International Journal of Data Science and Artificial Intelligence (IJDSAI)
Volume 02, Issue 04, July – August (2024)

RESEARCH ARTICLE

IOT BASED AIR QUALITY MONITORING USING DENSENET IN URBAN AREAS

M. Devaki [1, *], Jeyaraman Sathiamoorthy[2] and M. Usha [3]

[1] Department of Electrical and Electronics Engineering, Velammal College of Engineering and Technology, Madurai India.

[2] Department of Computer science and Design, RMK Engineering College (Autonomous), RSM Nagar, Kavarapettai, Gummidipoondi Taulk, Thiruvallur, 601206, India.

[3] Department of Master of Computer Application, MEASI Institute of Information Technology, Royapettah, Chennai 600014, India.

Corresponding e-mail: mde@vcet.ac.in

Abstract – Internet of Things is being used more and more 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 significant challenge in the current air quality monitoring system is its limited spatial coverage and accuracy. In this paper, a novel air quality monitoring using IoT is proposed to monitor the quality of the air efficiently in real time. Sensors are placed in the various traffic system to collect environmental data and processed it in Real Time Data Analytics Module (RTDM). DenseNet is used to predict the quality of air and classified into three classes namely pure, impure, and normal. The efficacy of the proposed technique has been evaluated using assessment actions such as accuracy, time efficiency, precision, F1 score, RMSE, MAPE, and MAE. By the comparison analysis, the proposed technique's accuracy rate is 10.08%, 17.64%, and 34.34% higher than the existing Ide Air, SMOTEDNN, and ETAPM-AIT techniques respectively.

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

1. INTRODUCTION

This Internet of Things (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, nitrogen dioxide, ozone, carbon monoxide, 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. The data is then analyzed using advanced analytics, providing significant insights into patterns and trends in pollution [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 particle matter, carbon monoxide, nitrogen dioxide, sulfur dioxide, ground-level ozone, volatile organic compounds, and carbon monoxide are associated with an increase in air pollution [6]. Industrial emissions and vehicular emissions are the main cause 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].

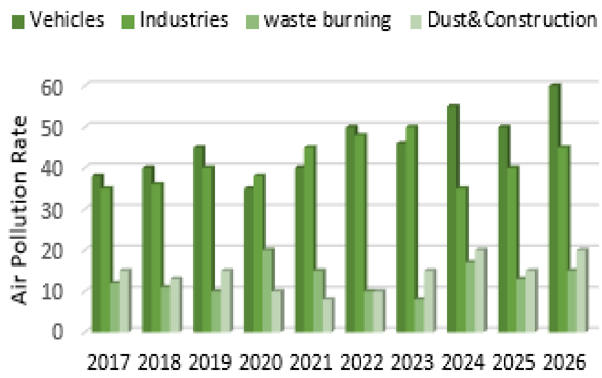


Figure 1. Air Pollution Rate

Figure 1 Shows the air pollution rate of 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 & construction. Year by year usage of vehicles increases and air pollution also increases. Nowadays vehicles are one of the mandatory things in our daily day to life [9]. Vehicle emissions cause the discharge of many pollutants into the atmosphere, such as particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NOx), and volatile organic compounds (VOCs). These contaminants can cause respiratory issues, poorer air quality, and the production of smog [10].

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. 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 IoT has been proposed. The following is a list of the paper's main contributions.

- 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).
- In the real-time data analytic module, the PCA technique is used to extract the features and it is transmitted to the DenseNet to predict the quality of the air. 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.
- We contrast the performance of the suggested model with other related strategies. The outcomes of our experiments were carried out in accordance with a thorough set of evaluation criteria,

The remainder of this research is explained as follows: Section II examines the study of the literature. Section III describes the proposed system in great depth. Section IV is the result and discussion, and Section V 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 are as follows:

In 2022, Asha, P., et.al.,[14] suggested an Artificial Intelligence-based Environmental Toxicology for Air Pollution Monitoring System facilitated by the Internet of Things (ETAPM-AIT). The primary drawback is that ETAPM-AIT systems rely on dependable internet access for data transfer and communication. 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., [15] suggested the novel air pollution classification model SMOTEDNN (Synthetic Minority Oversampling Technique with Deep Neural Network). The primary performance issue arises from rigorous pre-processing of the data and comprehensive hyperparameter optimization. In terms of accuracy, the unique model SMOTEDNN performed better than the other models from the current study and previous research, with a score of 99.90%.

