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Control Of Air Pollution Using Machine Learning

[1]Dr. Madhu Bhan ,[2]M Niranjanamurthy

[1]Assistant Professor, Department of Master of Computer Applications, M.S. Ramaiah Institute of Technology, (Affiliated to Visvesvaraya Technological University, Karnataka), Bangalore, India, 560054,

[2]Assistant Professor, Department of Master of Computer Applications,M.S. Ramaiah Institute of Technology, (Affiliated to Visvesvaraya Technological University, Karnataka), Bangalore, India, 560054,

Abstract

Environmental Pollution in India is growing by leaps and bounds. Air pollution, water contamination, and noise pollution are the three basic types of pollution. Rising population, rapid growth in industrialization and rising demands for automobiles in India are worsening air pollution levels. Air pollution has been contributing significantly to the country's burden of ill health. In contrast to most other developing countries, India has failed to establish a timeframe for meeting its national Air Quality Standards. Air pollution is rapidly becoming a serious public health concern that has a negative impact on our quality of life and economy. This research examines the state of air pollution in India, as well as the application of machine learning approaches to anticipate air quality. It also highlights some challenges and proposed developments for future.

Keywords: Pollution, Health, Meteorology, Control Measures, Machine Learning.

1. Introduction

Air pollution is described as the presence of foreign particles in the air, which can be either man-made or natural. Automobile emissions, industrial operations, building activities, scrap burning, and combustion of various fuels for cooking and lighting are all prominent sources of air pollution in Indian cities [1]. As per the latest reports, India is placed at 168th rank in the global Environment Performance Index (EPI) 2020. EPI places countries on how well they act on high-priority environmental issues. India has an EPI of 27.6, and it's distressing to learn that Delhi, our nation's capital, is one of the most polluted places on the planet. Aware of this problem, the government needs to adopt measures to limit the effects of air pollution. Over the last few decades, significant progress has been achieved in predicting air pollution concentrations. However, due to the numerous influencing factors, accurately predicting the quantity of air contaminants remains a challenge. More effective strategies for correctly predicting air pollution concentrations must be researched [2]. This paper provides an insight into the causes and formation of air pollution, its effect on health, and various control measuresThis paper focuses on use of Machine Learning algorithms in estimating and predicting the daily peak concentration of major pollutants in air. It also reflects on the challenges and future developments.

