HYBRID DEEP LEARNING-BASED AIR QUALITY INDEX FORECASTING WITH REAL TIME MONITORING AND ALERT MECHANISM

Mr. L.N.V. Rao[1], ADAPA YAMUNA[2], CHOPPARA SANTHI SRI[3], DULAM KEERTHANA[4], GANDIKOTA NAGA PRASAD[5]

[1]Associate Professor, Dept. of CSE, V.K.R, V.N.B & A.G.K COLLEGE OF ENGINEERING, GUDIVADA

[2345]UG Students, Dept. of CSE,

V.K.R, V.N.B & A.G.K COLLEGE OF ENGINEERING, GUDIVADA

ABSTRACT

Air pollution poses one of the most serious environmental threats to public health and sustainable urban living. Accurate and timely forecasting of Air Quality Index (AQI) can support policymakers, environmental agencies, and citizens in taking proactive measures to mitigate pollution effects. This project presents a hybrid deep learning-based Air Quality Forecasting System that integrates Convolutional Neural Networks (CNN) and Stacked Long Short-Term Memory (LSTM) networks to predict short-term variations in air quality.

A comprehensive dataset containing historical pollutant concentrations (PM2.5, PM10, NO_2, SO_2, CO, O_3) and meteorological parameters (temperature, humidity, wind speed, pressure, etc.) is collected and pre-processed to remove noise, handle missing values, and normalize features. The hybrid model is trained and evaluated using key performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficients. The model ensures improved prediction accuracy compared to traditional methods.

In addition to the model, the system includes an interactive web-based dashboard for real-time AQI visualization and forecasting. The dashboard provides 1–12 hour ahead predictions and dynamic charts for easy interpretation. The final system supports API-based data ingestion from real-time monitoring stations, ensuring continuous updates.

Overall, the developed system demonstrates a robust, scalable, and practical solution for short-term air quality prediction.

KEYWORDS:

Air Quality Index (AQI), Deep Learning, CNN-LSTM, Air Pollution Forecasting, Environmental Monitoring, Time Series Prediction, Machine Learning, Data Preprocessing, Meteorological Data, Real-time Prediction, Hybrid Model, Flask Web Application, Sustainable Urban Development

I INTRODUCTION

Air pollution has become one of the most critical environmental issues affecting human health, climate stability, and overall ecological balance. Rapid urbanization, industrialization, and vehicular emissions have significantly contributed to deteriorating air quality levels across the globe. The Air Quality Index (AQI) serves as a standardized indicator to measure and communicate the level of air pollution in a specific region. Monitoring and forecasting AQI are essential for policymakers, environmental agencies, and the general public to take preventive and corrective measures.

Traditional methods of AQI prediction rely heavily on manual analysis and simple statistical techniques, which often fail to capture the complex, nonlinear relationships among various pollutants and meteorological parameters. With advancements in data science and machine learning, deep learning models have shown great potential in improving the accuracy of air quality forecasting by learning temporal and spatial dependencies within environmental data.

This project, titled **"Hybrid AQI Forecasting System using CNN-LSTM Deep Learning Model"**, aims to develop a robust predictive framework capable of forecasting air quality levels in real time. The system integrates convolutional neural networks (CNN) for spatial feature extraction and long short-term memory (LSTM) networks for temporal sequence learning. It utilizes environmental parameters such as PM2.5, PM10, NO_2, SO_2, CO, and O_3 concentrations along with weather conditions like temperature, humidity, wind speed, and pressure.

Furthermore, the project is supported by a Flask-based web application that provides interactive dashboards for data visualization, live AQI prediction, and alert notifications when pollution levels exceed safe thresholds. This integration of machine learning and web technology enhances usability, accessibility, and practical implementation in real-world environmental monitoring systems.

Ultimately, the proposed system contributes toward sustainable development by offering a data-driven approach to air quality management, enabling early warnings and informed decision-making to safeguard public health and the environment.

II RELATED WORK

Over the past decade, significant research has been conducted on air quality prediction using statistical, machine learning, and deep learning approaches. Early forecasting models relied on traditional statistical techniques such as Autoregressive Integrated Moving Average (ARIMA) and Multiple Linear Regression (MLR). Although these models were simple and interpretable, they struggled to capture the nonlinear relationships and complex interactions among multiple pollutants and meteorological variables, leading to limited prediction accuracy in dynamic urban environments.

