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AN ATTENTION MECHANISM AND MULTIVIEW FUSION FOR ENHANCING DEEP LEARNING BASED AIR QUALITY INDEX PREDICTION

[1]Sathya K
Research Scholar
Department of Computer Science,
Erode Arts and Science College,
Bharathiar University,
TamilNadu, India

[2]Ranganayaki T
Associate Professor,
Department of Computer Science,
Erode Arts and Science College,
Bharathiar University,
TamilNadu, India

ABSTRACT—

Effective Air Quality Index (AQI) prediction supports global health, the domestic economy, and the ecosystem. Aiming at learning spatiotemporal attributes from past air quality statistics, a Robust Bootstrapped Convolutional Neural Network with a Long Short-Term Memory network (RBCNN-LSTM) was designed to predict AQI and its uncertainties. Nonetheless, the effect of various attributes on the predicted outcomes at different intervals was not analyzed, especially to predict PM2.5 concentration. Hence, this article develops an Attention-based RBCNN-LSTM (A-RBCNN-LSTM) network framework to improve the prediction of AQI and their uncertainties according to the forecasting of PM2.5 concentration over the next few days. This framework adopts the attention strategy with the RBCNN-LSTM for determining the significance of each attribute and allocating corresponding weights to all attributes and applies a multi-view fusion by sharing the weights across the views in all LSTM units to obtain the correlation between PM2.5 concentrations and other attributes. Such correlations are learned by the bootstrapped convex-CNN to predict the air quality and its uncertainties.The results show that the proposed method based on the A-RBCNN-LSTM has more competent to enhance the air quality forecasting that traditional state of art methods in terms of accuracy,precision,recall,F-Measure.

Keywords—Air quality index, Uncertainty, RBCNN-LSTM, PM2.5 concentration, Attention strategy, Softmax, Multi-view fusion

I. INTRODUCTION

The amount of fuel emitted by several companies and automobiles remains high as urbanization rates increase, substantially increasing air quality [1]. People's everyday lives are significantly impacted by air quality. Effective air quality forecasting has emerged as a key strategy for reducing pollution and maintaining air quality [2]. The globe has been quite worried about air quality statistics. For predicting air quality, time series data prediction techniques [3] have been frequently employed, along with conventional machine learning techniques [4]. But, the complex nonlinearity of air quality such as PM2.5 concentrations cannot be accurately captured by contemporary air quality prediction systems.

Deep learning-based prediction models can extract characteristics from the air quality data and have greater forecast accuracy [5]. Certain techniques simultaneously represent the temporal and spatial dependency of air quality information [6-8]. However, the effectiveness of commonly employed machine

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learning techniques varies greatly depending on the situation. Different factors, including temperature, wind speed, and spatial adjustment, have an impact on air quality. So, it is challenging to produce precise prediction accuracy using the popular single-model prediction technique. To solve this problem, many integrating models have emerged for air quality prediction, which considerably enhances the prediction capacity [9-11]. But, there is still a key issue to learn about how to combine the benefits of several models depending on the features of the database. Also, most of the frameworks predict acute air pollution in cities or an extensive region. A comprehensive spatial and temporal correlation was needed to define the air pollution occurrences timely.

To tackle all these problems, a spatiotemporal estimation paradigm for adaptable air pollution was encouraged by Mokhtari et al. [12]. Convolutional LSTM (ConvLSTM)-based multi-point frameworks have been created to assess concentrations concurrently at several areas (nodes) by taking spatiotemporal information correlations. On top of this ConvLSTM, Uncertainty Quantification (UQ) techniques including Monte Carlo (MC) dropout and Quantile Regression (QR) techniques were used to strengthen the framework. Nonetheless, the UQ techniques have many problems, and the following: (a) the analytical conclusions are troublesome because it was challenging to build a UQ with precise probabilistic strategies, which represent the modifications in the projected values. It is required to provide the dissemination of the data acquisition and the sampling probability to evaluate the uncertainty in the projected values. (b) In real-world prediction systems, particularly in crises, the ConvLSTM training methods, such as the MC dropout, QR, and the number of stochastic forward passes, were typically difficult to implement. Setting conceptual limits on the precision of the predictions or the capability of the resulting prediction framework was extremely difficult due to issues like non-convexity. Additionally, the ConvLSTM was often trained on the records with a lot of attributes and instances, which limits the usage of testing hypotheses that work with a limited set of parameters and asymptotically enormous numbers of instances.

