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Patent landscape study on deep learning models for spatio-temporal air quality forecasting

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Abstract

Accurate air quality prediction is urgently required due to the harmful impacts of air pollution on human health, sustainability, and livability. Air pollutants' nonlinear, dynamic, and spatiotemporal characteristics are hard to model using traditional statistical and physical models, particularly in complex urban areas. Therefore, deep learning-based methods have emerged as important ones, where LSTM models effectively modeled temporal dependencies and CNN models modeled spatial dispersion patterns. By learning both temporal and geographical correlations from large and diverse datasets, hybrid CNN-LSTM models have immensely improved the accuracy of predictions.

The complexity of the system has a risen due to the growing adoption of deeper architectures, data fusion techniques, adaptive learning strategies, and real-time system deployment platforms, resulting in a rise in patenting activities. There is a growing trend of using patents as a means to safeguard novel CNN-LSTM architectures, data pipelines, and end-to-end intelligent forecasting systems. Therefore, this paper will examine the patenting landscape of spatio-temporal deep learning models for air quality forecasting with a focus on innovation trends and the impact of system complexity on patent development.

Key words: Air quality forecasting, Air quality index, CNN-LSTM models, Patent landscape, Spatio-temporal prediction

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Introduction

Air quality forecasting has emerged as a critical application of urban governance, environmental sustainability, and health protection (Mujtaba *et al.,* 2025). According to the World Health Organization (WHO, 2025), substantial scientific evidence highlights the harmful effects of air pollution on human health, and emphasizes the importance of strong air quality governance, monitoring systems, and regulatory standards to safeguard public health. Air pollution is one of the leading environmental health risks globally, particularly in urban areas where industrial activities and transport demand are concentrated. Effective air quality monitoring and management systems are therefore essential for supporting policy planning, early interventions, and sustainable urban development (OECD, 2024). Though the traditional statistical and physics-based forecasting models have made a significant contribution to air quality modelling, their effectiveness in the complex urban environment is hampered by their inability to model the nonlinear dynamics of air pollutants (Havaei *et al.,* 2025; Zhang *et al.,* 2024). This has accelerated the adoption of deep learning and artificial intelligence models in air quality management, as these models are more adept at detecting complex patterns in large and varied environmental datasets (Li *et al.,* 2016). Hybrid models based on CNN-LSTM architectures have been successfully applied for forecasting urban air quality indexes, exhibiting outperformance over traditional deep learning models (Zhang and Li, 2022)

Air quality forecasting has progressed from individual algorithmic solutions to comprehensive intelligent systems because of recent advances in deep learning techniques, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and CNN-LSTM combined models (Zhou *et al.,* 2024). These models enhance the accuracy and resilience of forecasting by facilitating collaborative learning of temporal and spatial relationships (Hochreiter and Schmidhuber 1997; Qin *et al.,* 2019). Some review papers have extensively summarized various deep learning techniques for air quality forecasting, indicating the prominent use of CNN, LSTM, and hybrid models from recent research literature (Liao *et al.,* 2020). Increased network complexity, data integration strategies, adaptive learning methods, and real-time system development platforms have all contributed to the system-level complexity of the ongoing development of AI-based forecasting systems (Goodfellow *et al.,* 2016). Recent systematic surveys have further evidenced a fast increase in deep learning technology-based air quality prediction research due to massive environmental data and technological advancements in computing capacities (Zhang *et al.,* 2024).

Innovation management and intellectual property are also affected by the increasing complexity (Candelin-Palmqvist *et al.,* 2012). Patenting is an important approach to innovation protection, commercialization, and technology transfer because the development of end-to-end AI-enabled air quality forecasting platforms requires a lot of research spending and integration (Suominen *et al.,* 2023). According to World Intellectual Property Organization (WIPO, 2019), due to the maturity of technology and its industry significance, the number of patents in AI-enabled environmental technology has shown a sharp rise in recent years. The patent landscape of deep learning-based air quality forecasting remains scattered and less explored despite this growth (Utku *et al.,* 2025).

Instead of application-oriented forecasting approaches tailored to air quality and pollutant patterns, most patents today are centered on general AI or spatiotemporal modeling approaches, making it difficult to identify key inventors and development trends (Zhou *et al.,* 2018). In this context, the present study performs a comprehensive patent landscape analysis on spatio-temporal air quality forecasting approaches using deep learning. This study aims to identify innovation trends, identify technology gaps, and explain the role of model complexity in fuelling patenting activity in AI-enabled air quality management through the analysis of patents related to CNN, LSTM, and combined models.

Materials and Methods

The current study on the "Patent Landscape of Deep Learning Models (CNN/LSTM) for Spatio-Temporal Air Quality Forecasting" employed a systematic methodology to retrieve, assess, and analyze patents. cA comprehensive list of keywords was created to cover the variety of deep learning-based air quality forecasting systems. The keywords included forecasting, prediction, estimation, time-series analysis, sensor data, multi-source data, IoT, remote sensing, satellite data, meteorological data, air quality, air pollution, $PM_{2.5}$, PM_{10}, NO_x, NO_2, long short-term memory, LSTM, spatiotemporal model and hybrid neural network. Different combinations of these terms were used to generate Boolean search strings tailored to the syntax requirements of specific databases. Searches were conducted in the Title, Abstract, and Claims fields to obtain as much coverage as possible. We used the Lens.org (https://www.lens.org/), Google Patents (https://patents.google.com/), and PatSeer (https://patseer.com/) databases. The search turned up 564 patents from PatSeer, 410 from Google Patents, and 73 from Lens.org. All the results were combined into a single dataset. Duplicate records were identified and removed using patent numbers and family identifiers. After deduplication, a refined collection of 615 unique patents was obtained.