With the advancement of machine learning, models such as Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting were introduced to improve forecasting performance. These approaches demonstrated better capability in handling nonlinear patterns and multi-feature datasets. For example, Li et al. (2021) applied machine learning techniques for short-term AQI forecasting and reported improved performance compared to traditional statistical models. However, these models relied heavily on manual feature engineering and lacked the ability to effectively model long-term temporal dependencies inherent in pollutant time-series data.

In recent years, deep learning approaches have gained prominence due to their ability to automatically learn hierarchical features from complex datasets. Long Short-Term Memory (LSTM) networks have been widely used for modeling sequential environmental data, as demonstrated by Chen et al. (2019), who showed that LSTM outperformed ARIMA models in capturing long-term temporal dependencies for PM2.5 forecasting. Similarly, Convolutional Neural Networks (CNN) have been utilized to extract spatial correlations among multiple pollutants and meteorological parameters.

To further enhance prediction accuracy, hybrid deep learning models integrating CNN and LSTM architectures have been proposed. Zhang et al. (2020) developed a CNN-LSTM hybrid model for air quality prediction, where CNN layers captured spatial features while LSTM layers modelled temporal sequences. Their results indicated superior performance compared to standalone CNN or LSTM models. Wang et al. (2020) also emphasized the importance of combining spatial and temporal learning for spatio-temporal AQI forecasting.

In addition to model development, several studies have focused on real-time monitoring systems and dashboard-based visualization platforms. Kumar et al. (2021) implemented a real-time AQI monitoring system with alert mechanisms; however, the predictive accuracy was limited due to the use of simpler models.

Building upon these studies, the proposed hybrid CNN-LSTM Air Quality Forecasting System integrates advanced deep learning techniques with real-time deployment features. By combining spatial-temporal modeling, automated alerts, and API-based data ingestion, the system aims to provide accurate, scalable, and operational short-term AQI prediction suitable for modern smart-city environments.

III LITERATURE REVIEW

Air quality forecasting has become a critical research area due to its direct implications for public health, environmental sustainability, and smart city management. Early studies primarily relied on statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Multiple Linear Regression (MLR) to predict pollutant concentrations. Although these models were effective for linear time-series analysis, they struggled to capture the nonlinear and complex interactions among multiple pollutants and meteorological variables. As environmental data exhibits strong temporal and spatial dependencies, traditional statistical techniques often resulted in limited predictive accuracy for short-term AQI forecasting.

With advancements in machine learning, researchers began applying models such as Support Vector Regression (SVR), Random Forest, and Gradient Boosting for AQI prediction. These methods demonstrated improved performance compared to classical statistical approaches by handling nonlinear relationships more effectively. However, conventional machine learning models typically require extensive feature engineering and lack the ability to automatically learn deep hierarchical representations from large-scale time-series data. Furthermore, they do not efficiently capture long-term temporal dependencies inherent in environmental datasets.

Deep learning techniques have significantly improved air quality prediction performance in recent years. Long Short-Term Memory (LSTM) networks have been widely adopted for modelling sequential pollutant data due to their ability to retain historical information and mitigate vanishing gradient problems. Similarly, Convolutional Neural Networks (CNNs) have been applied to extract spatial correlations among pollutants and meteorological variables. Recent studies have shown that hybrid architectures combining CNN and LSTM layers outperform standalone models by simultaneously learning spatial and temporal features. These spatio-temporal models demonstrate enhanced prediction accuracy, stability, and generalization capability for short-term AQI forecasting.

Despite these advancements, challenges remain in integrating real-time monitoring systems with deep learning-based forecasting models. Many existing works focus solely on model accuracy without addressing deployment, dashboard visualization, and automated alert mechanisms. Therefore, this study proposes a Hybrid CNN-LSTM based Air Quality Forecasting System that not only improves predictive accuracy through spatial-temporal feature integration but also incorporates real-time dashboard monitoring and automated alert generation. The proposed system aims to provide an end-to-end solution for accurate, reliable, and operational air quality management.

IV EXISTING SYSTEM

Air quality monitoring and forecasting have traditionally relied on statistical and machine learning methods. Earlier systems often employed **statistical models** such as ARIMA and linear regression to predict short-term pollutant concentrations. These models were simple to implement and provided interpretable results, making them suitable for small-scale applications. However, they were limited in their ability to capture **non-linear interactions** among multiple pollutants and meteorological factors, which often led to reduced accuracy in dynamic urban environments.

