Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 09 Issue 01
2025

Research Article
https://doi.org/10.56979/901/2025

A Deep Learning Approach for Modeling Air Quality Dynamics using Historical Environmental Data

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Received: April 07, 2025 **Accepted:** May 24, 2025

Abstract: Deep learning (DL) has emerged as a powerful tool for air quality forecasting, yet achieving consistently high predictive accuracy remains a significant challenge. In order to improve the air quality and its index forecasts, a number of models have been used, with some adopting the hybridization approaches. In this research, Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) capabilities are combined to present a deep learning-based ensemble technique for simulating air quality dynamics using historical environmental data. The CNNs Model enhance the effectiveness of the ensemble model by extracting spatial information that can raise the accuracy of air quality dynamics predictions. Furthermore, the model's capacity to recognize intricate spatial-temporal patterns in environmental data is improved when CNNs are combined with artificial neural networks. Air quality dataset is used to train the proposed model and other deep learning models, including Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) used to predict air quality. The pre-processing techniques such as removing missing values, categorical value handling and label encoding, are applied on the dataset to enhance input quality. The proposed ensemble method is compared with other deep learning models and shows substantially better accuracy, precision, recall, and F1-score are 0.9985, 0.9988, 0.9984, and 0.9986, respectively. These validated deep learning-based models in air quality prediction can provide valuable insights for authorities and environmental organizations, supporting the development of data-driven pollution control measures and public health initiatives.

Keywords: Deep Leaning; Index Forecast; Environmental Data; Ensemble Learning; Air Quality; Prediction

1. Introduction

The environment, crops, and human health are all at risk from harmful air pollutants, which include dust, smoke, and gasses like sulfur dioxide and carbon monoxide. As cities and industries grow, the issue has gotten worse. It's interesting to note that this pollution is directly impacted by local weather [1]. The way pollution spreads and builds up is influenced by temperature, wind patterns, and humidity levels. For instance, while sluggish conditions cause polluted air to persist, powerful breezes can disperse it [2]. Communities and governments can take more intelligent measures to safeguard public health by comprehending these links and enhancing air quality forecasts [3].

The prediction ability of the Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) models for specific air pollutants like Particulate Matter 10 (PM10) and Sulfur Dioxide (SO2) has also been assessed using metrics like R-squared (R2), Mean Absolute Error

(MAE), Root Mean Square Error (RMSE), and Mean Squared Error (MSE). The accuracy of LSTM models was higher than that of MLP and RNN models. The LSTM model accurately forecasts PM10 and SO2 concentrations, according to tests comparing its efficacy to other candidates identified in the literature. This study provides intriguing new information about the application of deep learning models to pollution prediction [4].

They excel in air quality forecasting because they can depict complex temporal relationships, identify sequential dependencies, and account for missing data. In order to improve forecasting, the LSTM and Bidirectional Long Short-Term Memory (BiLSTM) networks introduce fresh pollution data into the LSTM and discard crucial information from previous observations due to weather and pollution [5]. Depending on the architectures, characteristics, and quality of the data, several experimental configurations are required to calibrate these models [6]. Machine learning and deep learning outperform traditional methods in handling large and complex data, uncovering intricate patterns, and accurately identifying pollution sources through remote sensing [7]. For regulating air quality in the context of urban planning and policy making, this provides them some data-driven and economical possibilities [8].

Wu & Lin (2019) showed that this simplified RNN variant can outperform regular LSTM (88.65%) while approaching RNN performance (94.73%) with an accuracy of 93.56% in air quality forecasting utilizing Gated Recurrent Units (GRUs) [9]. The findings demonstrate how well GRUs explain temporal pollution patterns using less computing power than LSTM, providing a well-rounded approach for time-series environmental data [10]. This study demonstrates that gated recurrent architectures are still viable options for sequential tasks involving the prediction of air quality [34].

Furthermore, predict the amount of ozone in Murcia's air quality was started in 2018. Artificial Neural Networks (ANNs), Decision Tree (DT), RF, and Logistic Regression (LR) were the four regression approaches that were utilized to forecast air quality using machine-learning algorithms [11]. Evaluating processing time and data quantities was the first step in creating the criterion for the optimal technique baseline. In terms of the accuracy of air quality forecasts, random forest regression outperformed the other datasets, which varied in size, location, and feature [12].

Time-series prediction, object identification, speech recognition, and classification are the large data analytical problems that have previously been tackled with deep learning approaches. These approaches utilized for the prediction of the data that can be handled in the condition of data [13]. Deep learning techniques have shown promising outcomes that utilized in the majority of relevant research studies addressing air pollution prediction. LSTM-fully connected neural network, a deep learning model designed to forecast the concentration of particle pollution at certain monitoring stations during a 48-hour period [14].

