Air Quality Monitoring with Prediction: Deep Learning

Sanjay Srivastava 12216665 Divya Bharti 12216619 Jatothu Bharath 12217044

Abstract**--** *Air quality monitoring and prediction are the most important part of sustainable urban living and public health safeguarding. Quick industrialization, vehicle exhaust, fuel combustion and energy generation has instead, only managed to intensify the atmospheric conditions, particularly amongst the heavily populated smart cities. Therefore, with these harmful pollutants like CO_2, NO_2, SO_2, and particulate matter (PM2.5 and PM10) in the air, a timely air quality assessment and prediction has become an urgent demand.Recent developments in DL have made it possible to build intelligent, data-driven models that are able to efficiently model highly nonlinear relationships between environmental parameters and pollutant levels. Deep learning architectures such as CNNs, RNNs, particularly LSTM networks, have exhibited significant success in AQI prediction through their ability to capture temporal and spatial dependencies in the environmental data. These models are more accurate, flexible and robust than traditional statistics and shallow ML.In this paper we present the design, architecture and implementation methodologies of a DL-based AQ D system. This is where the importance of deep neural models in deciphering pollutant concentration trends, predicting AQI values and issuing advance warnings against pollution spikes come into play. It also explores problems associated with data collection, sensor calibration, real-time processing, and model interpretability. Important future research trends included hybrid deep learning architectures, edge-based deployment for IoT-enabled air quality sensors, and explainable AI approaches to enhance transparency of air pollution forecasting.*

Index Terms—Air quality monitoring, deep learning, air pollution prediction, neural networks, environmental forecasting, LSTM, CNN, AQI prediction

I. INTRODUCTION

Air is among the most precious of natural resources—necessary for the continuation of all life. All living things, human, animal and plant alike, breathe air to survive. But amidst the rapid urbanization, industrialization and vehicular emissions, air quality has been critically compromised, endangering human health and the environment alike. Urban air quality and indoor air pollution rank as two of the world's worst pollution problems in the Blacksmith Institute Report (2008). The exponential increase in population, transit, and industry continues to contaminate the air at an unprecedented pace.

Air pollution creates a multitude of health hazards — both in the short term and long term. Short-term exposure causes eye, nose and throat irritation, headaches, allergic reactions and respiratory distress. Long-term exposure, conversely, can lead to chronic respiratory diseases, lung cancer, heart disease, and even damage organs such as the liver, kidneys, and brain. Air pollutants cause these and other environmental problems–like ozone depletion, acid rain, global warming, and ecosystem disruption–impacting agriculture, forests, and biodiversity. As a result, air quality monitoring, modeling, and prediction has grown to become an international scientific imperative.

For decades, different air quality models have been constructed. Previous approaches were based on statistical, mathematical and physical modeling), employing complicated equations to simulate atmospheric processes. While these models served as a basis for understanding the behavior of pollutants, they were hindered by a number of drawbacks such as

1. Limited accuracy in predicting pollution extremes (maximum and minimum levels);
2. Inability to adapt dynamically to changing environmental conditions;
3. Equal weighting to old and new data without learning temporal dependencies;
4. Computational inefficiency due to complex mathematical formulations;
5. Poor generalization capability across different geographical regions.

With the advent of computational intelligence, researchers started relying on data-driven methods, in particular Deep Learning (DL), to bypass the limitations of traditional models. Deep learning, in particular, shines when it comes to automatic feature extraction from non-linear environmental data and air quality monitoring and forecasting. Techniques like CNNs, RNNs, and LSTMs have been particularly effective at modeling spatial and temporal variations in air pollutant concentrations. For example, CNNs encode spatial dependencies between monitoring stations, while LSTMs capture the sequential behavior of pollutants driven by weather characteristics like temperature, humidity, wind speed and pressure.But far from these conventional approaches, deep learning-based air quality prediction methods can analyze large-scale sensor and satellite data in real-time, adapt to evolving environmental patterns, and enhance prediction accuracy with ongoing model retraining. These systems are not only able to provide AQI forecasts but are capable of providing early warnings of possible pollution spikes so that policymakers can intervene.

In this review paper, we present a comprehensive survey on Deep Learning-based Air Quality Monitoring and Prediction4. It investigates applying deep neural architectures to analyze environmental data, detect pollutant patterns, and predict AQI with enhanced precision. And in addition, it covers issues of data quality, model interpretability, computational burden and deployment in IoT-enabled smart city infrastructure.

II. AIR QUALITY EVALUTION

Air quality evaluation is an important aspect in the monitoring, analysis, and control of air pollution for a healthy and sustainable environment. The quality of the air around us defines its value for human, industrial and ecological requirements. Declines in air quality impact health, agriculture, and our general environment. Hence, methodical air quality consultation is imperative for fruitful environmental governance and strategy planning.Across the world, air quality monitoring agencies — including the Environmental Protection Agency (EPA) in the U.S. — maintain and regulate a list of common air pollutants, called criteria air pollutants, which have serious health and ecological impacts. These are Carbon Monoxide, Lead, Nitrogen Dioxide, Ozone, Particulate Matter (PM 10 and PM 2.5) and Sulfur Dioxide These contaminants are chiefly emitted via car exhaust, factories and coal burning. High levels of these can cause heart, lung and brain diseases, as well as environmental impacts like acid rain, smog and climate change.