As a result, the RBCNN-LSTM framework with a transfer learning mechanism [13] was developed for the effective prediction of AQI and its uncertainties. In this framework, the spatiotemporal attributes captured by the ConvLSTM were provided to the bootstrapped convexified CNN (convex-CNN) to obtain prediction intervals and quantify uncertainties in the projected values depending on the dissemination of the data acquisition and sampling probability. Then, the transfer learning was combined to execute UQ for both convex and non-convex CNNs. But, this framework cannot reflect the impact of various attributes on the prediction outcomes at various periods, particularly for predicting PM2.5 concentration.

Therefore, in this paper, an A-RBCNN-LSTM network framework is proposed for enhancing the prediction of AQI and its uncertainties. The main aim of this framework is to forecast the PM2.5 concentration related to the other attributes over the next few days. In this framework, the attention strategy is incorporated with the RBCNN-LSTM to determine the significance of each attribute and allocate corresponding weights to all attributes. The attention strategy involves 3 processes. Initially, the similarity score between multiple views such as PM2.5 concentration and other attributes is computed, which is acquired from the present condition of the neural unit. After that, this similarity score is regularized by the softmax function to obtain the weight coefficient of all LSTM unit output vectors. Moreover, a multi-view fusion is performed by sharing the weights across the views in all LSTM units to get the correlation between the PM2.5 concentration and other attributes. Further, such correlations are fed to the bootstrapped convex-CNN for predicting AQI and its uncertainties. Thus, by predicting the non-linear correlation between the PM2.5 concentrations, this framework enhances the accuracy of predicting air quality and its uncertainties.

The rest of this article is structured as follows: The studies related to the frameworks for predicting air quality are reviewed in Section II. The A-RBCNN-LSTM framework is described in

Section III, and its efficacy is shown in Section IV. The entire investigation is summarised in Section V, which also offers suggestions for improvements in the future.

II. LITERATURE SURVEY

Sun et al. [14] designed a Hybrid Deep Air Quality Predictor (HDAQP) framework comprising 1D CNN, LSTM, and DNN to predict PM2.5 concentrations. First, CNN was utilized to convolve the historical PM2.5 concentration information together with meteorological information to capture shallow attributes, whereas LSTM was utilized to capture the deep temporal attributes. Also, the DNN was applied to transfer those deep attributes into the absolute prediction outcomes. But, it has a high complexity, and an overfitting problem has occurred, which degrades the efficiency in the validation stage.

Nguyen et al. [15] presented the Genetic Algorithm (GA) and an Encoder-Decoder (ED) model to predict PM2.5. The GA was used to choose attributes and eliminates outliers for improving the prediction efficiency. The ED model with LSTM was used to avoid the constraints between the input and output, which helps to forecast the PM2.5 concentration. But, the computation time of this model was high.

Chen et al. [16] developed an integrated dual LSTM network structure for air quality prediction. Initially, the sequence-to-sequence method was applied to create a single-aspect prediction framework that acquires the estimated value of all elements in air quality information alone. All elements of air quality were considered in the multi-aspect estimation framework. Then, the influencing aspects of air quality such as the information on adjacent sites and climate data were considered. Moreover, the XGBoosting tree was applied to combine those frameworks and the absolute estimation was achieved by fusing the estimated values of the best subtree nodes. But, a few estimation values have outliers that impact the model accuracy.

