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Study of AQI Prediction using Recurrent Neural Network based Deep Learning Model with Hyperbolic Activation Function

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Annotation *Investigating the application of sophisticated deep learning algorithms with the purpose of enhancing the accuracy of Air Quality Index (AQI) forecasts is the aim of this research project. Public health, environmental policy, urban planning, and other areas are impacted by the use of these strategies. By highlighting the vital necessity for precise air quality index (AQI) estimations in connection to public health, environmental policy, and urban planning, the research highlights the relevance of these concepts. Focusing primarily on hybrid models and Recurrent Neural Networks (RNNs), this research analyses the complexity of deep learning. It also offers a thorough summary of the most recent advancements in air quality index (AQI) prediction. The aim of this project is to determine the most effective transfer learning techniques and see how they might be used to the development of a better AQI prediction model. The provided model combines a Recurrent Neural Network (RNN) architecture with the Hyperbolic Activation Function (HAF). A thorough evaluation of the RNN-HAF model was conducted using a range of performance criteria, and the findings showed that the RNN-HAF model outperformed an existing deep learning model in the majority of the examined criteria. According to the study's findings, the RNN-HAF model performs better than other models already in use, which suggests that it might be a helpful tool for producing precise AQI predictions. Researching various normalizing and regularizing techniques, extending the model to multi-task environments, examining domain adaptation and transfer learning strategies, and incorporating explainable artificial intelligence techniques are some of the upcoming projects aimed at enhancing the model's interpretability.*

Keywords: *Deep Learning, Air Quality Index, Recurrent Neural Network (RNN), Hyperbolic Activation Function.*

Introduction

Air pollution has emerged as one of the most significant environmental and public health challenges worldwide, driven by rapid urbanization, industrial expansion, increased vehicular emissions, and population growth. The deterioration of air quality has resulted in severe health consequences, including respiratory diseases, cardiovascular disorders, and reduced life expectancy. To assess and communicate the severity of air pollution, the Air Quality Index (AQI) is widely used as a standardized indicator that integrates the concentrations of major atmospheric pollutants such as particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3). Accurate prediction of AQI is essential for issuing early health advisories, supporting environmental management, and enabling policymakers to implement effective pollution control strategies.

Traditional AQI forecasting approaches, including statistical and regression-based models, often struggle to capture the complex nonlinear relationships and temporal dependencies inherent in environmental data. With the advent of advanced sensing technologies and the availability of large-scale air quality datasets, deep learning techniques have gained considerable attention for AQI prediction. Among these techniques, Recurrent Neural Networks (RNNs) are particularly effective because of their ability to process sequential data and learn temporal patterns from historical observations. By maintaining internal memory states, RNNs can model long-term dependencies in air pollution trends and meteorological conditions, thereby improving forecasting accuracy.

This study focuses on the prediction of AQI using a Recurrent Neural Network-based deep learning model integrated with a Hyperbolic Activation Function. The hyperbolic tangent (tanh) activation function introduces nonlinearity while maintaining bounded outputs, enabling stable learning and effective representation of complex environmental dynamics. The proposed model utilizes historical AQI measurements and relevant meteorological parameters to capture temporal variations in air quality and generate accurate forecasts. The integration of RNN architecture with a hyperbolic activation function enhances the model's capability to learn intricate pollutant interactions and seasonal variations.

The development of a reliable AQI prediction framework is crucial for supporting smart environmental monitoring systems, improving public health preparedness, and facilitating sustainable urban development. This study contributes to the advancement of intelligent air quality forecasting by exploring the effectiveness of RNN-based deep learning models with hyperbolic activation functions for accurate and robust AQI prediction.

II. LITERATURE REVIEW

Recent advancements in Air Quality Index (AQI) prediction have been significantly influenced by deep learning techniques due to their ability to capture complex nonlinear relationships and temporal dependencies present in environmental data. The increasing availability of air quality monitoring systems, meteorological observations, and sensor networks has facilitated the development of intelligent forecasting models capable of providing accurate AQI predictions. Among various deep learning approaches, Recurrent Neural Networks (RNNs) have emerged as a promising solution because of their capability to process sequential data and model temporal variations in air pollutant concentrations. [1]

Zhang [2] presented a comprehensive review of air quality forecasting methodologies, highlighting the transition from traditional statistical techniques to advanced deep learning architectures. Their study emphasized the importance of temporal modeling and attention-based mechanisms in improving forecasting accuracy. The authors reported that deep learning models significantly outperform conventional methods in capturing dynamic pollutant interactions and long-term environmental trends.