In 2022, Jabbar, W.A., et.al., [16] suggested the implementation of an outdoor-based LoRaWAN-IoT-AQMS (long-range wide area network-based Internet of Things air quality monitoring system). The primary drawback is the high network strain caused by the sensing node's constant data transmission to the cloud every 10 seconds. By contrasting the created LoRaWAN-IoT-AQMS results with experimental data from state-of-the-art Aeroqual air quality monitoring apparatus, the results are verified.

In 2022, Alvear-Puertas, V.E., et.al., [17] suggested the development of a portable, high-tech air-quality monitoring system that can assess local air pollution. Provide a suitable Internet of Things 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. Moreover, the memory consumption 14 Kbytes in flash and 3 Kbytes in RAM was lower in terms of bandwidth and power requirements.

In 2022, Zhu, Y., et.al., [18] suggested an improved, inexpensive, Internet of Things-based IAQ monitoring system that uses artificial intelligence to generate recommendations. The LSTM AI technique is used to forecast future CO2 levels based on the collected CO2 data. This activity is limited by the fact that accurate and dependable measurements are dependent on routine sensor calibration and maintenance. The proposed approach can forecast the steady state of CO2 with a margin of error of 5.5%.

In 2023, Guerrero-Ulloa, G., et.al., [19] suggested Ide Air, an inexpensive Internet of Things-based system for monitoring air quality. Ide Air was designed to detect the levels of hazardous gases in indoor environments and, in response, to trigger alerts and messages, unlock doors, or activate fans. Ide Air was developed using the TDDM4IoTS technique, which aided the developers in completing IoTS development chores more quickly. Early results show that Ide Air is running with a high degree of acceptance.

In 2023, Pant, J., et.al., [13] suggested an intelligent fuzzy-based indoor air quality monitoring system based on the Internet of Things (IoT). The proposed system uses sensors to gather data in real-time on-air quality measurements, including a PM10 and CO2 sensor. 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.

However, several related studies have been conducted to monitor the quality of the air. Moreover, there is a number of disadvantages in the existing methods like usage of more energy, high network load, computational complexity etc. This paper proposed a technique to eliminate these disadvantages, which is explained in the following session.

3. PORPOSED METHOD

The In this session, a novel air quality monitoring using IoT has been proposed to monitor the quality of the air in real-time. 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). In RTAM feature extraction process is done by 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 and suggests the route to the user and passes the information to the pollution control authority. The overall workflow of the proposed method is given in Figure 2.