Bekkar et al. [17] presented a CNN-LSTM with a spatial-temporal characteristic for predicting PM2.5 concentration. The spatial-temporal characteristic was created by fusing previous information on chemicals, climatological information, and PM2.5 concentration in the neighboring sites. Conversely, it was merely employed in Beijing, China because of the restriction of hourly open-access data.

Wang et al. [18] developed a novel model by integrating Chi-square Test (CT) and LSTM (CT-LSTM) network to predict air quality. In this model, CT was utilized to estimate the influencing aspects of air quality. The hourly air quality information and meteorological information were utilized to train the LSTM network for predicting the AQI level in Shijiazhuang of Hebei Province of China. But, it needs to predict the contaminants to limit air pollution and prevent human health.

Han et al. [19] designed a domain-related Bayesian deep-learning framework for long-term air pollution prediction in China and the United Kingdom (UK). Initially, domain-related data was combined into the robust statistical correlation between PM2.5 and PM10 as a normalization term. After that, an attention layer was added to extract the influential historical attribute and the recursive temporal relationship of air quality data. Further, the outcomes from various multi-step prediction schemes were merged depending on the related uncertainty measures. But, the key drawback was the absence of essential spatial or temporal attributes, which measure the event of air pollution.

Chau et al. [20] developed Weather Normalized Models (WNMs) depending on various deep learning structures to predict air contamination for various most typical urban chemicals. The effects of the COVID-19 lockdowns on air quality in Quito were measured by choosing the optimal WNMs. Moreover, the attribute significance for the optimal WNMs was identified and the correlation between temporal,

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meteorological characteristics and air toxins was analyzed. But, the training error was high, which needs to adjust the dropout rate and hyperparameters of deep learning models.

Yang et al. [21] addressed the impact of meteorological states on air quality prediction by explainable deep learning. First, the source information from air contaminant databases and the meteorological state databases were acquired. After that, the LSTM and Gated Recurrent Unit (GRU) frameworks were applied to predict air quality in various states. Moreover, the SHapely Additive exPlanation (SHAP) scheme was used to evaluate the explainability of the air quality frameworks. But, the SHAP scheme has a high computational cost and memory. The accuracy was degraded because of neglecting many attributes to reduce the computational cost and memory.

Ding et al. [22] developed a dynamic GRU for precise air quality prediction. Initially, an encoding scheme for the GRU network was adopted to represent the network model in a fixed-length binary string. Then, the reciprocal of the sum of the loss of all individuals was defined as the objective value for the iteration calculation. Moreover, the GA was utilized to calculate the data-dynamic GRU network model to improve the air quality prediction efficiency. But, it needs more influencing aspects related to the air quality like atmospheric conditions, human aspects, etc., to increase the accuracy.

Zhao et al. [23] designed a new statistical learning model combining the spatial correlation factors, attribute selection, and Support Vector Regression (SVR) for AQI estimation. In this model, correlation analysis and time series analysis were utilized to capture the spatial-temporal characteristics. Also, the historical AQI series of the desired location was changed by the trigonometric regression to remove the non-stationarity. Moreover, the attribute selection was performed by the Q-learning-based bee swarm optimization to increase efficiency. But, it did not determine spatial-temporal correlation, and it needs to consider additional aspects influencing concentration like temperature, humidity, etc.

III. PROPOSED METHODOLOGY

This section describes the A-RBCNN-LSTM framework in brief. An overall schematic representation of this study is illustrated in Figure 1.

