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Original Article

AIR-IoT ITINEARY: Deep DenseNet-Based Air Quality Monitoring Using Real-Time Sensors in Urban Areas

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Abstract - *The Internet of Things (IoT) is being used increasingly in the control and monitoring of air quality. Real-time data regarding air pollutants and other environmental parameters can be gathered by deploying IoT devices with sensors and connectivity capabilities. Rapid urbanization and industry cause increasingly serious problems with air quality. A pivotal challenge in the current Air Quality Monitoring (AQM) model is its limited spatial coverage and accuracy. In this paper, a novel AQM using the IoT (AIR-IoT ITINEARY) technique is proposed to gauge the atmospheric condition efficiently and instantly. Sensors are placed in the various traffic systems to collect environmental data and process it in the Real-Time Data Analytics Module (RTDM). DenseNet is used to predict the quality of air and is classified into three classes, namely pure and impure. If pollution levels exceed the threshold, it alerts the user and suggests an alternative route. The efficacy of the proposed AIR-IoT ITINEARY technique has been evaluated using assessment actions such as accuracy, time efficiency, precision, F1 score, RMSE, MAPE, and MAE. According to the comparison analysis, the proposed AIR-IoT ITINEARY technique's accuracy rate is 10.08%, 17.64%, and 34.34% higher than the existing IdleAir, SMOTEDNN, and ETAPM-AIT techniques, respectively.*

Keywords - *Air pollution, DenseNet, Sensors, Internet of Things, Real-Time Data Analytics Module.*

1. Introduction

IoT has transformed the field of air monitoring systems by bringing intelligent, networked technologies for gauging and analyzing air quality [1]. IoT-based air monitoring systems combine state-of-the-art sensor technology with wireless connectivity to allow real-time data gathering and transfer to cloud-based platforms [2]. These interconnected sensors may detect particles, ozone, carbon monoxide, nitrogen dioxide, and particulate matter, among other air contaminants [3]. The vast and continuous data collection capabilities of these sensors allow for precise and comprehensive indoor and outdoor air quality monitoring [4].

Air pollution has become a serious issue worldwide, particularly in emerging countries, due to the rapid rise of manufacturing and urbanization [5]. Dangerous levels of NO2, ground-level O3, CO, particle matter, sulfur dioxide, volatile organic compounds, and carbon monoxide are associated with an increase in air pollution [6]. Industrial emissions and vehicular emissions are the key causes of air pollution [7]. When companies grow, they emit a range of dangerous chemicals into the environment because they need fossil fuels for transportation, manufacturing, and electricity production [8]. Figure 1 shows the air pollution rate for the past and future few years. According to the graph, air pollution due to vehicles increases rapidly. The most important pollutants are vehicles, industries, waste burning, and dust and construction. Year by year, the usage of vehicles increases, and air pollution also increases. Nowadays, vehicles are one of the mandatory things in daily life [9]. Vehicle emissions contaminants can cause respiratory issues, poorer atmospheric conditions, and the production of smog.

In addition, the release of greenhouse gases resulting from industrial processes amplifies the effects of climate change, causing severe weather phenomena and disruptions to the ecosystem [10]. Climate change, which is connected to greenhouse gas emissions from air pollution, exacerbates the issue. Consequently, there is an increased frequency of catastrophic weather occurrences and ecological imbalances [11, 12]. To overcome these issues, a novel AIR quality monitoring using the IoT (AIR-IoT ITINEARY) technique has been proposed.

To monitor air quality, the majority of the methods use DL algorithms such as DNN [14], Elman Neural Network [13], LSTM AI [17], Autoencoder and LSTM [21]. However, these existing techniques have some drawbacks, like less accuracy, increased energy consumption, high network load, and computational complexity. Several features influence the effectiveness of the current AQM systems. To overcome these problems, the AIR-IoT ITINEARY method has been proposed to overcome the existing techniques problems.