The AQS, which is maintained by the EPA and state and local agencies, compiles real time air pollution and meteorological data from thousands of monitoring stations. This data consists of pollutant concentrations, weather parameters, and metadata describing each station's geographical and operational characteristics. Among other things, the AQS database is used to evaluate air quality levels and trends, support Attainment and Non-Attainment designations, assess SIPs, perform model based forecasting, and create CAA reports. While these monitoring networks have improved data availability, they remain plagued by inhomogeneous sensors distribution, gaps in data, and delays in real-time prediction. This underscores the increasing need for automated, intelligent models that can learn intricate air quality dynamics — a domain in which DL has exhibited impressive potential.

The OAQPS is responsible for developing and enforcing the NAAQS for each of the criteria pollutants. These standards are the basis for air quality management and are divided into primary standards, which protect human health (particularly vulnerable populations such as children, elderly, and those with respiratory diseases), and secondary standards, which protect environmental welfare, including crops, vegetation, wildlife, and property from damage. Various pollutants do various things — so they need their own exposure limits. Some have both short-term and long-term standards — for instance, O_3 and $PM_{2.5}$ have short-term (hour or daily) limits to reduce acute health impacts, and long-term (annual) limits to avoid chronic exposure. These standards form the basis for the Air Quality Index (AQI), a numerical indicator used to communicate pollution severity and health risk to the public. Deep Learning, in particular, has become a boon for precise air quality measurement and forecasting over the past few years. In contrast to traditional models, deep neural networks can directly learn useful spatial-temporal features from the raw environmental data, without explicit feature engineering. Deep architectures like CNN, RNN, and LSTM have shown great ability in modeling the pollutant concentration dynamics.

TABLE I: NAAQS TABLE LISTS ALL CRITERIA POLLUTANTS AND STANDARDS [3]

Pollutant	Primary/ Secondary	Averaging Time	Level	Form
Carbon Monoxide (CO)	Primary	8 hours	9 ppm	Not to be exceeded more than once per year
		1 hour	35 ppm	
Lead (Pb)	Primary and secondary	Rolling 3 month average	0.15 μ g/m_3	Not to be exceeded
Nitrogen Dioxide (NO2)	Primary	1 hour	100ppb	98th percentile of 1-hour daily maximum concentrations, averaged over 3 years
		1 year	53 ppb	Annual Mean

Ozone (O_3)	Primary and secondary	8 hours	0.07 ppm	Annual fourth-highest daily maximum 8-hour concentration, averaged over 3 years

TABLE II: AQI CLASSIFICATION [3]

AQI	Air Pollution Level
0-50	Excellent
51-100	Good
101-150	Lightly Polluted
151-200	Moderately Polluted
201-300	Heavily Polluted
300+	Severely Polluted

We have one important parameter called air quality index (AQI) which quantifies air quality in a region as shown in Table II. It is a number used by government agencies to communicate to the public how polluted the air is currently or how polluted it is forecasted to become. As the AQI increases, an increasingly large percentage of the population is likely to be exposed, and people might experience increasingly severe health effects. Different countries have their own air quality indices, corresponding to different national air quality standards.

III. AIR POLLUTION ANALYSIS AND . . MONITORING

Nowadays,solutions have become efficient and receive more attention. Using "Deep Learning" we can model air systems which are considerably dynamic, spatially expansive, and behaviourally heterogeneous. These models take data from variety of sources like sensors, satellites, public agencies etc. Advances in satellite sensors have provided new datasets for monitoring air quality at urban and regional scales. As per an article published by the Chicago policy Review [5], in contrast to traditional datasets that rely on samples or are aggregated to a coarse scale, "Deep Learning" is huge in volume, high in velocity, and diverse in variety. Since the early 2000s, there has been explosive growth in data volume due to the rapid development and implementation of technology infrastructure, including networks, information management, and data storage. Big data can be generated from directed, automated, and volunteered sources. Sometimes there are mismatches between data needs and availability, such as discrepancies between the available and the desired levels of resolution. Key to making big data actionable is harnessing, standardizing, and integrating the enormous amount of data. For instance, a modelling study carried out by D. J. Nowak et al. [6] using hourly meteorological and pollution concentration data from across the United States demonstrates that urban trees remove large amounts of air pollution that consequently improve urban air quality. Pollution removal (O3, PM10, NO2, SO2, CO) varied among cities with total annual air pollution removal by US urban trees estimated at 711,000 metric tons ($ 3. 8 billion value) . We will be

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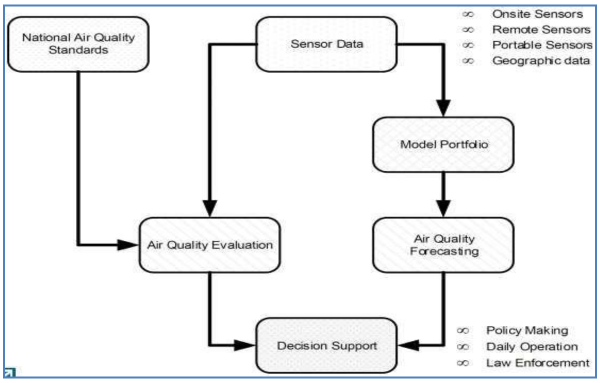


Fig. 1. Big data based decision support for air quality [7].

In a research work by J. Ditsela and T. Chiwewe [7], a model based on deep learning was presented to forecast the ground-level ozone concentration levels at different monitoring sites. Prediction was made by acquiring cross-correlation and spatial-correlation patterns between several air pollutants, whose continuous measurements were taken from air quality monitoring stations located throughout the Gauteng province, South Africa, including the City of Johannesburg.