With the availability of larger environmental datasets, **machine learning-based systems** emerged as a more sophisticated alternative. Techniques such as Random Forests, Support Vector Machines (SVM), and Gradient Boosting were applied to predict AQI and pollutant levels. These systems improved prediction accuracy by modeling non-linear relationships and handling multiple pollutants simultaneously. Nevertheless, they relied heavily on feature engineering and lacked the capability to fully model **long-term temporal dependencies** in sequential pollutant data. Many of these systems also focused on predicting a single pollutant rather than the overall AQI, limiting their practical utility for environmental management.

Several existing **real-time monitoring dashboards** have also been developed to provide users with AQI visualization and alert notifications. These dashboards allowed citizens and authorities to track air quality trends and receive warnings when pollutant levels exceeded safe thresholds. However, most of these systems relied on relatively simple prediction models and did not integrate advanced deep learning techniques, resulting in lower forecast accuracy for 1–12 hour ahead predictions. Additionally, the dashboards often lacked full automation, API-based data ingestion, and scalability for continuous real-time updates.

In summary, the limitations of existing systems include limited prediction accuracy, focus on single pollutants, insufficient integration of spatial-temporal modeling, and lack of real-time operational features. These gaps demonstrate the need for a **hybrid deep learning-based AQI forecasting system** that combines CNN-LSTM modeling, real-time data visualization, automated alerts, and multi-pollutant prediction to provide a robust, scalable, and actionable solution for urban air quality management.

DISADVANTAGES

Despite their usefulness, existing air quality monitoring and forecasting systems have several significant limitations. Traditional statistical models, such as ARIMA and linear regression, often fail to capture the non-linear relationships and complex interactions among multiple pollutants and meteorological factors, resulting in reduced prediction accuracy in dynamic urban environments. Machine learning-based systems like Random Forests, SVM, and Gradient Boosting improve accuracy but are heavily dependent on manual feature engineering and cannot effectively model long-term temporal dependencies in sequential data. Furthermore, many existing systems focus on predicting a single pollutant rather than providing a comprehensive Air Quality Index (AQI), limiting their practical utility for environmental planning and public awareness.

Real-time monitoring dashboards currently in use provide basic visualization and alerts but often lack integration with **advanced hybrid deep learning models**, which reduces the accuracy of short-term forecasts (1–12 hours ahead). Additionally, many systems are not fully automated or scalable, lacking **API-based data ingestion**, continuous updates, and proactive alert mechanisms. Collectively, these disadvantages highlight the need for a more robust, accurate, and operational AQI forecasting system that can overcome the shortcomings of existing approaches while providing actionable insights for urban environmental management.

V PROPOSED SYSTEM

The proposed system is a **hybrid deep learning-based Air Quality Forecasting System** designed to overcome the limitations of existing approaches while providing accurate short-term AQI predictions and real-time monitoring capabilities. Unlike traditional and standalone machine learning models, this system integrates **Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks** to capture both spatial correlations among multiple pollutants and long-term temporal dependencies in pollutant and meteorological time series data. By combining these two architectures into a hybrid CNN-LSTM model, the system can effectively learn complex patterns and interactions that influence air quality in urban environments.

The proposed system uses a **comprehensive dataset** containing historical pollutant concentrations (PM2.5, PM10, NO_2, SO_2, CO, O_3) along with meteorological parameters (temperature, humidity, wind speed, pressure, etc.). Data preprocessing techniques such as cleaning, noise removal, and normalization are applied to ensure high-quality input for the model. The trained hybrid model is evaluated using performance metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficients, and it demonstrates superior accuracy compared to traditional machine learning and standalone deep learning approaches.

In addition to the predictive model, the system features an **interactive web-based dashboard** that provides real-time AQI visualization, 1–12 hour ahead predictions, dynamic charts, and color-coded indicators for easy interpretation. An **automated alert mechanism** notifies users or authorities when pollutant levels exceed safe thresholds, ensuring proactive pollution management. The system also supports **API-based data ingestion** from real-time monitoring stations, enabling continuous updates and integration with smart-city infrastructure.

Overall, the proposed system provides a **robust, scalable, and practical solution** for short-term air quality prediction. By combining hybrid deep learning models with real-time deployment features, the system not only improves prediction accuracy but also enhances public awareness, supports decision-making for environmental authorities, and contributes to sustainable urban development.