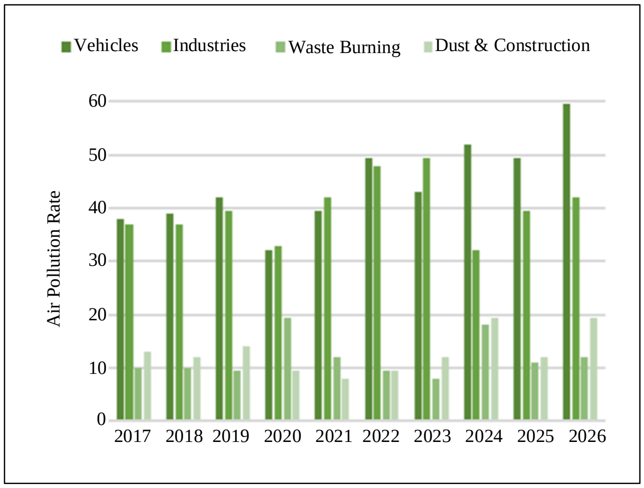

Fig. 1 Air pollution rate

The primary ideas of the paper are enumerated below:

- The novel RTDM technique combines with the densenet algorithm to predict the high efficiency of the air pollution threshold value.
- Initially, sensors in the traffic system collect the environmental data and transmit it to the IoT gateway. It processes the data and gives it to the RTAM.
- In the real-time data analytic module, the PCA technique is used to extract the features, and it is transmitted to DenseNet to predict the quality of the air, like pure and impure. Again, predicted data is given to the RTAM.
- RTAM gives the predicted data to the data storage, where all the data about the quality of the air is stored, and to the center. If the value of polluted air is above the fixed threshold value, it gives an alert and suggests the route to the user.
- The effectiveness of the suggested AIR-IoT ITINEARY model is contrasted with other related strategies. The outcomes of the analyses were performed in accordance with a thorough set of evaluation criteria.

The subsequent sections of this research are explained below: Segment 2 examines the study of the review. Segment 3 describes the suggested model in great depth. Segment 4 is the result and discussion, and Segment 5 is the conclusion.

2. Literature Survey

Several studies have utilized several techniques to monitor the quality of air in real-time. The following section covers a few of the current evaluation approaches, along with their disadvantages, as follows:

In 2022, Asha P. et al. [13] suggested an Artificial Intelligence-based Environmental Toxicology for AQM systems facilitated by the IoT (ETAPM-AIT). To assess the efficacy of the suggested ETAPM-AIT model, a comprehensive series of simulation analyses is conducted, and the outcomes are reviewed after 5, 15, 30, and 60 minutes.

In 2022, Haq, M.A. [14] suggested the novel air pollution classification model, SMOTEDNN. The primary performance issue arises from rigorous pre-processing of the data and comprehensive hyperparameter optimization. In terms of accuracy, the exclusive model SMOTEDNN performed well, with a score of 99.90%.

In 2022, Jabbar, W.A. et al. [15] suggested the implementation of an outdoor-based LoRaWAN-IoT-AQMS. By contrasting the LoRaWAN-IoT-AQMS results with experimental data from the innovative Aeroqual AQM apparatus, the results are verified.

In 2022, Alvear-Puertas, V.E. et al. [16] suggested the expansion of a conveyable, high-tech AQM system that can assess local air pollution. Provide a suitable IoT architecture with an edge-based time series database, MQTT, and a lightweight messaging protocol. The IoT nodes utilized to infer air quality had a performance rate of more than 90% in terms of pertinent data.

In 2022, Zhu Y. et al. [17] suggested an enhanced, inexpensive, IoT-based IAQM system that uses AI to generate suggestions. The LSTM AI technique is used to forecast future CO_2 levels based on the collected CO_2 data. The suggested method can predict the equilibrium level of CO_2 with an error margin of 5.5%.

In 2023, Guerrero-Ulloa, G. et al. [18] suggested IdleAir, an inexpensive IoT-based model for AQM. IdeAir was designed to detect the levels of hazardous gases in indoor environments and, in response, trigger alerts and messages, unlock doors, or activate fans. IdeAir was developed using the TDDM4IoTS technique. Early results show that IdeAir is running with a high degree of acceptance.

