A Review of Convolutional Neural Network Architectures for Air Quality Prediction

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Abstract: Steep increase in urbanization and industrialization has always contributed to air pollution around, delay in monitoring the air pollutant can risk ecological balance including human health. Therefore, accurate and timely prediction of air quality enables public health and supports effective policy interventions. Though many models are developed, here only Convolutional Neural Networks (CNNs) are focussed to make niche reviews, with their ability to draw spatiotemporal features from historical environmental data, have recently gained significant attention for air quality prediction. This review synthesizes findings from peer-reviewed studies published between 2020 - 2025, focusing on the application of CNNs in air quality modelling. The review explicitly examines and compares data sources, CNN architectures, and validation techniques used. However, challenges remain in model interpretability, and real-time deployment. This paper contributes a structured taxonomy of CNN-based approach, finds strengths and limitations, and highlights open research gaps.

Keywords: Convolutional Neural Networks, Air Quality Prediction, Deep Learning, AQI, Environmental Monitoring

I. INTRODUCTION

With growing industrialization, monitoring air pollution is essential as pollutants above the permissible limit are associated with respiratory and cardiovascular illnesses, premature mortality, and climate impacts. Developing a forecasting model for air quality is not simply an academic pursuit but a societal responsibility and right to live in an ambient atmosphere which was available prior to growing industries. Traditional models such as regression-based predictors or chemical transport simulations provide useful baselines, but they are computationally intensive and struggle to capture nonlinearities in atmospheric systems. The rise of deep learning has transformed forecasting paradigms. CNNs, originally developed for image recognition, have proven highly adaptable for environmental applications. Their ability to capture grid like pattern makes them particularly well-suited for the intricacies of air quality modelling. In this review a clear road map is drawn showing region, dataset size, validation technique, performance metrics used, this will enable to draw future trajectories of strength in CNN. It is pertinent to note, CNNs only began to appear in this research domain after 2020. Earlier studies, spanning from 2000 to 2014, predominantly employed shallow neural networks such as multilayer perceptron's (MLPs) and other ANN architectures.

II. METHODOLOGY

A sequential search was carried out across academic databases which include Google Scholar, Scopus, IEEE Xplore, Web of Science, and Science Direct. Review period under consideration is between 2020 to 2025, allowing the review to capture emergence of CNN only after 2015. Search terms included: "air quality prediction", "air pollution forecasting", "convolutional neural network", "CNN", "deep learning", "artificial neural network", and "multilayer perceptron (MLP)". Boolean operators (AND/OR) were used to refine queries, and reference lists of key reviews were also screened to identify additional studies and the studies were excluded if they:(i) focused on unrelated domains (e.g., medical imaging or non-environmental applications), (ii) lacked empirical results.

Screening and Selection:

The initial search yielded 78 articles. After title and abstract screening, and removing duplicates across databases through content-based comparison, reducing the pool to 43 unique studies. Following detailed eligibility checks based on the criteria above, 32 papers were finalized for inclusion in this review, a clear flow diagram for methodology is represented in Figure 1.

Data Extraction and Analysis: From each study, the following details were compared mainly data sources, CNN architectures (number of layers, kernel sizes, activation functions, use of hybrid models such as CNN-LSTM), Hyperparameter settings and training strategies along with Performance evaluation metrics (e.g., RMSE, MAE, R^2, accuracy)