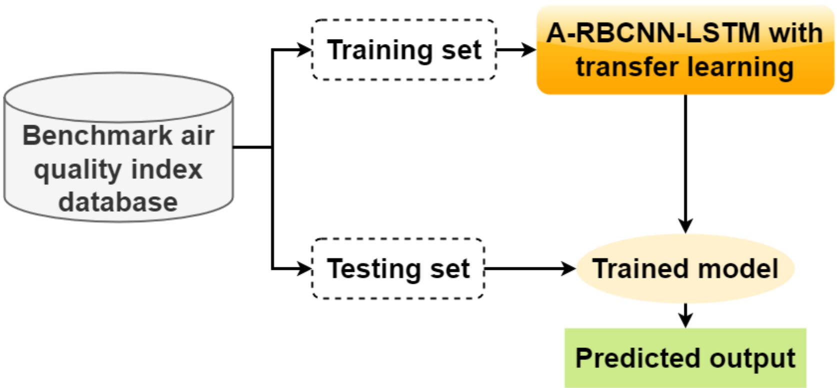

Figure 1. Block Diagram of the Presented Study

Initially, various benchmark AQI corpora are acquired from open sources, which are separated into training and test sets. Then, the training set is fed to the A-RBCNN-LSTM framework to learn the spatiotemporal correlations across multiple views of PM2.5 concentration and other attributes, which provides the trained A-RBCNN-LSTM network. Later, the trained network is validated by the test set for predicting AQI and its uncertainties.

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3.1 Dataset Description

Three separate AQI benchmark datas are used in this research. Ambient air quality is measured by Tamilnadu Pollution Control Board (TNPCB) through National Ambient Air Quality Monitoring Programme (NAMP) from Erode ,Salem and TirpurStations.The Central Pollution Control Board (CPCB) initiated a programme – National Air Quality Monitoring Programme (NAMP) to monitor air quality in the premises of Salem Sowdeswari College located nearby KondalampattyRoundane in Salem , Kumaran arts and science college in tirpur and CMP plot, SIDCO Industrial Estate in Erode.This database comprises name of the city, date, PM2.5, PM10, NO, NO_2, NO_x, NH_3, CO, SO_2, O_3, BP, AQI, and AQI-bucket of 24 hours data from August 2022 to March 2023.

Once all the corpora are acquired, 70% of data are taken as a training set and the remaining 30% are taken as a test set. In the learning stage, the training set is split into a series of examples. Also, the attribute set associated with the PM2.5 concentration, meteorological data, and air quality data is divided from the examples. Their values are standardized into the range between 0 and 1. The processed corpus is fed to the A-RBCNN-LSTM to get the trained network, which can be utilized in the testing stage to predict AQI and its uncertainty.

3.2 Attribute Extraction

For time-series prediction, the collected AQI corpora comprise the meteorological data, air quality data, and PM2.5 concentration at various intervals t. Every sample set x_n includes many attributes like PM2.5 concentration, wind speed, etc., at t_1, t_2 and t_n intervals. Each time-series observation is given to the ConvLSTM [12] to extract the spatiotemporal features from the past data. The output of the ConvLSTM is fed to the attention strategy to capture the correlation between the PM2.5 concentration and other attributes.

3.3 Attention Strategy

The attention unit can automatically weight the historical attribute states to enhance the prediction performance. The major concept of the attention strategy is obtained from the task of a person's visual attention, which rapidly discovers fundamental vicinities and focuses them to get highly comprehensive data. According to the PM2.5 concentration estimation, it could selectively give attention to a few more significant data associated with the PM2.5 concentration, allocates the weight for those, and discards the inappropriate data.

The attention strategy is split into 3 phases as portrayed in Figure 5. In this initial phase, the similarity score(S_t) between PM2.5 concentration and other attributes' values is determined by

$$S_t^j = \tanh\left(w_t\left[h_t^{PM2.5}, h_t^j\right] + b_t\right) \quad (1)$$

In Eq. (1),j is the sequential number of attributes, t is the present interval,w_t, h_t and b_t are the weight matrix, the result of the LSTM unit, and the bias values, correspondingly. This is the only method to determine the score that is acquired from the present condition of the neural layer, not the earlier condition.

