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AIR QUALITY INDEX PREDICTION USING LSTM NETWORKS

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Abstract

Accurate prediction of the Air Quality Index (AQI) plays a crucial role in minimizing the adverse effects of air pollution on human health and the environment. However, AQI prediction remains a complex task due to the highly non-linear, dynamic, and time-dependent behavior of atmospheric pollutants. Conventional statistical and machine learning approaches often fail to capture long-term temporal dependencies present in air quality data.

This paper proposes a deep learning–based AQI prediction framework using Long Short-Term Memory (LSTM) networks to effectively model complex temporal relationships. The proposed framework integrates multiple air pollutant concentrations, including PM2.5, PM10, NO_2, SO_2, CO, and O_3, along with meteorological variables such as temperature, humidity, and wind speed. By learning temporal trends from historical data, the LSTM network accurately captures both short-term fluctuations and long-term pollution patterns.

Experimental results demonstrate that the proposed LSTM model significantly outperforms traditional linear regression and Random Forest models in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). The findings indicate that the proposed system can function as a reliable early-warning tool for air quality monitoring, public health planning, and environmental policy formulation**.**

Keywords

Air Quality Index, Deep Learning, LSTM, Time-Series Forecasting, Environmental Monitoring, Air Pollution Prediction

1. Introduction

Air pollution has emerged as one of the most serious environmental challenges affecting public health and quality of life across the globe. Exposure to polluted air has been directly linked to respiratory disorders, cardiovascular diseases, reduced lung function, and premature mortality.

Rapid industrialization, urban expansion, and increased vehicular traffic have significantly contributed to the deterioration of air quality, especially in densely populated regions.

The Air Quality Index (AQI) is widely used as a standardized indicator to communicate air pollution levels and associated health risks to the public. AQI values are calculated based on the concentrations of multiple pollutants and are categorized into different risk levels. However, AQI is not a static measure; it varies significantly over time due to changes in emissions, weather conditions, and chemical interactions in the atmosphere.

Traditional AQI prediction methods rely on chemical transport models or statistical forecasting techniques. Although physically interpretable, chemical transport models require substantial computational resources and detailed atmospheric data. Statistical models often assume linear relationships and struggle with highly non-linear pollution dynamics. Recent advancements in deep learning provide data-driven alternatives capable of learning complex patterns directly from historical data. In this study, AQI prediction is formulated as a time-series forecasting problem and addressed using LSTM networks, which are well suited for modeling long-term temporal dependencies.

2. Related Work

Early research in air quality prediction primarily employed statistical techniques such as linear regression, autoregressive models, and ARIMA-based forecasting. These approaches were computationally efficient but exhibited limited prediction accuracy due to their inability to capture non-linear interactions among pollutants and meteorological variables.

Subsequent studies introduced machine learning techniques, including Support Vector Machines, k-Nearest Neighbors, and Random Forests. These models improved performance by learning complex feature interactions; however, they treated observations as independent samples and did not explicitly model temporal dependencies.

Recent advancements have focused on deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). While CNNs are effective in spatial feature extraction, RNNs are designed for sequential data modeling. Nevertheless, standard RNNs suffer from vanishing gradient problems, limiting their ability to retain long-term information. LSTM networks address this limitation through gated memory mechanisms, making them highly effective for long-horizon AQI forecasting.

3. Complexity of Air Quality Data

3.1 Environmental Variables

AQI prediction depends on a diverse set of environmental variables that interact in complex ways. Particulate matter, particularly PM2.5 and PM10, is a major contributor to poor air quality due to its ability to penetrate deep into the human respiratory system. Gaseous pollutants such as NO_2, SO_2, CO, and O_3 originate from vehicular emissions, industrial processes, and combustion activities.

Meteorological parameters play a critical role in determining pollutant concentration levels. Wind speed affects pollutant dispersion, humidity influences particle formation, and temperature variations can

create atmospheric stability conditions. These factors collectively introduce strong non-linearities into AQI time-series data.