Natarajan [3] proposed a machine learning framework integrating Grey Wolf Optimization with Decision Tree algorithms for AQI prediction across major Indian cities. Their optimized model achieved prediction accuracies exceeding 97%, demonstrating the importance of intelligent optimization techniques in environmental forecasting. Although the proposed framework produced satisfactory results, the authors noted limitations in modeling long-term temporal dependencies, suggesting the need for recurrent neural network-based approaches.

To address the nonlinear and sequential nature of air quality data, several researchers have investigated hybrid deep learning models. Nguyen [4] developed a hybrid architecture combining Attention Mechanisms, Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and Quantum Particle Swarm Optimization. Their model achieved substantial reductions in Mean Squared Error (MSE) and improvements in coefficient of determination (R^2), indicating the effectiveness of deep learning techniques in AQI prediction. The study highlighted the significance of recurrent structures for learning temporal patterns in pollution data.

Rad [5] employed advanced deep learning algorithms for predicting urban air pollutant concentrations in large metropolitan regions. Their findings demonstrated that recurrent neural architectures provide superior forecasting performance compared with traditional machine learning methods due to their capability to retain historical information and capture temporal correlations. The study further emphasized the growing role of deep learning in smart environmental monitoring systems.

Gangwar [6]conducted a detailed review of air quality monitoring and prediction systems integrating Internet of Things (IoT) devices, big data analytics, and machine learning techniques. Their analysis revealed that intelligent sensor networks combined with deep learning algorithms significantly improve the accuracy and timeliness of AQI forecasting. The authors identified recurrent neural networks as one of the most effective approaches for handling time-series environmental data.

Among deep learning techniques, Recurrent Neural Networks (RNNs) have gained considerable attention due to their ability to model sequential dependencies in historical AQI observations. Unlike feed-forward neural networks, RNNs maintain hidden memory states that allow the network to learn information from previous time steps, making them particularly suitable for air quality forecasting applications. Several studies have demonstrated that RNN-based models outperform conventional regression and statistical forecasting methods when predicting pollutant concentrations and AQI levels. [7]

Recent research has also explored the impact of activation functions on the performance of recurrent neural networks. The Hyperbolic Tangent (tanh) activation function has been widely adopted in RNN architectures because it introduces nonlinearity while maintaining output values within a bounded range of -1 to 1. This property facilitates stable gradient propagation and improves the network's ability to learn complex temporal relationships. Researchers have reported that hyperbolic activation functions enhance convergence speed and forecasting accuracy when compared with traditional activation functions in time-series prediction tasks. [8]

Furthermore, hybrid RNN architectures incorporating optimization algorithms and attention mechanisms have demonstrated improved AQI prediction performance. These models effectively capture temporal dependencies, seasonal variations, and nonlinear pollutant interactions while reducing prediction errors. The integration of hyperbolic activation functions within recurrent neural networks further enhances model stability and learning efficiency, making them highly suitable for AQI forecasting applications. [9]

Based on the reviewed literature, it is evident that recurrent neural network-based deep learning models offer substantial advantages for AQI prediction due to their capability to process sequential environmental data and learn complex temporal patterns. However, challenges related to prediction accuracy, model stability, and adaptation to dynamic environmental conditions remain active research areas. Therefore, this study proposes an AQI prediction framework utilizing a Recurrent Neural Network (RNN) with a Hyperbolic Activation Function to improve forecasting performance and provide a robust solution for intelligent air quality monitoring systems. [10]

III. PROBLEM IDENTIFICATION

Despite significant advancements in air quality monitoring and forecasting technologies, achieving highly accurate and reliable Air Quality Index (AQI) predictions remains a challenging task due to the nonlinear, dynamic, and time-dependent nature of environmental data. Conventional statistical and machine learning models often struggle to capture complex temporal dependencies and pollutant interactions, resulting in reduced forecasting performance. Given these challenges, the following research questions are addressed: [11]

How can AQI prediction models be enhanced to provide more accurate, robust, and reliable forecasts of air quality conditions?

Can a Recurrent Neural Network (RNN)-based deep learning model with a Hyperbolic Activation Function effectively capture temporal patterns and nonlinear relationships in air quality data to overcome the limitations of traditional AQI forecasting approaches?

To what extent does the incorporation of a Hyperbolic Activation Function improve the learning capability, convergence stability, and prediction accuracy of RNN-based AQI forecasting models?