Relevance screening and exclusion criteria: The technical significance and scope of each patent were evaluated, with the focus placed only on innovations that specifically applied CNN, LSTM, or hybrid deep learning architectures as AI models for the analysis of air quality parameters. This study Included patents related to pollutant detection, spatio-temporal modeling, and forecasting and prediction tasks carried out using deep learning approaches. A total of 261 patents were excluded, as they applied AI models to unrelated domains such as highway traffic control, elevator systems, and digital signal processing. Some of these relied on mathematical, statistical, or rule-based models instead of CNN/LSTM architectures, while others concentrated more on monitoring the overall IoT environment rather than predicting specific pollutants. The final dataset comprised 354 patents that were consistent with the objectives of the study.

Evaluation parameters and patent landscape mapping: The shortlisted patents were examined using the following fields of study: Type of model (e.g., CNN, LSTM, hybrid models); The objectives of AI (prediction, forecasting, and estimation); Spatial-temporal consideration (spatial modelling, temporal forecasting, or a combination of these techniques) and Detected elements (pollutants such as $PM_{2.5}$, PM_{10}, NO_x, NO_2, and others).

To illustrate the trends and revelations from the dataset, a number of graphs and comparative plots were made, including: Country-wise patent filing trend; Country-wise patent filing trend with respect to type of AI model; Country-wise patent filing trend with respect to purpose of AI model (prediction/ forecasting/ other); Spatio-temporal consideration vs. country-wise patent count and Types of elements identified vs. country-wise patent count. The effectiveness of time-aware spatial forecasting models in enhancing the precision of urban air quality prediction has been proven (Jayaraman *et al.,* 2023).

Results and Discussion

Analyzing the patent landscape for deep learning in air quality forecasts is challenging due to the dearth of pertinent patent data in publicly available sources. This section identifies general trends in deep learning patents and extrapolates their relevance to air quality forecasting. Research results have recently shown that improvements in the precision of air quality index prediction could be achieved by employing attention-based hybrid deep learning models and optimization techniques (Nguyen *et al.,* 2024).

Country wise patent filing trend: The patent landscape in this field is dominated by China (CN), with 295 files, followed by India (IN) with 30 and Korea (KR) with 15. The "Country wise Patent Filing Trend" graph makes this clear. Although in far smaller numbers (5 and 4 filings), the United States (US) and the World Intellectual Property Organization (WO) also show some involvement. Other regions like Australia (AU), Brazil (BR), Great Britain (GB), the European Patent Office (EP), and Taiwan (TW) show very little activity, each with only one file. The large number of filings in China indicate that the country is investing heavily in this field of intellectual property protection, development, and research. Strong government support and policy incentives, along with the quick industrialization of environmental and AI technologies, are likely driving these efforts. However, the lower numbers in other areas could be due to lack of R&D funding, a slower adoption of deep learning-based air quality forecasting technology, or dispersed patenting strategies. From the perspective of white space analysis, the graph clearly demonstrates opportunities for innovation and patent filing in under represented regions, including Europe, Brazil, Australia, and Taiwan. These areas show very little patenting activity, despite having strong corporate and academic backgrounds in environmental and AI research. The discrepancy suggests an opportunity for businesses, start-ups, and researchers in these countries to explore patenting opportunities and establish technological leadership. Furthermore, as shown by the small number of foreign filings through WO and EP, many innovations are still concentrated in domestic markets, especially in China and India, rather than being protected globally. This creates strategic room for cross-border patent extensions.

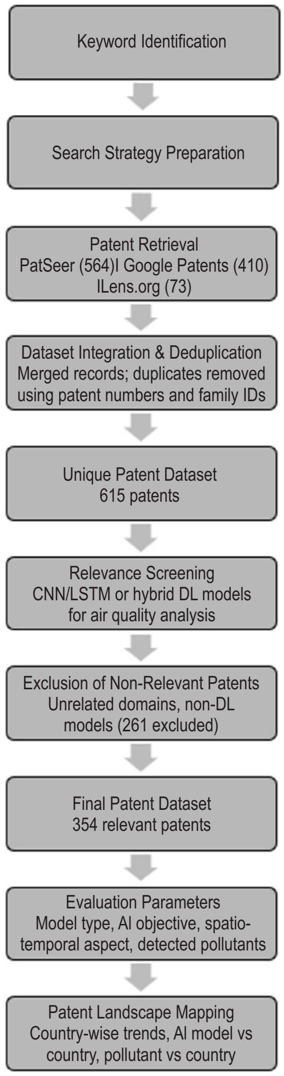

Fig. 1: Illustration of the search methodology used for Patent Landscape Analysis on Deep Learning Models (CNN/LSTM) for Spatio-temporal air quality forecasting.