Due to their inability to handle spatial-temporal dependencies, noise, and missing data, traditional air quality prediction models are unable to adequately represent the intricate, nonlinear relationships between pollution levels and environmental factors [15]. In order to overcome these obstacles and increase the accuracy of air quality forecasts, this research intends to use the ensemble deep learning techniques by incorporate the features of CNN and ANN that effectively captures spatial features and complex interactions to improve predictive accuracy. This will help with improved pollution control and public health decisions.

The contribution of this research are as follows:

- Proposed an ensemble deep learning model that combine convolutional neural networks for spatial feature extraction and artificial neural networks for learning complex relationship for modeling air quality dynamics.
- The preprocessing methods applied include handling missing values, categorical data encoding, and label encoding to ensure high-quality input for model training.
- Developed and tested CNN, ANN, RNN, and LSTM models for air quality prediction using historical environmental data.
- The performance of proposed model is evaluated used key evaluation metrics such as precision, recall, accuracy, and f1 score to assess their effectiveness in forecasting air quality dynamics.

The rest of the paper is summarize as follows: Section 2 presented the related work that are relevant to the proposed methodology. Section 3 explain the research methodology in which the ensemble deep learning model based on CNN and ANN is proposed. Section 4 discusses the results and discussion of proposed study. Section 5 represent the conclusion and future work of this research.

2. Related Work

In several instances, air pollution levels have been predicted through the significant use of statistical and machine learning approaches [16]. RMSE and MAE have been used to assess a number of models using data from Kolkata's government-run air pollution monitoring stations [17]. Based on the Holt-Winter scheme, the forecasting models indicated above have performed better than PM2.5, PM10, and SO2 time series, but better than deep-learning techniques Conv LSTM and Bi-LSTM in NO2 time series data [18]. There are different parameters used for the analysis of the selection for the data to predict the result using deep neural network model [19][20]. LSTMs are excellent at handling nonlinear interactions and capturing long-term patterns since air pollution data is time-dependent [21]. While using the spatial-temporal models to account for both time and geographical factors could lead to further improvements which validates the use of deep learning for air quality forecasting [22]. This study provides a solid basis for developing increasingly complex AI-powered pollution forecasting systems [23].

A hybrid CNN-LSTM model is proposed that achieved an accuracy of 89.91% in predicting air quality [8]. This model successfully captured both time-dependent and geographic pollution patterns by merging LSTM for temporal pattern learning with Convolutional Neural Networks (CNN) for spatial feature extraction [24]. This showed that hybrid deep learning architectures can further improve forecasting precision, outperforming single LSTM techniques [25]. The findings emphasize to essential is to incorporate spatial-temporal analysis into air quality models in order to increase the accuracy of predictions [26]. Mao et al. (2021) showed that Recurrent Neural Networks (RNNs) performed better than LSTM (88.65%) and CNN-LSTM (89.91%) models, achieving 94.73% accuracy in air quality prediction [27]. This increased accuracy shows that RNNs may successfully capture intricate temporal correlations in pollution data if they are appropriately optimized [28] [29]. This study establishes a standard for temporal modeling in studies on pollution prediction [9].

Artificial neural networks can forecast air quality with 92.74% accuracy, surpassing some conventional methods. Even though ANNs don't have the same temporal memory as RNNs or LSTMs, their excellent performance indicates that they can still be used for some pollution forecasting tasks, especially when working with environmental data that has been preprocessed or isn't sequential [30]. Although more sophisticated models would be required for complicated spatiotemporal interactions in air quality data, offers a crucial benchmark by demonstrating comparable results using deep learning [31]. Bidirectional LSTM (BLSTM) was used to forecast air quality and an accuracy of 92.62%. By processing data both forward and backward, BLSTMs outperform conventional LSTMs in capturing more thorough temporal interdependence in pollution trends [32]. This finding shows that BLSTMs are better at modeling complex time-series patterns, which makes them especially helpful for assessing changing pollution levels with delayed atmospheric impacts [33]. The study demonstrates how temporal feature learning in environmental forecasting problems can be improved via bidirectional designs.

