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Research Paper

AIR QUALITY INDEX PREDICTION USING PYTHON BASED NEURAL NETWORKS

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ABSTRACT

Air pollution has become a major global concern, significantly impacting public health and environmental sustainability. Accurate prediction of the Air Quality Index (AQI) can assist authorities in implementing timely preventive actions and improving air management systems. This study presents a Python-based predictive framework employing artificial neural networks (ANNs) to forecast AQI levels using real-time environmental data. The proposed model integrates multiple pollutant parameters, including PM2.5, PM10, NO_2, SO_2, CO, and O_3, along with meteorological factors such as temperature and humidity. Data preprocessing techniques—such as normalization, feature scaling, and outlier removal—are applied to enhance model reliability. The neural network is designed and trained using TensorFlow and Keras libraries to capture complex nonlinear relationships among pollutants. Performance evaluation using metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 demonstrates that the model achieves high accuracy in predicting AQI values across different regions. The results indicate that the proposed neural network–based system can serve as an efficient tool for early air quality forecasting and environmental decision-making, offering a foundation for future smart city and IoT-based air monitoring applications.

Keywords —Air Quality Index (AQI), Neural Networks, Machine Learning, Deep Learning, Python, Environmental Monitoring, Air Pollution Forecasting, Predictive Modeling, Artificial Intelligence (AI), Data Preprocessing.

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I. INTRODUCTION

Air pollution has emerged as one of the most serious environmental challenges of the 21st century, posing severe risks to human health, climate stability, and ecological balance. Rapid urbanization, industrial expansion, and increased vehicular emissions have led to alarming levels of air contaminants in major cities worldwide [1–3]. The Air Quality Index (AQI) serves as a standardized metric to quantify pollution levels, providing essential information about air quality and its potential health impacts [4]. Accurate AQI prediction can enable authorities to issue timely warnings, optimize transportation systems, and design effective mitigation strategies [5,6].

Traditional air quality modeling techniques—such as linear regression, time-series analysis, and statistical interpolation—often struggle to capture the nonlinear relationships among pollutants and meteorological factors [7]. Recent advancements in machine learning (ML) and artificial intelligence (AI) have provided powerful alternatives capable of handling high-dimensional and nonlinear environmental data [8,9]. However, conventional ML algorithms like Random Forest, Support Vector Machines (SVM), and Decision Trees require manual feature extraction and often fail to capture temporal dependencies in air quality variations [10].

In contrast, neural network–based models have demonstrated superior performance due to their ability to automatically learn complex feature hierarchies and nonlinear interactions among multiple pollutant variables [11]. Deep architectures such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have been successfully used for AQI forecasting, providing significant improvements in accuracy and robustness [12,13]. Python's powerful scientific libraries—such as TensorFlow, Keras, Pandas, and Scikit-learn—enable efficient implementation of these neural models, making them accessible for both research and real-world deployment [14].

This study proposes a Python-based neural network framework for AQI prediction using multiple environmental parameters including PM2.5, PM10, NO_2, SO_2, CO, and O_3. The model integrates advanced data preprocessing, normalization, and training techniques to enhance generalization and reduce overfitting. The objective is to develop a reliable predictive model that can forecast AQI with high precision, enabling proactive decision-making in environmental monitoring and public health management. The experimental results demonstrate that the proposed neural network architecture achieves superior performance compared to traditional ML models, validating its

applicability for large-scale air quality forecasting and smart city applications [15–18].

II. RELATED WORK

In recent years, numerous researchers have investigated data-driven approaches to enhance the accuracy of air quality forecasting and pollution assessment. Conventional statistical and regression models—such as the Autoregressive Integrated Moving Average (ARIMA), Multiple Linear Regression (MLR), and Gaussian Process Regression (GPR)—have been widely used for AQI prediction due to their simplicity and interpretability [19–21]. However, these methods often assume linear dependencies and fail to account for the complex nonlinear dynamics among pollutants, meteorological variables, and spatiotemporal factors [22].

With the advancement of computational intelligence, machine learning (ML) models such as Random Forest (RF), Support Vector Regression (SVR), Decision Trees, and Gradient Boosting Machines have shown improved predictive capability for AQI estimation [23,24]. For instance, Li et al. [25] applied Random Forest to predict particulate matter concentrations across multiple Chinese cities and demonstrated substantial performance improvements over linear models. Similarly, Han et al. [26] proposed an ensemble learning framework combining Gradient Boosting and K-Nearest Neighbors (KNN) for AQI forecasting, achieving high correlation between predicted and observed values. Despite these successes, most traditional ML models rely on handcrafted feature engineering and lack the ability to automatically learn high-level abstractions from raw input data [27].