Publication year wise patent filing trend: A clear upward trend in patent filings from 2017 to 2025 can be seen in the "Publication

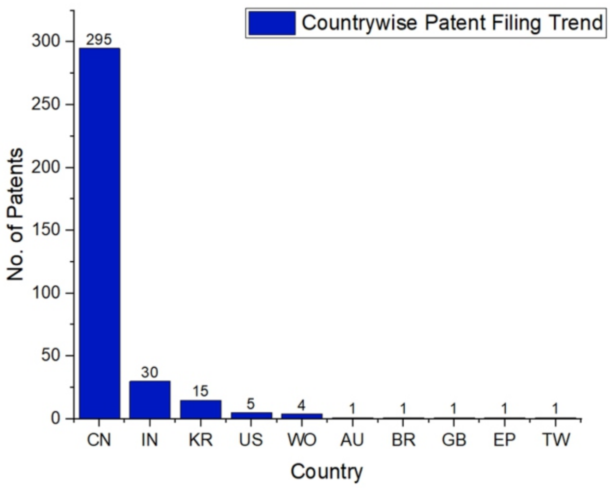

Fig. 2: Various jurisdiction and/or geographical distribution with patent count in Deep Learning Models (CNN/LSTM) for Spatio-temporal air quality forecasting. (Created Microsoft Power BI).

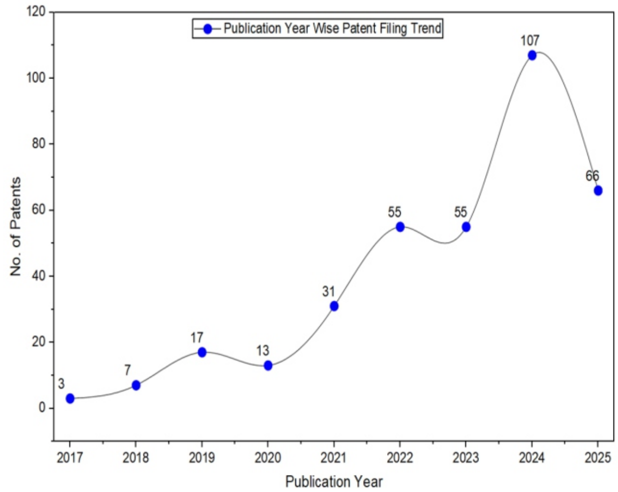

Fig. 3: Publication Year Vs Patent Count in deep learning models (CNN/LSTM) for spatio-temporal air quality forecasting.

Year-wise Patent Filing Trend" graph. The early years (2017–2020) show relatively low filing activity, with single-digit to low double-digit numbers, reflecting early acceptance and exploratory phase of technologies. Beginning in 2021, there is a discernible rise in filings, which nearly double to 55 in 2022 and 2023 after reaching 31 in that year. This implies that there is a rise in research, development, and innovation activity in the field under study. 2024 saw the largest increase, with 107 patents filed nearly twice as many as the previous year. This implies that invention output peaked, either due to fierce competition in the field, increased commercialization, or technological maturity. Even though 2025 shows a decline to 66 filings, the overall trend is still much higher than in the early years, suggesting a continuing level of interest and activity. This implies that the innovation ecosystem is still flourishing even though the peak filing may have levelled out, which is a sign of the industry's growing importance and room for growth.

Country wise patent filing trend with respect to type of AI model: The figure categorizes the number of patents filed in various countries according to Type of AI Model. AU: Australia; BR: Brazil; CN: China; EP: European Patent Office (EPO); GB: United Kingdom (Great Britain); IN: India; KR: South Korea; TW: Taiwan; US: United States of America; WO: World Intellectual Property Organization (WIPO)] China (CN) and the US (US) are the top two countries for developing spatio-temporal AI models, based on trends in patent filings by nation. With 229 filings in Deep Learning Models alone, China leads by a wide margin. As a result, deep learning is the most widely used and patented architecture, indicating how highly valued this technology is globally. Other contributors such as South Korea (KR), the European Patent Office (EP), and India (IN) show moderate levels of activity, primarily in deep learning and machine learning categories, highlighting the widespread reliance on deep learning and machine learning technologies, even though filings for alternative models such as transformers, simulation-based approaches, and statistical methods are still relatively low across all geographies. The white space study also identifies important opportunities for further innovation. Countries like Australia (AU), Brazil (BR), Great Britain (GB), Taiwan (TW), and even WIPO (WO) are still largely under represented geographically, despite the fact that applications in these countries are often in single digits. This suggests that there is untapped potential for expanding patent portfolios in these regions. Due to low level of patenting activity in Transformer Models, Simulation-based Models, and Statistical Models, there are clear technological gaps where new research and hybrid techniques may be developed. In order to improve air quality forecasts and gain early traction in under-patented fields, it may be necessary to move beyond deep learning and use alternative or mixed architectures.