Gated Recurrent Units (GRUs) proves the practical substitute for LSTMs when utilized to predict air quality with 93.56% accuracy [30]. By integrating forget and input gates into a single update gate, GRUs streamline the gating process of conventional LSTMs while preserving similar temporal modeling performance [10]. This architecture is especially well-suited for real-time forecasting systems since it effectively catches both long-term seasonal trends and short-term pollution spikes without the processing expense of LSTMs [34] [35]. Furthermore, artificial neural networks to estimate air quality with 92.74% accuracy, showing that ANNs don't have built-in temporal memory and it can nevertheless model complicated pollution patterns [36]. This is especially true when temporal dependencies are pre-processed or when feature engineering techniques are used [37]. The Summary of related work shown in Table 1.

Table Error! No text of specified style in document.**1.** Summary of the Related Work

References	Models	Accuracy
[38]	LSTM	88.65%
[39]	CNN-LSTM	89.91%

[40]	RNN	94.73%
[41]	ANN	92.74%
[42]	GRU	93.56%
[43]	BLSTM	92.62%

3. Proposed Methodology

The goal of air quality modeling is to provide as much information as possible on the many health and environmental effects that influence pollution levels. For deep learning models to be trained using regularly and reliably prepared data, the present interface must be preprocessed. In order to prevent data loss, this stage manages the missing values in a way that allows any imputation approaches to be used. In order to fit the model, categorical data is encoded using label encoding. Following processing, the data is divided into training and test datasets, with 80% going toward training and 20% going toward testing the created model. Several deep learning models, including CNN, ANN, RNN, and LSTM, have been required for forecasting air quality. Each model looks for any hidden patterns in the data on air pollution underwent testing and training. To improve prediction accuracy, the ensemble deep learning model based CNN and ANN is proposed. In order to differentiate in its non-trivial interrelations, the ANN learns to apply spatial features that CNN inherits from the dataset. The ensemble architecture outperforms all of the current architectures in terms of prediction by combining the best features of both systems. The performance metrics including recall, accuracy, and precision are used to evaluate the proposed method. These measurements' outcomes are also useful for predicting air quality. Figure 1 shows the proposed methodology.

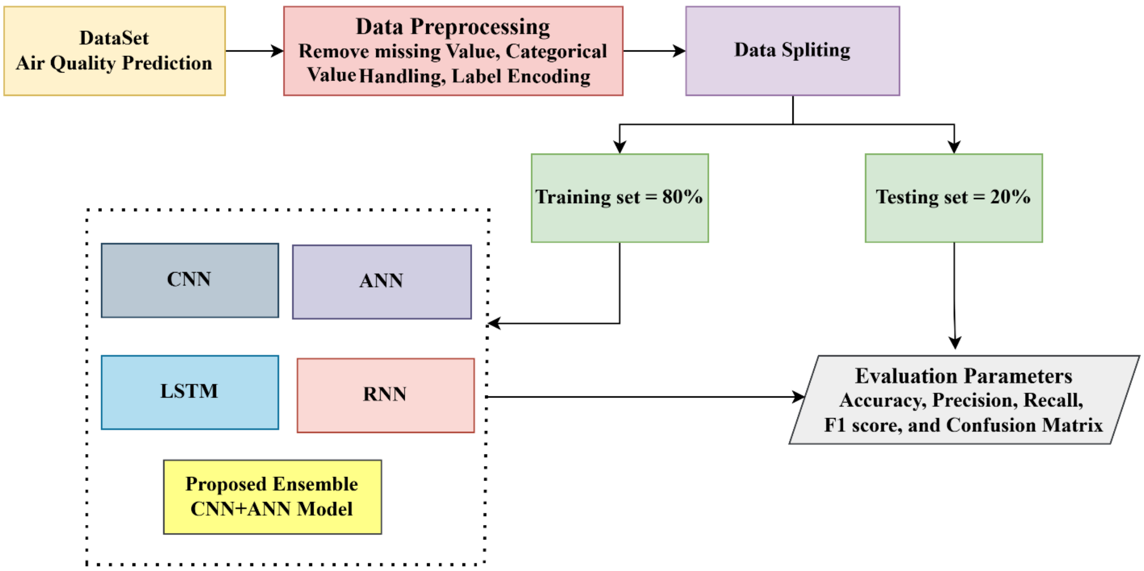

Figure 1. Proposed Methodology

3.1. Dataset Description

The data collected from this dataset demonstrates the air quality and its probable health effects varies in several areas, including Queens, Brooklyn, the Bronx, Manhattan, and Staten Island. It records seasonal and annual averages, allowing comparison of air pollution levels and associated health issues across summer, winter, and the entire year. While the Name category highlights the main themes as Emissions, Asthma-Related, Hospitalizations, and General Pollution, the Unique ID allows each item to be individually identified. It also specifies the type of data density, rates, concentration, or miles that should be in the Measure column. The location and geographic context of the measurements are specified by the Geo Type Name and the Geo Place Name. Seasonal trends are distinguished from yearly trends in the Time Period column. The start date denotes when the data gathering process started. The data value is a number that represents pollution or health impact measurements. Last but not least, the Air Quality Category outlines the air quality metrics that are used to evaluate its effects on public health.