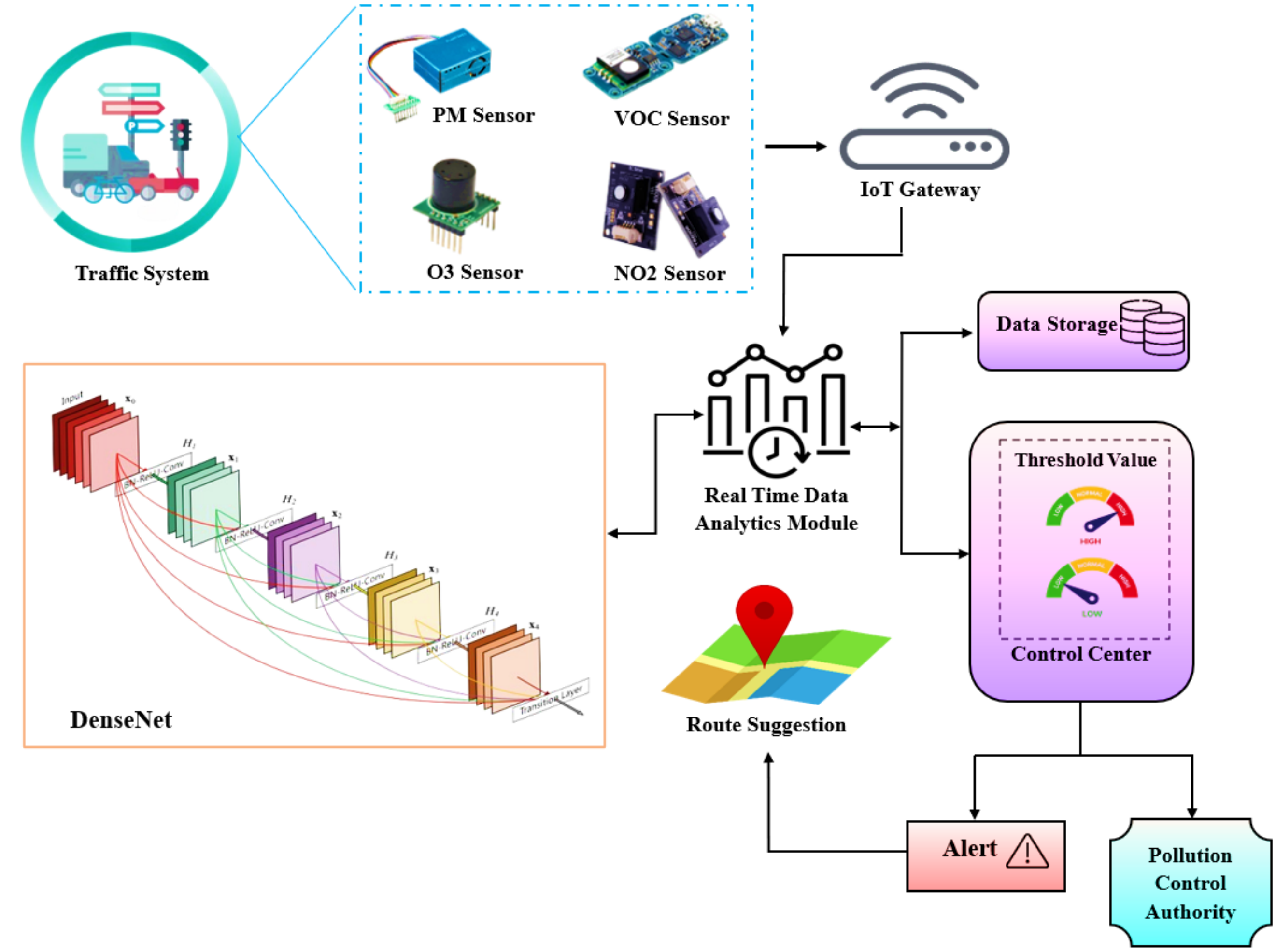


Figure 2. The Overall workflow of Proposed Methodology

3.1. Data Collection

Traffic System employs various sensors, including PM (particulate matter), VOC (volatile organic compounds), O3 (ozone), and NO2 (nitrogen dioxide) sensors collecting pollution data from a environment of urban areas. PM Sensor used to measure particulate matter (PM) concentration in the air, VOC Sensor used to detect VOCs present in the environment, O3 Sensor used to monitor ozone (O3) levels and NO2 Sensor used to measure nitrogen dioxide (NO2) concentration. These sensors are connected to an IoT Gateway, which transmits the collected data to a Real-Time Data Analytics Module.

3.2. Real-Time Data Analytics Module

The real-time data analytics module works in tandem to gather information on different pollutants, including nitrogen dioxide (NO2), CO, PM, ozone (O3), and sulphur dioxide (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 Principal Component Analysis (PCA) is used for extracting features from the sensor data.

3.2.1. Principal Component Analysis (PCA)

PCA is a common method for reducing feature dimensionality. However, it is limited in 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 data outline C as follows:

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

Determine C's covariance as follows:

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

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;

$$V_k = \frac{\sum_{j=1}^{L}\theta_f}{\sum_{j=1}^{N}\theta_f} \quad (3)$$

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.

$$g = X^t - V \quad (4)$$

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.

$$|\,\theta l - COV| = 0 \quad (5)$$

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

3.3. Dense Net

DenseNet (Densely Connected Convolutional Networks) is a deep learning architecture that introduces dense connectivity between layers. It is particularly effective in addressing the vanishing gradient problem and encourages feature reuse throughout the network. These dense connections enable information flow directly from early layers to later layers, facilitating better gradient flow, deeper networks, and improved feature propagation. The key idea behind DenseNet is a dense connection pattern in which every layer in a dense block receives feature maps from all layers that come before it and transmits its own feature maps to all layers that come after it. Because every layer has access to the feature maps created by every layer before it, this leads to feature reuse and helps the network learn more discriminative features.