Country wise patent filing trend with respect to purpose of ai model: The figure categorizes the number of patents filed in various countries according to Purpose of AI Model Used. The graphic illustrating the use of AI models in patent filings clearly shows that China (CN) leads nearly in each category, with predictive applications heavily represented. The most popular use, "prediction," with 239 patents from China alone, is followed by "forecasting," with 55 submissions, suggesting a strong emphasis on analysis of air quality data with an eye towards the future. India (IN) makes a moderate contribution with 16 prediction and 11 forecasting patents, while South Korea (KR) follows with 16 prediction submissions. The United States (US) and the World Intellectual Property Organization (WO) contribute a lower percentage, with only five and three prediction filings, respectively, and minimal forecasting activity.

The fact that other countries, including Australia (AU), Brazil (BR), Great Britain (GB), Taiwan (TW), and the European

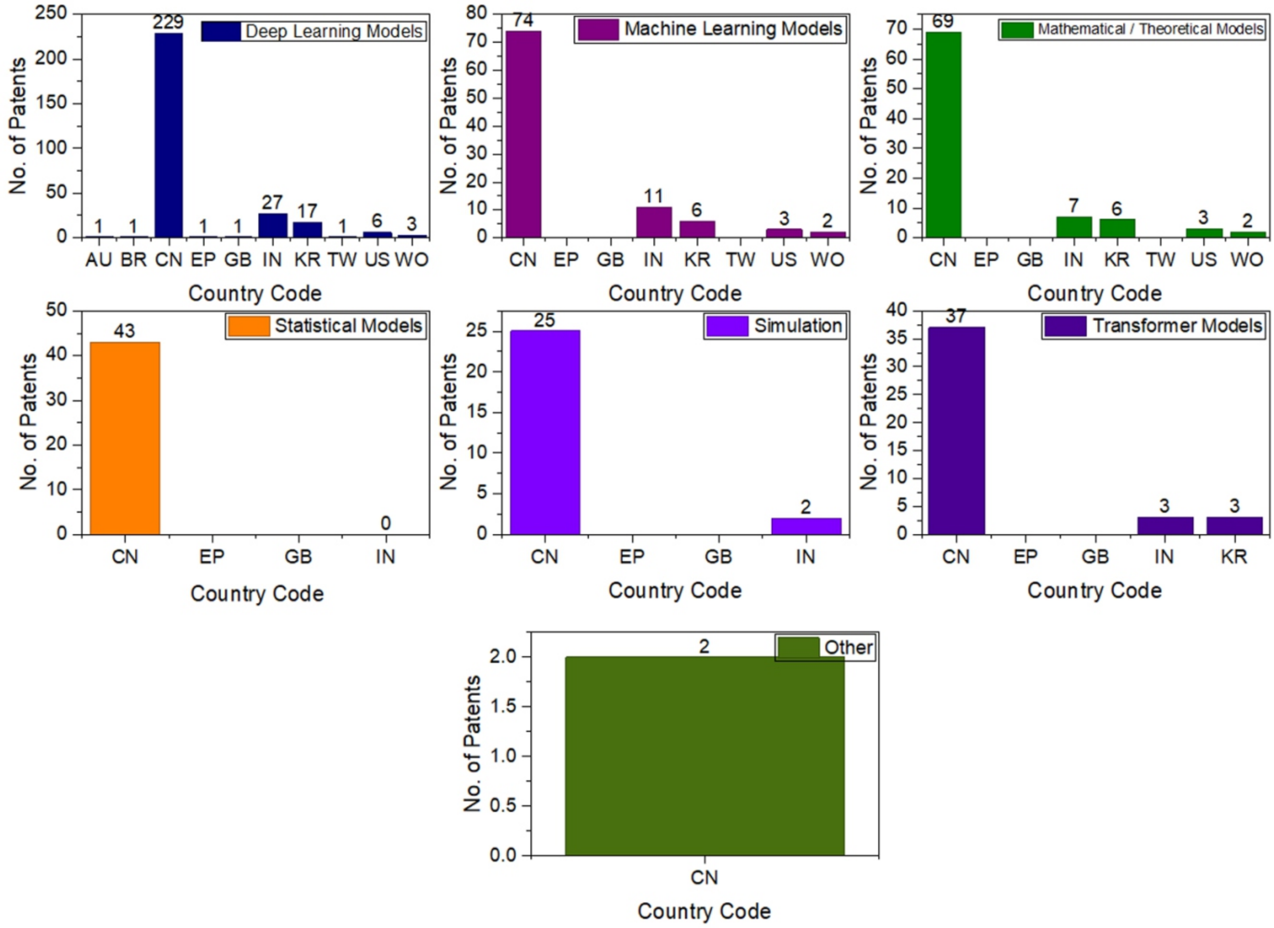

Fig. 4: Country-wise patent filing trend based on deep learning models (CNN/LSTM) for spatio-temporal air quality forecasting.

Patent Office (EP), only record one filing each in the prediction category highlight important geographic white areas where innovation and patent activity could be expanded. Despite prediction and forecasting dominance, purposes like "Classification," "Estimation," and "Detection/Alerting" are still dreadfully under represented. China leads with five classification patents, four estimate patents, and two identification patents, while India contributes two classification patents and one detection/alerting patent. Other specialized goals, such as "Recognition" and "Identification/Classification," are only reflected in one or two filings globally. This discrepancy in technology highlights important opportunities for additional research and patenting. The remarkably low activity in "Detection/Alerting" and "Estimation," in particular, suggests that there is still much to learn about developing AI systems that can accurately estimate air quality parameters from sparse or multi-source data or detect pollutant spikes in real time (Zhang *et al.*, 2024; Yu *et al.*, 2024).