In 2021, M. Zareb. et al. [19] suggested an intelligent fuzzy-based indoor AQM system based on the IoT. The suggested system's main drawback is that, when utilizing several sensors, it could use a lot of energy. The results of the experiment demonstrate how effective the recommended strategy is for tracking and enhancing indoor air quality.

In 2023, Paithankar, D.N. et al. [20] presented a novel method for constructing an IoT-powered AQM system. The portal monitoring nodes may run constantly on solar power or batteries and are made to be easily deployed. The studies' findings demonstrate that the suggested strategy is able to precisely track atmospheric conditions and reveal some of the trends in changes in atmospheric quality.

In 2023, Wei, Y. et al. [21] suggested a hybrid deep learning methodology to identify abnormalities from sequential data analysis, merging Autoencoder and LSTM. The proposed concept was tested using a CO2 historical dataset from a real-world deployment. The experimental results demonstrated that, in comparison to existing models of a similar nature, the suggested model works better and has a detection accuracy of 99.50% for abnormal CO2 readings.

3. Materials and Methods

In this section, a novel AIR quality monitoring using the IoT (AIR-IoT ITINEARY) technique has been proposed to monitor atmospheric quality continuously. Initially, sensors in the traffic system collect the environmental data and transmit it to the IoT gateway. It processes the data and gives it to the real-time data analytic module (RTAM). The RTAM feature extraction process is done using the PCA technique.

The feature-extracted data is transmitted to the DenseNet to predict the quality of the air. Again, predicted data is given to the RTAM, which is transferred to the data storage, where all the data about the quality of the air is stored and to the control center. In the control center, it checks the value of pure and impure air. If the value of impure is above the fixed threshold value, it gives an alert, suggests the route to the user, and passes the information to the pollution control authority. The overall workflow of the suggested AIR-IoT ITINEARY methodology is given in Figure 2.