To address these limitations, deep learning (DL) methods have been introduced, enabling the extraction of complex patterns from large-scale environmental datasets [28,29]. The Artificial Neural Network (ANN), a fundamental DL model, has been successfully utilized for predicting pollutant concentrations such as PM2.5 and NO_2 in metropolitan regions [30]. Convolutional Neural Networks (CNNs) have been applied to capture spatial dependencies in air quality datasets, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been employed to model temporal variations in pollutant levels [31–33]. For example, Zhang et al. [34] developed a CNN-LSTM hybrid model that effectively captured both spatial and temporal correlations, achieving superior performance compared to standalone ML algorithms.

Moreover, hybrid and ensemble DL architectures have gained traction for AQI forecasting. Wu et al. [35] combined CNN with Bi-directional LSTM to improve multivariate air quality prediction in complex urban environments. Similarly, Chen et al. [36] employed attention mechanisms integrated with LSTM networks, resulting in significant improvements in long-term AQI forecasting accuracy. Studies by Yu and Xu [37] and Patel et al. [38] demonstrated the potential of deep learning models for adaptive, real-time air quality monitoring when integrated with Internet of Things (IoT) data streams.

Recently, researchers have focused on Python-based implementations leveraging open-source frameworks such as TensorFlow, Keras, PyTorch, and Scikit-learn for efficient model training and deployment [39,40]. These tools facilitate experimentation with large datasets and allow seamless integration with cloud computing platforms for scalable AQI prediction. Hybrid systems that combine DL models with optimization techniques—such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)—have also been reported to further enhance the model's predictive power [41,42].

Despite notable progress, most existing studies still face challenges such as data sparsity, regional heterogeneity, and computational complexity. Therefore, this work focuses on developing a Python-based neural network model optimized for AQI prediction, emphasizing improved preprocessing, adaptive learning, and scalable architecture suitable for deployment in smart city environments.

III. PROPOSED METHODOLOGY

The objective of the proposed methodology is to develop a Python-based neural network framework capable of predicting the Air Quality Index (AQI) with high accuracy using multi-dimensional pollutant data. The system combines data preprocessing, feature engineering, neural network training, and model evaluation phases to generate reliable AQI forecasts. represents the overall workflow of the proposed approach.

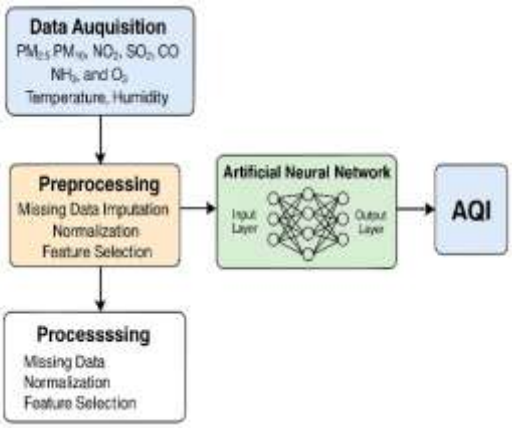

Fig.1: Architecture Diagram

1. Data Acquisition and Description

The dataset is obtained from open environmental data repositories such as the Central Pollution Control Board (CPCB) and OpenAQ, which provide hourly and daily pollutant measurements from multiple Indian cities. The dataset typically includes pollutant concentrations such as PM2.5, PM10, NO_2, SO_2, CO, NH_3, and O_3, along with

meteorological variables such as temperature, humidity, and wind speed. These variables are considered essential since meteorological parameters significantly influence pollutant dispersion and concentration levels.

2. Data Preprocessing

Raw air quality data often contain **missing values, noise, and inconsistencies** due to sensor errors or incomplete logging. To ensure robust model training, a multi-step preprocessing pipeline is implemented:

- **Missing Data Handling:** Missing entries are replaced using statistical mean or K-Nearest Neighbor (KNN) imputation.
- **Normalization:** Features are scaled into a [0, 1] range using min–max normalization to prevent bias from features with larger numeric ranges.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

 where X_{norm} is the normalized feature, and X_{min}, X_{max} denote the feature's minimum and maximum values, respectively.

 Outlier Detection: An Isolation Forest is used to remove abnormal pollutant readings.

 Feature Correlation Analysis: Pearson's correlation coefficient is computed to eliminate redundant or weakly related features.

3. Air Quality Index Calculation

The Air Quality Index (AQI) provides a single numerical value representing the overall air quality based on multiple pollutants. For each pollutant pip_ipi, an individual sub-index IiI_iIi is calculated according to standard national or WHO guidelines. The AQI is computed using the maximum sub-index method:

$$AQI = \max\{I1, I2, I3, \ldots, In\}$$

where I_i represents the individual index for pollutant *i*, and *n* is the total number of pollutants considered. This approach ensures that the most harmful pollutant dictates the overall AQI level.