Similarly, classification-based applications are still in their early stages, indicating that models meant to classify pollution episodes or identify the sources of pollution could use some innovation (Houdou *et al.*, 2024). Even though prediction and forecasting currently dominate the patent landscape, the underrepresented and underdeveloped regions have significant prospects for future growth and competitive advantage in AI-driven air quality applications.

Spatio-temporal consideration vs. country wise patent count: The figure categorizes the number of patents filed in various countries according to Spatio-Temporal Consideration. The bar graph analysis of "Spatio-Temporal Consideration vs. Country Wise Patent Count" shows clear global trends in patent applications. China (CN) is the top competitor with a significant lead, holding 213 patents related to spatial considerations, 28 related to temporal considerations, and 5 combining both spatio and temporal characteristics. This dominance is a reflection of China's strong emphasis on space-driven technological advancements and its considerable, albeit relatively small, emphasis on temporal and integrated spatio-temporal solutions. Outside China, South Korea and the European Patent Office have also made contributions, albeit on a much smaller scale. While EP

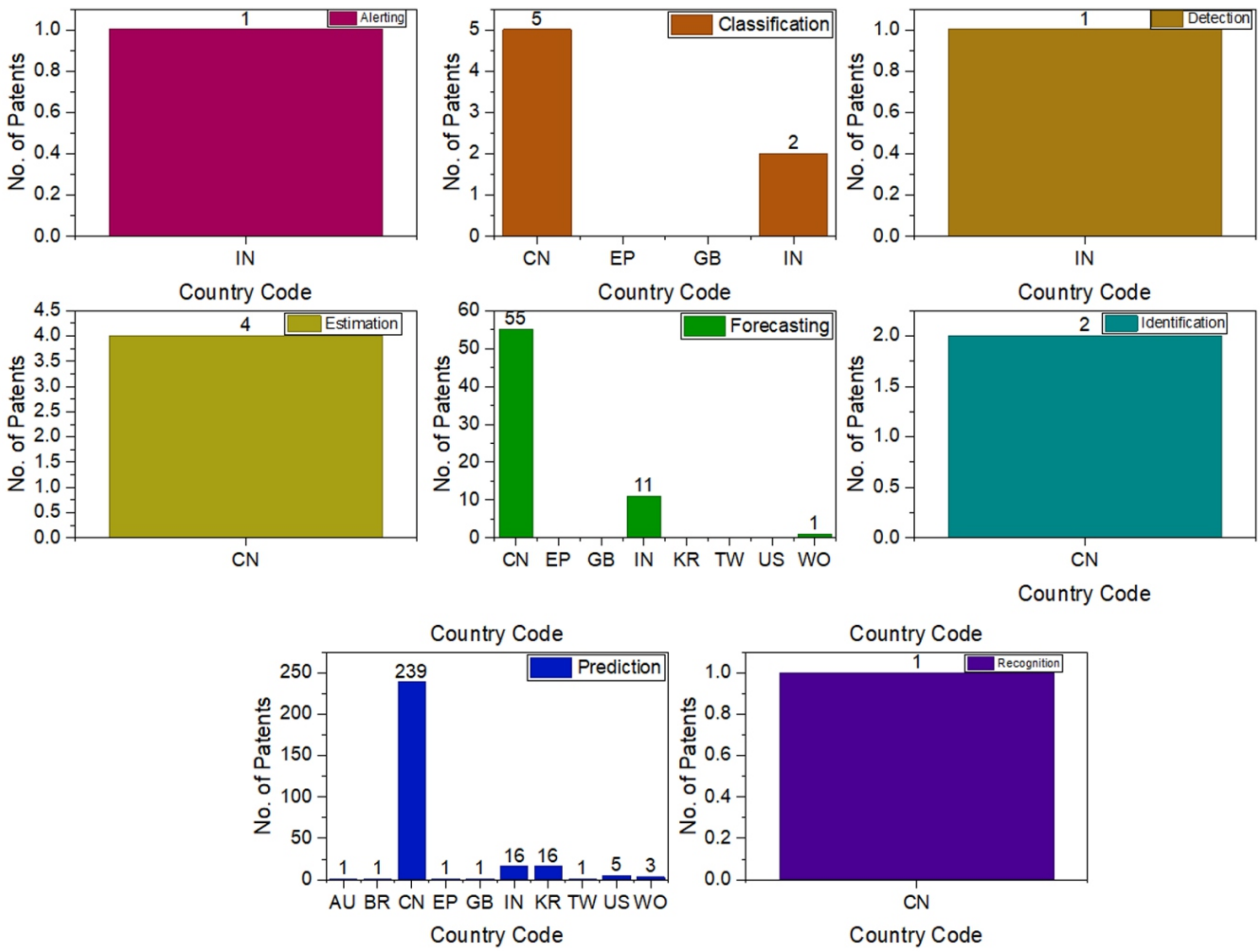

Fig. 5: Country-wise patent filing trend based on deep learning models (CNN/LSTM) for spatio-temporal air quality forecasting.