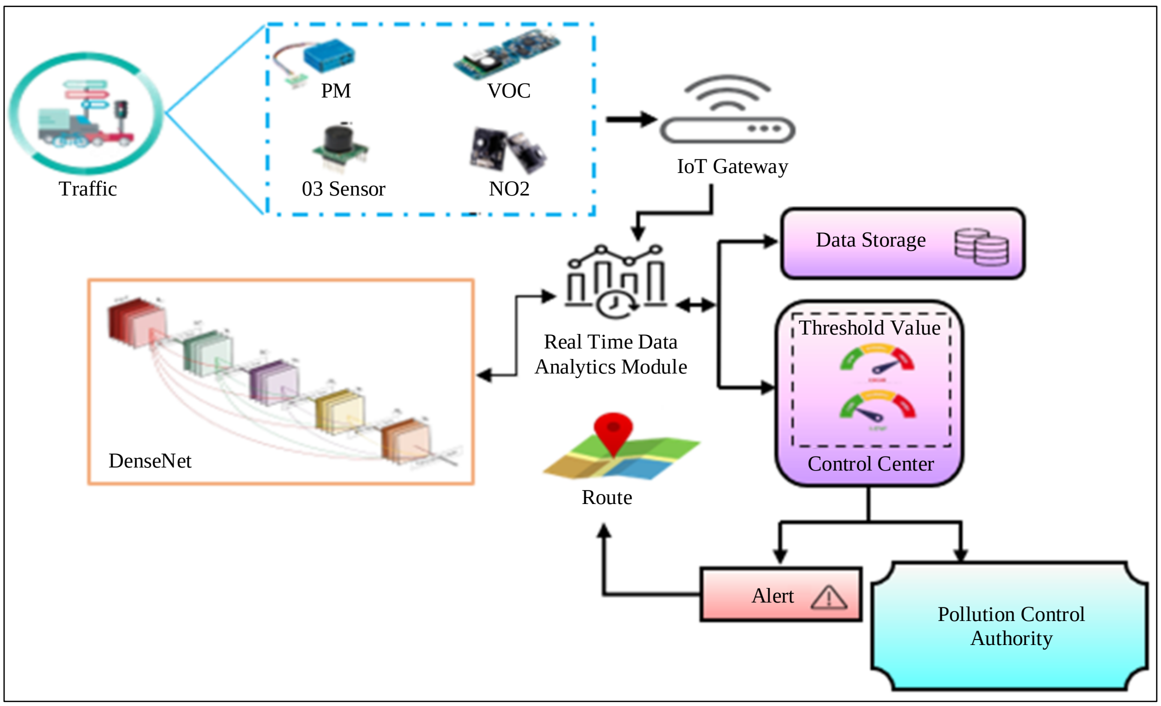

Fig. 2 Proposed AIR-IoT methodology

3.1. Data Collection

The traffic System employs various sensors, including PM (Particulate Matter), VOC (Volatile Organic Compounds), O3, and NO2 sensors, to collect pollution data from urban areas. PM sensors are utilized to measure PM concentration in the air; VOC detectors are utilized to detect VOCs present in the environment; O3 Sensors are used to monitor ozone (O3) levels; and NO2 Sensors are used to measure nitrogen dioxide (NO2) concentration. An IoT Gateway, which is linked to these sensors, sends the gathered data to a Real-Time Data Analytics Module.

3.2. Real-Time Data Analytics Module

It works in tandem to gather information on different pollutants, including NO2, CO, PM, O3, and SO2. This module does the feature extraction of the sensor data. Sensor data frequently comes in raw and noisy formats, making it unsuitable for direct analysis or for inclusion in machine learning algorithms. In feature extraction, key patterns and data from the measurements are extracted from the raw sensor data and converted into a more concise and comprehensible representation. Features of Datus collected from the sensors are extracted in the real-time data analytic module. The PCA is used for extracting features from the sensor information.

3.2.1. Principal Component Analysis

PCA is a unique methodology for reducing feature dimensional aspects. However, it is limited to complex feature spaces due to its linear nature. To address this, standard PCA is extended to nonlinear dimension reduction. Once features are normalized, PCA starts to be a helpful method. To minimize dimensionality in huge datasets, it finds the covariance matrix's eigenvectors with the largest eigenvalues. The definition of PCA algebraic is as follows: Calculate the mean of C for the data outline C as follows:

$$\theta = M(C) \tag{1}$$

Determine C's covariance as follows:

$$CU = C_{ov}(C) = M[(C-\theta)(C-\theta)^T \tag{2}$$

Count the eigenvalue θ_i, and eigenvector b_1, b_2,……...b_N, i= 1, 2……F of the covariance CoV. For the Covariance, the equation is solved CoV;

$$V_k = \frac{\sum_{j=1}^{L}\theta_f}{\sum_{j=1}^{N}\theta_f} \tag{3}$$

Information regarding a more compact measurement subspace can be found by selecting the first L eigenvalue that achieved the desired mutual range, which should be 83% larger than the size of the major segments.

$$g = X^t - V \tag{4}$$

Where V is the first data set to be knotted, and t represents the transfer matrix. Operating the main L eigenvector independently from n to K ($K \ll n$).) increases the number of variables or measurements.

$$|\,\theta l - C0V| = 0 \tag{5}$$

However, l for having dimensions that are more than CoV, gives the identity matrix the benefit of the doubt. Determine the θ_f Eigenvalues of the component L by calculating the percentage of data that is accounted for by the first component.

3.3. DenseNet

Densely Connected Convolutional Networks is a deep learning architecture that provides layers with dense connections. It is especially useful for solving the vanishing gradient issue and promoting feature reuse across the network. Through direct information flow from early layers to later layers made possible by these dense connections, deeper networks, greater gradient flow, and enhanced feature propagation are all made possible.

The network elements that comprise DenseNet are several dense blocks. The DenseNet Block can be represented as given in Equation (6).

$$y_{l+1} = E_l([y_0, y_1, \ldots, y_l]) \tag{6}$$

Here, $[y_0, y_1, \ldots, y_l]$ represents the concatenation of the feature map from each layer that came before it. The transformation $E_l(\cdot)$ typically consists of a series of operations, such as batch normalization, then a non-linear activation function (ReLU, for example), and then a convolution operation, which is given in equation (7)

$$E_l(y) = RELU\big(BN(M_l \times y)\big) \tag{7}$$

Here, M_l represents the weights of the convolution operation, × stands for batch normalization, represents the convolution procedure, and stands for the Rectified Linear Unit activation function (ReLU).

