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Special Issue on Digitalization of Smart Ecosystems

Deep-learning based visualization tool for air pollution forecast

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Abstract—This paper presents a comprehensive visualization tool that integrates real-time observation and sensing data with various forecasting models, including both numerical and deep-learning approaches. The developed software framework efficiently manages data flow, configures forecasting models, and visualizes monitoring and prediction information. Additionally, the tool features a newly-developed WebApp dashboard, providing users with an interactive platform for real-time data access and decision-making. This web-based deep-learning framework is designed to enhance environmental monitoring and forecasting, providing a valuable tool for both the authority as well as the general public.

***Index Terms**—Deep learning, WebApp, air pollution, monitoring, forecasting*

Air pollution is becoming a pressing issue affecting human health with 7.3 billion people worldwide facing air pollution levels considered unsafe, according to WHO statistics [1]. In Australia, the government has strongly committed to a Nature Positive Plan designed to improve the national environment with a major target *"to provide an authoritative source of high-quality environmental information"* [2]. Globally, ensuring the availability of reliable information for monitoring and forecasting air pollution remains crucial for effective policymaking and proactive interventions.

Recently, citizens have expressed increasing concern regarding real-time air quality information in their local areas, and demanded enhancements of air quality forecast in dealing with potential risks associated with exposure to air pollution. To this end, observations from air quality monitoring stations, sensing and meteorological information, along with data from numerical models, provide substantial input to a data-driven pipeline using machine learning (ML) or deep learning (DL) to improve the forecast accuracy for air quality.

Neural network-based forecasting models, including Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and probabilistic Bayesian Neural Networks (BNNs), have become valuable tools for time series estimation, particularly in air quality prediction [3]. To address the nonlinear and dynamic characteristics of multivariate air quality time series data, hybrid models that combine these approaches—such as LSTM-BNN, CNN-LSTM, and CNN-LSTM-BNN—have been developed [4]–[6]. Equipped with learning capability, those hybrid models have demonstrated robustness across various scenarios, ranging from normal conditions to extreme events, and have performed well even under data-constrained situations. This has motivated us to develop a visualization tool that can incorporate learning models to enhance the forecast performance.

The integration of multiple forecasting models, particularly DL networks, requires extensive data from numerous environmental variables, and thus, presents a challenging problem not only in the methodology but also in technical implementation. A reliable framework is therefore needed to optimize the data flow from various sources and facilitate communication with different servers and Application Programming Interfaces (APIs) to ensure the seamless presentation of air quality information online.

Deep learning forecasts, combined with real-time monitoring data from IoT-enabled sensor networks, can be visualized across several platforms in Europe and Asia [7], [8]. However, there remains a lack of a comprehensive presentation of the system architecture—from back-end data processing to front-end interactions. Furthermore, just a

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few tools are currently available that can provide recurrent statistics on model performance, making it difficult to evaluate the effectiveness of the models in use.

INTRODUCTION

The primary objective of our development is to provide a visualization tool operating on the high-performance computing (Science Data and Compute - SDC) facility, managed by the New South Wales Department of Climate Change, Energy, the Environment, and Water (NSW-DCCEEW), that can seamlessly integrate multiple forecasting models, encompassing both numerical models utilized by the Australian government and incorporating extensive DL algorithms. The WebApp dashboard is designed to interface with this DL framework, providing real-time updates on monitoring and forecasting to all stakeholders and users [9]. Such cloud-based software aims to provide comprehensive insights into air quality dynamics, aiding decision-makers in formulating effective strategies to tackle environmental challenges.

Notably, this forecast framework can accommodate the training and forecasting using data from multiple models (i.e., DL-based and numerical ones). Each model is tailored to provide air quality estimates, taking into account real-world conditions of data availability, optimized model configuration, and expected forecast scenarios. We selected three primary DL models based on their robust performance across different scales, from local to regional areas, and under various scenarios (e.g., local construction, urban development projects). The selected models are: (1) LSTM-BNN [4], (2) CNN-LSTM [5], and (3) CNN-LSTM-BNN [6]. These models have been recently developed and successfully tested. Correspondingly, the developed WebApp dashboard serving as an interface with this framework can update forecasting information and real-time observations collected from a wireless sensor network and air quality monitoring stations managed by the authority of NSW, Australia. This paper presents the backend architecture and the optimized operation of multiple DL models, incorporating them into our previous webpage design with front-end interactions to support the monitoring and forecasting system [9].