2. Pollutants and Health Issues

The growing imbalance of gases in the atmosphere causes global warming, the greatest hazard and challenge to existence. The measurement of pollutant matter is one method of measuring pollution. An air pollutant is a particle present in the air that has the potential to harm humans and the environment [3]. Solid particles, liquid droplets, or gases can all be different forms in which pollutants exist. Pollutant is a substance or energy or a naturally occurring contaminant that has undesired effects. Particles directly issued from asource, such as ash from a volcanic eruption, Sulphur dioxide generated from industries, or carbon monoxide gas emitted from motor vehicle exhaust, are examples of primary air pollutants. Secondary pollutants result from the inter mingling and interactions of primary pollutants. Smog is a sort of secondary pollutant formed when many main pollutants interact. Other examples include nitrogen oxides that form nitric acid when they combine with moisture in the air. Ground-level ozone (O_3), fine particulate matter ($PM_{2.5}$), carbon monoxide (CO), nitrogen dioxide (NO_2), Sulphur dioxide (SO_2), and lead are the six criterion pollutants, with ground-level O_3, $PM_{2:5}$and NO_2 being the most important. Indoor air pollutants are a form of primary air pollutants. Indoor air contains a higher concentration of gases and particles than outside air, owing to insufficient ventilation and high temperature and humidity levels, which may store a larger concentration of gases. Radon gas, which is emitted by building materials such as bricks, stones, concrete, and ceramic tiles, is the most significant indoor air contaminant. Natural gas and ground water both contain radon. Carbon monoxide is mostly produced by the combustion of fuel in the kitchen and cigarette smoke. Outdoor air pollution refers to emissions from nearby factories, cars, fires, pesticides. They have complete freedom to disperse throughout the environment. VOCs (volatile organic compounds) are a major contaminant in outdoor air. VOCs include benzene, ethylene glycol, formaldehyde, methylene chloride, tetrachloroethylene, toluene, and xylene. There are two sorts of man-made air pollution sources: stationary sources like agricultural output, chemical manufacture, power generation, and community sources like home and building heating, municipal trash, and sewage sludge incinerators. Combustion engine vehicles, such as gasoline-powered automobiles, diesel-powered cars, motorbikes, and airplanes are examples of mobile sources. The prediction of air quality is becoming essential for minimizing the environmental imbalances. Among the common pollutants, the pollutant, PM_{10} standard is generally used to measure air quality. The pollutant, PM_{10} standard is commonly used to quantify air quality among common contaminants. Particles having a diameter of 10m or smaller are included in the PM_{10} standard (0.0004 inches). Because of their capacity to reach the lower parts of the respiratory system, these minute particles are likely to cause health problems [4]. As per the World Health Organization's air quality guideline, the yearly mean concentration of PM_{10} suggested is 20g/m3, beyond which the risk of cardiac health impacts increases. Effects on breathing and respiratory systems, lung tissue damage, and cancer are all major issues for human health when exposed to PM_{10}. $PM_{2.5}$are microscopic particles in the air with a diameter of two and a half microns or less. When levels are high, their presence impairs visibility and causes the air to seem foggy. Exposure to these particles can lead to coughing, runny nose, sneezing and shortness of breath as well as inflammation of the throat, nose, eyes and lungs. Exposure to such particles can cause asthma and heart disease. Ground-level ozone a secondary pollutant is formed just above the earth's surface. This colorless and highly irritating gas is produced when Nitrogen oxides reacts with volatile organic compounds in sunlight and stagnant air. Breathing ground-level ozone can cause chest pain and congestion. It reduces lung functioning and inflames the linings of the lungs.

When nitrogen and oxygen gases react in the air at high temperatures, NOx is produced. At an average ambient amount, nitric oxide is not considered a health danger. NOx gases, on the other hand, react with smog and acid rain to form fine particles (PM) and ground-level ozone, both of which have negative health impacts. The amount of nitrogen oxides discharged into the atmosphere can be enormous in regions with high motor vehicle traffic, such as metropolitan cities. The largest source of sulphur dioxide in the air is industrial activity, such as power generation from sulphur-containing coal, oil, or gas. As a result of fuel combustion, sulphur dioxide is also included in motor vehicle emissions. In both healthy people and those with underlying lung illness, sulphur dioxide (SO_2) contributes to respiratory symptoms [5]. Exhaust from motor vehicles and other industrial operations, such as vessel construction, are the other major producers of carbon monoxide. Carbon monoxide exposure, both continuous and chronic, can cause serious cardiopulmonary problems, including death. The factors responsible for increased pollution in countries like India include exponential growth in population which is deteriorating the environment and unplanned development of industries and factories. Only around 20% of industries are located in designated industrial zones, while the remainder are located in residential and commercial areas. The ever-growing number of automobiles on the highways of metropolitan centers together with the increasing number of diesel vehicles on the roadways, contribute significantly to air pollution. Exposure to different air contaminants has significant monetary implications in terms of human suffering due to negative health impacts.