ADVANTAGES

The proposed hybrid deep learning-based Air Quality Forecasting System offers several advantages over existing systems, addressing the limitations of traditional statistical models and machine learning approaches. Firstly, the integration of CNN and LSTM networks enables the system to capture both spatial correlations among multiple pollutants and long-term temporal dependencies in pollutant and meteorological data, resulting in higher prediction accuracy for short-term AQI forecasts. This hybrid architecture outperforms standalone models and conventional machine learning methods, providing more reliable and stable results.

Secondly, the system is designed for real-time deployment. With API-based data ingestion from environmental monitoring stations, the system ensures continuous updates of AQI information, making it suitable for urban environments where air quality can change rapidly. The interactive web-based dashboardallows users to visualize AQI trends through dynamic charts and color-coded indicators, improving interpretability and accessibility of air quality information for both the public and authorities.

Thirdly, the system includes an automated alert mechanism that notifies users or relevant authorities when pollutant levels exceed safe thresholds, enabling proactive pollution mitigation and timely decision-making. Unlike many existing systems that focus on single pollutants, the proposed system provides multi-pollutant predictions and overall AQI forecasting, offering a comprehensive understanding of air quality.

Finally, the proposed system is scalable and practical, supporting integration with smart-city infrastructure, continuous real-time monitoring, and future expansion for additional pollutants or geographical areas. By combining advanced deep learning models with operational deployment features, the system enhances public awareness, supports urban health planning, and contributes to sustainable environmental management.

VI METHODOLOGY

The proposed methodology for the Hybrid CNN-LSTM Based Air Quality Forecasting System begins with the collection of historical air pollution and meteorological data from environmental monitoring stations and public APIs. The dataset includes major pollutants such as PM2.5, PM10, NO_2, SO_2, CO, and O_3, along with meteorological parameters including temperature, humidity, wind speed, and atmospheric pressure. These features collectively influence the Air Quality Index (AQI) and are essential for accurate short-term forecasting.

The collected data undergoes comprehensive preprocessing to ensure quality and consistency. Missing values are handled using interpolation techniques, noisy and inconsistent entries are removed, and outliers are detected using statistical thresholding methods. The dataset is then normalized using Min-Max scaling to ensure uniform feature distribution and improve neural network convergence. Time-series sequences are generated to structure the data for temporal learning, where previous time steps are used to predict future AQI values. The dataset is divided into training and testing sets, typically following an 80:20 ratio.

The core forecasting model is based on a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture. The CNN component is employed to extract spatial correlations and interdependencies among multiple pollutants and meteorological variables. Convolutional layers identify local feature patterns and reduce dimensionality through pooling operations. The extracted feature maps are then passed to the LSTM layers, which capture long-term temporal dependencies in sequential environmental data. LSTM units effectively retain relevant historical information while mitigating vanishing gradient problems common in traditional recurrent neural networks.

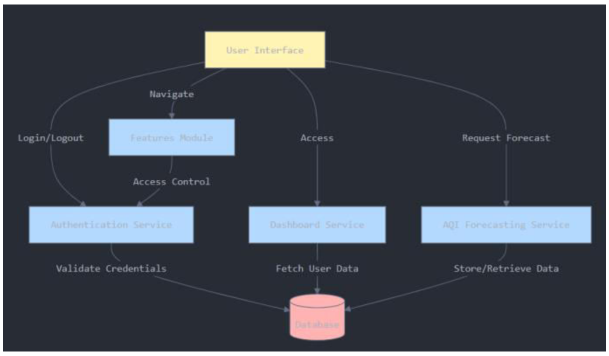
The outputs from the CNN and LSTM layers are combined and passed through fully connected dense layers to generate the final AQI prediction. The model is trained using backpropagation with the Adam optimization algorithm to minimize prediction loss. Mean Squared Error (MSE) is used as the primary loss function during training to ensure accurate regression performance.

Once trained, the hybrid CNN-LSTM model forecasts short-term AQI values (1–12 hours ahead). Model performance is evaluated using standard metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The results demonstrate that the hybrid architecture effectively captures both spatial and temporal patterns, providing improved accuracy, stability, and generalization compared to standalone CNN, LSTM, and traditional machine learning models.