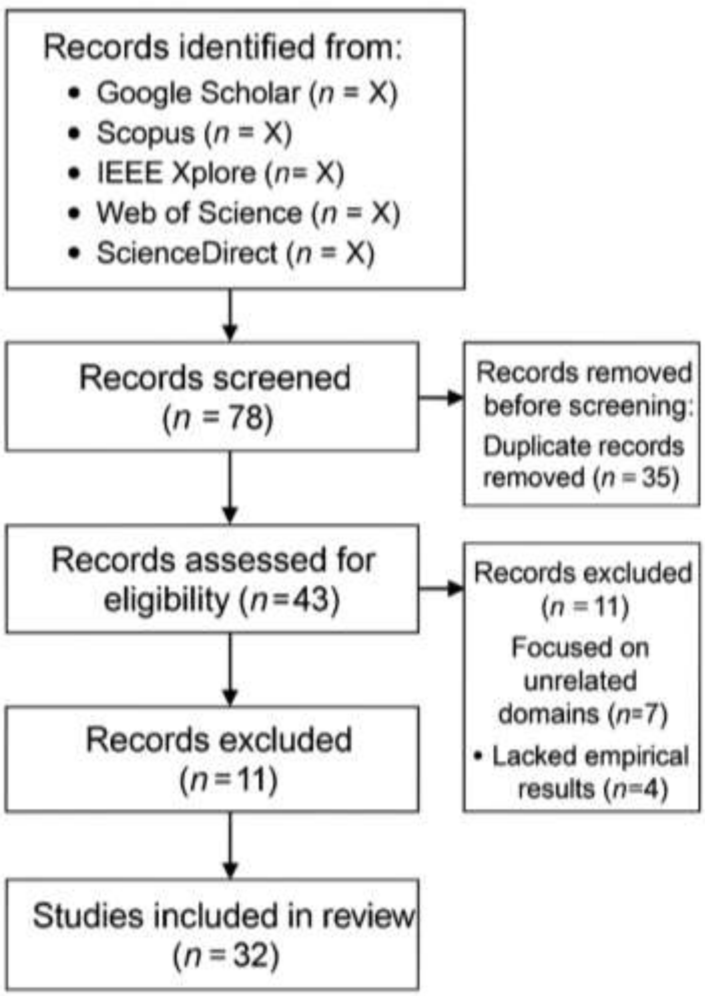

Fig 1. PRISMA-style flow diagram summarizing the study identification, screening, eligibility, and inclusion stages

III. RESULTS AND DISCUSSION

3.1 Pollutant and its region-specific study

While reviewing the study, pollutant and span of the study was recorded to ascertain the style of application done across the globe in the recent year which will enhance better view of CNN application. Table 1summarizes the **geographical locations, pollutant variables, and time durations** commonly used for training CNN-based air quality prediction models. Most studies have used data from **large metropolitan cities** such as **Hong Kong, Beijing, Shanghai, Tehran, Jakarta, London, and major Indian cities**. These areas are typically characterized by **dense traffic, industrial clusters, and frequent air quality fluctuations**, making them suitable for deep learning experiments. Most of the datasets include **fine particulate matter (PM2.5)** which is evident from Figure 2as the core pollutant variable, often accompanied by **PM10, SO_2,NO_2, CO, and O_3.** This aligns with global health priority indicators since PM2.5 and PM10 directly correlate with respiratory and cardiovascular health risks. Additionally, many studies incorporate **meteorological parameters** such as **temperature, humidity, wind speed, wind direction, and atmospheric pressure**, acknowledging that air pollutant dispersion and concentration are significantly influenced by weather dynamics. Another observation from the table is the **variation in dataset duration**. Several studies utilize **long-term multi-year datasets** (e.g., Beijing 2010–2014, London multi-year records, India 2015–2020), which help identify **seasonal and annual pollution trends**. Apart from this, some research was**short-term** (e.g., Jakarta's 2-month dataset, Hefei's 6-day urban episode), often focusing on **short-term forecasting or anomaly detection** rather than seasonal prediction. Furthermore, a few datasets originate from **indoor or controlled measurement environments** (e.g., Seoul Metro indoor and laboratory diesel simulations). These are used to develop **specialized CNN models** tailored for **industrial, occupational, or built-environment pollution studies**, indicating versatility in model adaptation