has five spatial patents, one temporal patent, and one combined spatiotemporal patent, KR has filed four spatial patents, three temporal patents, and one integrated patent. This implies that While Europe and South Korea are engaged in this area, their activities are insignificant in light of China's massive Undertakings (WIPO, 2019). The World Intellectual Property Organization (WO), Australia, Brazil, Great Britain, India, Taiwan, and the United States all have relatively low levels of involvement in this field, as evidenced by the minimal filings, which typically range from 1 to 5 patents per category. Overall, the graph indicates that spatial factors dominate patent activity in most regions, with the fewest number of patents combining both temporal and spatial considerations coming in last and fewer submissions based only on temporal considerations coming in second. This pattern reflects a global trend toward spatial applications in technology development, even though integrated spatio-temporal approaches remain an understudied and potentially complex field (Yu *et al.*, 2024; Zhao *et al.*, 2025).

From a white space perspective, spatio-temporal integration—which is still underrepresented in all countries—is the most promising field. The consistently low number of patents in this category highlights the potential for innovative inventions that simultaneously consider time and location. These advancements may prove particularly beneficial in domains such as advanced logistics optimization, predictive urban planning, and real-time environmental monitoring. Additionally, countries with low filing rates, such as Brazil, India, and Australia, are uncharted territories where innovators could lead the way early on by developing spatio-temporal technologies that meet local needs.

Additionally, certain application domains have clear white space opportunities. Possible areas include smart agriculture (combining spatial crop health monitoring with temporal growth cycles), environmental monitoring (tracking pollution spread over time), and predictive infrastructure maintenance (forecasting system failures based on spatial location and historical data patterns). Despite the fact that China currently leads the world in spatio-temporal patent activity, the lack of filings in the integrated spatio-temporal category, and the low contributions from different locations highlight the enormous potential that still exists. Innovators who focus on under represented regions and