DEEP-LEARNING AIR QUALITY FORECAST FRAMEWORK

Our DL integrated framework, shown in Figure 1, consists of three main units: (1) the flow of training and forecasting, (2) model configurations, and (3) outbound interactions with data sources from the API and the WebApp dashboard. The first two units are situated within the SDC and are tasked with overseeing the data management, optimizing model configuration, conducting model training and forecasting, and facilitating communication with external entities.

The process of model training on SDC is presented as follows:

- Real data are directly sourced from APIs of the NSW-DCCEEW and the Bureau of Meteorology (BOM) to retrieve updated air quality and meteorology information.
- Time series files undergo automatic stages of data processing, including missing data imputation, outlier filtering, and unreliable variable elimination.
- Processed data are prepared for training with multiple models based on configurations of different regions. This involves splitting, converting into tensors, and segmenting into input-output sequences.
- Models developed for stations that are grouped with respect to common characteristics can incorporate various DL structures such as LSTM-BNN, CNN-LSTM, and CNN-LSTM-BNN. This modular framework allows for predicting the levels of various air pollutants based on data availability, meteorological conditions, and regional characteristics.
- Pre-trained models are saved and easily loaded for forecasting by predefined configurations.
- Forecast performance is regularly evaluated using statistical metrics such as MAE, RMSE, Pearson's r, coefficient of determination R^2, and also means, standard deviations, and max bias errors between estimated values and ground-truth observations.
- Models are regularly retrained at predefined intervals with updated ground-truth data and adjustments for changes in data distribution to maintain the accuracy of predictions.

With this modular framework, the models for primary regions of NSW, namely South-West (SW) Sydney, Central-East (CE) Sydney, North-West (NW) Sydney, Lower (LW) Hunter, Illawarra, and Upper (UP) Hunter [10], will be combined in a dedicated pool of pre-trained models. Because each region exhibits distinct spatio-temporal concentration characteristics, the models are individually configured to optimize forecast performance. Consequently, different sets of hyperparameters are assigned to various regions, including DL technique choices, the number of layers, nodes, and input variables. Once new observations are updated from the API, the framework initiates the evaluation scheme to establish a baseline for optimization and to inform the user about the performance of the models.

The proposed DL air quality forecast framework (DLAQFF) operates on a high-performance computing (HPC) server specifically designed for deep learning and forecasting tasks. This server is equipped with advanced computational and storage capabilities, as outlined in the

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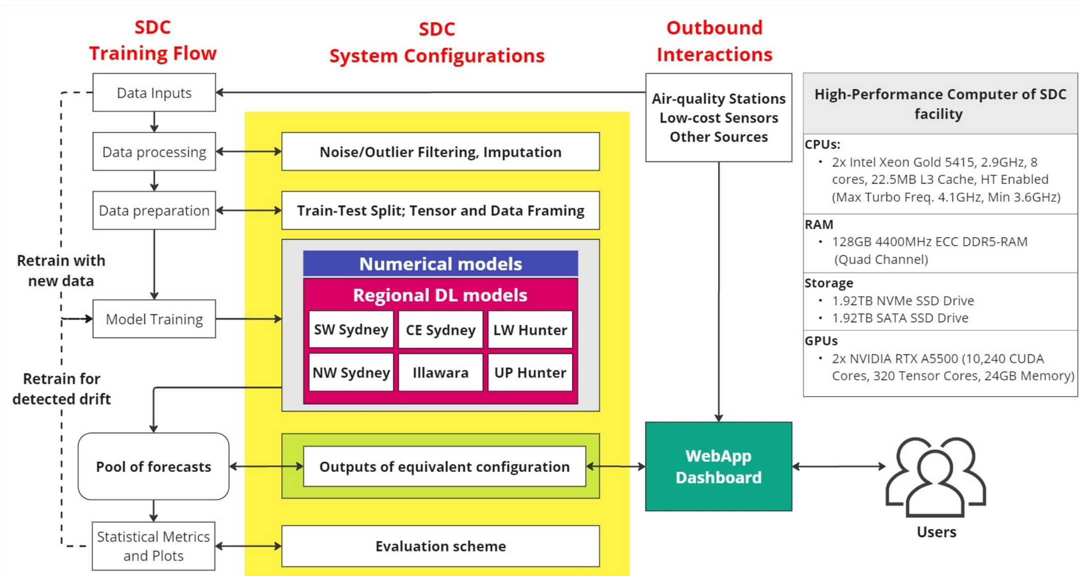