3.2. Deep Learning Models

In order to predict air quality, this study applies and assesses four deep learning architectures. CNN, RNN, LSTM, and ANN. The proposed model CNN+ANN combines the strengths of CNNs for spatial feature extraction and ANNs for learning complex nonlinear relationships, significantly enhancing air quality prediction performance. Trained on comprehensive historical environmental datasets, the model effectively identifies subtle pollution dynamics, outperforming standalone.

3.2.1. Convolutional Neural Networks

CNN-based air quality model uses 3D spatiotemporal tensors (Time × Latitude × Longitude × Features) to analyze pollution patterns across City. The time dimension represents seasonal and annual observations, while the spatial dimensions are derived from the dataset's exact location data ('Geo Place Name' for borough-level coordinates). The model can identify both geographical hotspots and temporal patterns in air pollution since it takes into account a number of parameters, such as pollution levels ,health implications (hospitalizations for asthma), and official air quality ratings. This method captures significant seasonal fluctuations in the data while preserving the real-world spatial linkages between monitoring locations. The design uses convolutional layers with 3×3 kernels to extract spatial patterns from geographically dispersed monitoring data after normalizing and interpolating missing values. Max-pooling is then used to reduce the dimensionality of the input. The CNN model Formula to predict the air quality is shown in Equation 1 and graphical representation shows in Figure 1. Through automated feature learning of environmental patterns, this method overcomes the constraints of existing non-spatial methods and effectively captures regional pollution trends by examining connections between contaminants and meteorological elements across sites.

$$\boldsymbol{Zi, j, k = m\sum n\sum Xi + m, j + n \cdot Wm, n, k + bk} \qquad 1$$

Where *k* is the output feature map for the *kth* filter at point (i, j). The measurements of air quality that average input values into geographic grids are indicated by the notation X_i+m, j+n. The above is known as (W_m, n, k) in relation to how the filter (kernel) functions as a feature extractor. The bias term, given the k-th filter, is (b_k). As it moves over the input data, the summing iterates across the filter's dimension.

3.2.2. Artificial Neural Network

The ability of Artificial Neural Networks (ANNs) to predict the intricate, nonlinear relationships between pollution levels and environmental factors makes them the most cutting-edge technology for air quality forecasting. Artificial neural networks are made up of interconnected layers of neurons, analyze input data, including pollution concentrations, weather conditions, vehicle emissions, and industrial activities, to uncover hidden patterns and temporal trends that allow for extremely accurate forecasts. Even in cases when interactions are nonlinear or involve several impacting elements, these networks are highly effective at identifying complex correlations in air quality data. ANNs can accurately predict future circumstances by learning from past pollution records, which supports targeted pollution mitigation techniques and early warning systems. The ANN model formula shows in Equation 2. It handle larger and more dynamic datasets to the incorporation of deep learning techniques, which has further improved their capability and flexibility. ANNs get even higher accuracy when paired with cloud computing and real-time sensor data, making them essential instruments for public health management and environmental monitoring.

$$\boldsymbol{y = f(i = 1\sum nwixi + b)} \qquad 2$$

Y represents the air quality projection, maybe this so-called pollution concentration. Temperature, humidity, pollution, and other factors may all be inputs to Xi. Wi. b denotes a bias. Wi will then provide the input features' contribution. F (·) is an activation function, e.g., ReLU or Sigmoid, which is responsible for inputting non-linearity to the model.

3.2.3. Long Short-Term Memory Network

Long Short-Term Memory (LSTM) networks are used to forecast air quality by examining emission records, weather data, and pollution data from the past. In order to efficiently capture temporal patterns and long-term relationships while avoiding vanishing gradient problems, the LSTM architecture makes use of memory cells and gating mechanisms (input, forget, output gates). It accurately multi-step forecasts are possible by the model's detection of nonlinear correlations between contaminants and environmental parameters through the processing of hourly data. This technology outperforms conventional approaches and offers trustworthy predictions to enhance public health initiatives and pollution control measures by learning complicated temporal dynamics. The LSTM model Mathematical formula shows in Equation 3.

$$\boldsymbol{Ct = ft \odot Ct - 1 + it \odot C{\sim}t} \quad (3)$$

Whereas, Ct-1 denotes the cell state of its ancestor, Ct describes the cell state at the moment. We discuss C~t, t element-wise multiplication, and forget gate ft, which controls the amount of past data that may be retained. The amount of additional data being entered is indicated by the input gate foot.

