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Investigation of Air Quality Index Forecasting Utilizing Convolutional Neural Networks with Stochastic Gradient Descent Optimization

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Abstract: Investigating the use of advanced deep learning methods with the aim of improving the accuracy of Air Quality Index (AQI) predictions is the aim of this research project. Using these approaches affects urban planning, environmental policy, and public health as well as other aspects. The study emphasizes the applicability of these ideas by stressing the critical need of accurate air quality index (AQI) estimates in relation to public health, environmental policy, and urban planning. Focusing especially on hybrid models and convolutional neural networks (CNNs), this study explores the complexity of deep learning. It also offers a thorough synopsis of the most current advancements in air quality index (AQI) prediction. This work aims to assess which transfer learning techniques are the most effective and evaluate their use in the development of an enhanced AQI prediction model. Combining the Stochastic Gradient Descent (SGD) optimizer with a Convolutional Neural Network (CNN) architecture, the presented model Using a range of performance criteria, a thorough evaluation was conducted on the CNN-SGD model and the findings revealed that, in most of the evaluated criteria, the CNN-SGD model exceeded a deep learning model currently in use. The findings of the research show that the CNN-SGD model developed shows better performance than other models presently in use, thereby positioning it as a possibly helpful tool for producing reliable AQI predictions. In order to improve the interpretability of the model, one of the future projects will be the research of several normalizing and regularizing approaches, the extension of the model to multi-task environments, the investigation of domain adaptation and transfer learning strategies, and the integration of explainable artificial intelligence methods.

Keywords: Deep Learning, Air Quality Index, Convolutional Neural Network, Stochastic Gradient Descent.

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I. INTRODUCTION

Particularly in view of the increasing urbanization and industrial activities causing the aggravation of global environmental problems, the quality of the air has become a main issue for those in charge of developing public policy, doing research, and guaranteeing public health. Among the several measures used to assess the quality of the air, the Air Quality Index (AQI) offers a consolidated view of the concentrations of several pollutants, such as particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), and carbon monoxide (CO), and translates these concentrations into a scale that conveys possible health risks to the general public. Not only is a correct prediction of the air quality index (AQI) necessary for the timely issuing of health warnings, but it also forms a fundamental component in the design of effective environmental policies and urban planning projects.

Recent advances in sensor technology, data collection, and computer techniques have transformed the mostly observational endeavour of the Air Quality Index (AQI) prediction into a highly complex predictive science. Machine learning and deep learning techniques have started substituting for conventional statistical models as they can record exact spatial and temporal fluctuations in air pollution concentrations. These approaches have been able to reach this because they allow one to learn from data. These intricate models include historical data on air quality, meteorological variables, emissions inventories, and satellite observations to attain a better degree of accuracy in their predicting of changes in the Air Quality Index. Notwithstanding these technological advances, there are still issues to be resolved. Among these difficulties include the necessity to control unexpectedly high pollution levels resulting from industrial mishaps or wildfires, sensor-related errors, and the essentially erratic character of atmospheric occurrences.

The building of thorough AQI prediction systems is not only a question of intellectual curiosity but also essential for reducing the negative consequences on the environment and protecting the general health of the population. Political authorities will be able to implement preventive measures as predictive capabilities rise; industry will be able to modify its activities to reduce emissions; and communities will be able to become more ready for events of poor air quality as predictive capacities keep growing. This thorough analysis of AQI prediction methods prepares the ground for next innovations aiming at combining environmental observation with useful results so that they might be used.

II. LITERATURE REVIEW

Deep learning methods have greatly affected recent advances in the prediction of the Air Quality Index (AQI). These approaches have demonstrated remarkably ability to identify complex and nonlinear patterns seen in air quality data. With an emphasis on the change from conventional statistical techniques to more advanced deep learning frameworks, Zhang et al. (2024) provide a thorough study of the evolution of ways for estimating air quality. Their research shows the effectiveness of spatial and temporal modelling as well as the integration of attention processes to improve the prediction model accuracy.

To forecast the Air Quality Index in major Indian cities, Natarajan et al. (2024) created a new machine learning model combining Grey Wolf Optimization and Decision Tree techniques. Development of this concept had place inside metropolitan settings. Their model demonstrated an amazing degree of accuracy when compared to conventional machine learning techniques, shown by performance measures showing accuracies for Visakhapatnam reaching 97.68%.