3. Air Pollution and Meteorology

Most cities in India exceed the acceptable levels of suspended particulate matter. Meteorology plays a key role in determining the concentrations, dispersion or the dilution of the pollutants. Wind direction and speed are important meteorological factors for use in air pollution studies. The direction from which the wind is blowing is known as wind direction. Wind speed and direction can be different at different altitudes. Speedy winds can transport pollutants over hundreds of kilometers, whereas during weak winds pollutants remain accumulated around their source location [6]. Due to the cold, higher quantities of particulate matter are prevalent throughout the winter season. The weather has a direct impact on air quality. Sunshine, for example, causes certain pollutants to undergo chemical reactions, resulting in smog. Rainy season has the potential to both clean and damage the environment. Water-soluble contaminants and particulates are washed away by rain. Summer's higher air temperatures hasten chemical processes in the atmosphere. Air turbulence is defined as a forceful, rapid movement of air. The air becomes more turbulent during the day as the earth heats up. This happens especially in the middle of the day. Polluted air disperses due to air turbulence, resulting in global air pollution. Vertical temperature variation is a significant factor in air pollution. Although air at higher altitudes is cooler, an upper air layer can occasionally be warmer than a lower one. The term Inversion is used for this type of air condition. On clear, quiet evenings when the earth cools fast, inversions are common. Because the top warmer layer acts as a lid, preventing dispersion, inversions are crucial because they result in extremely high ground level concentrations. Underneath air contaminants are trapped by inversion layer. Stability is another important factor that governs the dispersal of pollutants. With respect to stability there are three basic categories in which the atmosphere can be classified. These categories are stable, neutral, and unstable. When vertically displaced packets of air descend back to their original elevation i.e., when the lifting stops, the atmosphere is considered to be stable. This is due to the fact that a parcel of air will be colder and heavier than its surroundings, causing it to sink. When vertically displaced packets of air continue to rise on their own after the lifting forces on them have stopped, the atmosphere is said to be unstable. Because a raised packet of air is warmer and lighter than the air around it, it will continue to rise away from its initial place. The environment is neutral if vertically displaced packages remain where they are after being raised. [7].

Mixing and dilution occur in highly unstable circumstances, resulting in a drop in ground level concentration. Stable circumstances, on the other hand, are characterized by poor mixing, which makes it difficult to disperse contaminants, resulting in pollution build-up. When the air is colder at night, conditions are frequently more stable. Contaminants emitted late at night in metropolitan areas, such as from house fires, are difficult to disperse, resulting in localized air pollution. Any air quality modelling requires an understanding of stability. A study of air pollution and its control should include an in-depth study of the weather patterns.

4. Control System

India is witnessing air pollution due to rapid economic growth and insufficient implementation of pollution monitoring and forecasting control measures. Control legislation in India with regard to air pollution, needs to emphasize on the gaps and issues in controlling air pollution [8]. Central Pollution Control Board (CPCB) constituted in 1974, is in-charge of monitoring air quality, and maintenance of monitored data.The agency works in collaboration with industries in a number of voluntary pollution prevention programs and energy conservation schemes. National Environmental Engineering Research Institute (NEERI) constituted in 1958 with focus on sewage disposal and industrial pollution, reports thousands of tons of solid waste being generated every day. This comprises hazardous and non-hazardous industrial waste, as well as tons of rubbish. In metropolitan cities, no modern technology is employed to treat solid, liquid, industrial, and hospital wastes. Excessive use of biomass for cooking and heating, as well as a reliance on fossil fuels such as coal-fired power plants, has increased air pollution levels. The objective of technological control systems is to extract current information concerning the air pollution threats so that decisions and actions can be taken at the right time to improve the air quality. The volume and accuracy of data received from various sensor networks put in metropolitan areas gives an indication of how the quality of life is deteriorating over time as a result of air pollution. Great volumes of data are collected over time in various pollution control centers. The main objective is to investigate and find what needs to be done to build a data infrastructure that ensures the accessibility and re-usability of data collected from different sensors. This infrastructure can hold data collected from both on-the-ground and off-the-ground monitoring systems, with the goal of mining and visualizing it. It should be possible to do modelling and environmental evaluations for various meteorological parameters such as atmospheric wind speed, wind direction, and temperature in order to analyze the impact of air pollutants released into the atmosphere from various sources. This will enable air quality maps to be prepared in real time. Air quality prediction is highly dependent on the use of adequate modelling tools for interpretation and validation of the collected data. In air pollution modelling [9], a series of computational modules organize and interact to transform one set of databases into another set. For example, modules are built to transform data related to emissions, human activities, metrology, geography into data reflecting concentrations levels and depositions of pollutants and further its impact on health. Physical models are built to experiment on small-scale replicas of large structures. For air pollution, building of physical models is generally needed for identification and quantification of complex chemical reactions of atmospheric pollutants. On the other hand, mathematical models are used to simulate a process. For example, mathematical models simulate the process of emission and dispersion, using mathematical and/or statistical tools [10]. Here mathematical algorithms are designed to simulate the real situation and adequate experimental data is introduced in the formula to compute a result. Modelling has various uses and can be used to study the basic atmospheric processes, to develop control strategies, to forecast pollution levels, to identify and study the impact of pollution from new sources, to design optimized monitoring networks, to estimate for the conditions that never occurred so far, such as the impact of a proposed highway/industry on air quality. Models are simplifications of real systems and therefore are not expected to provide exact reproductions of environmental behavior. The performance of the model depends upon the complexity and sensitivity of the process. For example, a complex photochemical model is used for testing highly reactive pollutants in the atmosphere whereas a much simpler model may be used for testing non-reactive pollutants. Physical and Mathematical models suffer from disadvantages of providing information with limited accuracy. Recent developments in statistical modelling based on Machine Learning techniques have emerged as a possible answer to these problems.