The study employed years of historical air quality data received via IoT-enabled sensor networks. Rather than depending upon conventional numerical modeling or large-scale computational simulations, the deep neural network was trained to learn automatically the spatial-temporal dependencies and pollutant interaction patterns. These networks would be able to estimate ozone in real time from sensor readings like NO_2, CO, SO_2, temperature, and humidity, thus providing a lean and adaptable system for air quality estimation. The model utilized spatial feature learning (to capture patterns between neighboring stations) and temporal sequence modeling (to model pollutant development with time), creating a combined system that enabled environmental decision-making and early warning systems.likewise, in a prominent study by Y. Zheng et al. [8], a deep learning-based forecasting architecture was presented that forecasted air quality measurements for the following 48 hours from multi-source information. It took into account present and predicted meteorological conditions as well as current and past air quality readings gathered from monitoring stations over tens of hundreds of kilometers in China.The predictive model proposed consisted of four key components:

Temporal Predictor: A model that employed recurrent neural network (RNN) architecture to learn temporal patterns and seasonal trends in local air quality observations.

Spatial Predictor: A module that used convolutional neural network (CNN) architecture to represent spatial correlations between multiple stations, observing the impact of pollution transport from neighboring areas.

Dynamic Aggregator: A deep learning layer that was specifically developed to dynamically integrate predictions from both spatial and temporal predictors, maximizing the accuracy of predictions under changing meteorological conditions.

Inflection Predictor: A deep reinforcement learning mechanism that has been added to recognize and respond to unexpected changes or inflection points in pollutant levels, for example, sudden spikes due to weather changes or sudden surges in emissions.

This combined deep learning architecture showed better performance in predicting short-term air quality levels against traditional statistical and regression-based approaches. Through the use of spatio-temporal deep architectures, the model attained improved generalizability, robustness, and explainability, hence its appropriateness for large-scale deployment in the smart city context.

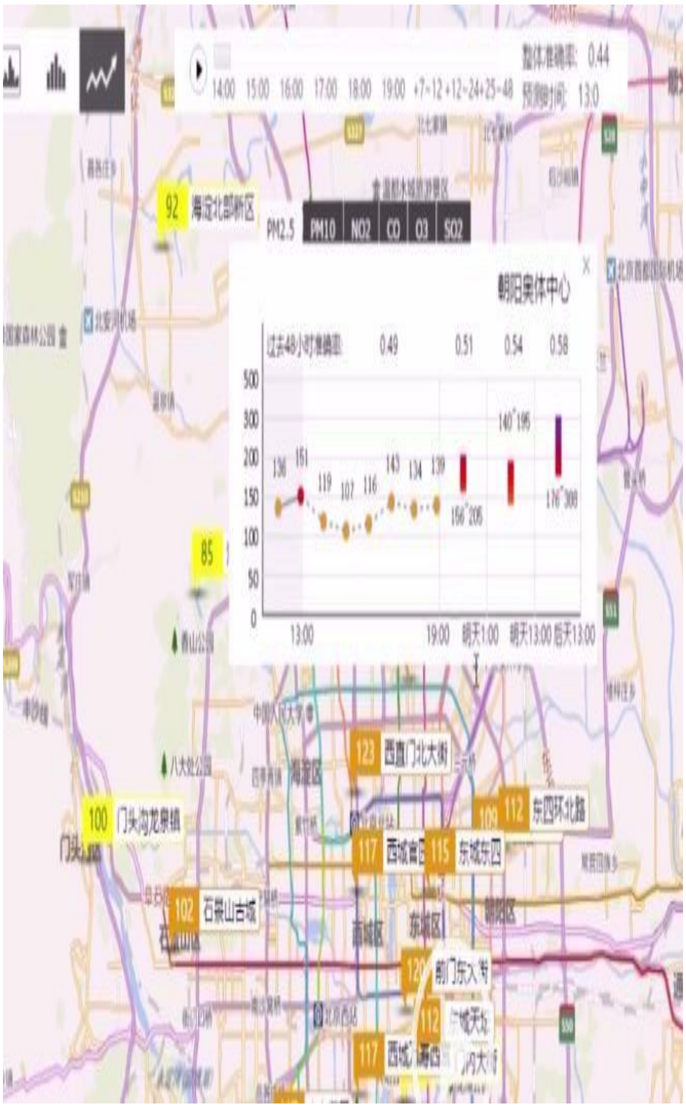


Fig. 2. Data map [8].

They evaluate the model with data from 43 cities in China, surpassing the results of multiple baseline methods. They have deployed a system with the Chinese Ministry of Environmental Protection, providing 48-hour fine-grained air quality forecasts for four major Chinese cities every hour. The forecast function is also enabled on Microsoft Bing Map and MS cloud platform Azure as shown in Fig. 2. The prime advantage of this method is that their technology is general and can be applied globally for other cities.

J. A. Engel-Cox *et al*. in [9] compared qualitative true color images and quantitative aerosol optical depth data from the Moderate Resolution Imaging Spectro-radiometer (MODIS) sensor on the Terra satellite with ground-based particulate matter data from US Environmental Protection Agency (EPA) monitoring networks. They covered the period from 1 April to 30 September 2002. Following were some of the interesting facts about this approach:

1) Using both imagery and statistical analysis, satellite data enabled the determination of the regional sources of air pollution events, the general type of pollutant (smoke, haze, dust), the intensity of the events, and their motion.
2) Very high and very low aerosol optical depths were found to be eliminated by the algorithm used to calculate the MODIS aerosol optical depth data.
3) Correlations of MODIS aerosol optical depth with ground-based particulate matter were better in the eastern and Midwest portion of the United States (east of 100°W).