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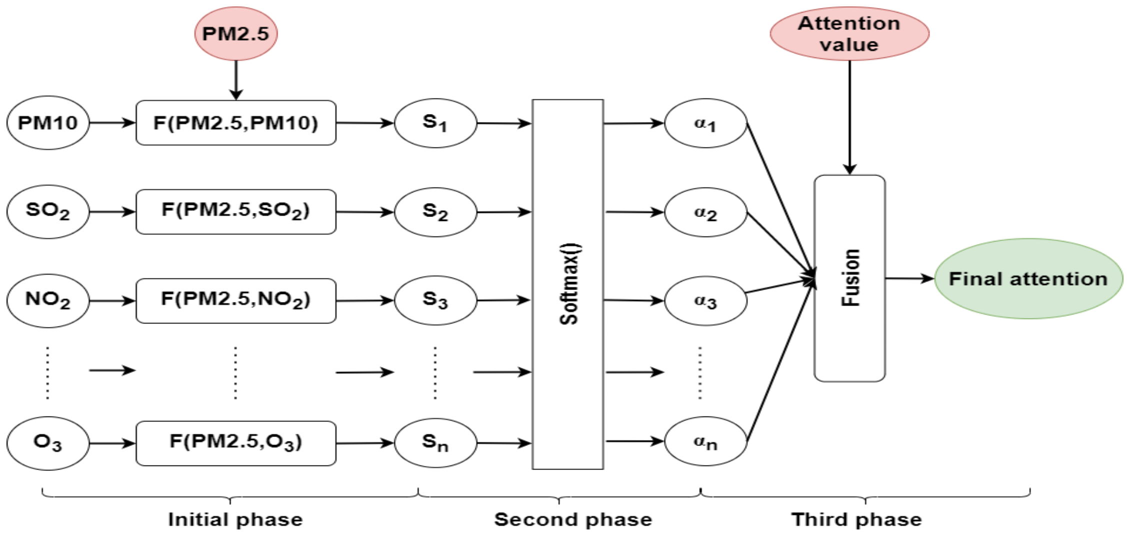

Figure 5. Different Phases in Attention Strategy

In the second phase, the softmax function is applied to regularize the similarity score and obtain the weight coefficient α of all LSTM units' outcome vectors as:α

$$\alpha_t^j = \frac{e^{\left(s_t^j\right)}}{\sum_{j=1}^{n} e^{\left(s_t^j\right)}} \qquad (2)$$

In the third phase, the attention strategy executes the multi-view fusion on the vector outcome by all LSTM units and the weight coefficient to obtain the absolute attention values c of all attributes.The outcome of the attention unit, i.e. the absolute attention value is provided to the bootstrapped convex-CNN [13] for training the presented framework. Later, the air quality and its uncertainties are predicted if the test set is applied to the trained framework. An entire architecture of the A-RBCNN-LSTM network is shown in Figure 6.

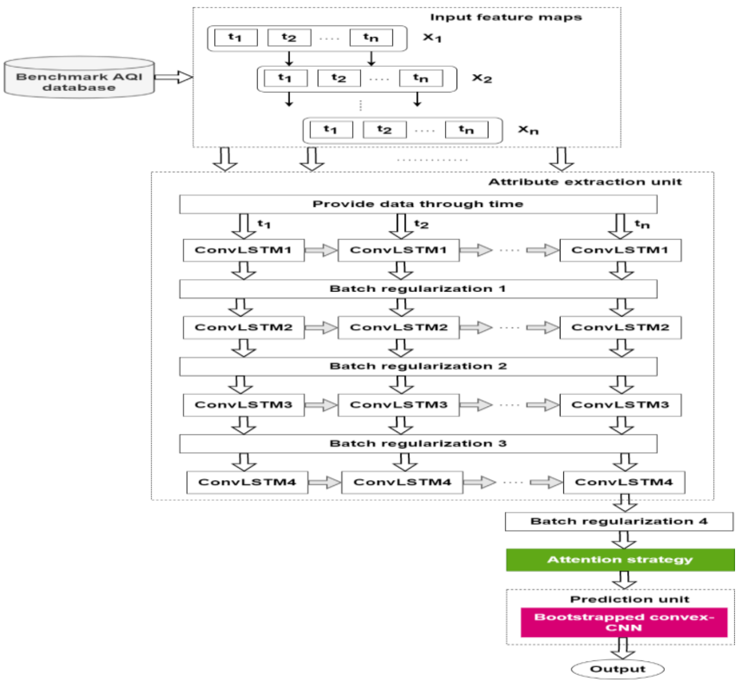

Figure 6. Architecture of A-RBCNN-LSTM for AQI Prediction

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Thus, according to the attention value between PM2.5 concentration and other attributes, the bootstrapped convex-CNN is trained for AQI prediction precisely.