The output of DenseNet is classified into two classes: pure and impure. These data are again sent back to the real-time data analytic module, where they are transferred to the data storage and control center. The information is stored in the data repository for the purpose of future use.

3.3.1. Algorithm

Densenet Algorithm
Input: Batch size B, Maximal iteration step n, Compression ratio r, and a pre-trained densenet DN Output: The densenet with the highest compression ratio 1. Determine the amount of actions performed by the agent, A, based on the compression ratio, r 2. Perform step=1 to n iterations 3. A set of matrices is given, $m = \{m_{01}, m_{02}, \ldots, m_{0B}\}$, which represents B uncompressed Densenets DN 4. When a=1 to A do 5. The initial state of m is encoded by the encoder network as $T = \{T_{a1}, T_{a2}, \ldots, T_{aB}\}$ 6. After receiving the state T as input, the policy network zeroes a path in m to create a new $m = \{m_{a1}, m_{a2}, \ldots, m_{aB}\}$ 7. To get the incentive O, the dense networks denoted by m are tested on the validation set. 8. O updates both the policy network and the encoder network 9. End for 10. End for

3.4. Control Centre

In the control centre, it checks the value of pure and impure air. When a process deviates from its expected operating range, these thresholds are predetermined boundaries or levels that are used to initiate particular actions or alerts.

A control center's principal objective is to make sure that processes remain within reasonable bounds, maintain efficiency, and guard against problems or breakdowns. If the value of impure is above the fixed threshold value, it gives an alert suggests a route to the user, and passes the information on to the pollution control authority.

3.5. Bioaerosol Sampling

The MAS-100 air sampler, a 400-hole impactor plate with several jets with a 100 L/min flow rate and an optimal efficiency suction pump that constantly observes airflow, was the sampling apparatus utilized. The resultant air stream is directed onto a 90 mm-diameter agar surface in a typical Petri dish. This device can collect up to 1000 L per run, sense the air flow entering the device, and adjust the aspirated air to a steady flow of 100 L/min. On the agar surface, the airborne bacteria impaction speed is roughly 11 m/s, or stage 5 of the traditional six-stage Andersen-impactor.

4. Results and Discussion

Within this segment, the observational findings of the suggested AIR-IoT ITINEARY framework are studied, and effectiveness is discussed in terms of multiple performance measures.

The proposed AIR-IoT ITINEARY framework is developed and assessed using the Python programming language along with libraries on a Windows operating system with an Intel Core i7 CPU and 16GB RAM. This investigation assesses the efficacy of the proposed strategy using the pollution dataset from the CityPulse EU FP7 Project. The proposed AIR-IoT model's effectiveness is contrasted with ETAPM-AIT [13], SMOTEDNN [14], and IdeAir [18].

4.1. Description of Dataset

The CityPulse EU FP7 Project's pollution dataset, which has 8 features total, was used in the experiment. These features are ozone, carbon monoxide, particulate matter, sulphur dioxide, longitude, latitude, nitrogen dioxide, and timestamp. The 17568 samples in the dataset were taken at intervals of five minutes. The EPA's AQI standard is presented for each sample value.

The performance of various levels of MAPE, RMSE, and MAE across the network is displayed in Figure 3. It shows that performance can be somewhat improved by adding extra nodes after each layer has 300 nodes. This model demonstrated the best performance. The recommended route in a low-pollution area is shown in Figure 4. The amount of pollution throughout the entire path for a user traveling from a source to a destination will be forecasted, and if the quantity is excessive, a warning will be displayed so the user can reroute his travel. The proposed map provides the user with an alternate path to the location where air pollution is at a minimum.