Initial analysis of the algorithms suggested that aerosol optical depth (AOD) values calculated based on the sulfate-abundant aerosol model would be more effective in predicting ground-level particulate matter (PM) concentrations. But additional exploration found that the dependency of AOD on ground-level PM concentration is extremely nonlinear and dependent on a number of meteorological and atmospheric variables like humidity, temperature, wind speed, and planetary boundary layer height.. In one of the researches carried out by J. Zhu et al. [10], as shown in Fig. 3. This paper concludes about the air quality which is not covered by monitoring stations with S-T heterogeneous urban big data. However, estimating air quality using S-T heterogeneous big data poses challenges.The challenges are due to the time complexity when processing the massive volume of data. this research proposes to discover the region of influence (ROI) by selecting data with the highest causality levels spatially and temporally. This combined deep learning model illustrated better performance in the prediction of short-term air quality levels than typical statistical and regression approaches. Utilizing spatio-temporal deep structures, the proposed model achieved improved generalizability, resilience, and explainability, which makes it applicable to large-scale implementation in smart cities.

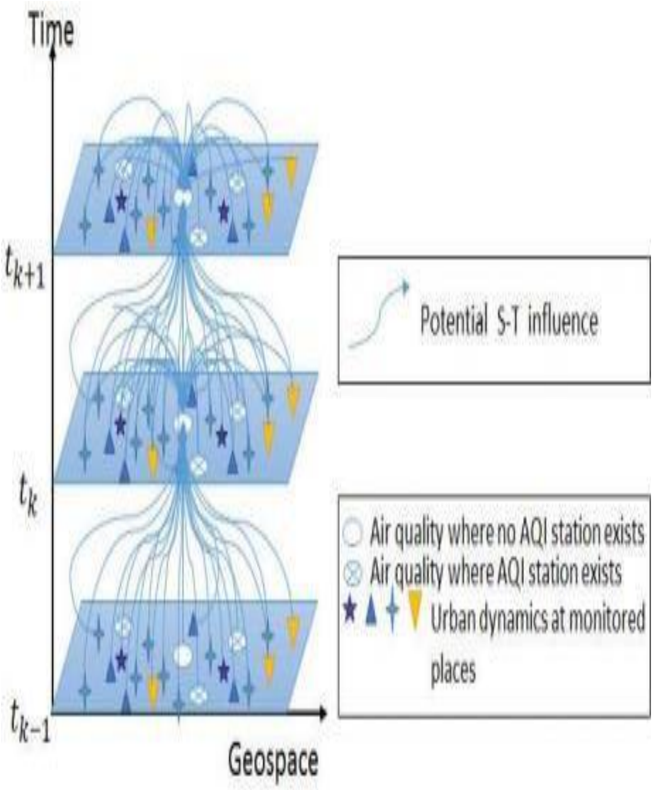
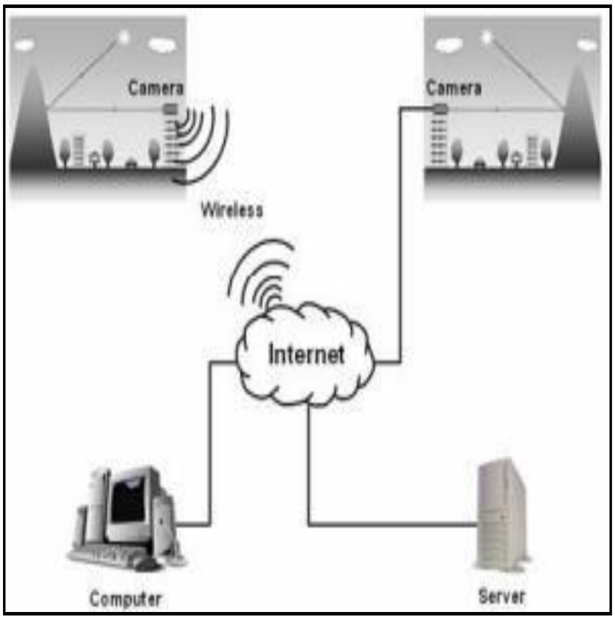


Fig. 3. The influence of S-T urban dynamic on air quality [10].

Results show that the research achieved higher accuracy using “part” of the data than “all” of the data. This may be explained by the most influential data eliminating errors induced by redundant or noisy data.



1. Fig. 4. The schematic set-up of IP camera as remote sensor to monitor air quality [11].

In one of the studies carried out by C.J. Wong *et al.* [11], the aim is to develop a state-of-art reliable technique to use surveillance camera for monitoring the temporal patterns of PM10 concentration in the air. Once the air quality reaches the alert thresholds, it provides warning alarm to alert people to prevent from long exposure to these fine particles. This is important for people to avoid adverse health effects like asthma, heart problems etc. In this study, an internet protocol (IP) network camera was used as an air quality monitoring sensor. It is a 0.3 mega pixel charge-couple-device (CCD) camera integrates with the associate electronics for digitization and compression of images. The approach is as below:

1) The network camera was installed on the rooftop of the school of physics. The camera observed a nearby hill, which was used as a reference target.
2) At the same time, this network camera was connected to network via a cat 5 cable or wireless to the router and modem, which allowed image data transfer over the standard computer networks (Ethernet networks), internet, or even wireless technology.
3) Then images were stored in a server, which could be accessed locally or remotely for computing the air quality information with a newly developed algorithm. The results were compared with the alert thresholds. If the air quality reaches the alert threshold, alarm will be triggered to inform us this situation.

The newly developed algorithm was based on the relationship between the atmospheric reflectance and the corresponding measured air quality of PM10 concentration as shown in Fig. 4. In situ PM10 air quality values were measured with DustTrak meter and the sun radiation was measured simultaneously with a Spectro-radiometer. Regression method was used to calibrate this algorithm. Still images captured by this camera were separated into three bands namely red, green and blue (RGB), and then digital numbers (DN) were determined. The results of this study showed that the proposed algorithm produced a high correlation coefficient (R^2) of 0.7567 and low root-mean-square error (RMS) of plusmn 5 mu g/m3 between the measured and estimated PM10 concentration.