FIGURE 1. Deep-Learning Air Quality Forecast Framework (DLAQFF) on Science Data and Compute (SDC) facility

Table at the top-right of Figure 1. With powerful CPUs, substantial memory, and top-tier GPUs, the server is well-suited to handle the intensive demands of model training and inference.

SOURCES OF DATA

Data and studied regions

The data used for training and evaluating DL models are sourced from the API, covering the period from January 1st, 2018 to August 31st, 2023, encompassing over 50,000 hourly data points for each variable. Model training was conducted for multi-input and multi-output configurations, incorporating historical observations of interested pollutants from all stations and sensors in NSW, Australia. Additionally, meteorological variables and auxiliary pollutants such as temperature, relative humidity, wind speed and direction, concentrations of nitrogen oxide, nitrogen dioxide, and carbon dioxide, are considered contributing factors for comprehensive experiments, testing, validation and verification [4] from two main sources, including observations and generated values from numerical models. After validating the proposed methods for three DL models using historical data, we implemented these models into our DLAQFF. The framework is integrated with regularly updated data from state-run stations [10] and undergoes daily retraining with new data. Additionally, the models are retrained whenever our evaluation scheme detects data drifts based on the statistical performance of the models' estimates as depicted in the flow on the left of Figure 1.

Observations

In NSW, real-time monitoring focuses on key air pollutants, including particulate matter with aerodynamic diameters below 2.5 μm and 10 μm ($PM_{2.5}$ and PM_{10}), along with four gases: carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) [10]. Additionally, crowdsourced sensors are utilized for localized data collection. Figure 2 (left) depicts an air quality monitoring station alongside co-located sensors in the inlet (here the PurpleAirs) during testing and calibration in the Lidcombe suburb. Once thoroughly tested, these sensors are strategically positioned to enhance spatial resolution in remote areas.

Predicted values from numerical models

Air pollutant concentrations are regularly estimated for effective management of air quality according to the national standards set by the Australian government's National Environment Protection Measures (NEPMs) [11]. This is accomplished using various numerical models, such as dispersion models (e.g., Chemical Transport Model - CTM [12]), integrated with meteorological models (e.g., the Conformal Cubic Atmospheric Model - CCAM, Weather Research and Forecast - WRF [13]). Despite the limitations inherent in these complex models, their predicted values reflect air dynamics trends from atmospheric science that can be applied to enhance the accuracy of our developed models [4], which remains the utmost requirement from the Department.

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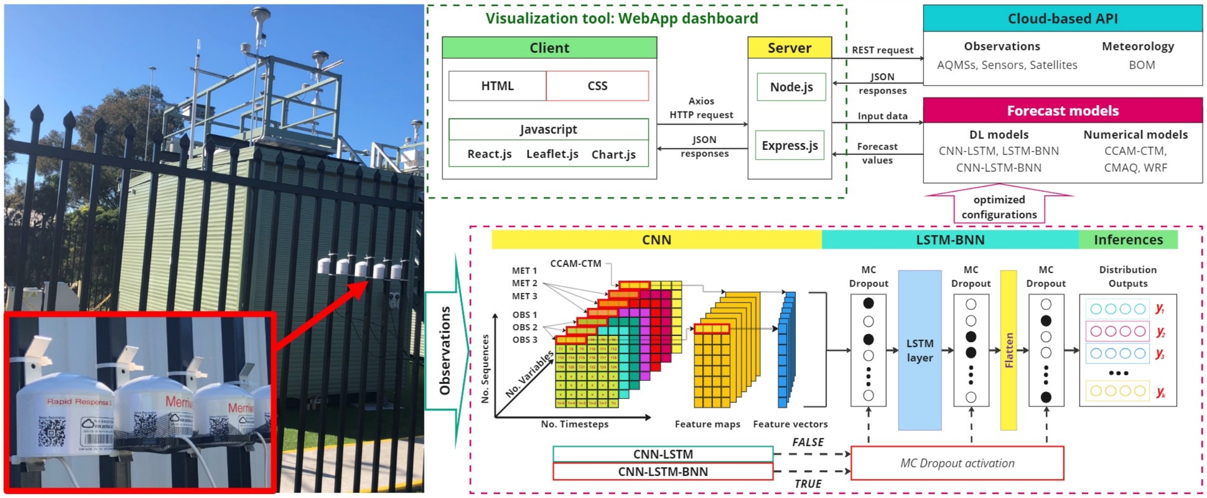