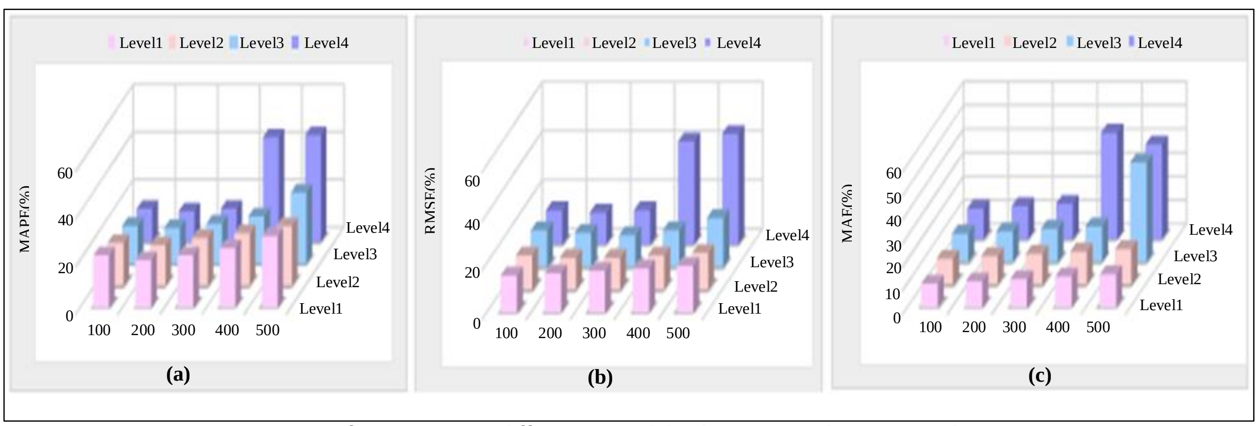

Fig. 3 Performance across different network levels (a) MAPE (b) RMSE, and (c) MAE.

Fig. 4 Android application showing pollution less route

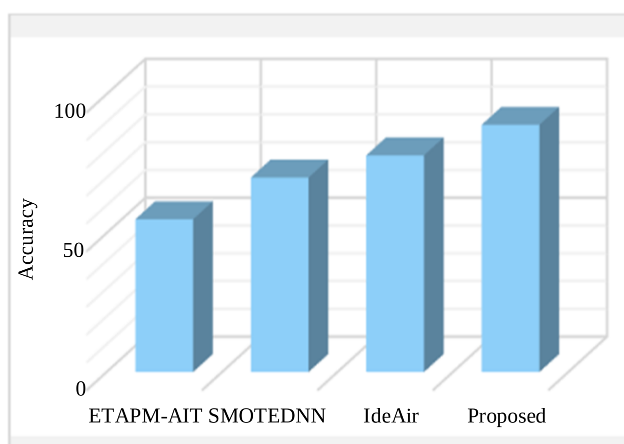

Fig. 5 Performance comparison in terms of accuracy

In Figure 5, the proposed AIR-IoT ITINEARY technique and the existing methods, such as ETAPM-AIT [13], SMOTEDNN [14], and IdeAir [18], are contrasted for accuracy using the CityPulse EU FP7 Project's pollution dataset. Accuracy is a crucial element that illuminates the evaluation of a particular classifier's performance. The accuracy of the AIR-IoT technique is increased by 10.08%, 17.64%, and 34.34% as compared to the ETAPM-AIT, SMOTEDNN, and IdeAir methods.

Figure 6 shows the performance comparison of the suggested AIR-IoT ITINEARY method and the existing ETAPM-AIT [13], SMOTEDNN [14], and IdeAir [18] methods in terms of F1-score, accuracy, and precision using the CityPulse EU FP7 Project's pollution dataset. The accuracy of the proposed AIR-IoT ITINEARY system is increased by 10.08%, 17.64%, and 34.34% and the precision is increased by 9.59%, 18.56%, 17.93% and the F1-score is increased by 8.79%, 16.96%, 36.85% as compared to the IdeAir, SMOTEDNN, and ETAPM-AIT methods, respectively.