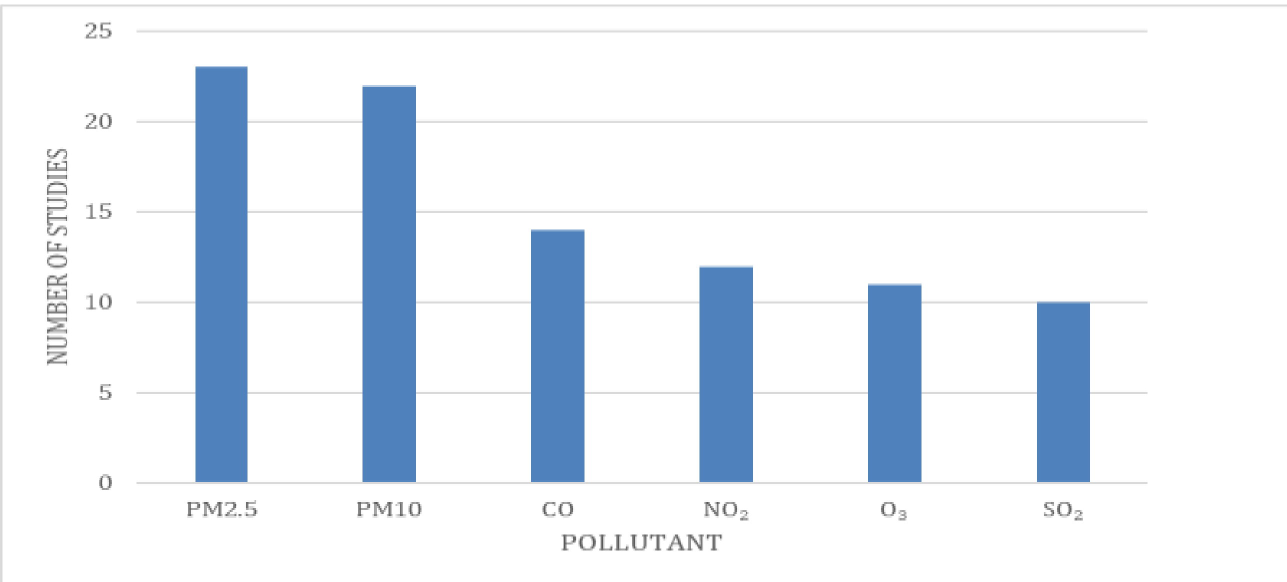

Fig 2. Number of studies categorized by targeted pollutant

TABLE I:
DATASET EMPLOYED IN THE REVIEWED STUDIES

Author(s)	Pollutant	Region/City	Time Span
Q. Zhang, Y. Han, V. O. K. Li, and J. C. K. Lam, 2022	PM2.5, PM10, NO_2, SO_2, O_3, CO	Hong Kong	16 months (Dec 2018 – Mar 2020)
Q. Zhang, Y. Han, V. O. K. Li, and J. C. K. Lam, 2022	PM2.5, PM10, NO_2, SO_2, O_3, CO	Beijing	19 months (Jan 2017 – Jul 2018)
Y. Liu, Z. Wang, W. Zhang, and Y. Wang, 2021	PM2.5, PM10, NO_2, SO_2, O_3, CO, meteorological data	Beijing, China	Jan 1, 2010 – Dec 31, 2014
Y. Lu and K. Li, 2023	PM2.5, PM10, NO_2, SO_2, O_3	China (multi-station network)	2015 – 2020
M. Faraji, S. Nadi, O. Ghaffarpasand, S. Homayoni, and K. Downey, 2022	PM2.5, Meteorological parameters (humidity, temperature, wind speed, wind direction, pressure, dew point)	Tehran, Iran	Dec 7, 2016 – Feb 27, 2019
B. Cui, M. Liu, S. Li, Z. Jin, Y. Zeng, and X. Lin, 2023	PM2.5, PM10, SO2, NO2, CO, O3, meteorological data (temperature, pressure, dew point, rainfall, wind direction,	Beijing, China	Jan 1, 2013 – Jan 1, 2017

	wind speed)		
R. Rabie, M. Asghari, H. Nosrati, M. Emami Niri, and S. Karimi, 2024	O3, NO2, CO, SO2, PM2.5, PM10, AQI	Tehran, Iran	March 2018 – March 2023 (5 years)
K. Elbaz, W. M. Shaban, A. Zhou, and S.-L. Shen, 2023	PM2.5 (main pollutant), PM10, SO2, O3, NO2, Temperature	Shanghai, China	May 2014 – Dec 2014
M. Goudarzi, A. Karimian, A. Maleki, and H. Khosravi, 2021	PM2.5, PM10, NO_2, SO_2, CO, O_3, meteorological variables (temperature, humidity, pressure, wind speed, wind direction)	Tehran, Iran	Jan 1, 2014 – Dec 31, 2019
A. A. Abbood, R. F. Mansour, and S. Kadry, 2022	PM2.5, PM10, SO_2, NO_2, CO, O_3, meteorological variables (temperature, humidity, wind speed, wind direction, pressure)	Baghdad, Iraq	Jan 2015 – Dec 2020
M. Mohammadi, A. Al-Fuqaha, M. Guizani, and J. Oh, 2020	PM2.5, PM10, SO_2, NO_2, CO, O_3, meteorological parameters (temperature, pressure, dew point, wind direction, wind speed, precipitation)	Beijing, China	2010 – 2014
Y. Gong, 2023	PM2.5, PM10, SO_2, NO_2, CO, O_3, meteorological parameters (temperature, humidity, wind speed, wind direction, pressure)	Zhoushan, China	Jan 2019 – Dec 2021
Z. Guo, C. Yang, D. Wang, and H. Liu, 2023	NO, NO_2, CO, CO_2, Temperature, Humidity, PM10, PM2.5	Seoul, South Korea	April (year not specified, single month data)
K. Alnowaiser, et al., 2024	PM10, PM2.5, NO_2, NO, NH_3, Nox, SO_2, CO, Benzene, O_3, Toluene, AQI, AQI_Bucket	23 Indian cities (Delhi, Mumbai, Bangalore, Kolkata, Chennai, Hyderabad, Ahmedabad, Jaipur, etc.)	Jan 2015 – Jul 2020
J. Wang, L. Jin, X. Li, S. He, M. Huang, and H. Wang, 2022	SO_2, O_3, PM2.5, NO_2, PM10, CO + meteorological factors (temperature, humidity, wind, weather)	Shijiazhuang, Hebei Province, China	Jan 1, 2018 – Jun 30, 2021
T. H. Putri, R. E. Caraka, T. Toharudin, Y. Kim, R.-C. Chen, P. U. Gio, A. D. Sakti, R. S. Pontoh, I. R. Pratiwi, F. A. L. Nugraha, T. S. Azzahra, J. J. Cerelia, G. Darmawan, D. Y. Faidah, and B. Pardamean, 2024	PM2.5	Kemayoran, Central Jakarta, Indonesia	21 April 2022 – 21 June 2022
H. Özarslan and İ. Uluocak, 2026	Nox	Türkiye (lab-based diesel engine setup)	Not explicitly stated (controlled lab experiments)
S. Wang and Y. Zhang, 2025	CO, NO_2, O_3	Nanjing, China; Dongguan, China	Oct 2019 – Sep 2020 (1year, mobile sensor data); PALM-4U simulations under 48 emission/wind scenarios
S. Xia, R. Zhang, L. Zhang, T. Wang, W. Wang, 2025	PM2.5, PM10	Hefei, China (urban residential area)	2–7 July 2021 (6 days, 12h/day, 6:00–18:00)
F. Illescas-Martinez, L. Garcia, A.-J. Garcia-Sanchez, R. Asorey-	PM2.5, PM10, NO2, O3, SO2	London, UK	Hourly data (multi-year, total logs: NO2: 14,542,549; PM10:

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Cacheda, J. Garcia-Haro, 2025			12,259,789; PM2.5: 5,215,538; PM1: 948,976; O3: 3,951,554; SO2: 1,715,564)
Kun Lei, Mingya Wang, Mingshi Wang, QingWei Liu, Fan Zhang, MingFei Xing, Wei Wu, Fengcheng Jiang, Xiaoming Guo, Qiao Han, Fayang Guo, Huiyun Pan, Kewu Liu, Jing Wang, Zhengbo Yu, 2025	PM2.5, O3	Jiaozuo City, Henan Province, China	January 2019 – October 2024
Ahmed Khan Salman, Yunsoo Choi, Deveshwar Singh, Sagun Gopal Kayastha, Rijul Dimri, Jincheol Park, 2025	Ozone (O3)	South Korea (nationwide, 400 monitoring stations)	2016 – 2021 (training: 2016–2019, validation: 2020, testing: 2021)
Gimhan Attanayake, Mahesh Senarathna, Mike Bergin, David Carlson, Prakash V. Bhave, Gayan Bowatte, Nalin Harischandra, 2025	PM2.5	Sri Lanka (nationwide, 24 AQM sites)	November 2022 – February 2024
S. Palanivel Rajan, R. Rahul, T. Jegan, S. Yasar Arafath, 2025	Not explicitly listed (general air pollutants mentioned)	Tamil Nadu, India	Not explicitly stated (historical datasets referenced)
Fareena Naz, Muhammad Fahim, Adnan Ahmad Cheema, Bradley D.E. McNiven, Tuan-Vu Cao, Ruth Hunter, Trung Q. Duong, 2025	PM2.5, NO2, O3, PM10, SO2	Northern Ireland, UK (Belfast)	1440 hours (used for experimental analysis)
Yangwen Yu, Victor O. K. Li, Jacqueline C. K. Lam, Kelvin Chan, Qi Zhang, 2025	PM2.5, PM10, NO2, SO2, O3	Hong Kong	1 Jan 2019 – 31 Dec 2021 (3 years, hourly data)
Yesanna Pininta Lamria Marpaung, Hilal H. Nuha, Dita Oktaria, Hassan Sailellah, 2024	Ozone (O3) noted as main pollutant; AQI used as indicator	Bekasi City, Indonesia	Not explicitly stated (reference to October 1, 2023 AQI event)
J. Wang, X. Li, L. Jin, J. Li, Q. Sun, H. Wang, 2022	PM2.5, CO, O3, NO2, PM10, SO2 (used for AQI calculation)	Shijiazhuang City, Hebei Province, China	1 Jan 2017 – 30 Jun 2021 (4.5 years)
Yibin Chen, Xiaomin Chen, Ailan Xu, Qiang Sun, Xiaoyan Peng, 2022	Ozone (O3), NO, NO2, SO2, CO	Beijing, China	1 Jan 2014 – 31 Jul 2021 (daily maximum 8-h average ozone, 2769 observations)
S. Tsokov, M. Lazarova, and A. Aleksieva-Petrova, 2022	PM10, NO2, O3	Sofia, Bulgaria	2018 – 2020

3.2. Evaluation of Different CNN and Hybrid CNN Architectures for Air quality

Table 2 presents a comparative evaluation of different CNN-based architectures used for air quality prediction. The performance indicators clearly show that hybrid CNN models outperform standalone CNN models. Pure CNN architectures are good in extracting spatial characteristics of pollutant distribution, but they do not fully capture the time-dependent behavior of air pollutant variation. As a result, their predictive accuracy is lower, reflected through comparatively higher RMSE and MAE values. Models that integrate CNN with recurrent neural network layers such as LSTM, GRU, or BiLSTM are with superior prediction accuracy. The reason is that CNN layers identify pollution patterns and feature correlations, while the recurrent layers learn temporal trends, seasonal effects, and lag relationships among pollutant concentrations. For instance, CNN-LSTM and CNN-GRU models generally achieve lower RMSE and higher R^2 values, indicating more reliable forecasting performance. Apart from this, CNN-BiLSTM models often show the highest accuracy among hybrid design due to the bidirectional memory pattern it considers in both past and future pattern dependencies, improving better pattern recognition to even sudden pollutant changes. Contrary, 3D-CNN based models perform well in studies involving spatial-temporal grids, where pollutant distribution across regions is modeled together. A notable pattern from Table 2 is that models trained on datasets that include meteorological variables outperform those using air pollutant data alone. This reinforces the fact that factors such as temperature, wind speed, humidity, and pressure significantly influence pollutant formation and dispersion.