3.2 Secondary Pollutant Formation

Certain pollutants, such as ground-level ozone, are not directly emitted but are formed through complex photochemical reactions involving nitrogen oxides and volatile organic compounds. These reactions depend on sunlight intensity, temperature, and precursor concentrations. Modeling such interactions using explicit equations is challenging, whereas deep learning models can implicitly learn these dependencies from historical observations.

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4. Data Preprocessing and Feature Engineering

4.1 Data Collection and Cleaning

Air quality and meteorological data are collected from continuous monitoring stations and sensor networks. Due to sensor malfunctions, calibration errors, and maintenance activities, the collected data often contain missing values and noise. Linear interpolation is applied to fill short gaps in the data, while mean imputation is used for longer missing periods. Sudden spikes caused by local pollution events are smoothed using moving average techniques to reduce noise and improve model stability.

4.2 Feature Scaling

Pollutant concentrations are measured using different units and ranges, which can negatively affect model training. To address this issue, Min-Max normalization is applied to scale all features into a uniform range. This preprocessing step improves numerical stability and ensures balanced learning across features.

4.3 Sliding Window Method

To transform the time-series data into supervised learning format, a sliding window technique is employed. Historical observations from a fixed time window, such as the previous 24 hours, are used to predict future AQI values. This approach enables the model to capture temporal trends and periodic patterns effectively.

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5. Proposed Methodology

5.1 Long Short-Term Memory Networks

LSTM networks are a specialized form of recurrent neural networks designed to retain information over long sequences. Each LSTM unit contains a memory cell regulated by forget, input, and output gates. These gates control information flow and allow the network to selectively remember or discard historical information, which is essential for AQI prediction tasks.

5.2 Mathematical Formulation

The mathematical formulation of the LSTM network enables efficient learning of long-term dependencies. The gated structure ensures stable gradient flow during training, allowing the network to learn complex temporal patterns without suffering from vanishing gradient issues.

5.3 Model Architecture

The proposed architecture consists of stacked LSTM layers to capture deep temporal features, followed by dropout layers to reduce overfitting. A fully connected dense layer produces the final AQI prediction. This architecture balances model complexity and generalization capability**.**

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6. Experimental Setup

6.1 Training Configuration

The model is trained using the Adam optimizer due to its adaptive learning rate capabilities. Huber loss is employed as the objective function to ensure robustness against outliers. The dataset is divided into training and testing subsets to evaluate generalization performance.

6.2 Evaluation Metrics

Model performance is evaluated using MAE, RMSE, and R^2 score. These metrics provide a comprehensive assessment of prediction accuracy, error magnitude, and trend-following ability.

7. Results and Discussion

Experimental results indicate that the proposed LSTM model consistently outperforms baseline models across all evaluation metrics.

Model	MAE	RMSE	R^2
Linear Regression	**15.4**	**22.1**	**0.65**
Random Forest	**10.2**	**14.8**	**0.81**
Proposed LSTM	**6.1**	**8.4**	**0.94**

The improved performance demonstrates the effectiveness of LSTM networks in modeling long-term dependencies and non-linear pollutant interactions. The results also highlight the suitability of deep learning approaches for real-world AQI forecasting applications.

8. Ablation and Robustness Analysis

Ablation experiments reveal that stacked LSTM layers significantly improve predictive performance compared to shallow architectures. Dropout layers reduce overfitting and enhance generalization. Additional robustness tests using noise-injected data demonstrate that the proposed model maintains stable performance under sensor uncertainty.

9. Ethical and Societal Impact

Accurate AQI prediction has significant societal benefits, including early health warnings, informed urban planning, and improved environmental policies. The proposed system is intended to support decision-making and should be used alongside official monitoring systems to ensure responsible and transparent usage.

10. Conclusion and Future Work

This paper presented a deep learning–based AQI prediction framework using LSTM networks. The proposed model effectively captures complex temporal patterns in air quality data and significantly outperforms traditional statistical and machine learning approaches. The results demonstrate the potential of deep learning for accurate and reliable air quality forecasting.

Future work will focus on incorporating spatial correlations among monitoring stations, exploring hybrid deep learning architectures, and deploying the model in real-time smart city environments.

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