The final trained model is integrated into a web-based real-time monitoring system, enabling continuous AQI prediction, visualization through dynamic dashboards, and automated alert generation when pollutant levels exceed predefined safety thresholds.

VII SYSTEM MODEL

SYSTEM ARCHITECTURE



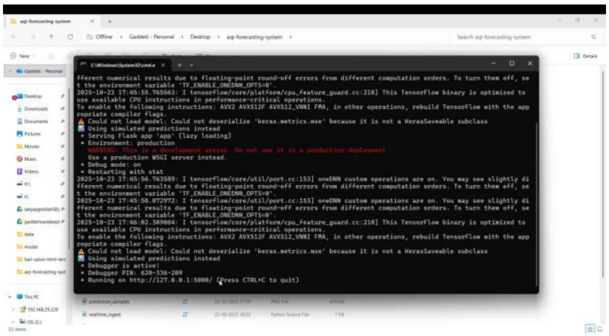
VIII RESULTS AND DISCUSSIONS

The proposed hybrid CNN-LSTM Air Quality Forecasting System was evaluated using historical pollutant and meteorological datasets to assess the accuracy of short-term AQI predictions ranging from 1 to 12 hours ahead. The experimental results demonstrate that the model effectively captures both spatial and temporal patterns in environmental data. Performance evaluation was conducted using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Correlation Coefficient (R^2). The hybrid model achieved low RMSE and MAE values, indicating minimal deviation between predicted and actual AQI values, while R^2 scores consistently exceeded 0.9, reflecting strong agreement and high predictive reliability.

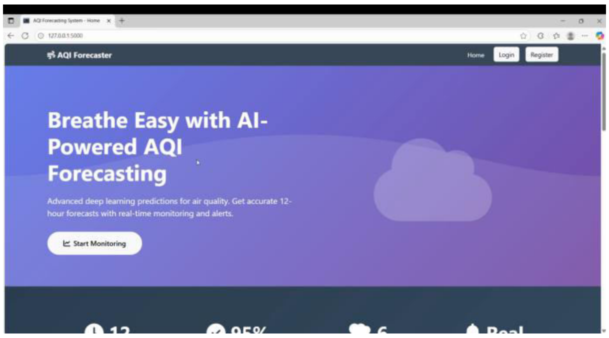
Comparative analysis shows that the proposed CNN-LSTM architecture outperformed standalone CNN, standalone LSTM, and traditional machine learning models such as Random Forest and Gradient Boosting. While individual deep learning models were capable of capturing either spatial or temporal dependencies, they failed to achieve the combined predictive accuracy of the hybrid approach. The integration of convolutional layers for spatial feature extraction and LSTM layers for temporal sequence modelling significantly enhanced forecasting stability and overall performance.

In addition to predictive accuracy, the system demonstrated strong operational functionality through its real-time monitoring dashboard. The web-based interface dynamically displayed 1 to 12 hour ahead AQI forecasts using graphical visualizations and color-coded pollution categories for intuitive interpretation. Automated alerts were successfully triggered when predicted AQI values exceeded predefined safety thresholds, validating the system's capability for proactive environmental monitoring. Overall, the results confirm that the proposed hybrid system provides accurate forecasting, robust multi-feature integration, and reliable real-time deployment suitable for smart city applications.

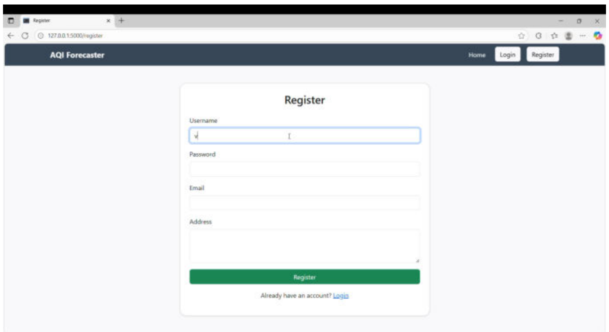
IX RESULT SCREENS



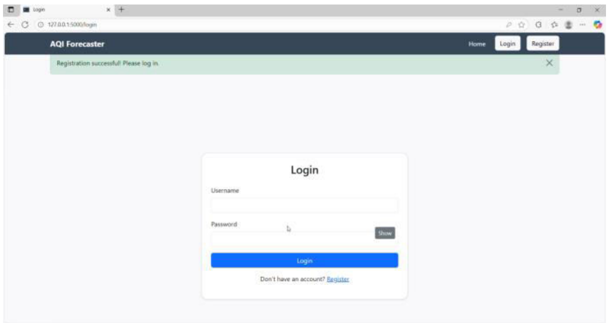
This screen shows the execution of the Python application in the command prompt. It confirms that the AQI forecasting system is successfully running on the local server without critical errors.