Hybrid models have been investigated in order to solve the nonlinear and stochastic aspects of air pollution. Nguyen et al. (2024) demonstrated a strong hybrid deep learning design. Using Quantum Particle Swarm Optimization, Attention Convolutional Neural Networks, Autoregressive Integrated Moving Average models, and Long Short-Term Memory networks supplemented in this architecture are included. By means of a 31.13% decrease in Mean Squared Error and a 2% increase in R-squared values when compared to traditional models, this model clearly shown a much superior predictive ability. Furthermore, the construction of prediction models about the air quality in megacities has benefited very significantly from the use of deep learning techniques. Sophisticated deep learning models were used in a study by Rad et al. (2025) to predict the quantities of certain air pollutants in Tehran, Afghanistan. Their studies show that, in terms of exposing the complex dynamics of urban air pollution, deep learning is better than more traditional methods of machine learning.

Combining Internet of Things (IoT) sensors, huge data analytics, and machine learning has helped the systems used to monitor and forecast air pollution to be much better. Gangwar et al. (2023) investigated the most current studies in this field holistically. They highlighted the need of smart devices in the data collection and analysis process on air quality, therefore enhancing the timeliness and accuracy of predictions. Apart from providing thorough understanding of the subtleties of air pollution dynamics and supporting the development of more efficient mitigating strategies, the results of these studies together show the great influence deep learning and hybrid models have on the prediction of air quality index (AQI).

Most notably in the fields of environmental monitoring, time-series forecasting, and the analysis of spatio-temporal data, recent advancements in prediction models using convolutional neural networks (CNNs) have resulted in an increase in their application over a wide spectrum. Predictive modelling uses CNN architectures because of their great ability to identify hierarchical feature representations generated from raw data inputs and precise spatial patterns. Its use in this industry results from this capacity. In the subject of Air Quality Index (AQI) prediction, models grounded on convolutional neural networks have been extensively used. This is so because these models can automatically extract from geographically dispersed pollution measurements (Wang et al., 2022; Li et al., 2023; Duan et al., 2023) automated features from multivariate time-series data.

More recently, studies have shown that hybrid convolutional neural network models combined with recurrent neural networks—more especially, Long Short-Term Memory networks—are effective in estimating the air quality index. Wang et al. (2022) proposed a CNN-ILSTM model with notably higher prediction accuracy by utilizing localized spatial variables via CNN layers. This was achieved simultaneously using advanced LSTM units to concurrently resolve long-term temporal relationships. By means of comparison with traditional models such as standalone deep learning support vector machines (LSTM), this hybrid method has been shown to be more successful in terms of metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Attention processes included into CNN-based models has produced a significant increase in AQI prediction accuracy. Li et al. created a CNN-LSTM-Attention model in 2023 that could independently find the most important spatio-temporal traits found in air pollution datasets. Particularly in the setting of multi-city AQI prediction tasks, the attention-enhanced hybrid models outperformed conventional CNN and LSTM models based on their results.

Furthermore, the integration of convolutional neural networks with statistical models like the autoregressive integrated moving average has attracted a lot of interest in the scholarly debate of the present. Duan et al. (2023) developed a great approach for tackling both linear and nonlinear parts of AQI datasets in which ARIMA, CNN, and LSTM were included into a model that was then enhanced using the Dung Beetle Optimizer technology. When it came to forecasting air quality indicators throughout a range of urban areas, the results of their experiments revealed that hybrid statistical-deep learning models produced enhanced generalization abilities. Combining convolutional neural networks with Quantum Particle Swarm Optimization will help Nguyen et al. (2024) significantly advance their use. This enabled CNN-LSTM hybrid frameworks' efficient hyperparameter modification within themselves. Their findings showed significant decreases in prediction error rates and increases in resilience when they applied them to noisy AQI datasets gathered from different sensors. Furthermore one of the novel uses of convolutional neural networks in the area of air quality index predictions is image-derived data inputs. Zhang et al. (2023) employed landscape photos to ascertain the degrees of air pollution by means of feature extraction applied using convolutional neural networks. This effectively linked quantitative air quality statistics with ambient visual data. These results clarify the possibilities of multimodal CNN-based prediction systems in the scope of environmental monitoring projects.