A DenseNet consists of several dense blocks that make up the network. Multiple convolutional layers with batch normalization and a non-linear activation function (usually ReLU) make up each dense block. The output of each layer within the dense block is concatenated with the feature maps of all preceding layers and fed as input to the subsequent layers within the same dense block. The DenseNet Block can be represented as given in equation (6)

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

Here, $[y_0, y_1, \ldots., y_l]$ denotes the concatenation of the feature map from all the preceding layers. 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)

$$E_l(y) = RELU\big(BN(M_l \times y)\big) \quad (7)$$

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). Transition layers are included in between dense blocks to limit the expansion of feature maps and lower computational complexity. These layers include a batch normalization step, a 1x1 convolution operation for dimensionality reduction, followed by average pooling which is given in equation (8)

$$y' = AvgPool(E([y_0, y_1, \ldots., y_{l-1}]) \quad (8)$$

Here, y' represents the output feature maps after passing through the transition layer, and AvgPool denotes the average pooling operation. Overall, DenseNet facilitates feature reuse and enables the network to be more parameter-efficient compared to traditional architectures, leading to improved performance, especially in tasks with limited training data. The output of the DenseNet is classified into two classes as pure and impure. These data are again sent back to the real time data analytic module where these data are transferred to the data storage and control centre. The data stored in the data storage for the purpose of future use.

3.4. Control Centre

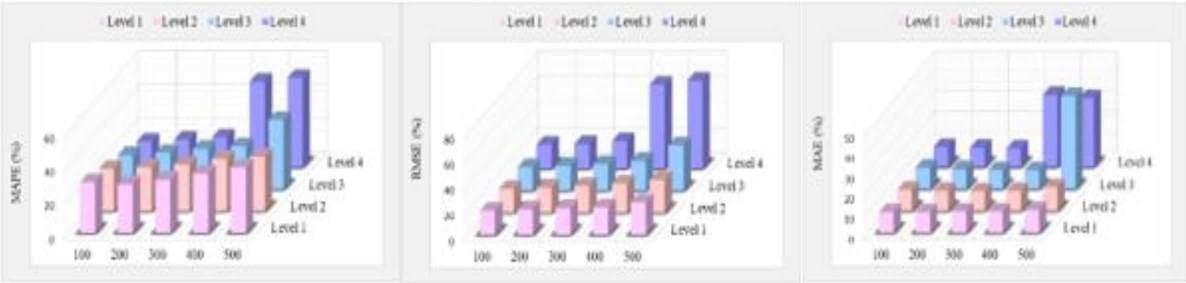
In control center it checks the value of pure and impure air. When a process deviates from its expected operating range, these thresholds are predetermined boundaries or levels that are used to initiate particular actions or alerts. A control center's principal objective is to make sure that processes remain within reasonable bounds, maintain efficiency, and guard against problems or breakdowns. If the value of impure is above to the fixed threshold value it gives alert and suggest the route to the user and pass the information to pollution control authority.

4. RESULTS AND DISCUSSIONS

The proposed method's experimental results are analyzed and a discussion of performance is done in terms of numerous evaluation metrics within this section. The proposed framework is developed and assessed using the Python programming language along with libraries (such as sci-kit-learn, TensorFlow, Kera's, NumPy, and HDF5) on a Windows operating system with an Intel Core i7 CPU and 16GB RAM. The effectiveness of the suggested method is evaluated in this paper using the City Pulse EU FP7 Project's pollution dataset. The proposed model's effectiveness is contrasted with ETAPM-AIT [14], SMOTEDNN [15], and Ide Air [19]. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Accuracy, Precision, F1-Score, and time efficiency are used to assess the performance of the suggested Air IoT approach.

4.1. Description of dataset

The City Pulse EU FP7 Project's pollution dataset, 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. EPA's AQI standard is presented for each sample value.



(a) (b) (c)

Figure 3. Performance Across Different Network Levels (a) MAPE (b) RMSE (c) MAE

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. Our model demonstrated the best performance. Adding more nodes to each layer would lead to overfitting and an unnecessarily long training period. Using a four-layer layout with 400 or 500 nodes in each layer, these can be easily illustrated because the validation error builds up quickly.