TABLE II:
COMPARATIVE EVALUATION OF CNN-BASED AIR QUALITY PREDICTION MODELS

Author(s), Year	Model Name	Performance Metric
Q. Zhang, Y. Han, V. O. K. Li, and J. C. K. Lam, 2022	Deep-AIR (Hybrid CNN-LSTM)	MAPE (14.4% PM2.5, 13.8% PM10 in Hong Kong; 17.9% CO in Beijing), R^2 (0.94 Hong Kong, 0.90 Beijing for 1-hr forecast)
S. Tsokov, M. Lazarova, and A. Aleksieva-Petrova, 2022	Hybrid CNN-LSTM with GA optimization	MAE = 16.753 ± 0.384, RMSE = 24.312 (Wanliu station, best result)
Y. Lu and K. Li, 2023	CNN-BiLSTM	RMSE = 9.39, MAE = 6.88, R^2 = 0.82
M. Faraji, S. Nadi, O. Ghaffarpasand, S. Homayoni, and K. Downey, 2022	3D CNN-GRU	Hourly forecast: R^2 = 0.84, RMSE = 7.15 μg/m³, MAE = 4.64 μg/m³; Daily forecast: R^2 = 0.78, RMSE = 6.44 μg/m³, MAE = 8.89 μg/m³
B. Cui, M. Liu, S. Li, Z. Jin, Y. Zeng, and X. Lin, 2023	Transformer; CNN-LSTM-Attention	Transformer: R^2 = 0.944, EVS = 0.946, MAE = 2.239×10^{-2}, MSE = 0.112×10^{-2}; CNN-LSTM-Attention: R^2 = 0.836, EVS = 0.836, MAE = 2.362×10^{-2}, MSE = 0.161×10^{-2}
R. Rabie, et al., 2024	CNN-BiLSTM	R^2 up to 97% (Pounak & Shadabad), ~95% (Gisha)
K. Elbaz, W. M. Shaban, A. Zhou, and S.-L. Shen, 2023	3D CNN-GRU with Attention	MAPE = 15.6%, MAE = 17.13, MASE = 21.57; CNN-LSTM (MAPE = 19.3%, MASE = 23.98); 3D CNN (MAPE = 27.6%); 1D CNN (MAPE = 29.5%)
M. Goudarzi, A. Karimian, A. Maleki, and H. Khosravi, 2021	CNN-LSTM (applied to Tehran AQ dataset)	RMSE = 6.41 μg/m³, MAE = 4.12 μg/m³, R^2 = 0.87
A. A. Abbood, R. F. Mansour, and S. Kadry, 2022	Deep CNN-LSTM	RMSE = 7.23, MAE = 5.46, R^2 = 0.91
M. Mohammadi, A. Al-Fuqaha, M. Guizani, and J. Oh, 2020	CNN-LSTM	RMSE = 8.21, MAE = 5.62, R^2 = 0.89
Y.-P. Gong, 2023	CNN-BiLSTM	RMSE = 5.92, MAE = 3.74, R^2 = 0.93
Z. Guo, C. Yang, D. Wang, and H. Liu, 2023	RF-CNN-GRU	MAE = 8.61, MAPE = 0.2494, RMSE = 10.56, R^2 = 0.8704
J. Wang, L. Jin, X. Li, S. He, M. Huang, and H. Wang, 2022	CNN-AGU (CNN + Attention Gate Unit)	CNN-AGU: MAE = 11.205, MSE = 243.47, R^2 = 0.918 (best); Compared with CNN-LSTM, CNN-GRU, BD-LSTM and others, CNN-AGU showed superior accuracy
T. H. Putri, R. E. Caraka, T. Toharudin, Y. Kim, R.-C. Chen, P. U. Gio, A. D. Sakti, R. S. Pontoh, I. R. Pratiwi, F. A. L. Nugraha, T. S. Azzahra, J. J. Cerelia, G. Darmawan, D. Y. Faidah, and B. Pardamean, 2024	CNN-LSTM, CONV-LSTM	CNN-LSTM: MAE = 7.35, RMSE = 9.32, MAPE = 17.92%; CONV-LSTM: MAE = 6.52, RMSE = 8.55, MAPE = 16.39%
S. Liu and Y. Hu, 2025	Transformer with Factor Analysis; CNN-BiLSTM-Attention with Discrete Wavelet Transform	Transformer (Factor Analysis): R^2 = 0.945, RMSE = 7.82, MAE = 5.41; CNN-BiLSTM-Attention (DWT): R^2 = 0.951, RMSE = 7.36, MAE = 5.02
H. Özarslan and İ. Uluocak, 2026	CNN-LSTM, CNN–GRU, LSTM, GRU	CNN-LSTM: RMSE = 0.0727, MAE = 0.0016, R^2 = 0.996; CNN–GRU: RMSE = 0.0812, MAE = 0.0019, R^2 = 0.994; LSTM: RMSE = 0.0946, MAE = 0.0021, R^2 = 0.992; GRU: RMSE = 0.1013, MAE =