3.2.4. *Recurrent Neural Network*

An RNN-based system for predicting air quality that analyzes temporal pollution patterns using LSTM. In order to capture both short-term spikes and long-term seasonal trends, the system uses bidirectional recurrent layers to handle time-aligned pollution and meteorological data. Time-series cross-validation and various accuracy metrics are used to assess model performance, comparing the efficacy of each architecture for various forecasting horizons. The RNN model Mathematical formula shows in Equation 4.

$$\boldsymbol{ht = tanh(Whht - 1 + Wxxt + b)} \quad (4)$$

At time t, ht is the hidden state that is capturing historical data because of the prior hidden state. HT-1. Temperature, humidity, or the amount of a contaminant in the air are examples of inputs that occur at time t, denoted by xt. Controlling the hidden states by defining weight matrices Wx that control the influence of both current and historical input. The bias term is B. Tanh is the model's activation function that ends linearity.

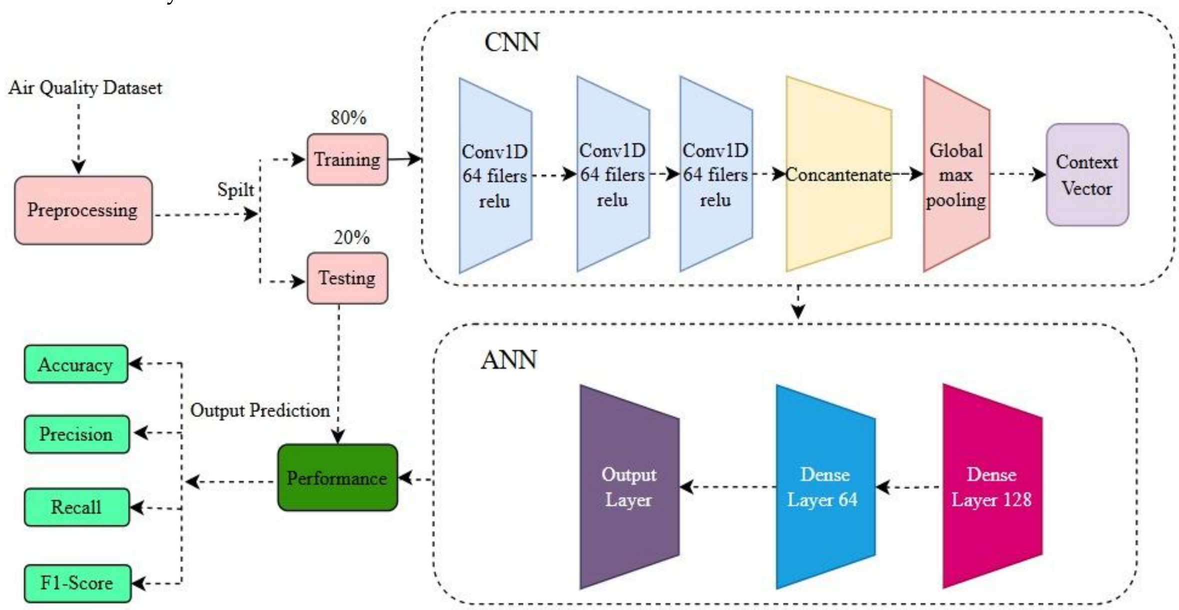

Figure 2. Ensemble CNN-ANN Model

3.2.5. *Proposed Ensemble Model*

This study develops an ensemble deep learning model by incorporate the ability of CNN and ANN to improve air quality forecasting by combining spatial pattern recognition with nonlinear relationship modeling. The CNN extracts regional pollution features from environmental data, while the ANN processes these along with meteorological inputs to capture complex atmospheric interactions. The performance evaluation using accuracy, precision, recall, and RMSE metrics, and the ensemble model outperforms individual approaches in handling spatial variability and temporal dynamics. This robust framework enables precise, real-time air quality predictions to support environmental decision-making. The proposed CNN-ANN model Mathematical formula shows in equation 5.

$$\boldsymbol{Y^\wedge = fANN(fCNN(X))} \qquad 5$$

Where $f\ CNN$ is the feature extractor that uses the CNN model to extract spatial patterns and dependencies from the data, X stands for the input data for air quality (i.e., pollution levels, meteorological traits). Typically, features are extracted from any patterns that would support ANN. $f\ ANN$ defines intricate associations by acting on retrieved characteristics. $Y^\wedge$ represents the anticipated value for air quality.