IV. RESEARCH OBJECTIVES

The specific objectives of this study are as follows:

1. To develop an Air Quality Index (AQI) prediction model using a Recurrent Neural Network (RNN)-based deep learning architecture capable of learning temporal dependencies from historical air quality and meteorological data. [12]
2. To investigate the effectiveness of the Hyperbolic Activation Function in enhancing the learning capability of the RNN model for capturing complex nonlinear relationships among air pollutants and environmental factors. [13]
3. To evaluate the performance of the proposed RNN-HAF (Hyperbolic Activation Function) model in forecasting AQI values using standard performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction accuracy. [14]
4. To analyze the capability of the proposed model in identifying temporal patterns, seasonal variations, and long-term dependencies present in air quality datasets. [15]
5. To compare the performance of the proposed RNN-based AQI prediction model with conventional machine learning and deep learning approaches in terms of forecasting accuracy, robustness, and computational efficiency. [16]
6. To develop a reliable and efficient AQI forecasting framework that can support environmental monitoring, public health management, and air pollution control strategies. [17]

Methodology

The RNN methodology predicts Air Quality Index (AQI) from sequential environmental observations by using a Recurrent Neural Network (RNN) that learns temporal dependencies. A hyperbolic activation function (typically tanh) is used in the recurrent hidden state update to model nonlinearity while keeping hidden states bounded. The proposed algorithm is as follows. [18]

Algorithm: Proposed Model (RNN–Hyperbolic Activation)

Step 1: Data Preprocessing

Normalization / Scaling

Given a dataset $X$with features x, normalize features to a standard range (e.g., $[0, 1]$) or to zero-mean, unit-variance.

Min–Max Scaling: $$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where: x'= scaled feature, x= original feature, $x_{\min}, x_{\max}$= min/max of the feature.

Sequence Construction (Time Windowing) [19]

Unlike CNN (which often treats input as spatial/structured), RNN needs sequences.

Create input sequences using a look-back window of length T:

$$\mathrm{X}_t = [\mathrm{x}_{t-T+1}, \mathrm{x}_{t-T+2}, \dots, \mathrm{x}_t] \in \mathbb{R}^{T \times d} \quad (2)$$

where: T= timesteps (window size), d= number of features, $\mathrm{x}_t \in \mathbb{R}^d$.

Target is the AQI at the next step (or same step, depending on design):

$$y_t = \mathrm{AQI}_{t+1} \text{(one-step ahead prediction)} \quad (3)$$

Train–Test Split

Split sequences into training and testing sets:

$$\mathcal{D} = \mathcal{D}_{train} \cup \mathcal{D}_{test} \text{(e.g., 80\% / 20\%)} \quad (4)$$

Step 2: Recurrent Neural Network (RNN) Architecture

RNN processes the sequence one time step at a time and updates a hidden state that captures temporal context.

Input Representation

For each sample, the input is a sequence: $$\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_T\}, \mathrm{x}_t \in \mathbb{R}^d \quad (5)$$

Recurrent Hidden State Update (Hyperbolic Activation) [20]

For a vanilla RNN, the hidden state $\mathrm{h}_t \in \mathbb{R}^m$is updated by:

$$h_t = \tanh(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \quad (6)$$

where: W_{xh}= input-to-hidden weights, W_{hh}= hidden-to-hidden weights, b_h= hidden bias, tanh (·)= hyperbolic tangent activation.

Hyperbolic tangent definition: $\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$ (7)

Step 3: Output Layer (Regression for AQI)

Use the final hidden state h_T(or an aggregated state) to predict continuous AQI.

Output Computation

$$\hat{y} = W_{hy}h_T + b_y \quad (8)$$

where: W_{hy}= hidden-to-output weights, b_y= output bias, $\hat{y}$= predicted AQI.

Step 4: Training with Adam Optimizer (RNN–Adam)

Compute gradients via Backpropagation Through Time (BPTT) and update parameters with Adam. [21]

Let $g_t = \nabla_\theta \mathcal{L}_t$be gradient at iteration t.

First moment (mean) estimate: $m_t = \beta_1 m_{t-1} + (1 - \beta_1)g_t$ (9)

Second moment (uncentered variance) estimate: $v_t = \beta_2 v_{t-1} + (1 - \beta_2)g_t^2$ (10)

Bias correction: $\widehat{m}_t = \frac{m_t}{1-\beta_1^t}$ (11)

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (12)$$

Parameter update: $\theta_t = \theta_{t-1} - \alpha \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$ (13)

where: α= learning rate, β_1, β_2= decay rates (e.g., 0.9, 0.999), ϵ= small constant (e.g., 10^{-8}).