FIGURE 2. Air-quality stations with colocated sensors (left) and the client-server architecture of the WebApp dashboard with the general LSTM-BNN, CNN-LSTM and CNN-LSTM-BNN models (right)

VISUALIZATION TOOL

Our visualization tool, developed with data fusion from various sources for the DLAQFF, was implemented in the form of a WebApp dashboard [9], allowing users to access real-time monitoring data from air-quality stations and sensor networks, along with estimated values forecast with a selected DL technique embedded in the proposed framework. The high-level client-server architecture of the dashboard with communications between developed modules is illustrated in the unit "Visualization tool: WebApp dashboard" at the top middle of Figure 2.

Client interface design

The client interface of this web-based dashboard prioritizes delivering an intuitive user experience and informative air quality visualization. Here, we employed core front-end web development technologies, including HTML (HyperText Markup Language), CSS (Cascading Style Sheets), and JavaScript, to ensure cross-platform compatibility and accessibility. Utilizing React.js, one of the most popular JavaScript frameworks, allowed us to leverage its component-based approach and extensive functionalities. This choice promotes the reusability and scalability of the dashboard, making future maintenance easier.

Given the need to spatially illustrate time-series ambient information across the state of NSW, the tool [9] features the integration of web-mapping and data visualization libraries. Leaflet.js, a trusted Geographic Information System framework used by various meteorological bureaus, was integrated into our platform to facilitate user-friendly interactions within our geographical area of interest. Additionally, the Chart.js library was complementarily used with Leaflet.js, ensuring comprehensive visualization in both spatial and temporal aspects of air quality observations and deep learning forecasts. The dashboard interface was designed in consultation with forecast scientists from the DCCEEW and non-expert representatives. The goal was to reduce complexity while providing large amounts of useful information in an accessible manner. To this end, the incorporation of DL models is essential for the backend operations of the dashboard, as presented in this paper.

Server interface design

The server of the dashboard acts as an intermediate hub, orchestrating the communication and transport of data from the established database on SDC facility to the interactive frontend. To ensure cross-platform development within our integrated framework, we employed Node.js, a JavaScript runtime environment, as a skeletal foundation to build the back-end structure. Here, Node.js offers scalability, high performance, and efficiency by efficiently handling a multitude of asynchronous requests.

Built on top of Node.js is the Express.js web application framework. This widely-used tool is lightweight, unopinionated, and middleware-compatible, facilitating a rapid and robust development process. In our application, Express.js also provided a variety of HTTP utility methods essential for RESTful API development and imperative for implementing a standardized data transmission protocol between the client and the server. The synergy between Node.js and Express.js presented here a suitable server-side design for a real-time and data-intensive application in our DL-based air quality forecast dashboard.

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DL incorporation into the visualization tool

In air quality modeling, accurately quantifying uncertainty and generating probabilistic predictions are crucial for informed decision-making and risk assessment concerning pollution levels [4]. Our visualization tool's DL models are structured with a general architecture that stacks a CNN layer onto the LSTM-BNN network, with LSTM layers intermittently supplemented by Monte Carlo (MC) dropout layers to enhance robustness and enable uncertainty estimation [14], as depicted in Figure 2. In this general architecture, the CNN-LSTM-BNN model is employed when the MC dropout layers are activated during the forward pass of inference [14]. Conversely, these layers are skipped when using the CNN-LSTM model for inference. During training, the models' hyperparameters (e.g., number of layers, number of nodes, dropout rates) are optimized using Bayesian methods, which balance the prediction intervals and accuracy of probabilistic inference [6]. The trained models with optimized parameters are then stored to create a pool of forecasts, ready to be served upon user requests, as presented in the bottom left corner of Figure 1.