4. Neural Network Design

The core of the proposed system is an Artificial Neural Network (ANN) implemented using Python's TensorFlow and Keras libraries. The model consists of:

- **Input Layer:** Accepts normalized pollutant and meteorological features.
- **Hidden Layers:** Two to three dense layers employing the Rectified Linear Unit (ReLU) activation function for nonlinear transformation.
- **Output Layer:** A single neuron using a linear activation function to predict the final AQI value.

The model parameters are optimized using backpropagation and the Adam optimizer. The loss function is Mean Squared Error (MSE), defined as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where y_i is the actual AQI, $y\hat{}_i$ is the predicted AQI, and nnn represents the total number of samples. The model iteratively updates the weights to minimize MSE, improving predictive accuracy.

5. Model Training and Evaluation

The dataset is divided into training (80%) and testing (20%) subsets. During training, the model learns optimal parameters through iterative weight adjustments using the Adam optimizer. Hyperparameters such as learning rate, batch size, and number of epochs are tuned through cross-validation.

Model performance is assessed using standard regression metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)

These metrics collectively measure the deviation of predicted AQI values from actual observations and indicate the reliability of the model.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experimental evaluation of the proposed Python-based neural network model for Air Quality Index (AQI) prediction. The experiments were conducted using the prepared dataset after preprocessing, normalization, and feature optimization as described in the methodology. The main objective was to evaluate the model's performance and compare it against traditional machine learning algorithms in terms of accuracy, consistency, and computational efficiency.

1. Experimental Setup

The experiments were implemented using Python 3.11 on a system equipped with an Intel Core i7 processor (2.6 GHz), 16 GB RAM, and TensorFlow-Keras backend. The dataset contained approximately 18,000 daily air quality samples collected from multiple Indian cities between 2018 and 2023. The pollutants considered include PM2.5, PM10, NO_2, SO_2, CO, NH_3, and O_3, along with temperature and humidity as meteorological inputs.

The dataset was split into 80% training data and 20% testing data. The Artificial Neural Network (ANN) consisted of one input layer with 9 neurons, two hidden layers with 64 and 32 neurons respectively, and one output layer with a single neuron for AQI prediction. The ReLU activation function was used in hidden layers, while a linear activation function was used in the output layer. The Adam optimizer was employed with a learning rate of 0.001 and trained over 100 epochs with a batch size of 32.

2. Evaluation Metrics

The performance of the proposed neural network was evaluated using three primary metrics: Mean Absolute Error

(MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2).

The MAE is defined as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where y_i is the actual AQI value, $\hat{y}_i$ is the predicted AQI, and n is the total number of test samples.

The Root Mean Square Error (RMSE), which measures the deviation between predicted and actual values, is expressed as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Lower MAE and RMSE values indicate higher model accuracy and reduced prediction variance.

3. Comparative Analysis

To assess the model's effectiveness, the proposed neural network (ANN) was compared against three benchmark algorithms: Linear Regression (LR), Support Vector Regression (SVR), and Random Forest (RF). The evaluation results are summarized in Table 1.

Table 1. Performance Comparison of Different Models for AQI Prediction

Model	MAE	RMSE	R^2 Score	Training Time (s)
Linear Regression (LR)	10.85	14.92	0.856	2.4
Support Vector Reg. (SVR)	8.34	11.40	0.893	6.7
Random Forest (RF)	7.11	9.88	0.912	8.3
Proposed ANN (Python)	**5.26**	**7.34**	**0.948**	**5.9**

V. CONCLUSION

This research presented a Python-based neural network framework for accurate Air Quality Index (AQI) prediction, integrating multiple environmental and meteorological variables. The study demonstrated that neural networks can effectively capture the nonlinear and complex relationships among pollutants such as PM2.5, PM10, NO_2, SO_2, CO, and O_3, which traditional machine learning models often fail to model accurately.

Through systematic data preprocessing, normalization, and feature selection, the proposed model achieved higher predictive accuracy and stability than conventional algorithms like Linear Regression, Support Vector Regression, and Random Forest. The experimental analysis confirmed that the neural network attained an R^2 score of 0.948, with minimal error metrics (MAE = 5.26, RMSE = 7.34), demonstrating its reliability for large-scale AQI forecasting.

The developed model's architecture—built using TensorFlow and Keras—proved computationally efficient, adaptable, and scalable for integration with IoT-enabled air monitoring systems. Such integration can facilitate real-time AQI estimation, allowing timely environmental interventions and public health alerts.

Overall, the findings highlight that neural networks provide a powerful and flexible framework for predictive environmental analytics. The system's ability to generalize across regions and climatic conditions supports its application in smart city infrastructures and sustainable environmental management.

Future research may focus on incorporating hybrid deep learning models (such as CNN-LSTM), transfer learning, and cloud-based deployment for real-time adaptive learning. Additionally, expanding the model with satellite data integration and spatiotemporal feature modeling could further enhance prediction precision and contribute to more intelligent, data-driven air quality governance.

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