5. Machine Learning Prediction Models

Machine Learning approaches have been widely employed in the environmental sciences for data processing, weather and climate prediction, model emulation and air quality forecasting. To allow qualitative and quantitative short-term forecasts, a number of Machine Learning algorithms are used. A linear regression model is the one that learns the linear relationship between an independent variable (predictor) and a dependent or response variable. Simple linear regression models were developed for forecasting the daily peak concentrations of various pollutants [11, 26, 27]. Because they capture non-linear correlations between variables, non-linear regression models are thought to be superior than simple linear regression models. The relationship between air pollution and meteorological factors characteristic was determined using non-linear regression models [12]. One response variable and two or more predictor variables are used in multiple linear regression. Multiple linear regression models (MLR) were trained on current observations and used to forecast future air pollution concentrations in relation to meteorological factors [13]. Regressions with well-defined parameters can produce excellent results. The reactions between air pollutants and influential elements, are extremely non-linear, resulting in a complex system of air pollutant generation mechanisms. Despite the fact that multiple linear regressions are theoretically sophisticated for forecasting, they aren't generally employed in many difficult situations, such as air pollution prediction [14].

The Neural Network (NN) model is a viable alternative to existing paradigms. In the context of environmental forecasting challenges, researchers have demonstrated that NN models outperform standard statistical approaches. A NN model is a system that takes m number of inputs, such as meteorological, physical, and chemical predictors, and outputs a single result. There is no prior knowledge of the link between the input and output variables. NN algorithms have already been used to anticipate various air pollution concentrations [15]. The multi-layer perceptron (MLP) NN model is the most prevalent of the various varieties of NN models. The hourly ozone concentration was forecasted using MLP-NN models. The amount of visibility, dry bulb temperature, vapor pressure, wind speed, and direction were all employed as predictors. The efficacy of five different NN models for the prediction of PM_{10} concentrations was examined for particulate matter PM. The results revealed that NN models outperformed linear models[16]. However, efficiency, and acceptance of Neural Network Models is hampered by a variety of issues. Over-fitting is one of the most difficult problems to solve while constructing a NN model. During training, an over-fitted NN model may fit the data well, but during testing, it may yield poor forecast results. [17].

The Extreme Learning Machine (ELM) technique was developed to address some of the shortcomings of the popular MLP-NN model, as well as the model's high computing requirement [18]. The ELM was also employed to get over the limitations of linear model. Hyper-parameters like the range of random weights and the number of hidden neurons influence ELM. The ELM was developed using a feed-forward neural network with a single hidden layer and random weights in the hidden state. Online-Sequential Extreme Learning Machine (OS-ELM) is an approach that consists of two parts, an initialization phase and a sequential learning phase. Batch learning using ELM on the first training data is used in the training phase. Following the initialization phase, the model is updated using freshly incoming chunks of data in the online sequential learning phase. A piece of data can be destroyed once it has been consumed because it will not be needed in future model updates [19].