Data inputs for DL models are regularly obtained from the cloud-based API via REST requests, facilitating communication with the dashboard. These inputs consist of observations and meteorological data, which are referred to as OBS and MET respectively. Observations are integrated with numerical predictions (i.e., CCAM-CTM) and processed through the CNN layers to capture spatio-temporal features across extensive time steps and involved variables. The extracted features are then transformed into vectors and forwarded to LSTM and MC dropout layers for recurrent predictions over a specified number of future time steps. Ultimately, the model generates outputs representing the forecast distribution across various locations of interest (y_i).

Given the variability in air pollution dispersion arising from the distinct topography and ambient characteristics of specific locations, it becomes imperative for the optimal configuration of models to adapt across both temporal and spatial dimensions. Accordingly, the configurations of the models are customized through optimization procedures to accommodate diverse regions, forecast horizons (e.g., 24-hour, 48-hour, 72-hour forecast horizons), contributing factors (such as meteorological data and secondary pollutants), and model types [4]. Subsequently, forecast values are generated for all models across every region of NSW and stored on the SDC facility and accessible upon user request. The accuracy of the visualization tool for each model used is continually validated with newly recorded observations from the API through the evaluation scheme within the framework, as specified in the bottom middle of Figure 1.

RESULTS

To implement and evaluate this visualization tool with DL framework integration, we begin with backend integration testing to ensure that the DL models function as expected and the APIs operate correctly. The developments of these models were reported in [4], [6]. Next, we test the communication between the frontend [9] and backend to confirm that data flow smoothly and the user interface responds properly. Finally, we deploy the software system in a staging environment, monitor it for issues post-launch based on feedback from internal users, and perform regular maintenance to keep the system running efficiently. The demonstration of this tool is in this Link.

The dashboard appearance of our visualization tool is presented in Figure 3, which includes the following main interactive sections.

1) Selection panel (left side of dashboard) includes three sub-sections: (i) drop-down list for choosing parameters in deep learning forecast files (i.e., region of interest, type of air pollutant, output horizons, forecast model, and starting date to make forecast), (ii) visibility function of different monitoring layers, and (iii) legend explaining marker symbols used in the map.
2) Interactive map (middle section) presents observed and forecast air pollution information across NSW. These data are displayed at the selected locations of the monitoring stations, which are marked by square icons. When a specific station is selected on this map, a line chart shows retrospective observations (in black) alongside forecast values (in blue) derived from the highly accurate model of user's selection.
3) Air quality ranking panel (right side of the dashboard) shows information on the ranking of observed Air Quality Index (AQI) from AQMSs in the selected region, along with the highest level of air pollutant concentration recorded at a station in the regional forecast.
4) Statistical panel (bottom section) presents the updated validation comparing the latest predictions of the forecast model with the available observations.

Before launching the dashboard, we thoroughly evaluated all its functions and tested the data flows between the backend and frontend by using console windows with online monitoring and diagnostic interface. Figure 4 illustrates the main components showing backend data flowing correspondingly to the equivalent frontend functions, including API data to stations, DL processed data to forecast profiles, and evaluated data to statistical analysis.