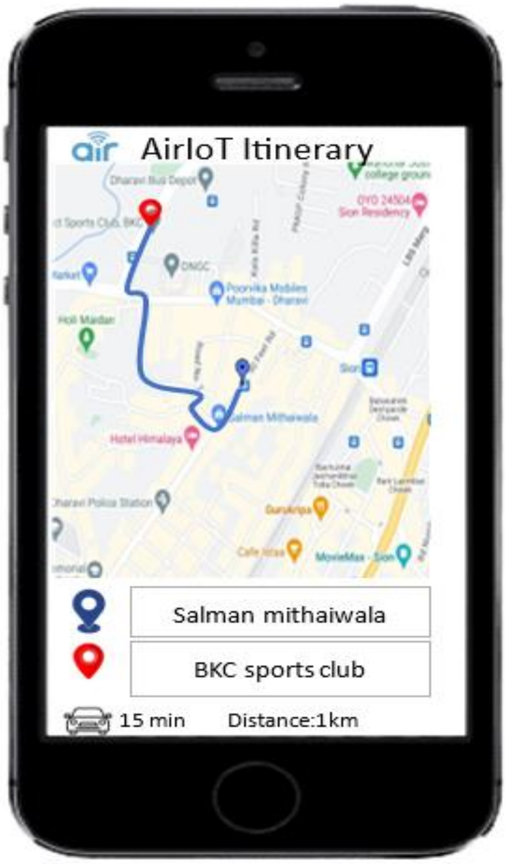


Figure 4. Android Application showing Pollution less Route

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.

In Figure 5, the proposed technique, and the existing method such as ETAPM-AIT [14], SMOTEDNN [15], and Ide Air [19] are contrasted for accuracy using City Pulse 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 Ide Air methods.

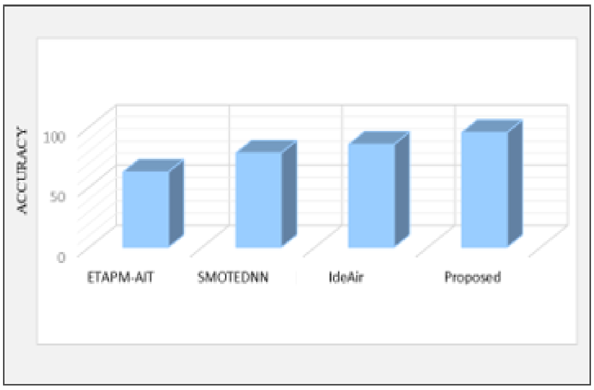


Figure 5. Performance Comparison in terms of accuracy

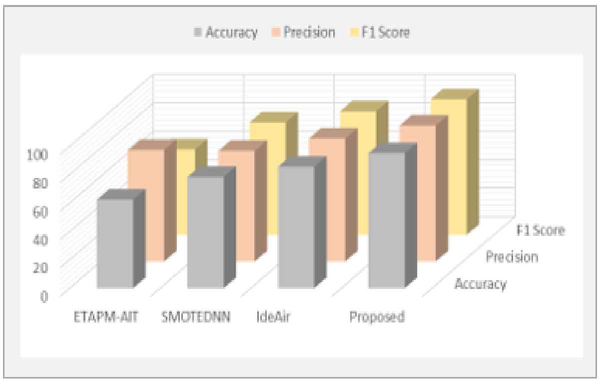


Figure 6. Performance of models on dataset

Figure 6 shows the performance comparison of the proposed Air IoT method and the existing ETAPM-AIT [14], SMOTEDNN [15], and Ide Air [19] methods in terms of accuracy, precision and F1-score using City Pulse EU FP7 Project's pollution datasetThe accuracy of the proposed system is increased by 10.08%, 17.64% ,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 Ide Air, SMOTEDNN, and ETAPM-AIT methods respectively.