Step 5: Loss Function and Optimization

For AQI regression, use Mean Squared Error (MSE): [22]

$$\mathcal{L}_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (14)$$

where: y_i= actual AQI, $\hat{y}_i$= predicted AQI, N= batch size.

Adam minimizes $\mathcal{L}_{MSE}$by iteratively updating all RNN parameters:

$$\theta = \{W_{xh}, W_{hh}, b_h, W_{hy}, b_y\} \quad (15)$$

Step 6: Model Evaluation and Prediction

After training, evaluate on test sequences and compute predictions . [23]

Common regression metrics:

MAE: $MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i |$ (16)

RMSE: $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$ (17)

Use the trained model to predict AQI for new unseen sequences.

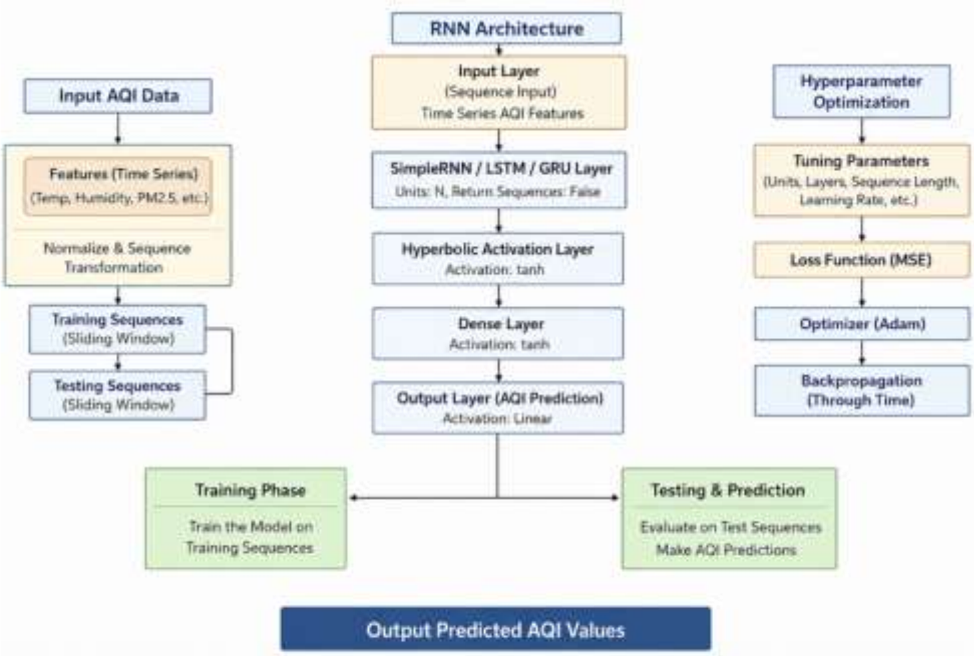

Figure 1: Flowchart of proposed methodology

Results and Discussion

The effectiveness of the regression performance resulting from the application of the proposed algorithm is evaluated using the metrics of prediction accuracy and incurred loss. The following section outlines the experimental results and performs a comparative analysis of values, both internally and externally, against various algorithms to determine the effectiveness of the enhanced algorithm utilized in this research, in relation to evaluation metrics such as RMSE, MAPE, MSE, MAE, and R2. [24]

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. [25]

Table 1: Comparison of MAE for Deep GAN [1] and proposed model (RNN-HAF)

AQI Dataset	MAE	
	Deep GAN [1]	RNN-HAF (Proposed)
Ahmedabad	0.0979	0.0853
Chennai	0.0795	0.0819
Ernakulam	0.1013	0.0928