4. Results and Discussion

This section uses performance indicators including accuracy, precision, recall, and F1-score to assess the validity of the suggested model and other deep learning models. While precision lowers false positives by calculating the ratio of genuine positives to all anticipated positives, accuracy quantifies the percentage of cases that are correctly classified. By contrasting true positives with false negatives, recall assesses the model's capacity to consistently identify events. For comparison analysis, the CNN, RNN, LSTM, and ANN models were each applied separately in this study. However, our ensemble model based on CNN and ANN overcomes the drawbacks of standalone designs by integrating spatial feature extraction with nonlinear pattern recognition, resulting in higher performance. The prediction robustness is increased by the ensemble technique, especially when it comes to incorporating complicated atmospheric interactions and regional differences in air quality.

4.1. Performance of CNN Model

While it performed better in comparison to competing models, the CNN model has raised the performance. After 30 training epochs, the network's accuracy (0.9804) demonstrating the model's remarkably high capacity for self-generalization. The precision of model (0.9805), indicating that it is a very effective positive event identifier. All things considered, f1 score (0.9804) and recall score (0.9804) demonstrate its capacity to detect any competent pattern without producing a significant number of false negatives. Table 2 displays the CNN model's findings and Figure 3 shows the confusion matrix.

Table 2. CNN Model Performance

Epoch	Accuracy	Precision	Recall	F1 score
5	0.9173	0.9163	0.9161	0.9166
10	0.9359	0.9364	0.9364	0.9368
15	0.9582	0.9585	0.958	0.9583
20	0.9704	0.9706	0.9704	0.9704
25	0.9756	0.9758	0.9755	0.9756
30	0.9804	0.9805	0.9804	0.9804

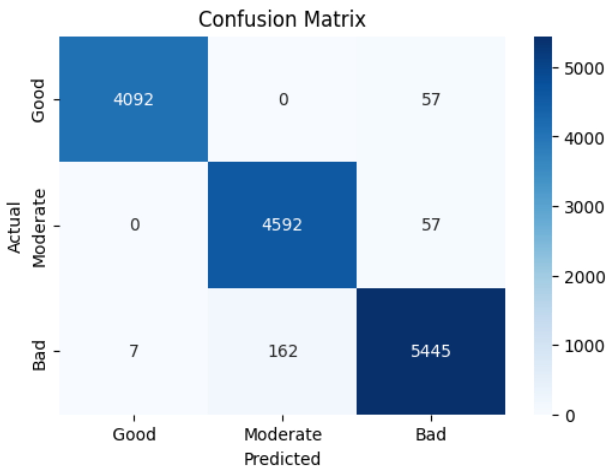

Figure 3. Confusion Matrix of CNN Model (Epoch 30).

4.2. Performance Evaluation of ANN

The ANNs performed exceptionally well on the classification tests, with a classification accuracy (0.9909) across 30 epochs. As a result, the results are balanced in terms of f1 score (0.9909), recall (0.9909), and precision (0.9910). It also confirms that all measurements have predictive significance. As a consequence, the ANN model is relevant to the final findings shown in Table 2. These findings highlight the importance of trend data and suggest that ANN might enhance generalization abilities. This confusion matrix is shown in Figure 3.

Table 3. ANN model Performance

Epoch	Accuracy	Precision	Recall	F1 score
5	0.9122	0.912	0.9122	0.9127
10	0.9357	0.9363	0.9355	0.9359
15	0.9582	0.9585	0.958	0.9583
20	0.9724	0.9728	0.9722	0.9725
25	0.9812	0.9815	0.981	0.9813
30	0.9909	0.9910	0.9909	0.9909

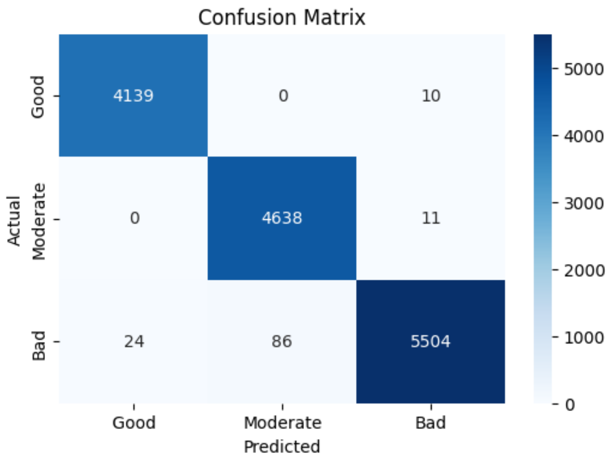

Figure 4. Confusion Matrix of ANN Model (Epoch 30).