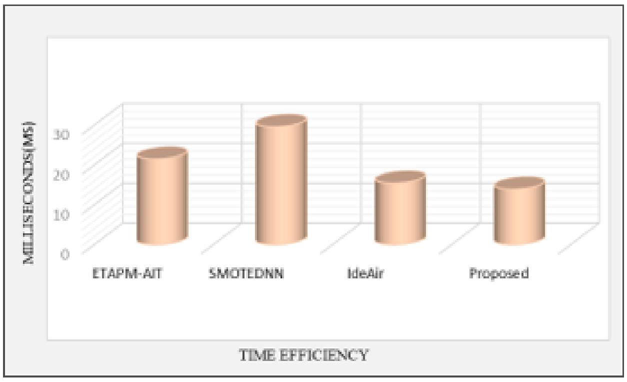


Figure 7. Performance Comparison in terms of time efficiency

Figure 7 displays the time efficiency of the proposed Air IoT technique and existing ETAPM-AIT [14], SMOTEDNN [15], and Ide Air [19] methods. How quickly and effectively the system can gather, process, and disseminate information concerning air pollution levels is referred to time efficiency. The proposed system's time of 13.87 milliseconds is relatively quick compared to ETAPM-AIT, SMOTEDNN, and Ide Air techniques which take 21.45 milliseconds, 29.56 milliseconds, and 15.39 milliseconds, respectively. It shows that the proposed technique takes less time to process compared to the existing methods.

5. CONCLUSION

In this paper, a novel air quality monitoring using IoT has been proposed to monitor the quality of the air in real time. The quality of air is predicted using DenseNet Model which classifies the quality into 3 classes as pure, impure, and normal. The proposed system's effectiveness is assessed using The City Pulse EU FP7 Project's pollution dataset. The proposed framework is developed and assessed using the Python programming language The performance of the proposed method is evaluated by MAE, RMSE, MAPE, Accuracy, Precision, F1-Score and time efficiency. According to the comparative analysis, the accuracy of the proposed system is increased by 10.08%, 17.64% and 34.34% as compared to the Ide Air, 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 localised human activity and microclimate conditions.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

FUNDING STATEMENT

Not Applicable.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

REFERENCES

[1] G. Marques, N. Miranda, A. Kumar Bhoi, B. Garcia-Zapirain, S. Hamrioui and I. de la Torre Díez, "Internet of things and enhanced living environments: measuring and mapping air quality using cyber-physical systems and mobile computing technologies", *Sensors*, vol. 20, no. 3, pp. 720, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] T. Alam, "Cloud-based IoT applications and their roles in smart cities," *Smart Cities*, vol. 4, no. 3, pp. 1196-1219, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] S.A. Meo, F.J. Almutairi, A.A. Abukhalaf, O.M. Alessa, T. Al-Khlaiwi and A.S. Meo, "Sandstorm and its effect on particulate matter PM 2.5, carbon monoxide, nitrogen dioxide, ozone pollutants and SARS-CoV-2 cases and deaths", *Science of the Total Environment*, vol. 795, pp. 148764, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] V. Barot, V. Kapadia and S. Pandya, "QoS enabled IoT based low-cost air quality monitoring system with power consumption optimization", *Cybernetics and Information Technologies*, vol. 20, no. 2, pp. 122-140, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] M. Sahoo and N. Sethi, "The dynamic impact of urbanization, structural transformation, and technological innovation on ecological footprint and PM2. 5: evidence from newly industrialized countries", *Environment, Development and Sustainability*, vol. 24, no. 3, pp. 4244-4277, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] I. Manisalidis, E. Stavropoulou, A. Stavropoulos, and E. Bezirtzoglou, "Environmental and health impacts of air pollution: a review", *Frontiers in public health*, vol. 8, pp. 14, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] E. Hernandez-Rodriguez, D. Kairúz-Cabrera, A. Martinez, R.A. González-Rivero and O. Schalm, "Low-Cost Portable System for the Estimation of Air Quality", *In The conference on Latin America Control Congress*, pp. 287-297, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] J. Chatkin, L. Correa, and U. Santos, "External environmental pollution as a risk factor for asthma", *Clinical reviews in allergy & immunology*, pp. 1-18, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] A. Gil, "Challenges on waste-to-energy for the valorization of industrial wastes: Electricity, heat and cold, bioliquids and biofuels", *Environmental Nanotechnology, Monitoring & Management*, vol. 17, pp. 100615, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] A. Dandotiya, and H.K. Sharma, "Climate change and its impact on terrestrial ecosystems", *In Research Anthology on Environmental and Societal Impacts of Climate Change*, pp. 88-101, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] W. Al-Delaimy, V. Ramanathan, and M. Sánchez Sorondo, "Health of people, health of planet and our responsibility: Climate change, air pollution and health", pp. 419, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] K.L. Ebi, J. Vanos, J.W. Baldwin, J.E. Bell, D.M. Hondula, N.A. Errett, K. Hayes, C.E. Reid, S. Saha, J. Spector, and P. Berry, "Extreme weather and climate change: population health and health system implications", *Annual review of*