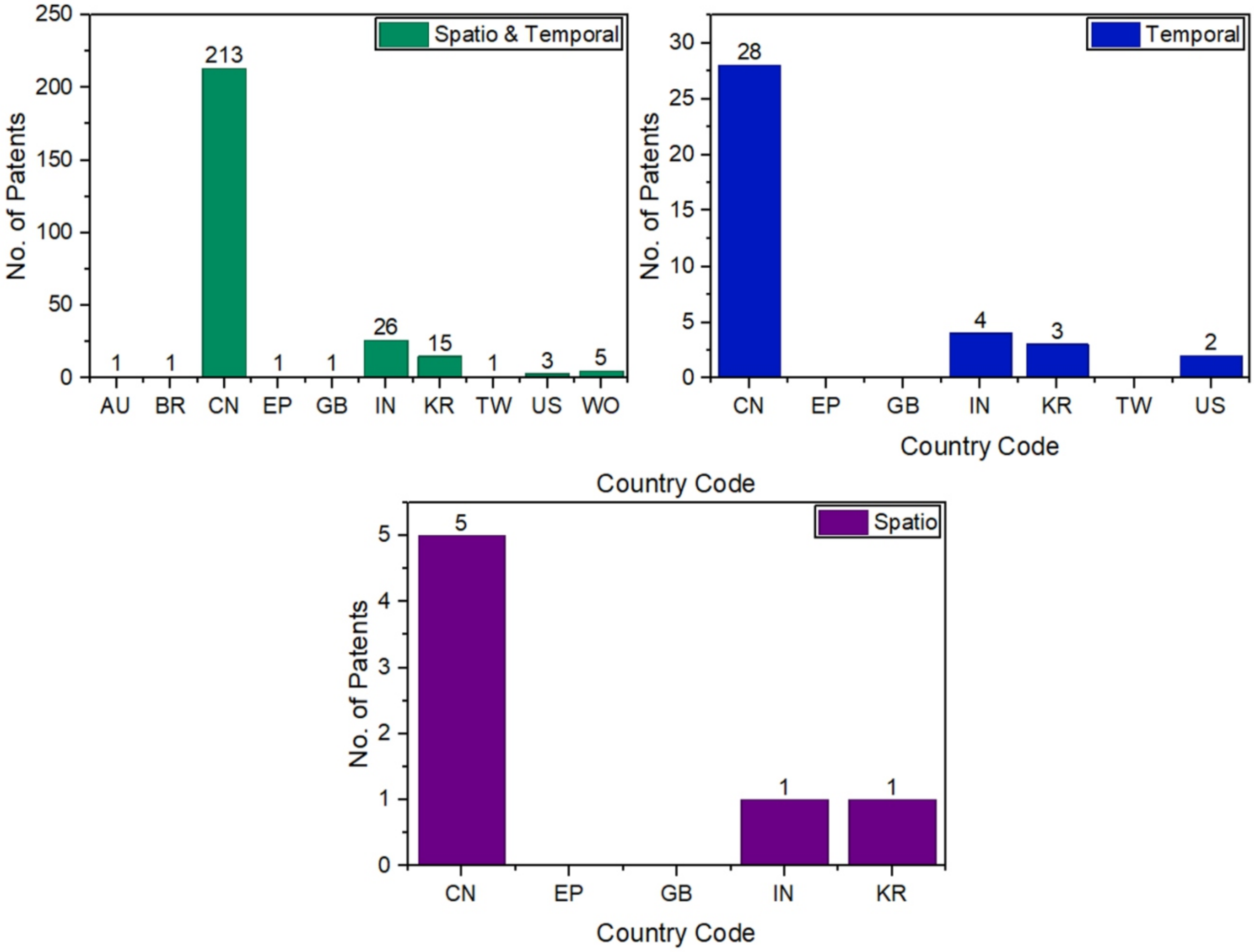

Fig. 6: Country-wise patent filing trend based on deep learning models (CNN/LSTM) for spatio-temporal air quality forecasting.

application-specific fields may have an impact on future developments in spatio-temporal technologies.

Types of elements identified vs. country wise patent count: The figure categorizes the number of patents filed in various countries according to the Types of Elements Identified. The bar graph "Types of Elements Identified vs. Country Wise Patent Count" displays the global distribution of patents related to different element kinds. China is by far the largest patent holder in several different categories, with 169 patents in particulate matter, 110 in carbon compounds, and 84 in nitrogen compounds. China's dedication to combating major pollutants and advancing technology in the domains of environmental and material science is demonstrated by this dominance (WIPO, 2019; OECD, 2024). India is also active, with 70 patents in carbon compounds and 66 in other/not specific elements, showing a wide focus on developing flexible solutions in this field. European jurisdictions, particularly Great Britain and the European Patent Office, also make significant contributions. In the latter category, the European Patent Office has 110 patents, while Great Britain has an impressive 172 in carbon compounds and 84 in Other/Not Specific Elements. This suggests a concentrated regional focus on carbon-related technologies, likely driven by stringent environmental and industrial regulations. South Korea demonstrates selective innovation and moderate activity in these areas with two patents in nitrogen compounds and eleven in carbon compounds. However, the United States, Taiwan, and the World Intellectual Property Organization (WO) only record a very small number of submissions, typically in the single digits, indicating that patenting activity in the highlighted element category is relatively low.

One important finding across the dataset is that sulfur compounds and oxidants remain the least patentable categories worldwide, with few filings from all areas. This suggests a sizable innovation gap that could be a lucrative area for additional research and technological development. Observing white space reveals several opportunities. The most prominent white area is sulfur compounds and oxidants, where there is a immense scope for improvement in materials engineering, chemical processing,