IV. PREDICTIVE MODELING USING . MACHINE LEARNING

Machine learning (ML) is the branch of computer science which makes computers capable of performing a task without being explicitly programmed. There are many research papers that focus on classification of air quality evaluation using machine learning algorithms. Most of these articles use different scientific methods, approaches and ML models to predict air quality. S. Y. Muhammed *et al.* in [12] points out that machine learning algorithms are best suited for air quality prediction. Some of them are discussed below.

A. Optimization of ANN Parameters for Accuracy

Artificial neural Network model tries to simulate the structures and networks within human brain. The architecture of neural networks consists of nodes which generate a signal or remain silent as per a sigmoid activation function in most cases. A. Sarkar *et al.* in [13] points out that the ANNs are trained with a training set of inputs and known output data. For training, the edge weights are manipulated to reduce the training error. E. Kalapanidas *et al.* in [14] use a feed forward multi-perceptron network consisting of 10 input nodes, 2 hidden layers of 6 and 4 nodes respectively Current developments have also improved the ability of ANNs in air quality forecasting by adding adaptive learning rates, dropout regularization, and batch normalization, which enhance the robustness and avoid overfitting. Moreover, deep neural network (DNN) versions of ANNs enable the extraction of high-level abstract features from large and complex air quality data. Deep architectures can capture the complex correlations among meteorological parameters and pollutant concentrations effectively.

In addition, hybrid ANN designs that integrate convolutional and recurrent layers have been found to be capable of managing both spatial and temporal relationships in air pollution data, allowing for more precise forecasting of pollutant patterns. In addition to enhancing prediction performance, these models facilitate the determination of essential environmental variables affecting air quality dynamics, which can lead to smart, data-actuated environmental monitoring systems. and 1 output node as shown in Fig. 5.

1) The step functions at the nodes of the hidden layers are all Gaussian. The training process is the error back propagation, where there has been 5-6 working hours until the network performed well against the training set.
2) Many less successful trials have been made, trying networks with different architectures.
3) The architecture of the ANN used for experimentation along with the previous techniques, an inductive top down decision tree was used, in particular the Oblique Classifier (OC1) which has been reported to have an improved performance over

the standard decision tree algorithms like ID3, C4.5 and their inherits.

4) The whole idea of OC1 is that the tree might split at each node according to the algebraic sum of several attributes, not just one as is the case with the standard C4.5 programs.

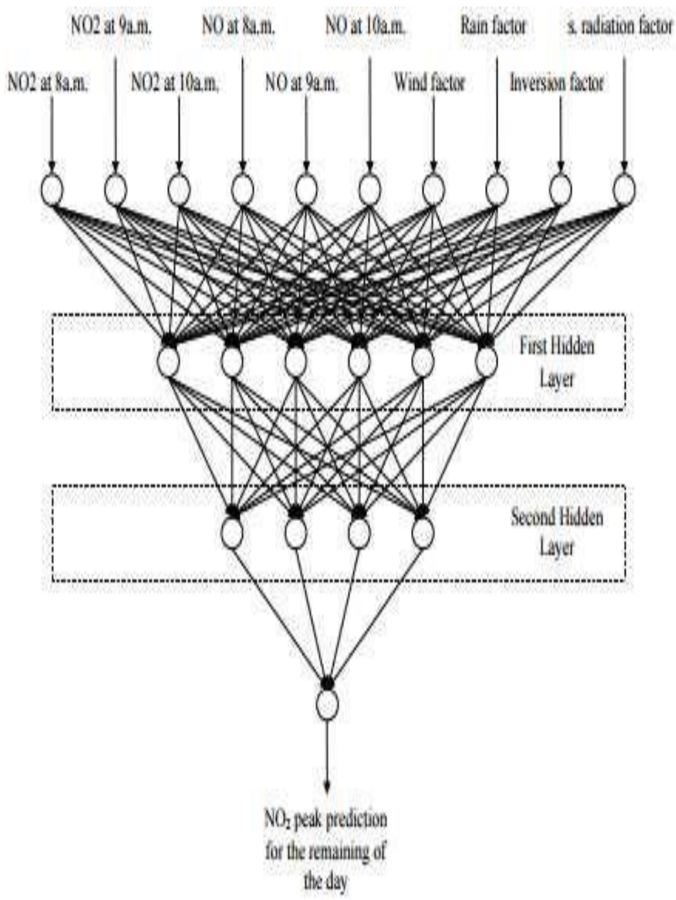


Fig. 5. ANN model for air quality [14].