public health, vol. 42, no. 1, pp. 293-315, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] P. Asha, L.B.T.J.R.R.G.S. Natrayan, B.T. Geetha, J.R. Beulah, R. Sumathy, G. Varalakshmi and S. Neelakandan, "IoT enabled environmental toxicology for air pollution monitoring using AI techniques," *Environmental research*, vol. 205, pp. 112574, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] M.A. Haq, "SMOTEDNN: A novel model for air pollution forecasting and AQI classification", *Computers, Materials & Continua*, vol. 71, no. 1, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] W.A. Jabbar, T. Subramaniam, A.E. Ong, M.I. Shu'Ib, W. Wu and M.A. de Oliveira, "LoRaWAN-based IoT system implementation for long-range outdoor air quality monitoring", *Internet of Things*, vol. 19, pp. 100540, 2022[CrossRef] [Google Scholar] [Publisher Link]

[16] V.E. Alvear-Puertas, Y.A. Burbano-Prado, P.D. Rosero-Montalvo, P. Tözün, F. Marcillo and W. Hernandez, "Smart and Portable Air-Quality Monitoring IoT Low-Cost Devices in Ibarra City, Ecuador", *Sensors*, vol. 22, no. 18, pp. 7015, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Y. Zhu, S.A. Al-Ahmed, M.Z. Shakir and J.I. Olszewska, "LSTM-based IoT-enabled CO2 steady-state forecasting for indoor air quality monitoring", *Electronics*, vol. 12, no. 1, pp. 107, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] G. Guerrero-Ulloa, A. Andrango-Catota, M, Abad-Alay, M.J. Hornos, and C. Rodríguez-Domínguez, "Development and assessment of an indoor air quality control IoT-based system", *Electronics*, vol. 12, no. 3, pp. 608, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] J. Pant, H. Pant, D. Rautela, P. Sethuramaligam, R. Iyer and V. Birchha, "automated indoor air quality monitoring using an intelligent IoT fuzzy-based approach". [CrossRef] [Google Scholar] [Publisher Link]

AUTHORS

M. Devaki completed UG in Electrical & Electronics Engineering from Raja College of Engineering & Technology, Anna University, Tirunelveli during the year 2011with 82% (First Class with Distinction), completed PG in Power Systems from Velammal College of Engineering & Technology, Anna University, Chennai during the year 2015 with 8.59 CGPA (First Class with Distinction). Currently pursuing Ph.D. in Electrical Engineering, Anna University, Chennai. She has 12 years of teaching experience. Currently working as Assistant Professor in the Department of EEE, Velammal College of Engineering & Technology, Madurai, Tamilnadu, India. Her research area includes Power Quality Improvement, Monitoring, Renewable Energy Sources and Internet of Things (IoT).

Jeyaraman Sathiamoorthy is currently working as a Professor RMK Engineering College, Kavarapettai in Chennai. He has completed M. Tech (CIT) and Ph. D from Manonmaniam Sundaranar University, Tirunelveli. He has 20 years of teaching experience and she has published papers in Network Security in National and International journals and has presented in International Conferences and Seminars. His current area of interest is Programming Languages, Algorithms and ad-hoc networks especially MANET, VANET, FANET and Underwater Communication.

M. Usha is currently working as a Professor cum Assistant Director in MEASI Institute of Information Technology, Chennai. She has completed M.C.A. and M. Phil in Computer Science from Bharathidasan University, Trichy. She has also done her M. Tech (CIT) and Ph. D from Manonmaniam Sundaranar University, Tirunelveli. She has 20 years of teaching experience and she has published papers in Network Security in National and International journals and has presented in International Conferences and Seminars. Her current area of interest is Operating Systems, Algorithms and ad-hoc networks especially MANET, VANET, FANET and Underwater Communication.

Arrived: 23.07.2024
Accepted: 22.08.2024