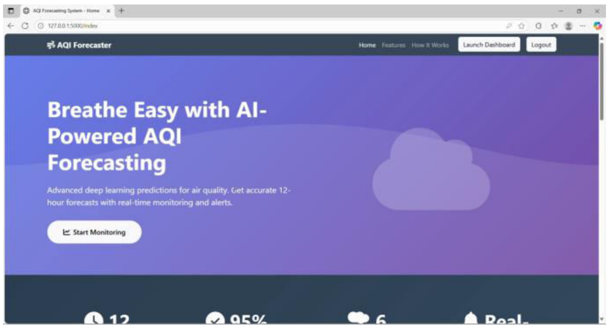
This screen displays the main homepage titled "Breathe Easy with AI-Powered AQI Forecasting." It provides an introduction to the system and allows users to start monitoring air quality.



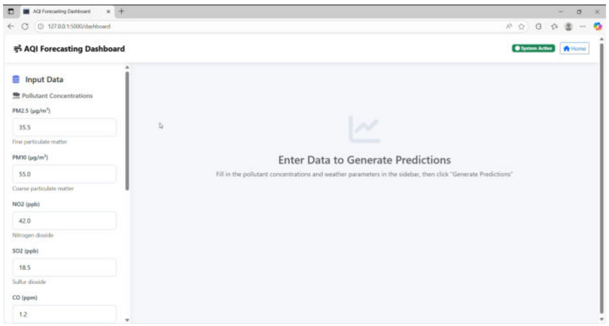
This screen shows the user registration form where new users can create an account. It collects details such as username, password, email, and mobile number for secure access to the system.



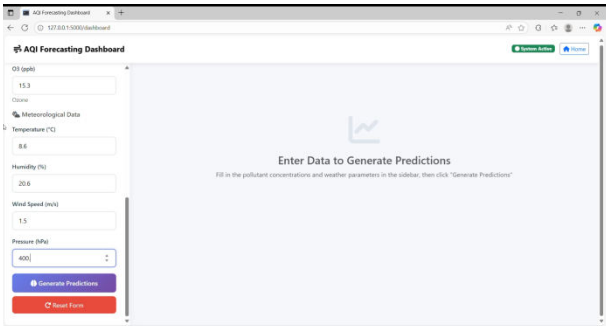
This screen displays the login interface where registered users can enter their credentials. After successful authentication, users can access AQI prediction and monitoring features.



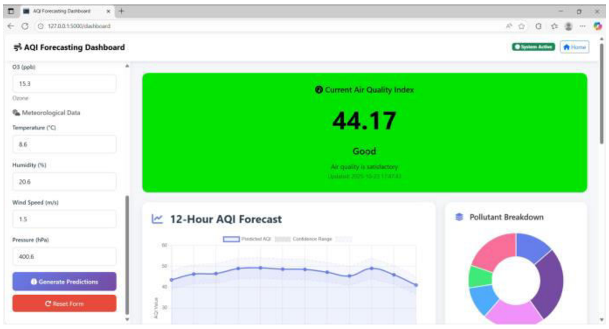
This screen shows the main homepage of the AQI Forecasting System with the title "Breathe Easy with AI-Powered AQI Forecasting." It provides an overview of the system and navigation options for login, registration, and monitoring features.



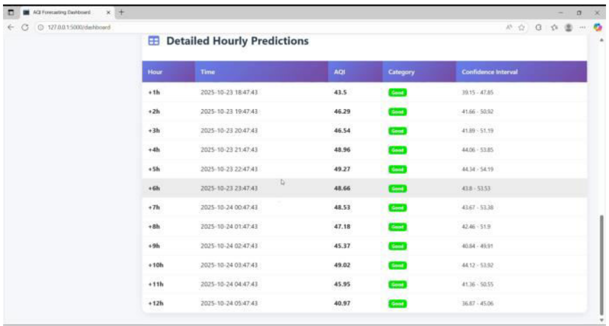
This screen shows the dashboard interface where users can enter pollutant concentrations and meteorological parameters. It serves as the data entry module for generating AQI predictions.