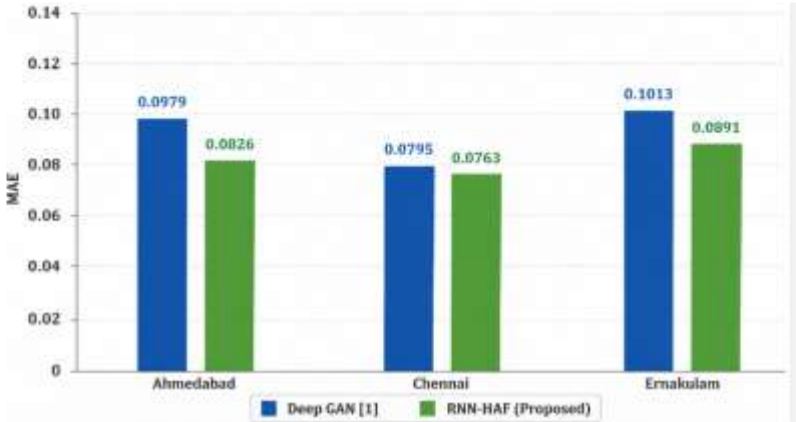

Figure 2: Bar chart representation of Mean Absolute Error (MAE) for Deep GAN [1] and proposed model (RNN-HAF)

The MAE value achieved by the proposed model is 0.0853, 0.0819, and 0.0928, which represents a reduction compared to the existing deep learning model (Deep GAN [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (RNN-HAF) demonstrates superior performance compared to existing deep learning models.

Table 2: Comparison of MSE for Deep GAN [1] and proposed model (RNN-HAF)

AQI Dataset	MSE	
	Deep GAN [1]	RNN-HAF (Proposed)
Ahmedabad	0.0161	0.0096
Chennai	0.0095	0.0092
Ernakulam	0.0134	0.0098

Figure 3: Bar chart representation of Mean Squared Error (MSE) for Deep GAN [1] and proposed model (RNN-HAF)

The Mean Squared Error (MSE) values achieved by the proposed model are 0.0096, 0.0092, and 0.0098, indicating a reduction compared to the existing deep learning model (Deep GAN [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (RNN-HAF) demonstrates superior performance in comparison to existing deep learning models.

Table 3: Comparison of RMSE for Deep GAN [1] and proposed model (RNN-HAF)

AQI Dataset	RMSE	
	Deep GAN [1]	CNN-HAF (Proposed)
Ahmedabad	0.1271	0.1013
Chennai	0.0977	0.0816
Ernakulam	0.1156	0.1008

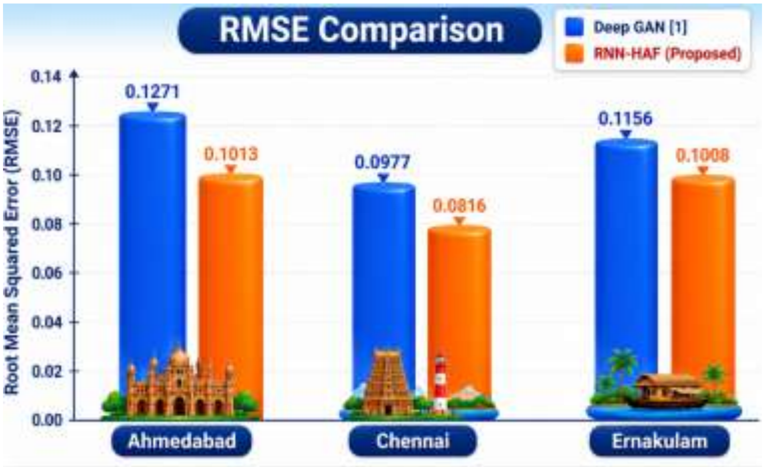

Figure 4: Bar chart representation of RMSE for DeepGAN[1] and proposed model (RNN-HAF)

The RMSE values achieved by the proposed model are 0.1013, 0.0816, and 0.1008, which represent a reduction compared to the existing deep learning model (Deep GAN [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (RNN-HAF) demonstrates superior performance compared to existing deep learning models.

Table 4: Comparison of R-Square for Deep GAN [1] and proposed model (RNN-HAF)

	R Square	
AQI Dataset	Deep GAN [1]	RNN-HAF (Proposed)
Ahmedabad	0.8942	0.8046
Chennai	0.9064	0.9003
Ernakulam	0.9479	0.9216