IV. EXPERIMENTAL RESULTS

In this section, the effectiveness of the A-RBCNN-LSTM framework on 3 kinds of benchmark AQI corpora is examined by executing it in MATLAB 2019b. Then, such effectiveness regarding various metrics is compared with the existing frameworks: RBCNN-LSTM [13],CNN-LSTM [17]. The metrics utilized for analysis are the following:

- Accuracy: It measures the framework's competence in precisely estimating the AQI of new instances.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive + False\ Negative\ (FN)} \quad (5)$$

  In Eq. (5), TP indicates the quantity of positive data that are precisely estimated as positive, TN indicates the quantity of negative data that are precisely estimated as negative, FP indicates the quantity of negative data that are imprecisely estimated as positive and FN indicates the quantity of positive data that are imprecisely estimated as negative.
- Precision: It is computed as:

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

- Recall: It is calculated as:

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

- F-measure:It is measured by

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (8)$$

Table 1 provides the results of the proposed and existing AQI prediction frameworks tested on the air quality data for predicting AQI at the Erode.

Table 1. Performance Comparison between Existing and Proposed AQI Prediction Frameworks on Air quality data in Erode

Metrics	CNN-LSTM	RBCNN-LSTM	A-RBCNN-LSTM
Accuracy (%)	84.63	88.55	90.18
Precision (%)	83.28	86.02	89.08
Recall (%)	84.04	86.55	89.70
F-measure (%)	83.66	86.28	89.39

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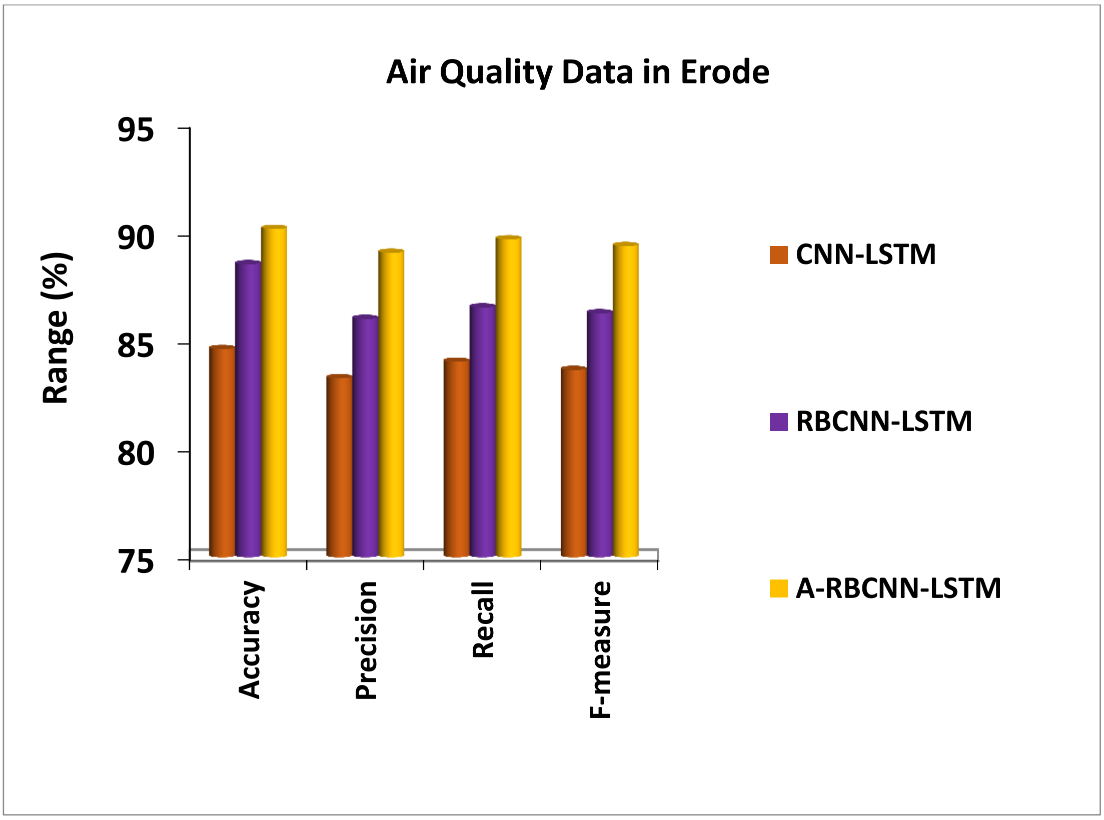