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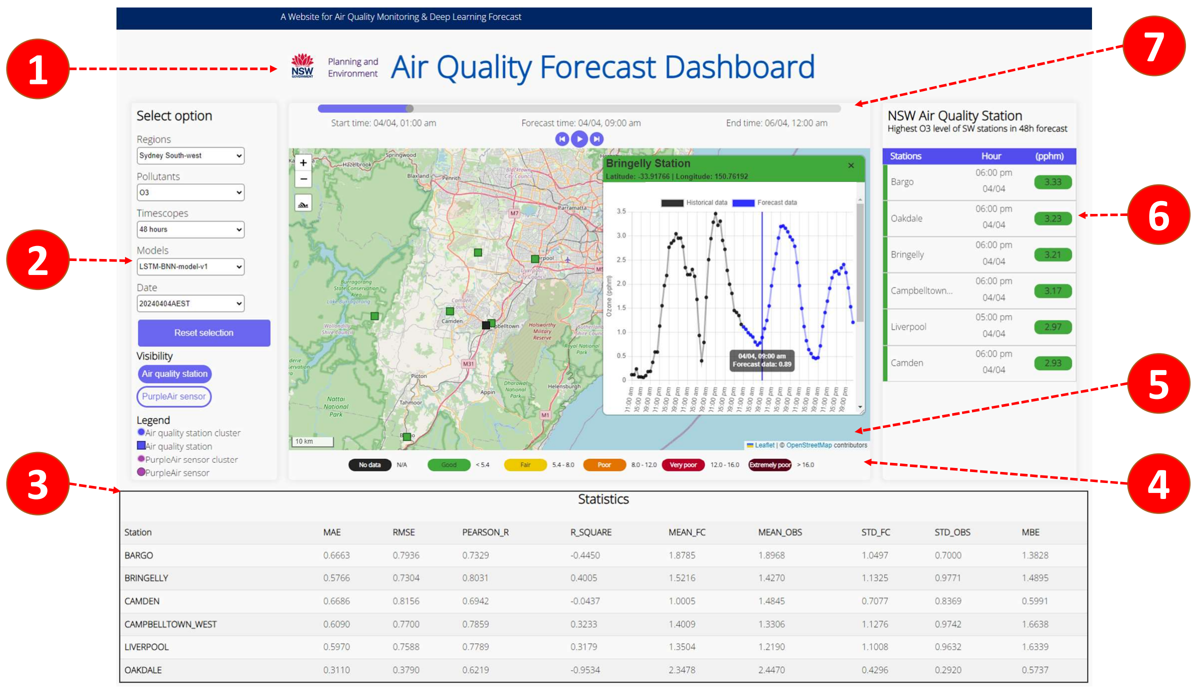

FIGURE 3. Interface of the visualization tool with main sections: (1) Title of dashboard, (2) Selection panel, (3) Statistic panel, (4) Air quality category legend, (5) Interactive map with plots, (6) Air quality ranking panel, and (7) Playback time slider

Auxiliary functions for user interfaces

Our visual interface was meticulously crafted to meet accessibility criteria for general users while also conforming to established standards within the field of atmospheric science. The color codes and categorization of pertinent air pollutants, as regulated by NSW-DCCEEW, are consistently applied in the classified bar beneath the interactive map. Additionally, the playback time slider facilitates automatic navigation through the forecast timeline by controlling a vertical indicator on the line chart to consecutively display the level of air pollution at a specific timestamp. This synchronization also entails a responsive color-coded animation for markers on the map based on the AQI of their respective forecast data points. Below the statistical panel, the dashboard provides approved precautionary measures for the general public and sensitive groups to follow with respect to observed or forecasted air quality.

Regular observation and forecast updates

From the backend, DL models can be regularly updated with data from monitoring stations and sensor networks, while the SDC records new values to ensure a continuous feed of the latest air quality data at the input. This process is crucial for generating timely and accurate predictions. Once retrieved, the raw data undergo a series of automatic preprocessing steps within our framework, encompassing data cleaning, feature engineering, and handling of missing values, culminating in a complete data format ready for model training. It is also designed to mitigate the drift issue [15] in air pollution forecasting, which may arise from seasonal shifts or the impact of extreme weather conditions. Consequently, at a predetermined 24-hour interval (i.e., daily), the models are retrained with the latest data to project air quality for the upcoming 12, 24, 48, and 72 hours. These projections are then compared with the predictions from the numerical model for regular calibration. The estimated data, stored in the database in CSV format, is readily available for visualization upon user request. As such, new observations are regularly updated and after retraining, and all models are used for generating forecasts during runtime.