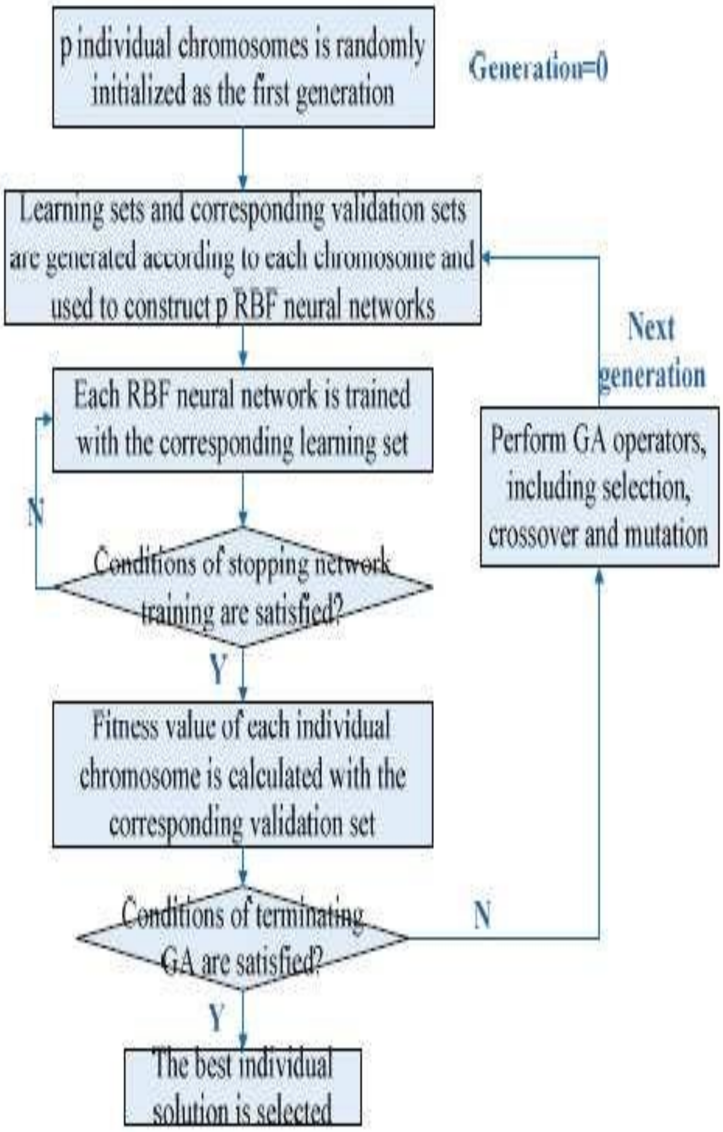


Fig. 6. Flow of genetic algorithm based ANN [15].

B. Evolutionary Training of Artificial Neural Networks (GA-ANN)

H. Zhao *et al*. in [15] used an improved ANN model called GA-ANN in which GA (genetic algorithm) is used to select a subset of factors from the original set and the GA-selected factors are fed into ANN for modeling and testing as shown in Fig. 6. In the experiments, air quality monitoring data and meteorological data (9 candidate factors) of Tianjin, China from 2003 to 2006 are utilized for modeling, and the data in 2007 is utilized for performance evaluation. Three models, including GA-ANN, normal ANN and PCA-ANN, are compared. The correlation coefficients of GA-ANN, which are calculated between monitoring and predicting values are both higher than the other two models for S02 (sulfur dioxide) and N02 (nitrogen dioxide) predicting. The results indicate that GA-ANN model performs better than another two models on air quality predicting.

C. *Interpreting Feature in Random Forests*

Random forests follow a technique as per [16] where several decision trees are built based on subsets of data and an aggregation of the predictions is used as the final prediction as shown in Fig. 7. R. Yu *et al.* in [17] used a random forest approach for predicting air quality (RAQ) for urban sensing systems. The data generated by urban sensing includes meteorology data road information, real-time traffic status and point of interest (POI) distribution. The random forest algorithm is exploited for data training and prediction. Compared with three other algorithms, this approach achieves better prediction precision. They used the standard of China, where the AQI is based on the levels of six atmospheric gases, namely sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates smaller than 10 μm in aerodynamic diameter (PM10), suspended particulates smaller than 2.5 μm in aerodynamic diameter (PM2.5), carbon monoxide (CO), and ozone(O_3), measured at the monitoring stations throughout each city. The AQI value is calculated per hour according to a formula published by China's Ministry of Environmental Protection. The approach is explained below:

1) In the RAQ algorithm, all data are collected from the urban sensing system including air monitoring station data, meteorology data, traffic data, road information and POI data and necessary features are extracted from heterogene. In the experiments, one-month data from 4 May 2015 to 5 June 2015 is collected.
2) In their testing period, they used a total of 2701 data to test this algorithm and Shenyang is divided into 1258 grids corresponding to 34 rows and 37 columns.

In Shenyang, this algorithm finally results in an overall precision of 81% for AQI prediction. This experimental result outperforms that of Naïve Bayes, Logistic Regression, single decision tree and ANN. These data are directly or indirectly available on the Internet. This shows that the algorithm could be easily applied for other cities throughout the entire country.

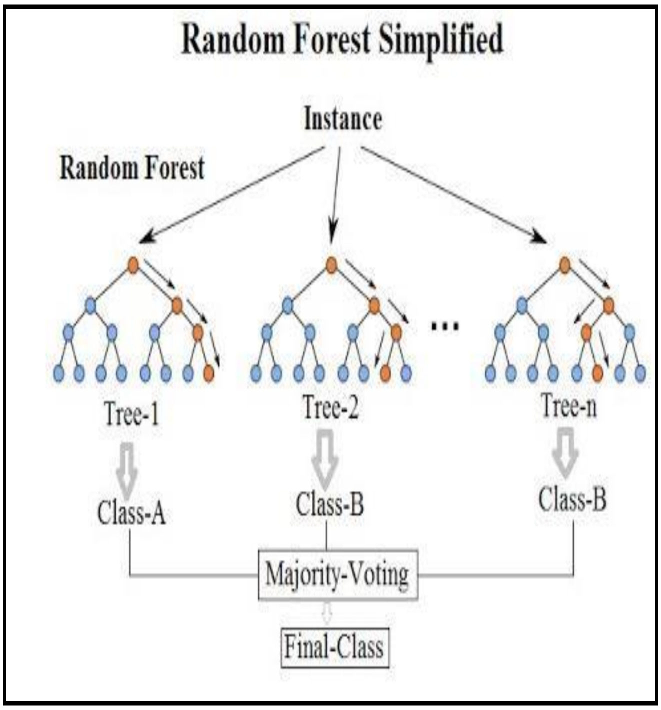


Fig. 7. Random Forest Simplified [16].

