Review on Advances in Machine and Deep Learning Methods for Forecasting Air Pollution

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Abstract-
This study aims to evaluate the impact of ML and DL approaches on air pollution predictions. Air pollution is becoming an increasingly pressing environmental and public health concern, and this study focuses on their predictive power in particular. The purpose of this research is to examine different methods for capturing the intricate patterns and correlations observed in air pollution data over time. ML and DL methodologies, including decision trees, support vector machines, CNNs, and RNNs. This study investigates the ways in which these methodologies improve the precision and dependability of predictions by utilising diverse data sources and facilitating real-time forecasting. In addition, it addresses persistent obstacles such as restricted data accessibility and the ability to interpret models, suggesting that researchers, politicians, and technology developers work together as a solution. By combining different data sources and allowing for real-time applications, the results imply that using ML and DL algorithms substantially improves the precision of air pollution prediction. Data trustworthiness and deep learning model comprehensibility are two ongoing issues. The future of weather forecasts, especially in densely populated urban areas, appears bright with the combination of atmospheric models, data from high-resolution sensors, and advanced machine learning algorithms. Lessening air pollution and its negative impacts on people and the planet calls for concerted action and fresh approaches.
Keywords- Collaborating on air pollution forecasts, using machine learning and deep learning

I. INTRODUCTION

The goal of this study is to examine the most recent developments in the use of deep learning and machine learning for the prediction of air pollution. Reliable projections of future air quality are more crucial than ever before due to the growing number of worries about the ill consequences of air pollution on both humans and the planet. Traditional methods often fail to capture the complex [1]–[4]. On the other hand, data-driven modelling offers ML and DL techniques hope for the future. By allowing the extraction of useful insights from big and diverse datasets, ML and DL methods have transformed AI pollution prediction. Decision trees, support vector machines, and random forests are some of the most well-known machine learning techniques used for air quality prediction. Surprisingly adept in detecting complex data patterns and adjusting to new circumstances, these algorithms [5]–[9].

Fig.1 Air pollution Forecasting[10]

Because of its ability to learn hierarchical data representations on its own, A subfield of machine learning (ML), deep learning (DL) has revolutionised the process of making predictions about air pollution. Neural networks, both deep and superficial, as well as recurrent and convolutional, are extensively used in this domain. [11]–[13]. Deep neural networks (DNNs) are highly suitable for complicated modelling of relationships in data with a large number of dimensions, whereas convolutional neural networks (CNNs) excel at extracting spatial and temporal aspects from pollutant concentration maps. Recurrent Neural Networks (RNNs) have a notable efficacy in time series forecasting problems due to their sequential modelling capacity. The accuracy and reliability of air pollution forecasts have been significantly improved with the incorporation of ML and DL techniques into these systems. These models have the capability to integrate diverse input data sources, such as meteorological data, satellite imaging, and sensor readings, in order to comprehensively capture the complex fluctuations in air quality[14]–[17]. In addition, ML and DL models are great for real-time forecasting because of their adaptability and ability to alter on their own. Despite their great effectiveness, air pollution forecasting models based on ML and DL still face challenges. The quality and diversity of the training data have a major impact on how well these models work. Problems with data availability, missing values, and heterogeneity are among the many obstacles that could make model development and deployment challenging. Additionally, there is still concern about the understandability of complex deep learning models, which is a shame because gaining the trust and approval of stakeholders requires an understanding of the underlying processes that drive forecasts. An exhaustive overview of current state-of-the-art methods for predicting air pollution using ML and DL algorithms is the goal of this study. In order to shed light on the pros and cons of these algorithms and designs, this study will analyse their principal applications in this field. We will also examine potential applications of these techniques to mitigate air pollution's harmful impacts on human and environmental health.

RELATED WORK

Drewil 2022 et al. There is a serious issue with air pollution, which includes made worse by a lot of things, including emissions from industries and cars. Predicting pollution levels is of utmost importance, particularly when employing LSTM deep learning models. Nevertheless, the task of choosing the most suitable hyper parameters for LSTM models can present difficulties. This study suggests employing a hybrid methodology that combines the Genetic Algorithm and LSTM in order to enhance the precision of forecasting[18].