		0.0024, R^2 = 0.990
S. Wang and Y. Zhang, 2025	Attention-based CNN (CNN-attention)	R^2 = 0.987, RMSE = 0.15 mg/m³; improvements of 3.8–6.1% with observational data and attention mechanism
S. Wang and Y. Zhang, 2025	CNN (baseline)	R^2 range = 0.67–0.84, RMSE = 0.20–0.56, MAE = 0.18
S. Wang and Y. Zhang, 2025	Sensor-CNN-attention	R^2 up to 0.842, RMSE = 0.150–0.153 mg/m³
Sihan Xia, Ruinan Zhang, Lei Zhang, Taiyang Wang, Wei Wang, 2025	CNN-based PM2.5 Prediction (compared with ANN)	CNN validation accuracy 75–90%; best R^2 = 0.88 (radii 100m & 140m); ANN R^2 = 0.74; CNN improved by 0.14
Fernando Illescas-Martinez, Laura Garcia, Antonio-Javier Garcia-Sanchez, Rafael Asorey-Cacheda, Joan Garcia-Haro, 2025	M-CNN-BiLSTM (best for NO2)	RMSE = 7.64, R^2 = 0.82, MAE = 5.73, Accuracy = 0.94 (NO2)
Fernando Illescas-Martinez et al., 2025	LSTM (best for O3)	Best performance for O3 (quantitative values not fully shown in extract)
Fernando Illescas-Martinez et al., 2025	GRU (best for PM2.5)	GRU most efficient for PM2.5 (quantitative values not fully shown in extract)
Fernando Illescas-Martinez et al., 2025	BiLSTM (best for PM10)	BiLSTM most efficient for PM10 (quantitative values not fully shown in extract)
Kun Lei, Mingya Wang, Mingshi Wang, QingWei Liu, Fan Zhang, MingFei Xing, Wei Wu, Fengcheng Jiang, Xiaoming Guo, Qiao Han, Fayang Guo, Huiyun Pan, Kewu Liu, Jing Wang, Zhengbo Yu, 2025	PSO-CNN-BiLSTM (SHAP explainable)	O3 (short-term t+1–t+3): RMSE = 17.43–17.89, MAE = 13.13–13.80, R^2 = 0.88; O3 (6h ahead): RMSE = 19.93, MAE = 15.36, R^2 = 0.85; PM2.5 (t+1): RMSE = 13.94, MAE = 8.96, R^2 = 0.89; PM2.5 (t+6): RMSE = 23.76, R^2 = 0.67; Compared with LSTM, CNN, XGBoost, persistence baseline – PSO-CNN-BiLSTM superior beyond 1h horizon; PSO reduced computation time (22h vs Grid 78h, Random 33h).
Ahmed Khan Salman, Yunsoo Choi, Deveshwar Singh, Sagun Gopal Kayastha, Rijul Dimri, Jincheol Park, 2025	Temporal CNN (TCNN)	Day 1: R = 0.87, IOA = 0.93, RMSE = 9.89 ppb; Day 2: R = 0.82, IOA = 0.90, RMSE = 11.38 ppb; Day 3: R = 0.80, IOA = 0.89, RMSE = 12.00 ppb; Cross-validation (149 stations): Day 1 R = 0.85, IOA = 0.92, RMSE = 9.65 ppb; Compared to CMAQ Day 1 (R = 0.62, IOA = 0.76, RMSE = 19.10 ppb). MCD uncertainty quantification: R = 0.89 between RMSE and standard deviation; SSREL = 0.14 ppb, SSRAT = 0.95 (calibrated).
Gimhan Attanayake, Mahesh Senarathna, Mike Bergin, David Carlson, Prakash V. Bhave, Gayan Bowatte, Nalin Harischandra, 2025	RF-CNN (Random Forest + Convolutional Neural Network pipeline)	RF (test set): RMSE = 8.151 µg/m³, NRMSE = 55.92%, MAE = 5.791 µg/m³, MAPE = 52.08%, Pearson r = 0.519, Spearman r = 0.471, Spatial r = 0.412; RF-CNN (optimal, SF=0.1): RMSE = 4.726 µg/m³, NRMSE = 32.42%, MAE = 3.318 µg/m³, MAPE = 25.69%, Pearson r = 0.873, Spearman r = 0.871, Spatial r = 0.978 (p=0.00013); Station-wise results: NRMSE < 42%, MAPE < 31%; best Spearman r, Pearson r > 0.74 across most sites.
S. Palanivel Rajan, R. Rahul, T. Jegan, S. Yasar Arafath, 2025	ANN and CNN (comparative approach for air quality	MAE = 0.037, R^2 = 0.9998, RMSE = 0.4522