D. *Tree-Based Learning Model*

Decision tree model is a tree model in which each branch node represents a choice between several alternatives, and each leaf node represents a decision as per [18] as shown in Fig. 8. It is a supervised learning technique which uses a predictive model to map observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). In [19] S. Deleawe *et al.*, create mapping from features to classification with a decision tree model which uses entropy to select an ordering of feature values to consider in the concept rule description to predict CO2 levels in air. Since a decision tree generates decision rules as its model, the researchers have used it to understand the attributes that were most influential in predicting the air quality class. The decision tree they employed has a confidence factor of 0.25. They used the Weka implementation of the learning algorithms.

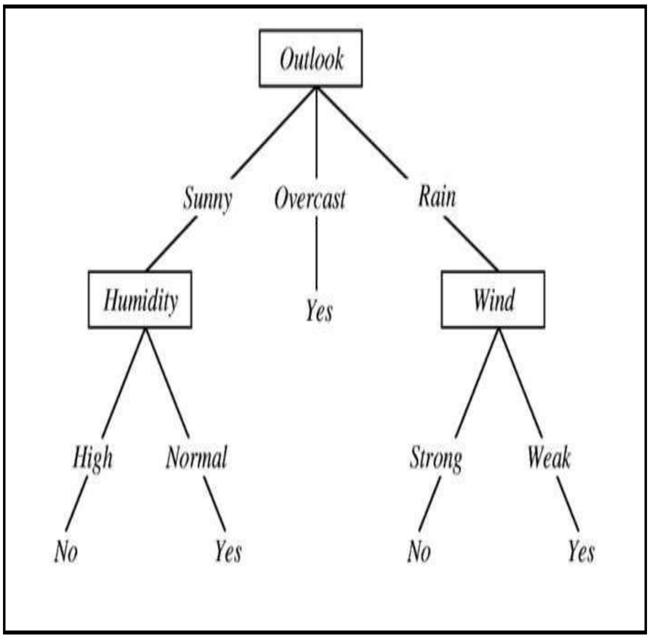


Fig. 8. Decision tree algorithm [18].

E. *Optimized Support Vector Framework*

W. F. Ip *et al.*, in [20] use Least Squares Support Vector Machines (LS-SVM) as shown in Fig. 9. It is a novel type of machine learning technique based on statistical learning theory used for regression and time series prediction which overcomes most of the drawbacks of MLP and has been reported to show promising results. In this paper, researchers report a forecasting model based on LS-SVM for the meteorological and pollution data that shows promising results. Further research then widened the applicability of LS-SVM by incorporating methods based on deep learning feature extraction techniques, such as CNNs and LSTM networks. These hybrid models grasp both the efficiency of LS-SVM in regression accuracy and the excellent representational power of deep networks, thus paving the way for more robust prediction frameworks. The integration of LS-SVM with deep feature encoding aids in handling high-dimensional data with better interpretability, thereby contributing to more reliable air quality forecasting systems that can aid policymakers and environmental agencies in informed decision-making. LS-SVM is a more powerful variant of the traditional SVM with a high capability in improving the prediction accuracy of air quality parameters, as depicted in Fig. 9. LS-SVM is a learning approach developed from statistical learning theory for regression with an excellent capability to handle nonlinear mapping problems.

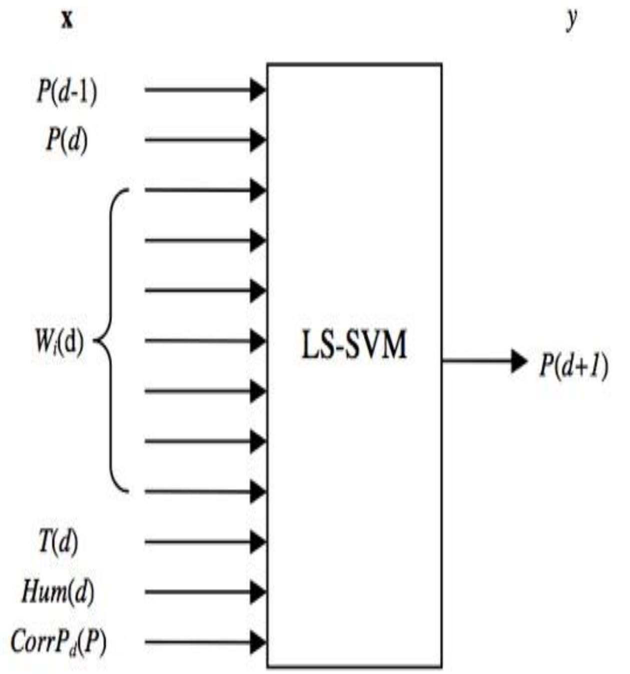


Fig. 9. AP-LSSVM for air quality prediction

Unlike standard SVMs, LS-SVM simplifies the optimization process by turning the quadratic programming problem into a set of linear equations to significantly reduce the computational complexity and improve convergence speed.