Kumar 2022 et al. The reliance of humans on air underscores the pressing need to tackle its declining quality, especially in urban regions. Using mobile devices, the cloud, and machine learning, this study aims to foretell how polluted the air will be in the future.The system endeavours to offer real-time air quality predictions using an Android application by gathering and evaluating data, which encompasses weather conditions[19].

Zhang 2022 et al. Due to the serious health risks posed by urban air pollution, accurate monitoring and forecasting are essential. Through the incorporation of several domain-specific attributes, the Deep-AIR model—a hybrid CNN-LSTM architecture—enhances the comprehension of spatial-temporal information. Better predictions for places like Beijing and Hong Kong, as well as more accurate estimates of fine-grained pollution, put the model ahead of the state-of-the-art models. It reveals important indicators for different types of contaminants [20].

Shakya 2022 et al. predicting the daily air quality index using pollutant concentrations as predictors, this study use the GRU model. The number of neurons, number of epochs, and learning rate are all hyper parameters that may be optimized using ADAM. The model's accuracy is assessed using metrics like MSE, RMSE, MAE, or R^2, which show that the air quality index is estimated with a high degree of precision[21].

Kothandaraman 2022 et al. Air pollution, and PM2.5 in particular, is a big concern, and it has prompted a lot of studies. Results from the MAE, MAPE, and RMSE metrics show that XGBoost, AdaBoost, random forest, and KNN are the most reliable of the proposed machine learning models. Compared to the current method, these models provide more accurate predictions for both the PM2.5 pollutant and air quality levels [22].

TABLE.1 LITERATURE SUMMARY

Author/year	Method/model	Research gap	Parameters	Ref.
Barot/2022	Bidirectional LSTM with attention mechanism for air pollution prediction.	Limited exploration of attention mechanisms in air pollution prediction.	Attention mechanism's impact on air pollution prediction efficacy.	[23]
Mani/2022	MLR for AQI prediction, ARIMA for forecasting.	Lack of exploration into advanced ML techniques for AQI prediction.	Utilization of advanced ML techniques for AQI prediction.	[24]
Yarragunta/2021	Supervised machine learning techniques for	Lack of comprehensive comparison of ML algorithms	Comparative evaluation lacking among machine	[25]

Mokhtari/2021	Forecasting air pollution crucial; propose ConvLSTM model with uncertainty estimation.	Limited research on dynamic air pollution forecasting with uncertainty estimation.	Optimize ConvLSTM parameters for accurate dynamic air pollution forecasting.	[26]

II. OVERVIEW OF MACHINE LEARNING METHODS

The term machine learning refers to a broad category that includes many different methods that aim to teach computers to recognize patterns and draw conclusions from data without human intervention or code. These methodologies have brought about a significant transformation in several sectors, ranging from healthcare to finance and beyond. Below is a succinct summary of several fundamental machine learning techniques[27]–[29].

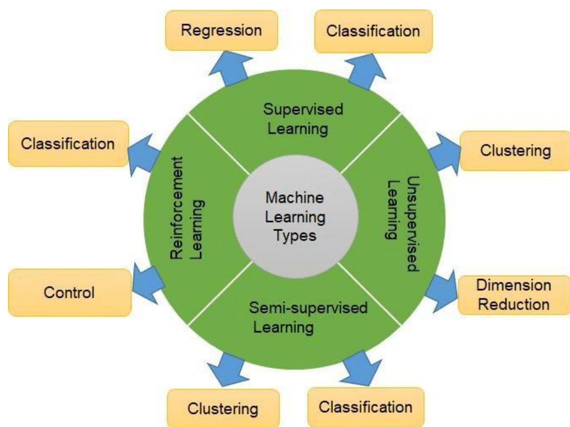

Fig. 2 Overview of Machine learning[30]

- A supervised learning algorithm gains knowledge by comparing labelled data set inputs with their matching outputs. To train the model to use previously unseen data for predictions, one must comprehend the relationship between the input and output variables. For classification problems, many people use logistic regression, decision trees, support vector machines (SVMs), or neural networks; nonetheless, when it comes to regression tasks, linear regression is always the best option.