4.3. Performance Evaluation of LSTM

Long short-term memory performs exceptionally well in categorization tests, with an accuracy grade of 0.9661. The f1 score is 0.9661, precision (0.9667), and recall (0.9661) shows the effectiveness of model. Table 3 shows the performance of LSTM model with different epoch. The confusion matrix shown in Figure 4.

Table 4. LSTM Model Performance

Epoch	Accuracy	Precision	Recall	F1 score(N)
5	0.9105	0.911	0.9103	0.9106
10	0.9287	0.9292	0.9285	0.9288
15	0.9453	0.9458	0.9451	0.9454
20	0.9556	0.956	0.9555	0.9557
25	0.9608	0.9613	0.9607	0.9609
30	0.9661	0.9667	0.9661	0.966

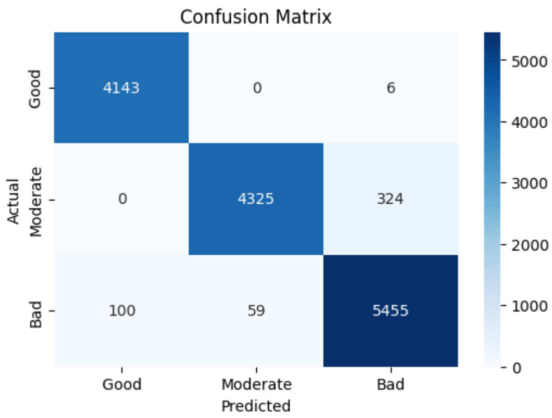

Figure 5. Confusion Matrix of LSTM Model (Epoch 30).

4.4. Performance Evaluation of RNN

The RNN model performed well with an accuracy of (0.9704) epoch 30. The precision of model (0.9706), recall (0.9704), and f1 score (0.9704), demonstrate that a sizable portion of positive predictions are made accurately. Table 4 displays the RNN performances. Figure 5 shows the RNN model's confusion matrix.

Table 5. RNN Model Performance

Epoch	Accuracy	Precision	Recall	F1 score
5	0.9123	0.913	0.9121	0.9126
10	0.9356	0.9362	0.9354	0.9358
15	0.9482	0.9485	0.948	0.9483
20	0.9567	0.9571	0.9565	0.9568
25	0.9635	0.964	0.9633	0.9636
30	0.9704	0.9706	0.9704	0.9704

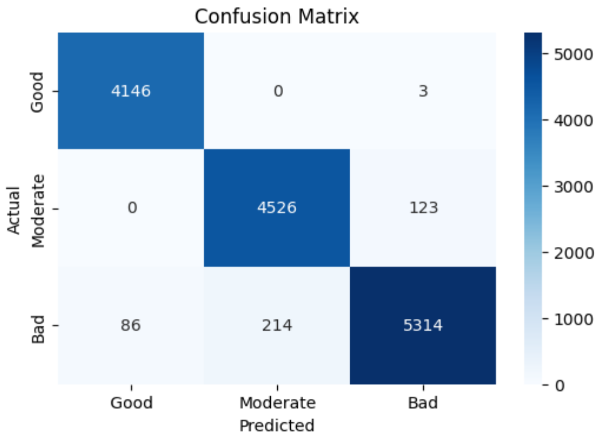

Figure 6. Confusion Matrix of RNN Model (Epoch 30).

4.5. Performance Evaluation of Proposed Ensemble Model

The ensemble convolutional neural networks and artificial neural network proposed for the classification outperform other test models according to the assessment criterion. It shows higher f1-score (0.9986), recall (0.9984), precision (0.9988), and accuracy 0.9985 for 25 epochs. The proposed models' performance is displayed in Table 5. The proposed model's confusion matrix is shown in Figure 6. This demonstrates how the ANN's sequential learning capabilities aid in the characteristics that the CNN collects to create an excellent model.

Table 6. Ensemble Model Performance

Epoch	Accuracy	Precision	Recall	F1 score

5	0.9201	0.9205	0.92	0.9202
10	0.9403	0.9407	0.9402	0.9404
15	0.9858	0.9861	0.9857	0.9859
20	0.9906	0.9909	0.9905	0.9907
25	0.9985	0.9988	0.9984	0.9986
30	0.9854	0.9857	0.9854	0.9854