	prediction in Tamil Nadu)	
Fareena Naz, Muhammad Fahim, Adnan Ahmad Cheema, Bradley D. E. McNiven, Tuan-Vu Cao, Ruth Hunter, Trung Q. Duong, 2025	AirVCQnet (VMD + CNN + QLSTM hybrid model)	PM2.5: R^2 = 0.84, RMSE = 1.81, MAE = 1.36; NO2: R^2 = 0.92, RMSE = 4.84, MAE = 3.86; O3: R^2 = 0.91, RMSE = 5.34, MAE = 4.04; PM10: R^2 = 0.81, RMSE = 3.31, MAE = 2.34; SO2: R^2 = 0.80, RMSE = 0.50, MAE = 0.34; Performance gain vs classical model: +14% (PM2.5), +2% (O3), +12% (PM10), +4% (SO2).
Yangwen Yu, Victor O. K. Li, Jacqueline C. K. Lam, Kelvin Chan, Qi Zhang, 2025	CTDI (CNN-Transformer-based Spatial-Temporal Data Imputation)	Case 1 (low missing 2–10%): MAPE = 14.06% (10% missing); Case 2 (high missing 20–60%): MAPE = 18.57% (60% missing); Case 3 (real-world avg 2.46% missing): superior to baselines; Case 4 (severe 24.60% missing): superior to baselines; Case 5 (real-world masks 2.29–23.13% missing): consistently outperformed baselines; Ablation: temporal transformer critical; urban data ('AU') improved convergence vs air-only ('A').
Yesanna Pininta Lamria Marpaung, Hilal H. Nuha, Dita Oktaria, Hassan Sailellah, 2024	CNN (Integrated with IoT-based weather station data)	RMSE = 1.2639, MAE = 1.2637, MAPE = 0.63583%, R^2 = 0.98819; 9 out of 10 experiments achieved high accuracy
Fareena Naz, Muhammad Fahim, Adnan Ahmad Cheema, Bradley D. E. McNiven, Tuan-Vu Cao, Ruth Hunter, Trung Q. Duong, 2025	AirVCQnet (VMD + CNN + Quantum LSTM hybrid)	PM2.5: R^2 = 0.84, RMSE = 1.81, MAE = 1.36; NO2: R^2 = 0.92, RMSE = 4.84, MAE = 3.86; O3: R^2 = 0.91, RMSE = 5.34, MAE = 4.04; PM10: R^2 = 0.81, RMSE = 3.31, MAE = 2.34; SO2: R^2 = 0.80, RMSE = 0.50, MAE = 0.34; Performance gain vs classical VMD-CNN-LSTM: +14% (PM2.5), +2% (O3), +12% (PM10), +4% (SO2).
Pu-Yun Kow, Chia-Yu Hsu, Wei Sun, Yun-Ting Wang, Li-Chiu Chang, Fi-John Chang, 2025	Hybrid CNN-Transformer (3D CNN + dual 1D CNN + Transformer)	CNN-Transformer outperformed Transformer in all subcatchments; S1: R^2 improved by 50%, RMSE reduced by 19%; S2: R^2 +24%, RMSE −12%; S3: R^2 +25%, RMSE −9%; Water discharge events (E11): RMSE CNN-Transformer = 7.15–14.38 vs Transformer 8.43–17.33; Industrial pollution events (E2, E3, E13): CNN-Transformer RMSE = 12.47–22.1 vs Transformer RMSE = 17.91–27.9; Detected 100% of 66 severe pollution events and 89% of water discharge events; Training epoch <10s, inference <2s.
Jingyang Wang, Xiaolei Li, Lukai Jin, Jiazheng Li, Qiuhong Sun, Haiyao Wang, 2022	CNN-ILSTM (Convolutional Neural Network + Improved LSTM with Conversion Information Module)	CNN-ILSTM: MAE = 8.4134, MSE = 202.1923, R^2 = 0.9601, Training Time = 85.3s; Outperformed baseline models: SVR (R^2=0.8750, MAE=19.2644), RFR (R^2=0.8905, MAE=15.364), MLP (R^2=0.9106, MAE=13.6186), LSTM (R^2=0.9447, MAE=9.4974), GRU (R^2=0.9411, MAE=11.0032), ILSTM (R^2=0.9508, MAE=9.2420), CNN-LSTM (R^2=0.9466, MAE=9.2314), CNN-GRU (R^2=0.9478, MAE=9.0615). Compared with ILSTM: R^2 +0.0093, MAE −0.8286, MSE −46.7311; Compared with CNN-