  Unsupervised learning seeks to discover latent structures or patterns in data without labels, as opposed to supervised learning's labelling of data. Hierarchical clustering and K-means clustering are two examples of clustering methods used to group similar data points together. Principal component analysis (PCA) and t-distributed stochastic neighbour embedding (t-SNE) are two dimensionality reduction methods that can enhance data visualisation and comprehension [31]–[34].
- The concept of semi-supervised learning involves the integration of supervised and unsupervised learning techniques.

- By integrating a small bit of labelled data with a big amount of unlabeled data, it enhances learning accuracy. This method really shines when getting tagged data is a hassle or costs a lot of money. By integrating a small bit of labelled data with a big amount of unlabeled data, it enhances learning accuracy. This method really shines when getting tagged data is a hassle or costs a lot of money. of an agent to engage with an environment with the objective of optimising the accumulation of rewards. During its learning process, the agent goes through iterative experiments, where it receives feedback based on its actions, which might be either incentives or punishments. Q-learning and deep Q-networks (DQN) are widely recognised algorithms in the field. There are various applications of reinforcement learning in the fields of robotics, gaming, and autonomous systems.
- One subfield of machine learning, deep learning makes use of layered artificial neural networks to derive hierarchical data representations. In many fields, including generative modelling, natural language processing, image and speech recognition, and convolutional neural networks (CNNs) for picture recognition or recurrent neural networks (RNNs) for sequential data analysis, deep learning models have shown remarkable success.

These methods exemplify the fundamental principles of contemporary machine learning, each possessing distinct advantages and practical uses. A comprehensive grasp of the principles and capabilities of machine learning techniques is required in order to proficiently employ them in addressing practical challenges.

III. Deep Learning Techniques for Air Pollution Forecasting

Air pollution prediction is one area where deep learning approaches have shown promise, thanks to their ability to understand complex patterns in large datasets. Several noteworthy strategies include:

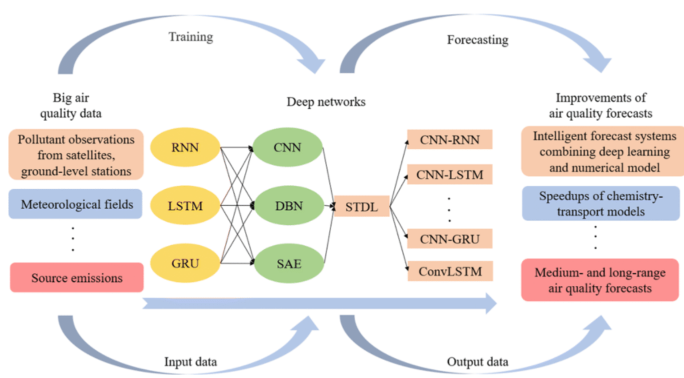

Fig. 3 Air quality forecasting using deep network designs and learning[35]

Air quality data, including data collected from sensor networks or satellite imagery, can be expertly analyzed using Convolutional Neural Networks (CNNs) for spatial and temporal trends. CNNs can accurately estimate pollutant concentrations across various locations and time intervals by utilising convolutional filters to extract features from raw sensor readings or picture pixels.

The focus is on RNNs, or Recurrent Neural Networks. Recurrent neural networks (RNNs) excel in representing time correlations in air pollution data, such as the hourly or daily fluctuations in pollutant levels. The recurrent connections of RNNs enable them to catch sequential

- patterns or long-term associations, making them ideal for time series forecasting problems. So
- Using variants of networks like Gated Recurrent Unit (GRU) & Long Short-Term Memory (LSTM) is a typical way to handle the issue of fading gradients and successfully capture long-range interactions.
  [25], [29], [36], [37].
- By simulating real-world observations as accurately as possible, Generative Adversarial Networks (GANs) offer a unique approach to air pollution forecasting. GANs can enhance the diversity and resilience of forecasting models, particularly in situations with limited or partial data, by training a generator network to generate accurate pollution patterns and a discriminator network to differentiate between actual and synthetic data.

The utilisation of deep learning techniques has the capacity to improve the precision and dependability of air pollution forecasting systems, hence leading to improved public health outcomes and environmental management strategies.