As Liu et al. (2023) clearly indicate, Spatiotemporal Convolutional Networks (ST-CNN) represent a major advancement in CNN-based prediction research. In the field, this represents a significant development. These networks enable to efficiently depict variations in air quality index (AQI) across large geographic areas by means of the deft integration of spatial and temporal convolutional layers. This model has been shown to be useful for projecting complex degrees of air quality index (AQI) at both urban and regional levels. Furthermore under investigation is the potential to anticipate the air quality index (AQI) by means of CNN models grounded on graphs. Chen et al. (2023) presented a hybrid approach able to effectively manage the spatial dependency among urban monitoring stations. Graph convolutional networks (GCN) and convolutional neural networks (CNNs) combined under this paradigm. By means of their investigation, they were able to demonstrate that the accuracy of spatial measurements significantly improved when graph-based learning was included into CNN architectures. Particularly when combined with long-term memory networks, attention mechanisms, optimization algorithms, and statistical models, these studies show both individually and collectively that convolutional neural network-based prediction models provide strong and accurate solutions for the forecasting of air quality indexes and a range of environmental monitoring efforts.

III. PROBLEM IDENTIFICATION

In light of these challenges, the problem is as follows:

- How can AQI prediction models be enhanced to provide more accurate and reliable forecasts?
- Can machine learning techniques, particularly transfer learning, be leveraged to overcome the confines of traditional AQI forecast models?

IV. RESEARCH OBJECTIVES

The precise aims of the investigation are delineated as follows:

- Investigate the use of transfer education to develop an accurate and efficient AQI prediction model by adapting pre-trained models from related fields.
- Identify the most suitable transfer learning techniques (e.g., fine-tuning, feature extraction) for AQI prediction tasks.

V. METHODOLOGY

The pseudo code of proposed methodology CNN-SGD is as follows:

Step 1: Import necessary libraries

(Libraries such as NumPy, Keras, TensorFlow, etc., would be used in actual code)

Step 2: Data Preprocessing

Load AQI data, including pollutant levels, temperature, humidity, and geographical data

Convert data into appropriate format (gridded data, images, or structured time-series)

Normalize or scale the features as needed (e.g., Min-Max scaling, Standardization)

train_data, test_data = load_and_preprocess_data()

Step 3: Divided the Data

Split data into drill, validation, and test sets

“x_train, y_train = train_data”

“x_val, y_val = validation_data”

“x_test, y_test = test_data”

Step 4: Build the CNN Prototypical

Initialize the CNN model (Consecutive API or Functional API in Keras)

model = initialize_CNN_model()

Convolutional Layer 1

model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(height, width, channels)))

Pooling Layer 1

model.add(MaxPooling2D(pool_size=(2, 2)))

Convolutional Layer 2

model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))

Pooling Layer 2

model.add(MaxPooling2D(pool_size=(2, 2)))

Flatten the 2D data to 1D

model.add(Flatten())

Fully Connected Layer

model.add(Dense(units=128, activation='relu'))

Output Layer (Predict continuous AQI value)

model.add(Dense(1, activation='linear'))

Step 5: Compile the Model with SGD Optimizer

Define the loss function and optimizer

model.compile(optimizer='SGD',

loss='mean_squared_error')

Step 6: Train the Model

Fit the model on the training data using Stochastic Gradient Descent optimizer

Set number of epochs, batch size, and validation data

model.fit(x_train, y_train, epochs=50, batch_size=32, validation_data=(x_val, y_val))

Step 7: Evaluate the Model

Evaluate the model on the test set to check the accuracy and performance

test_loss = model.evaluate(x_test, y_test)

Step 8: Predict AQI for new data

Use the trained model to predict AQI levels for new, unseen data

predictions = model.predict(x_new_data)

Step 9: Post-Processing (Optional)

If needed, map the predictions back to AQI categories (Good, Moderate, Unhealthy, etc.)

or apply any other transformations to the output

End of the process

VI. EXPERIMENTS AND RESULTS

The assessment of the proposed system's efficacy is presently in progress, employing a variety of performance metrics. This section demonstrates the comprehensive investigation undertaken via model experimentation, coupled with an in-depth analysis of the comparative evaluations being performed. The examination of regression results indicates the classification of cities in India into tiers of pollution: high, medium, and low. The forthcoming section will elucidate the outcomes of the simulations carried out in Ahmedabad, Chennai, and Ernakulam.