		LSTM: R^2 +0.0135, MAE −0.818, MSE −56.3220; Compared with CNN-GRU: R^2 +0.0123, MAE −0.6481, MSE −46.4466.
Pratyush Muthukumar, Emmanuel Cocom, Kabir Nagrecha, Dawn Comer, Irene Burga, Jeremy Taub, Chisato Fukuda Calvert, Jeanne Holm, Mohammad Pourhomayoun, 2021	GCN + ConvLSTM (Two-stage model)	First frame prediction accuracy: 91.24% (46h ahead); RMSE for frames 1–5: 0.000751 → 0.002823; NRMSE for frames 1–5: 0.0876 → 0.2510; Sensor-specific RMSE (first vs fifth frame): Lancaster 0.001451 vs 0.003932, Glendora 0.001233 vs 0.003841, Santa Clarita 0.001028 vs 0.003405, Reseda 0.001115 vs 0.003639, LA-Main St 0.000834 vs 0.003213, Long Beach 0.000750 vs 0.003069, Long Beach-710 0.000901 vs 0.003118.
Pawan Gupta, Sundar A. Christopher, 2009	Artificial Neural Network (Multilayer Perceptron)	ANN improved PM2.5 estimation accuracy vs regression: Hourly PM2.5: R = 0.74, APE = 33%; Daily mean PM2.5: R = 0.78, APE = 24%; TVM baseline R = 0.60, MVM R = 0.68; Bias ≈ −6.2 μg/m³; ANN outperformed regression in ~65% of stations (e.g., Covington, KY: R = 0.83, RMSE = 6.3 μg/m³, APE = 30%); Weaker improvement or degradation at coastal stations (e.g., Naples, FL: R = 0.50, APE = 39%).
Aman Kataria, Vikram Puri, 2022	CNN-LSTM-BOA (Bayesian Optimization Algorithm) hybrid with IoT sensors	Dataset 1: CNN-LSTM-BOA Accuracy = 0.981, R^2 = 0.964, MAE = 12.0923, RMSE = 21.6932; Ensemble: Accuracy = 0.977, R^2 = 0.968, MAE = 15.4625, RMSE = 24.1207; LSTM: Accuracy = 0.969, R^2 = 0.931, MAE = 15.8970, RMSE = 23.9681; CNN-LSTM: Accuracy = 0.972, R^2 = 0.959, MAE = 14.8967, RMSE = 23.1369. Dataset 2: CNN-LSTM-BOA Accuracy = 0.973, R^2 = 0.951, MAE = 17.9656, RMSE = 27.9843; Ensemble: Accuracy = 0.967, R^2 = 0.949, MAE = 23.6978, RMSE = 37.2059; CNN-LSTM: Accuracy = 0.978, R^2 = 0.936, MAE = 26.6985, RMSE = 30.8562; LSTM: Accuracy = 0.955, R^2 = 0.915, MAE = 19.8975, RMSE = 31.5289.

CNNs performance is above the statistical baselines (e.g., regression, ARIMA) and shallow neural networks by capturing non-linear spatiotemporal dependencies in pollutant dynamics [14], [17], [25]. Even with relatively modest datasets (~8,000–10,000 hourly samples), shallow CNNs demonstrated gains over multilayer perceptron's and regression-based predictors [23], [24]. Bigger datasets (>20,000 samples), often incorporating more than one sources such as ground stations, meteorology, and satellite data, enabled deeper or hybrid CNN-LSTM architectures that improved generalization and stability [14], [17], [25], [32]. CNNs also proved to accustom across different input domains: satellite imagery [17], [29], fused spatiotemporal observations [2], [13], [16], and even non-traditional inputs such as urban photos [3].

At the same time, limitations emerged. Dataset availability strongly restricted architecture choice like smaller datasets forced the use of shallow CNNs with heavy regularization, limiting predictive gains [23], [27]. Handling of missing values was not the same—some studies applied interpolation, statistical imputation, or machine learning–based approaches [10], [19], while others did not report their strategy, raising reproducibility concerns [20].

Overall, CNN is moving ahead in air quality Prediction. Yet, their effectiveness depends heavily on size of the data and diversity, missing-value handling, and rigorous validation protocols.

VI. CONCLUSION

This review concludes that **hybrid CNN-based deep learning models, supported by comprehensive air quality and meteorological datasets, represent a promising approach for accurate and timely air pollution forecasting**. Future research should focus on developing lightweight and interpretable hybrid models that can be deployed across different urban environments, while ensuring standardization in data preprocessing and model evaluation protocols to enhance comparability and applicability of results. Indoor air quality remains underexplored [3],Model will perform well locally but lack cross-regional validation [12], [15] and inconsistent handling of missing values reduce model reliability [2], [4], [10],[19]. Suggested future work requires extending research to indoor/IoT environments and link forecasts with public health [7], [9], [11].And needed to perform cross-city and multi-pollutant validation for robustness [12], [15].

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DECLARATIONS

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