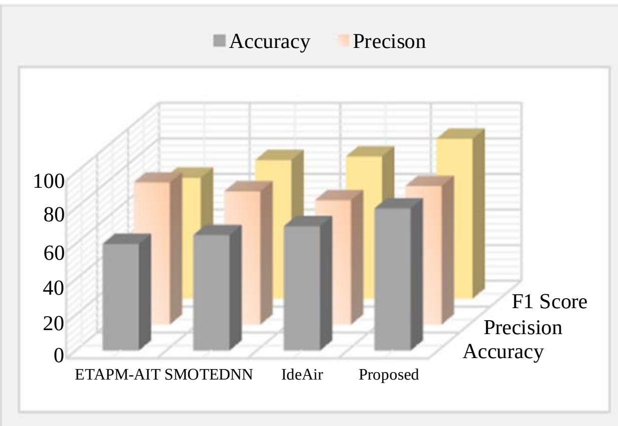

Fig. 6 Performance of models on the dataset

Figure 7 displays the time efficiency of the proposed AIR-IoT ITINEARY technique and existing ETAPM-AIT [13], SMOTEDNN [14], and IdeAir [18] methods. Time efficiency refers to how quickly and effectively the system can gather, process, and disseminate information concerning air pollution levels. The proposed system's time of 13.87 milliseconds is relatively quick compared to ETAPM-AIT, SMOTEDNN, and IdeAir techniques, which take 21.45 milliseconds, 29.56 milliseconds, and 15.39 milliseconds, respectively. It shows that the suggested technique takes less time to process compared to the existing methods.

The normalized RMSE (NRMSE) rate of the suggested AIR-IoT model in comparison to alternative deep learning models is displayed in Figure 8. Many kinds of NRMSE exist. One way to calculate RMSE is to divide it by the variation between the real data's maximum and minimum values. NRMSE is a superior method for comparing models or datasets with different scales. The formula that was applied to compute it is,

$$NRMSE = \frac{RMSE}{Max(D_j)-Min(D_j)}$$

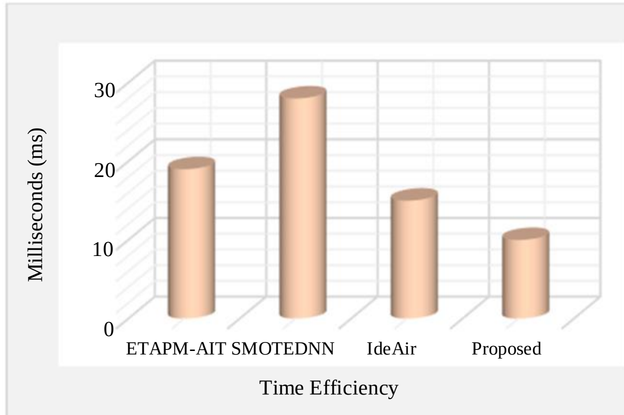

Fig. 7 Time efficiency performance evaluation

Table 1. NRMSE rate comparison with alternative deep learning models

Methods	100	200	300	400	500
ETAPM-AIT	24.52	21.98	17.43	14.67	12.5
SMOTEDNN	13.03	12.48	11.22	10.08	9.29
IdeAir	12.21	10.82	11.65	9.92	9.09
Proposed	8.20	7.9	7.61	7.01	6.19

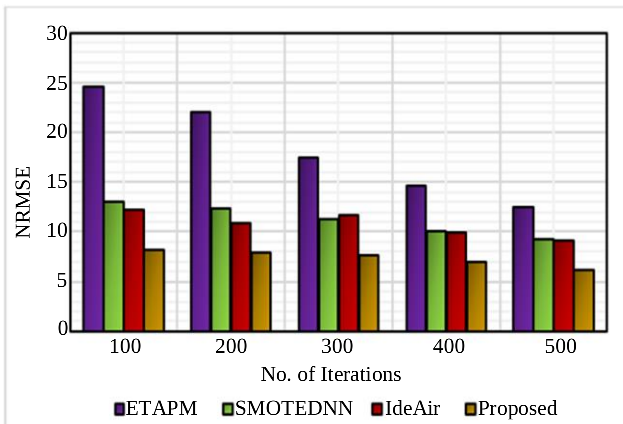

Fig. 8 Comparing performance with RMSE

The coefficient of variation of the mean absolute error (CvMAE) rate between the proposed AIR-IoT model and other deep learning models is displayed in Figure 9. Consequently, the CvMAE rate can be decreased by utilizing the suggested AIR-IoT model. The CvMAE equation is:

$$CvMAE = \frac{MAE}{Average\ reference\ concentration}$$

Table 2. Comparing the MAE rate to other models using deep learning

Methods	1hr	2hr	3hr	4hr	5hr
ETAPM-AIT	10.53	10.16	9.68	9.01	8.01
SMOTEDNN	10.6	9.4	8.7	7.72	6.27
IdeAir	8.91	8.14	7.62	6.85	5.69
Proposed	8.35	7.94	7.49	6.67	5.43

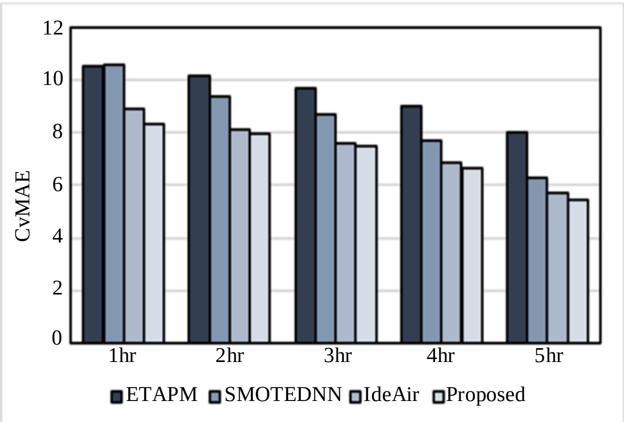

Fig. 9 Comparison of several models using CvMAE

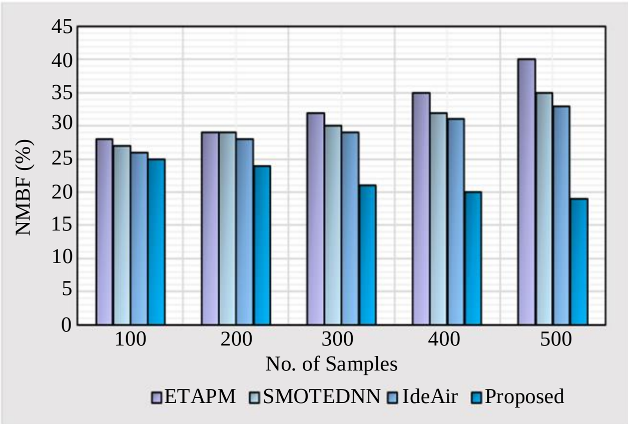

Fig. 10 Comparing performance using NMBF

The Normalized Mean Bias Factor (NMBF) of the suggested AIR-IoT model compared with alternative deep learning models is displayed in Figure 10. NMBF assumes that observations represent the whole truth and is, therefore, more sophisticated than traditional metrics.

5. Conclusion

In this paper, a novel AIR quality monitoring using the IoT (AIR-IoT ITINEARY) technique has been proposed to measure air quality on a live basis. The quality of the atmosphere is predicted using the DenseNet Model, which classifies the quality into 2 classes: pure and impure. If pollution levels exceed the threshold, it alerts the user and suggests an alternative route. The proposed system's effectiveness is assessed using the CityPulse EU FP7 Project's pollution dataset. The proposed framework is developed and assessed using the Python programming language. MAE, RMSE, MAPE, Accuracy, Precision, F1-Score, and time efficiency measure the effectiveness of the suggested AIR-IoT ITINEARY methodology.

According to the comparative analysis, the accuracy of the proposed AIR-IoT ITINEARY system is increased by 10.08%, 17.64%, and 34.34% as compared to the IdeAir, SMOTEDNN, and ETAPM-AIT methods, respectively. Future research may concentrate on offering hyper-localized air quality predictions rather than merely city-wide or regional forecasts. This can entail creating models that consider localized human activity and microclimate conditions.

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