Figure 7. Analysis of Different AQI Prediction Frameworks on Air Quality Data in Erode

Figure 7exposes the efficiency of different AQI prediction frameworks tested on the air quality data in Erode. It realizes that the accuracy, precision, recall, f-measure of A-RBCNN-LSTM is performed better than the CNN-LSTM and RBCNN-LSTM.

Table 2 provides the results of the proposed and existing AQI prediction frameworks tested on the CPCB air quality index Salem for predicting AQI.

Table 2. Performance Comparison between Existing and Proposed AQI Prediction Frameworks on CPCB Air Quality Index Data Salem

Metrics	CNN-LSTM	RBCNN-LSTM	A-RBCNN-LSTM
Accuracy (%)	84.93	89.12	91.25
Precision (%)	83.37	87.79	90.15
Recall (%)	84.19	87.7	90.48
F-measure (%)	83.78	87.74	90.32

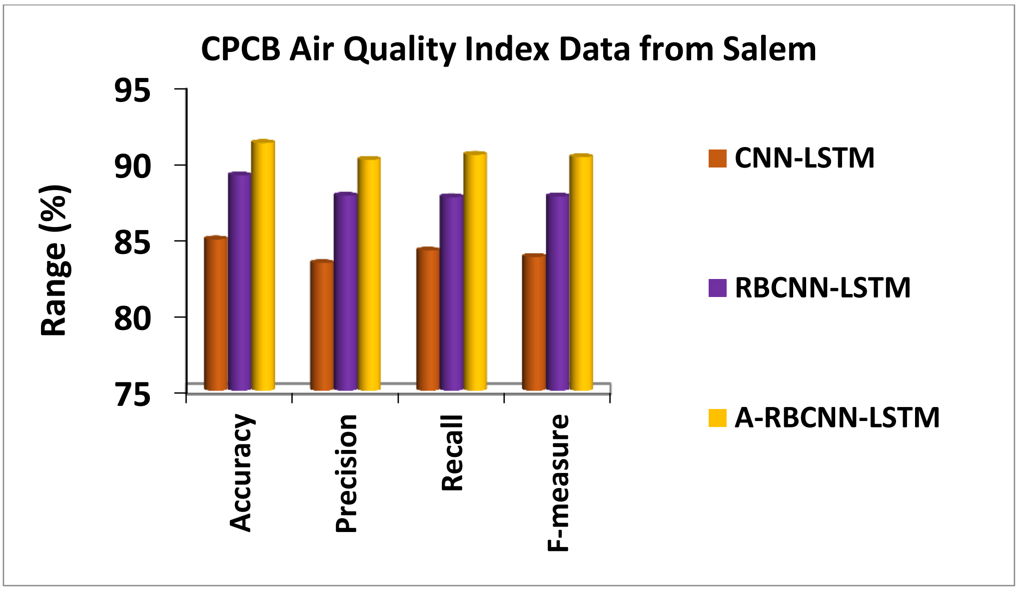

Figure 8. Analysis of Different AQI Prediction Frameworks on CPCB Air Quality Index Data 2020

Figure 8 exhibits the efficiency of different AQI prediction frameworks tested on the CPCB air quality index data from Salem. It realizes that the accuracy , precision, f-measure and recall of the A-RBCNN-LSTM is performed better than the other models such as CNN -LSTM and RBCNN-LSTM.