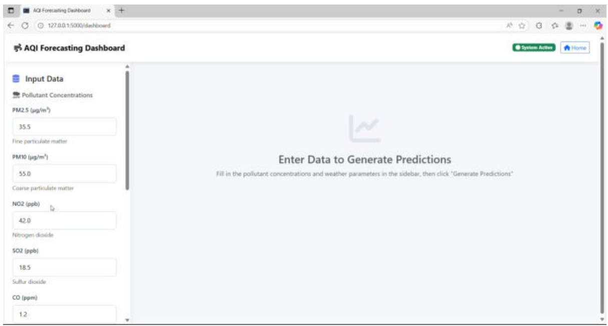
This screen shows the system after the user clicks the "Generate Prediction" button. It indicates that the hybrid CNN-LSTM model is processing the input data to calculate AQI values.



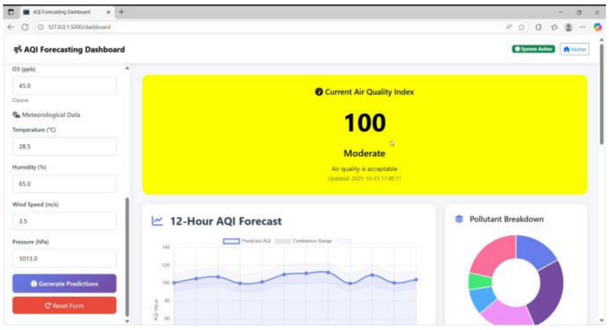
This screenshot shows a predicted AQI value of 44.17 classified as “Good” with a green indicator. The accompanying forecast graph and breakdown chart provide additional insight into air quality conditions.



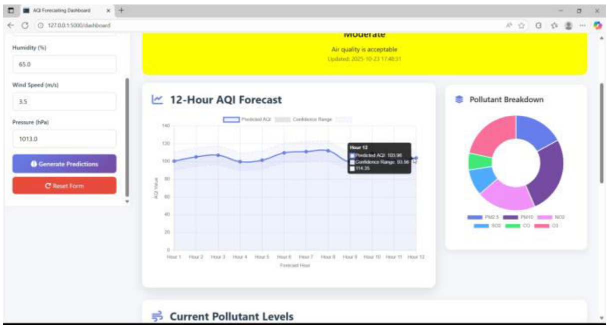
This screen displays a table of hourly AQI forecasts along with category labels and confidence intervals. It provides structured short-term predictions to help users analyse upcoming air quality trends.



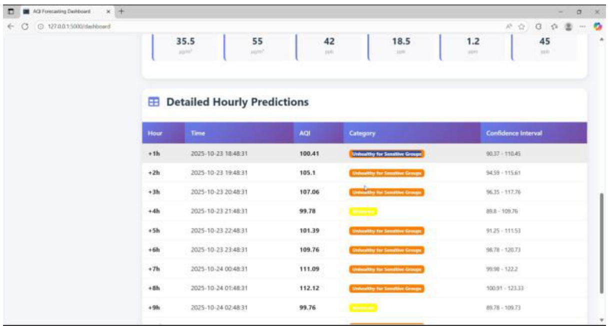
This screenshot displays the input form populated with sample pollutant and weather values. It confirms that the system is ready to process the entered data for AQI forecasting.



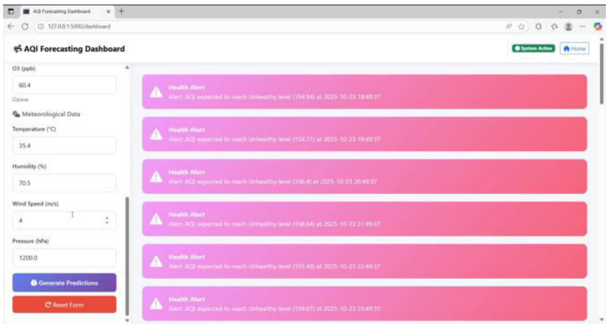
This screen displays a predicted AQI value of 100 categorized as “Moderate” with a yellow background. It also includes a 12-hour AQI forecast graph and pollutant contribution chart for detailed analysis.