IV. COMPARATIVE ANALYSIS OF MACHINE AND DEEP LEARNING APPROACHES

Artificial intelligence encompasses two separate fields, namely machine learning and deep learning, each possessing unique properties and uses. A comparative examination of different methodologies is presented herein:

A. Data Representation and Feature Engineering:

- Machine Learning: Feature engineering is a pivotal component in conventional machine learning, wherein domain expertise is employed to manually extract pertinent features from unprocessed data. Subsequently, these characteristics are employed to train models.
- Deep Learning: Through the utilisation of several levels of abstraction, deep learning effectively obviates the necessity for manual feature engineering by autonomously acquiring hierarchical representations of data. Deep neural networks have the capability to acquire complex patterns directly from unprocessed data, including but not limited to images, text, or sensor readings.

B. Performance and Scalability

- Machine Learning: Traditional machine learning algorithms may encounter difficulties when dealing with data that has a high number of dimensions or intricate patterns, resulting in limitations in their effectiveness.
- Deep Learning: Deep neural networks and other deep learning models are very good at handling large datasets and capturing complicated connections across datasets. They routinely outperform more traditional machine learning methods on a wide range of tasks, including picture recognition, NLP, and speech recognition[32], [38]–[40].

C. Interpretability

- Machine Learning: Decision trees & linear regression are two examples of traditional machine learning models that offer straightforward explanations that help to comprehend how the models arrive at their predictions.

  Deep Learning: Deep learning models, particularly deep neural networks with multiple layers, are commonly regarded as opaque systems, as comprehending the precise decision-making mechanism can be difficult. The interpretation of deep learning models, including techniques such as feature visualisation and attribution algorithms, remains a subject of ongoing research.

D. Data Efficiency and Generalization

- Machine Learning: In order to attain good performance, particularly for intricate jobs, conventional machine learning algorithms sometimes necessitate a significant quantity of labelled training data.
- Deep Learning: Deep learning models, specifically those incorporating extensive architectures such as convolutional and recurrent neural networks, have exhibited robust generalisation abilities and are capable of acquiring significant representations from comparatively limited datasets, provided that the model possesses adequate capacity and consistent regularisation techniques.

While both machine learning and deep learning aim to derive insights from data, their approaches differ in representation learning, performance qualities, interpretability, and data efficiency. Which of these methods works best depends on a number of things, including the problem's characteristics, the accessibility of pertinent data, and the required degree of clarity.

V. Future Directions and Challenges in Air Pollution Forecasting

- Future directions in air pollution forecasting may involve integrating advanced machine learning techniques with high-resolution sensor data and atmospheric modeling.
- Challenges include improving model accuracy, especially in complex urban environments.
- Enhancing the interpretability of deep learning models is crucial.
- Addressing data quality issues is a significant challenge.
- Incorporating real-time data streams is necessary.
- Considering the impacts of emerging pollutants and climate change is crucial.
- Collaborative efforts among researchers, policymakers, and technology developers will be essential.

VI. Conclusion

Ultimately, the field for air pollution prediction has been greatly enhanced by the rapid development of ML and DL methods. Concerns regarding the detrimental impacts of air pollution on people and the environment have increased, and this has addressed the urgent need for reliable forecasts. A number of machine learning algorithms, including decision trees and support vector machines, as well as deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated outstanding proficiency in identifying intricate relationships and patterns within air pollution data sets.

By enabling the integration of numerous data sources and paving the way for the use for real-time forecasting applications, these methods have led to significant improvements in the accuracy and reliability of predictions. There are ongoing difficulties, such as those associated with limited data availability, incomplete data, and the ability to understand the model. To effectively tackle these difficulties, it is imperative to foster collaboration among scholars, politicians, and technology developers.

We should expect future air pollution predictions to be a hybrid of atmospheric modelling, data from high-resolution sensors, and sophisticated machine learning algorithms. The accuracy of models in complex urban environments will also be a focus. In addition, addressing issues with data quality and making deep learning models more interpretable are critical for making headway. The application of ML and DL techniques to air pollution forecasting has the potential to reduce the negative effects of air pollution on human health and the environment through collaborative and creative ways.

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