Table 3 provides the results of the proposed and existing AQI prediction frameworks tested air quality data for predicting AQI at the Tirpur stations.

Table 3. Performance Comparison between Existing and Proposed AQI Prediction Frameworks on Air Quality Data from Tirpur

Metrics	CNN-LSTM	RBCNN-LSTM	A-RBCNN-LSTM
Accuracy (%)	84.23	88.8	90.64
Precision (%)	84.08	87.61	89.23
Recall (%)	84.16	87.49	90.13
F-measure (%)	84.12	87.55	89.68

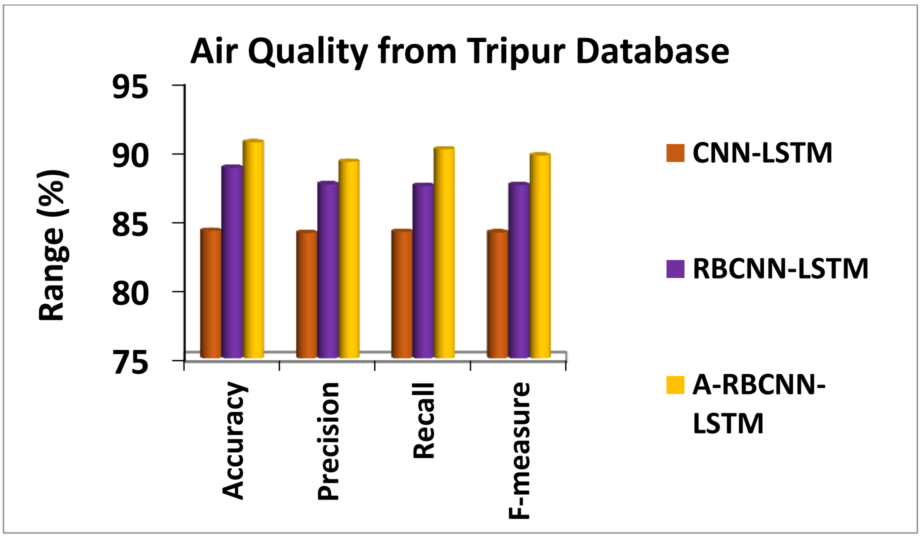

Figure 9. Analysis of Different AQI Prediction Frameworks on Air Quality Database Tirpur

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Figure 9 displays the efficiency of different AQI prediction frameworks tested on the air quality database tirpur. These classification metrics of A-RBCNN-LSTM models results the prediction of air quality and uncertainties is much better than CNN-LSTM and RBCNN-LSTM frameworks.

V. CONCLUSION

In this study, the A-RBCNN-LSTM framework was developed for accurately predicting AQI and its uncertainties. First, different air quality data corpora were acquired from various open sources. Then, the ConvLSTM was applied to get the spatiotemporal attributes from the past information on air pollutants. Such attributes were passed to the attention module to determine their significance and set related weights to each attribute according to the similarity score between PM2.5 concentration and other attributes. The similarity score was standardized by the softmax function and the multi-view fusion was applied to get the correlation between PM2.5 concentrations and other attributes by sharing the weights across the views in all LSTM units. Those correlations between multiple views were further fed to the bootstrapped convex-CNN for predicting the air quality and its uncertainties. Finally, the experimental results proved that the A-RBCNN-LSTM has an accuracy compared to the other AQI prediction frameworks.

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