately contributing to more effective pollution forecasting and control strategies. Our future work includes the implementation of hybrid machine learning models for predicting atmospheric pollution. This includes combining deep learning models, such as CNNs and RNNs, with traditional machine learning algorithms such as RF or SVM to capture both spatial and temporal pollution patterns effectively. Moreover, we plan to evaluate the above-described hybrid machine learning models in the region of Ioannina, Greece, where pollution with PM is very intensive during the winter. We plan to apply and validate HM in the region of Ioannina, Greece, utilizing real-world air quality data. This will enable us to assess model performance under specific environmental conditions and evaluate their adaptability to localized pollution dynamics.

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