In the work, LS-SVM was integrated with meteorological and pollutant datasets to construct a forecasting framework that can learn complex functional relationships between atmospheric variables and pollutant concentrations. The results showed superior generalization performance, especially in the case of short-term air quality prediction tasks. The LS-SVM model had captured dynamic variations in the concentration of such prevalent pollutants as $PM_{2.5}$, NO_2, and O_3, thus showing promising potential for real-time environmental applications. Deep learning-based feature extraction methodologies, including CNNs and LSTM networks, have significantly improved the predictive capability of hybrid air quality models. Particularly, CNNs are proven to be very effective in capturing spatial correlations among environmental parameters, such as pollutant concentration distributions across different geographic regions. By applying multiple convolutional and pooling layers, CNNs are able to automatically learn spatial hierarchies and extract high-level representations from complex environmental datasets without the need for manual feature engineering.

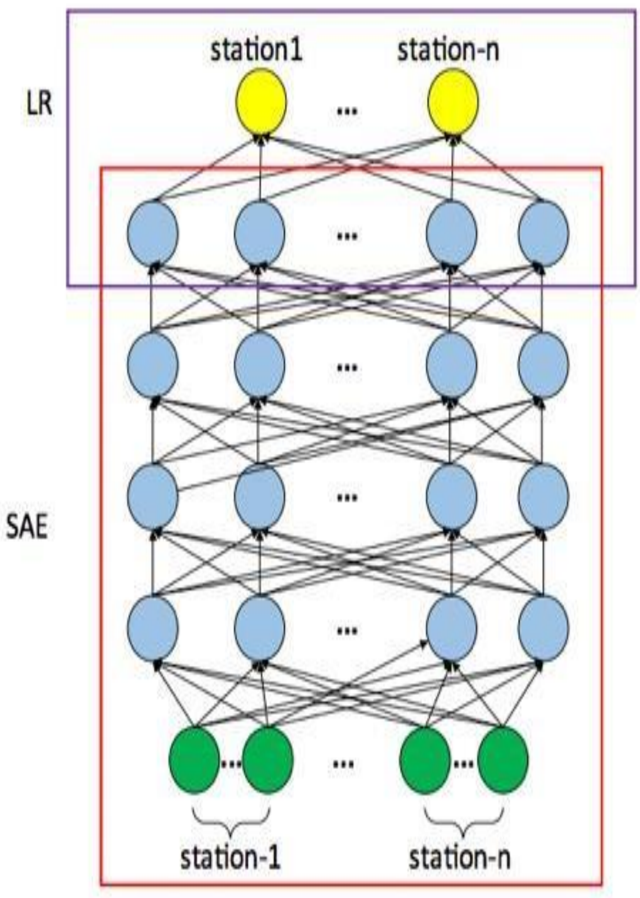


Fig10 AP-LSSVM air modelling quality prediction

F. *Deep Predictive Modeling Network*

L. Xiang *et al.* in [21] use a novel spatiotemporal deep learning (STDL)-based air quality prediction method as shown in Fig. 10. It inherently considers spatial and temporal correlations is proposed. A stacked auto-encoder (SAE) model is used to extract inherent air quality features, and it is trained in a greedy layer-wise manner. Compared with traditional time series prediction models, their model can predict the air quality of all stations simultaneously and shows the temporal stability in all seasons. Moreover, a comparison with the spatiotemporal artificial neural network (STANN),

auto regression moving average (ARMA), and support vector regression (SVR) models demonstrates that
We present a comparison table in Table IV which dives a tabular comparison of the research papers studied in this section. It talks about the purpose of study, model proposed, parameters considered and data-source referred. Finally, we present a Table V which gives a comparison of various pros and cons of all these model.

V. KEY LIMITATIONS AND RESEARCH . IMPERATIVES

Case 1: *Data Reliability and Validation*

The accuracy of air quality prediction models strongly relies on the reliability of sensor data. Faulty readings, due to sensor drift, hardware issues, or environmental interference, can lead to large errors in prediction. This emphasizes the development of real-time data validation and correction mechanisms integrated with deep learning frameworks that ensure consistently high-quality input for training and prediction.

Case 2: *Real-Time Multi-Level Monitoring and Prediction*

There is a further need for the integration of a real-time system for multi-level air quality monitoring, considering the advances in sensing and IoT technologies. Several dynamic factors such as emission levels, wind speed, humidity, and time variations are important for modeling air quality. There is a need for further evolution of deep learning models in such spatiotemporal complexities that can handle real-time monitoring and prediction across different environmental layers within smart cities.

Case 3: *Dynamic Modeling and Hybrid Deep Learning Frameworks*

Most state-of-the-art models are limited to specific geographical regions or short-term datasets. Next-generation systems should be based on adaptive and hybrid deep learning architectures, such as CNN-LSTM or Transformer-based models, that can model temporal-spatial variations of pollutant variables. Such models will need to change dynamically with environmental variations in order to enhance generalization and provide more reliable predictions in various urban settings.

VI. CONCLUSIONS

With the rapid growth of IoT infrastructures and deep learning technologies, real-time air quality monitoring and prediction systems have become one of the critical steps toward smarter and more sustainable cities. The existing studies focused on deep learning-based air quality evaluation methods were reviewed and analyzed, indicating an increasing shift from traditional statistical and physical models to data-driven intelligent systems From the review of different deep learning architectures such as CNNs, LSTMs, and hybrid models, the distinct improvement offered by these techniques in capturing complex spatial and temporal dependencies of environmental variables is evident. Such advances go beyond improving the accuracy of pollution prediction to proactive support in environmental decision-making. However, ensuring data reliability, model interpretability, and real-time adaptability remains a challenge. Future research needs to be directed toward integrating high-quality sensor data with deep learning frameworks that are scalable and consider various environmental conditions. By addressing these challenges, air quality monitoring systems powered by deep learning can play a transformational role in safeguarding environmental health and improving the quality of urban life.

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