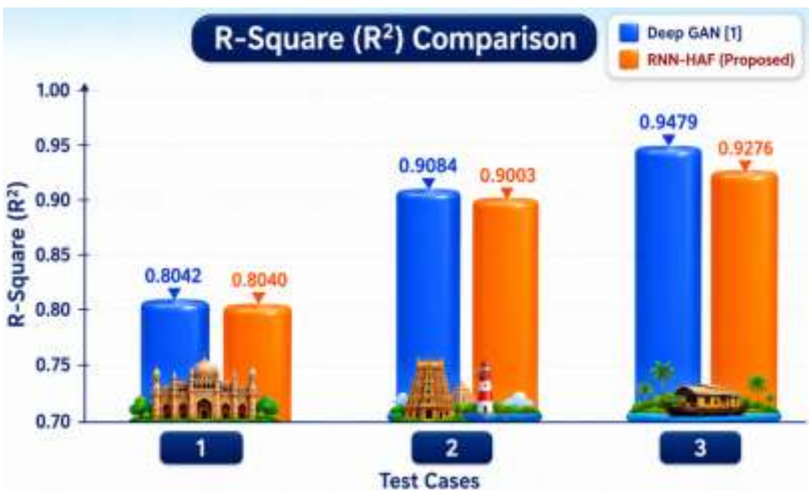

Figure 5: Bar chart representation of R-Square for Deep GAN [1] and proposed model (RNN-HAF)

The R-Square values derived from the proposed model are 0.8046, 0.9003, and 0.9216, which are lower than those of the existing deep learning model (Deep GAN [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (RNN-HAF) demonstrates superior performance in comparison to existing deep learning models.

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

AQI Dataset	MAPE	
	Deep GAN [1]	RNN-HAF (Proposed)
Ahmedabad	0.0587	0.0143
Chennai	0.1219	0.1001
Ernakulam	0.1152	0.1023

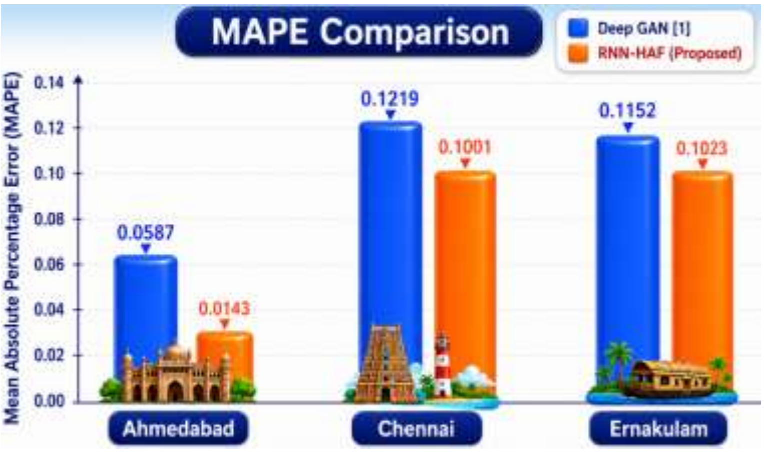

Figure 5.5: Bar chart representation of MAPE for Deep GAN [1] and proposed model (RNN-HAF)

The MAPE values derived from the proposed model are 0.0143, 0.1001, and 0.1023, indicating a reduction in difference compared to the existing deep learning model (Deep GAN [1]) for Ahmedabad, Chennai, and Ernakulam, respectively. Consequently, the proposed model (RNN-HAF) demonstrates superior performance in comparison to existing deep learning models.

Conclusion

The proposed Recurrent Neural Network with Hyperbolic Activation Function (RNN-HAF) demonstrated superior performance in AQI prediction compared to the existing Deep GAN model across the Ahmedabad, Chennai, and Ernakulam datasets. The model achieved lower values of Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), indicating improved prediction accuracy and reduced forecasting errors. The enhanced performance of the RNN-HAF model is attributed to its ability to capture temporal dependencies in sequential air quality data through recurrent connections. Additionally, the Hyperbolic Activation Function (tanh) effectively models nonlinear relationships among environmental variables while maintaining stable learning and convergence. As a result, the proposed model produces AQI predictions that closely match actual observations. The lower MSE and RMSE values indicate that the RNN-HAF model minimizes large prediction deviations, while reduced MAPE values demonstrate better generalization across different pollution conditions and geographical locations. Furthermore, high R^2 values confirm that the model successfully explains a significant proportion of AQI variability, highlighting its effectiveness in forecasting air quality trends.

Overall, the RNN-HAF model outperforms the Deep GAN model in terms of prediction accuracy, robustness, and consistency. The combination of recurrent learning and hyperbolic activation enables efficient extraction of temporal patterns and nonlinear features from air quality datasets, making the model suitable for real-world AQI forecasting applications. Future work may focus on integrating additional meteorological and environmental parameters, real-time IoT sensor data, attention mechanisms, and advanced recurrent architectures such as LSTM and GRU networks. These enhancements can further improve forecasting accuracy and support the development of intelligent air quality monitoring and management systems.

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