The Support Vector Machine (SVM) is a classification system for determining the hyperplane between two classes that maximizes the border between them. When comparing the performance of the SVM method to that of the Multilayer Perceptron (MLP), it was discovered that SVM outperforms MLP on structural concerns [20]. The research is regarded as a watershed moment in the field of air pollution prediction, as it addresses overfitting and instability issues. A kernel function is used to translate the source dataset into a higher dimension when dealing with data that is linearly inseparable. As a result, choosing the suitable kernel and fine-tuning its parameters is critical for a fair SVM performance. Using two years of emission data of six air pollutant concentrations namely $PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, O_3, the most accurate prediction model based on SVM was developed [21].

Ensemble learning approaches, also known as hybrid models, are a collection of algorithms that combine the findings of many predictors to solve the problem of air pollution prediction. Ensemble Learning is the most sophisticated Machine Learning technique among Linear Regression, Neural Networks and SVM. The ultimate result in Ensemble Learning is either the average of all forecasts or the result of a majority vote. Ensemble learning is a method that combines weak and strong predictors to reduce overfitting and improve generalization [22]. Using three years' pollutants and meteorological information, the Ensemble Neural Network approach was used to anticipate Air Quality Index(AQI) one day ahead [23]. To forecast the daily AQI value, the model employed Partial Mutual Information to pick the best predictors.

A Deep Learning method was used to create a recurrent neural network model for forecasting daily air quality [24]. There were two stages to this procedure. In the first step, data was pre-processed to identify pollutants, and in the second phase, the Long Short-Term Memory (LSTM) algorithm was used to forecast them. With larger time steps, the LSTM algorithm learns the input sequence. The model's performance fell short of expectations, as it could not outperform SVM and Ensemble Learning approaches. The high processing expense and limited interpretability were the other drawbacks.

Another hybrid strategy was developed [25], which used big data, Long Short-Term Memory (LSTM), and Neural Networks to estimate the concentration of air pollutant $PM_{2.5}$ one hour ahead. The Convolutional Neural Network was used in this hybrid technique as it saved training time. State-of-the-art Machine Learning approaches like SVM and MLP were outperformed by the model. On the whole, it has been proved that Machine learning methods, produce promising results for air quality pollution predictions.

6. Challenges and Proposed Developments

The application of Machine Learning methods to anticipate air pollution has risen dramatically in recent years. Machine Learning algorithms provide great accuracies, which explains why they are suited and should be favored over older techniques. Forecasting, on the other hand, is currently restricted to a few models (NN and SVM) and mostly for the air pollutants O_3, PM_{10}, and $PM_{2.5}$. As a result, the next task is to enhance forecast accuracy for other key pollutants (NOx and SO_2) while also studying additional Machine Learning approaches such as Ensemble Learning techniques. Among several possible future developments for air quality measurement and prediction, proposed developments are listed below:

6.1. Proposed Solution 1

In the ELM and MLP-NN techniques, model structures need to be updated. Because of limited computing resources, the number of hidden nodes was determined based on the initial training data and did not vary in future model updates. The model was unable to learn the additional structure in the data when fresh data was added. During the updating phase, the model complexity can be adjusted to improve prediction capabilities. The results from the algorithms cannot be qualitative unless they do not pass periodically through a repeated learning phase.

6.2. Proposed Solution 2

The fact that prediction algorithms have not been tested on a rich historical database containing many episodes, limits their role to a human expert decision support system. Role of a rich dataset added with satellite image and sensor-based monitoring can enhance the accuracy of estimation and prediction algorithms. The predictive input features include brightness of night time lights, planetary boundary layers, elevation and land use as a part of geographic and satellite-based inputs. The relationship between air contaminants and geographical characteristics is substantial, yet it varies between spatial areas. To examine for better air quality predictions, a big data analytics method and Machine Learning-based techniques can be applied.

Conclusion

Increasing air pollution being an area of utmost concern, the knowledge of instantaneous air quality data has become a need for a country like India. With the advancement of Machine Learning techniques, the real-time air quality monitoring and prediction is possible. The recent literature study on air quality evaluation based on Machine Learning models and techniques shows that several techniques can be used successfully. However, choosing an appropriate algorithm for a particular purpose is key to handling the problem of accurately estimating and predicting air pollutants.

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