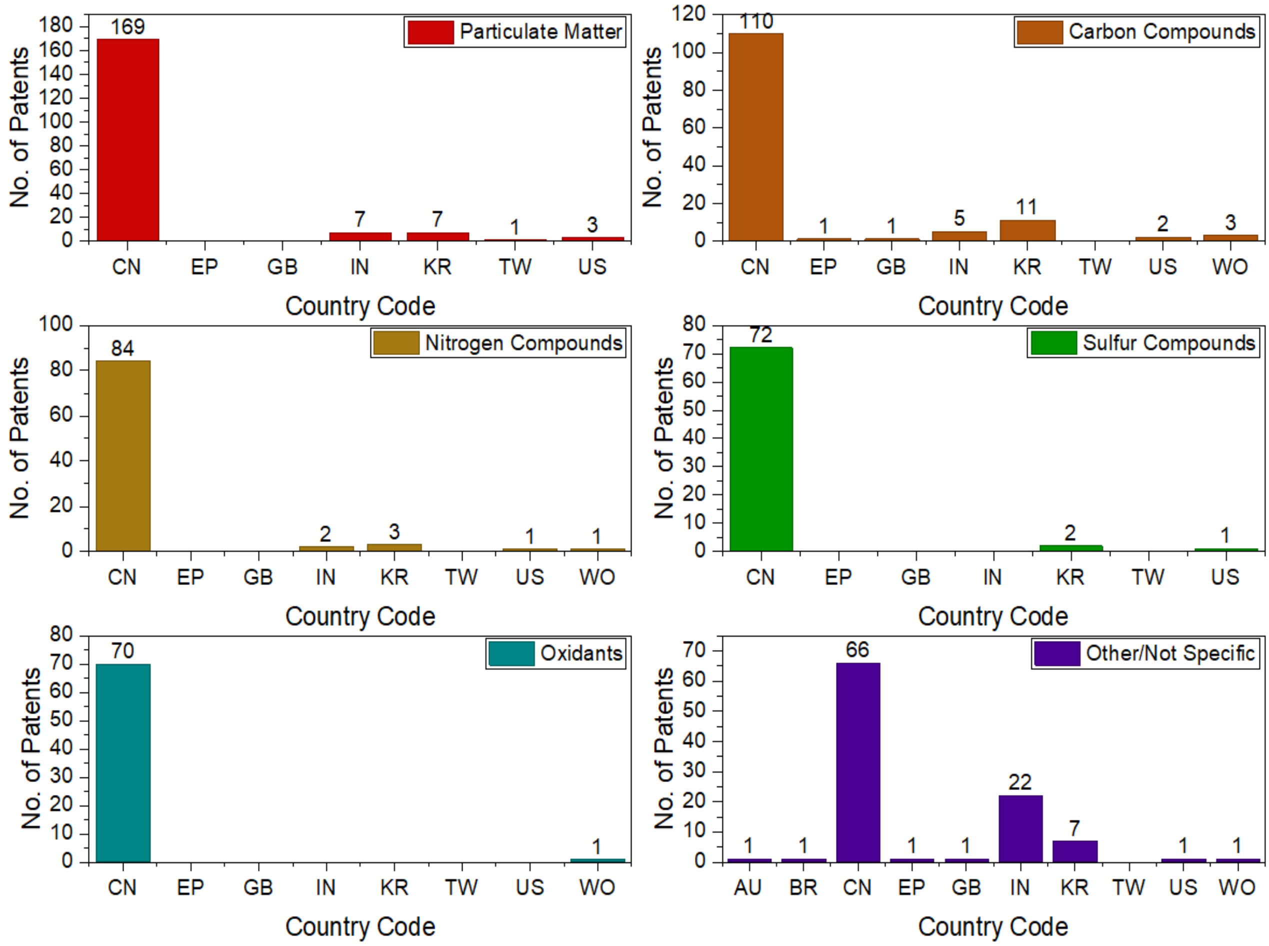

Fig. 7: Country-wise patent filing trend based on deep learning models (CNN/LSTM) for spatio-temporal air quality forecasting.

and emissions control despite the lack of patent activity. Additionally, underrepresented regions like the US, Taiwan, and WO give inventors the chance to research technologies in fields like particulate matter, carbon compounds, and nitrogen compounds—all of which are currently dominated by China. Another possible white area is cross-category improvements, where integrated solutions that address different element types—such as systems that can filter both nitrogen compounds and particulate matter—remain largely unexplored. Furthermore, even in patent-heavy categories like carbon compounds and particulate matter, there is still room for novel or specialized applications, such as adapting particulate capture systems for industrial material recycling or other unorthodox uses.

In conclusion, although China, India, and European jurisdictions are leading the way in patenting innovations related to key pollutants, significant opportunities still exist in under-patented fields like sulfur compounds and oxidants, as well as in places with little activity like the US and Taiwan. Investigating integrated, multi-element systems and creative applications within well-patented categories can also reveal unexplored opportunities for innovation.

Trends, Relevance, and Challenges in Patent Analysis for Air Quality Forecasting: Deep learning patents are rapidly increasing due to applications in different of industries (Questel, 2021). The report states that the United States, China, and Japan are the top donors; research institutes and large technology companies are also significant participants. However, it doesn't specifically address air quality forecast, suggesting that relevant patents could be included in broader deep learning applications. Given the widespread use of CNN and LSTM in environmental monitoring, some patents most likely cover applications for air quality forecasting. For example, because spatio-temporal deep learning models can be applied to many different fields, they may be patented with methods for predicting pollution concentrations (Yu *et al.,* 2024), however, without access to specialized patent databases like the USPTO and WIPO, a comprehensive analysis remains elusive. The primary barrier is the lack of publicly available patent landscape studies for this specific application. Because standard web searches yield academic publications rather than patent filings, there is a gap in the readily available information. Future studies could use patent databases to identify key innovators, patent assignes, and technological trends in this field.

Synthesis of findings and future perspectives: This paper offers an in-depth patent landscape analysis of deep learning models, specifically CNN, LSTM, and hybrid CNN-LSTM models for spatio-temporal air quality forecasting. The results show a major shift from conventional statistical and physics-based models to intelligent and data-driven models, and hybrid CNN-LSTM models have been identified as the most dominant and efficient models for air quality index and pollutant concentration forecasting. Analysis reveals that the significant rise in patenting over the past few years has been driven by the increasing complexity of architecture, which is sustained by the presence of deeper networks, attention mechanisms, optimization methods, and multi-source data fusion. This is a manifestation of the increasing translation of research into practical air quality forecasting systems. However, incompleteness, real-time sensor integration, and interpretability continue to be significant barriers to widespread adoption.Recent implementations include integrating deep learning-based air quality prediction models with web platforms to enable real-time monitoring and increased accessibility to a wider community (Rahman *et al.,* 2024).

The development of effective deep learning models that can process noisy and incomplete data is essential from a future research perspective (Safonova *et al.,* 2023). In addition, the application of explainable AI techniques such as SHAP and LIME may improve the transparency of model and its implementation (Abekoon *et al.,* 2025). A better understanding of competitive dynamics and technology gaps can also be achieved by examining under represented patent sources and innovation clusters (Maghsoudi *et al.,* 2025).The development and use of interpretable and explainable machine learning models for air quality forecasting have been highlighted as a way to enhance transparency and trust for decision-making purposes (Houdou *et al.,* 2024).

In conclusion, this research work has shown that deep learning has brought a revolution in spatio-temporal air quality forecasting. In an attempt to further develop environmental monitoring systems and facilitate public health and sustainable urban development initiatives, it will be essential to overcome the existing technological and innovative challenges (Li *et al.,* 2025).

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