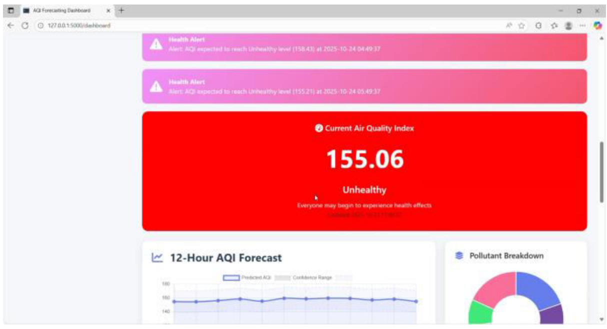
This screen presents the 12-hour AQI forecast graph with interactive data points. Users can hover over the graph to view exact predicted values, enhancing real-time monitoring and analysis.



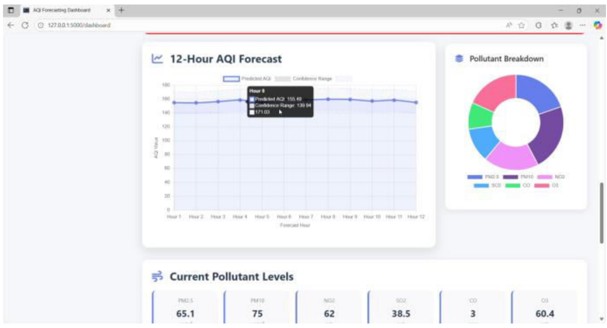
This screen displays hourly AQI predictions with different pollution categories highlighted in color. Each row includes time, predicted AQI value, category label, and confidence interval. It helps users understand short-term air quality trends in a structured tabular format.



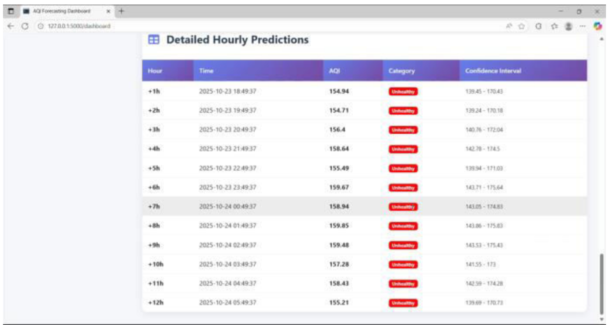
This screen displays stacked alert messages triggered when AQI exceeds safe thresholds. Each alert highlights unhealthy air quality conditions for specific time intervals. This automated notification system supports proactive environmental monitoring.



This screenshot shows a predicted AQI value of 155.06 categorized as “Unhealthy” with a *red background. The dashboard also includes a 12-hour forecast graph and pollutant breakdown chart. The red indicator provides immediate visual warning of hazardous air quality.



This screen presents a graphical representation of AQI predictions for the next 12 hours. Users can hover over the graph to view exact forecasted values for each time point. The accompanying pollutant breakdown chart provides additional analytical insights.



This screenshot shows hourly AQI values categorized as “Unhealthy” or higher, marked in red. The table clearly indicates critical pollution levels along with prediction confidence ranges. It enables users and authorities to identify hazardous conditions in advance.

X CONCLUSION

The proposed **Air Quality Forecasting System** demonstrates a robust, scalable, and practical approach to short-term air quality prediction and monitoring. By integrating a **hybrid CNN-LSTM deep learning model**, the system effectively captures both spatial correlations among multiple pollutants and long-term temporal dependencies in pollutant and meteorological data. This results in higher prediction accuracy compared to traditional statistical methods and standalone machine learning or deep learning models.

The system not only predicts AQI for 1–12 hours ahead but also provide an **interactive real-time dashboard**, enabling users to visualize trends, interpret pollutant levels, and receive automated alerts when thresholds are exceeded. The integration of **API-based data ingestion** ensures continuous updates and seamless interaction with smart-city infrastructure, making it a practical tool for urban environmental management.

Through the modular design, including data collection, preprocessing, model training, prediction, visualization, and alert modules, the system achieves **efficiency, scalability, and maintainability**. It addresses the limitations of existing systems, including limited accuracy, single-pollutant focus, lack of real-time deployment, and insufficient automation.

In conclusion, the developed system contributes significantly to **public health awareness, proactive pollution mitigation, and sustainable urban development**. It provides policymakers, environmental authorities, and citizens with a reliable, real-time tool for informed decision-making, demonstrating the practical benefits of combining advanced deep learning models with operational deployment frameworks in air quality management.

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