Table 1: Comparison of MAE for existing deep learning model and proposed model (CNN-SGD)

AQI Dataset	MAE	
	Existing deep learning model [1]	CNN-SGD (Proposed)
Ahmedabad	0.0979	0.0841
Chennai	0.0795	0.0512
Ernakulam	0.1013	0.0918

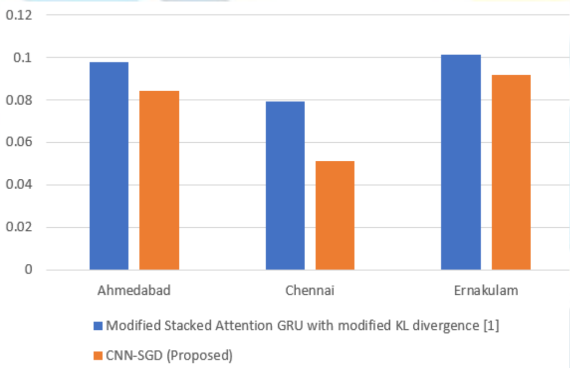

Figure 1: A visual depiction of the Mean Absolute Error (MAE) for both the established deep learning model and the proposed model utilizing Convolutional Neural Networks with Stochastic Gradient Descent (CNN-SGD).

The MAE value achieved by the proposed model is 0.08419, 0.05128, and 0.0918, which represents a reduction compared to the existing deep learning model (Existing deep learning model [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (CNN-SGD) demonstrates superior performance compared to existing deep learning models.

Table 2: A Comparative Analysis of Mean Squared Error for Established Deep Learning Models and the Proposed CNN-SGD Framework

AQI Dataset	MSE	
	Existing deep learning model [1]	CNN-SGD (Proposed)
Ahmedabad	0.0161	0.0098
Chennai	0.0095	0.0091
Ernakulam	0.0134	0.0097

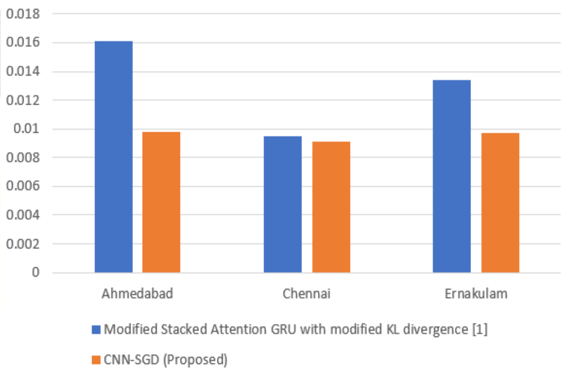

Figure 2: Graphical representation of MSE for existing deep learning model and proposed model (CNN-SGD)

The Mean Squared Error (MSE) values achieved by the proposed model are 0.0098, 0.0091, and 0.0097, indicating a reduction compared to the existing deep learning model (Existing deep learning model [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (CNN-SGD) demonstrates superior performance in comparison to existing deep learning models.

Table 3: A Comparative Analysis of RMSE Between the Established Deep Learning Model and the Proposed CNN-SGD Model

AQI Dataset	RMSE	
	Existing deep learning model [1]	CNN-SGD (Proposed)
Ahmedabad	0.1271	0.1015
Chennai	0.0977	0.0817
Ernakulam	0.1156	0.1004

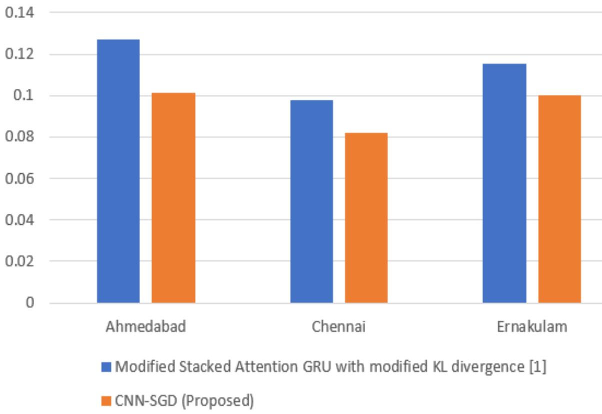

Figure 3: A graphical depiction illustrating the RMSE for both the current deep learning model and the proposed model (CNN-SGD).