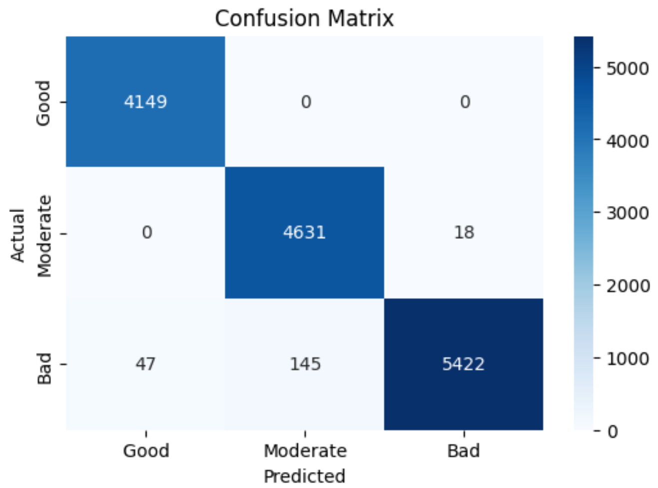

Figure 7. Confusion Matrix of Proposed CNN+ANN Models (Epoch 25).

4.6. Performance Analysis of All Models

The advancements achieved in each method were demonstrated by the performance of CNN, ANN, RNN, and LSTM across dataset. Each model outperforms the others in every way: CNN concentrates on spatial information, LSTM manages vanishing gradients, RNN detects sequence bias, and ANN handles basic classification tasks. Tested experiments demonstrate that ensemble model outperforms the individual models in classification through improved feature representation and sequence pattern learning. The performance evaluation of all models shown in Figure 7.

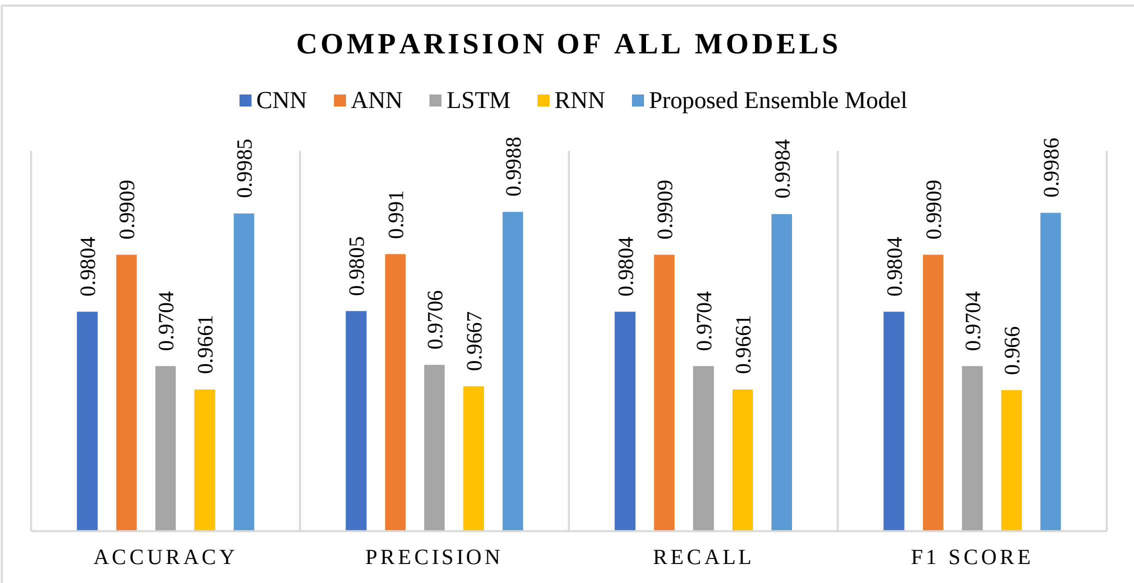

Figure 8. Performance Analysis of All Models

5. Conclusion and Future Work

In this research, the proposed ensemble deep learning model based on CNN and ANN is proposed for air quality forecasting, demonstrating superior performance compared to standalone CNN, ANN, RNN, and LSTM architectures. By fusing ANN's ability to describe intricate nonlinear interactions with CNN's ability to extract spatial information from environmental data, the suggested ensemble model successfully overcomes the drawbacks of conventional models and produces predictions that are incredibly precise. The experiments shows that the model performs exceptionally well, surpassing other baseline models achieving accuracy (0.9985), precision (0.9988), recall (0.9984), and F1-score (0.9986). The ensemble model is more robust than single CNN, ANN, LSTM and RNN models because of its integrated approach, which better captures global pollutant patterns and spatiotemporal dependencies. These results demonstrate the promise of ensemble deep learning architectures for environmental modeling, especially for forecasting air quality with high precision. This research can be improved in future by adding more environmental factors and optimizing hyper-parameters for better prediction.

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