CONCLUSION

In this paper, we have presented a deep learning-based framework that exhibits several essential features for accurate and efficient air quality forecasting. These include real-time data retrieval, automated data preprocessing, and the capability to train multiple deep-learning models tailored to various forecasting scenarios, such as seasonal variations and different concentration levels. Noteworthy are the

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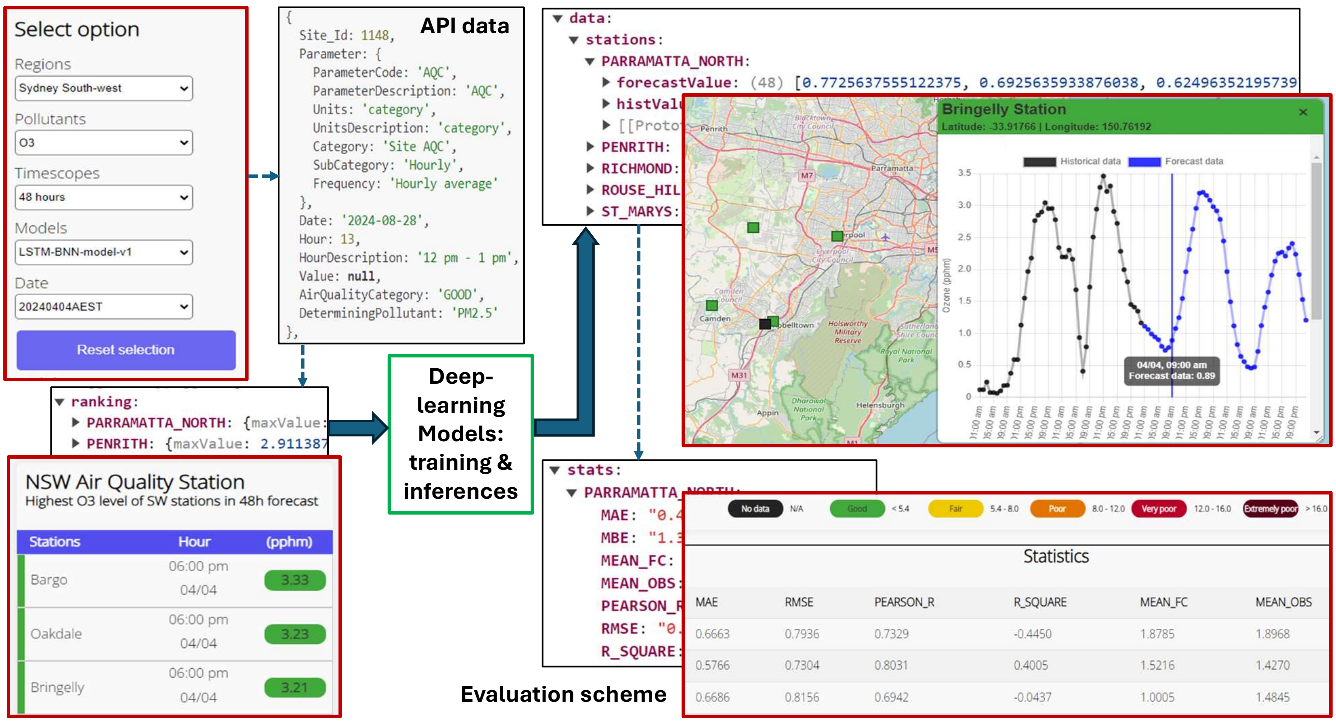

FIGURE 4. Functional tests for dataflow from backend to frontend

three deep learning models employed, namely LSTM-BNN, CNN-LSTM, and CNN-LSTM-BNN, which amalgamate the strengths of convolutional neural networks, long short-term memory networks, and Bayesian neural networks to enhance spatio-temporal pattern recognition and mitigate prediction uncertainties. Additionally, we have developed a comprehensive dashboard that seamlessly integrates predictive models, enabling real-time monitoring and accurate forecasts across New South Wales. This informative visualization tool employs advanced algorithms developed to provide stakeholders with timely insights, offering precise and actionable data for the region. Through these advancements, our framework stands out to contribute to improving air quality management and decision-making processes and is expected to address the ecological concerns of local residents. The prototype is presently under the final stage of NSW-DCCEEW commissioning before it can be released to the public. Further evaluations including a user study on this visualization tool will be among our future work. Besides, this visualization tool can be enhanced to include extreme event detection (e.g., bushfires, dust storms) and climatology analysis functions.

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