The RMSE values achieved by the proposed model are 0.1015, 0.0817, and 0.1004, which represent a reduction compared to the existing deep learning model (Existing deep learning model [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (CNN-SGD) demonstrates superior performance compared to existing deep learning models.

Table 4: A Comparative Analysis of R-Square Values for the Established Deep Learning Model Versus the Proposed CNN-SGD Model

AQI Dataset	R Square	
	Existing deep learning model [1]	CNN-SGD (Proposed)
Ahmedabad	0.8942	0.8041
Chennai	0.9064	0.9001
Ernakulam	0.9479	0.9218

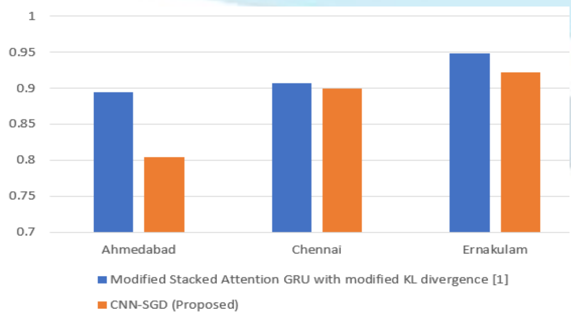

Figure 4: A graphical depiction of the R-Square values for the current deep learning model in comparison to the proposed CNN-SGD model.

The R-Square values derived from the proposed model are 0.8041, 0.9001, and 0.9218, which are lower than those of the existing deep learning model (Existing deep learning model [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (CNN-SGD) demonstrates superior performance in comparison to existing deep learning models.

Table 5: Comparison of MAPE for existing deep learning model and proposed model (CNN-SGD)

AQI Dataset	MAPE	
	Existing deep learning model [1]	CNN-SGD (Proposed)
Ahmedabad	0.0587	0.0142
Chennai	0.1219	0.1002
Ernakulam	0.1152	0.1021

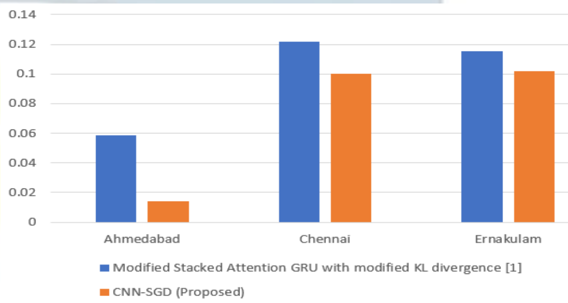

Figure 4: Graphical representation of MAPE for existing deep learning model and proposed model (CNN-SGD)

The MAPE values derived from the proposed model are 0.0142, 0.1002, and 0.1021, indicating a reduction in difference compared to the existing deep learning model (Existing deep learning model [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (CNN-SGD) demonstrates superior performance in comparison to existing deep learning models.

VII. CONCLUSION AND FUTURE WORK

The suggested CNN-SGD model demonstrates superior performance compared to the current deep learning model across various metrics, including MAE, MSE, RMSE, R-Square, and MAPE. The suggested model demonstrates a reduced MAE value (0.08419, 0.05128, 0.0918) and MSE value (0.0098, 0.0091, 0.0097) in contrast to the current deep learning model [1]. The suggested model exhibits reduced R-Square values (0.08041, 0.9001, 0.9218) in contrast to the current model deep learning model [1]. The suggested model demonstrates reduced MAPE values (0.0142, 0.1002, 0.1021) in contrast to the current deep learning model [1]. In summary, the proposed model demonstrates superior performance compared to the current deep learning model across these metrics. The proposed model is anticipated to serve as an invaluable instrument for enhancing the efficacy of deep learning systems across a multitude of applications.

Future research focuses on the crucial need for a new technological development or improvements in medical image processing in order to treat cancer tissues a little bit more quickly. In order for clinicians to provide a better-informed diagnosis, these advancements must also be focused on producing more precise outcomes. However, by enhancing the associated highlighted features, this proposed system design might be improved in the future.

- Investigate different normalization and regularization strategies (e.g., instance normalization, group normalization) in combination with CNNs.
- Extend the architecture to a multi-task setting where tumor localization and type classification are performed simultaneously.
- Explore domain adaptation or transfer learning approaches to handle multi-institutional data, addressing dataset shift problems.

Incorporate explainable AI (XAI) techniques for better interpretability and acceptance in clinical workflows.

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