Review of IoT-based AI analysis method through real-time indoor air quality and health effect monitoring

- Focusing on indoor air pollution that are harmful to the respiratory organ -

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Abstract

Everyone is aware that air and environmental pollutants are harmful to health. Among them, indoor air quality directly affects physical health such as respiratory rather than outdoor air. However, studies that have analyzed the correlation between environment and health information have been conducted through public data targeting large-scale cohorts, and dissertations through real-time data analysis are insufficient. Therefore, in order to collect environmental and health data from various data sources and monitor and analyze real-time, this dissertation will review environmental detection sensor development and indoor air quality monitoring system studies based on Internet of things, and research how to use wearable devices for health monitoring systems. In addition, availability of big data and artificial intelligence analysis and prediction have increased, investigating algorithmic studies for accurate prediction of hazardous environments and health effects. In terms of health effects, techniques to prevent respiratory and related diseases were reviewed.

Keywords: Air pollution; Artificial intelligence; Health effect; Indoor Air quality; Internet of Things; Respiratory disease

1. Introduction

Many studies have shown that air pollution has a direct negative effect on human health. According to the World Health Organization, there are many toxins that have adverse impacts on health, pollutants with the strongest evidence for public health concern include Particulate Matter (PM), Carbon Monoxide (CO), Ozone (O_3), Nitrogen Dioxide (NO_2), and Sulfur Dioxide (SO_2). The PM is an especially important source of health risks, as these very small particles can penetrate deeply into the lungs, enter the bloodstream, and travel to organs causing systemic damages to tissues and cells [1].

Chronic respiratory disease is one of the world's leading causes of death. Every year, more than 3 million people, or 6% of the world's deaths, die from Chronic Obstructive Pulmonary Disease (COPD). COPD is a non-curable progressive life-threatening long condition which restricts airflow in the lungs and causes dysfunction and serious illness [2].

The causes of air pollution vary and appear differently depending on the situation. The main sources of outdoor pollution come from residential energy, vehicles, power generation, agriculture and waste incineration and industry for cooking and heating. The main sources of pollution at home are cooking, burning fuels such as wood and coal in inefficient stoves or open stoves, resulting in a variety of pollutants, including PM and Volatile Organic Compounds (VOCs) [3]. Indoor air pollution induces an early significant impairment of airways function and subclinical cardiovascular damage. A long-term PM and Black Carbon (BC) exposure, in the case of the older participants, were associated to a significant burden of COPD and cardiovascular dysfunction[4]. Exposure to these environmental pollutants has a wide range of adverse health consequences for adults and children[5] and even fetal[1], ranging from respiratory diseases to cancer[6], stroke[7], cardiovascular disease[8], premature death, and cognitive ability[9]. Many studies have been conducted through comparison of exposure between cities by collecting information from cohort and public environment sites, and empirical studies through data of experiment are insufficient. Due to these data restrictions, there is a lack of explanation for individual-level heterogeneity. The sectors of Artificial Intelligence (AI) such as Machine Learning (ML), Deep Learning (DL) are rapidly expanding, affecting wide ranges of industry. Recently AI revolutionizes health care. AI technologies have the perfect platform to thrive and mature with the growing adoption of electronic health records, development in computational power, continuous monitoring systems, and availability of big data. It has become an important clinical decision-making tool that allows for personalized diagnoses, solutions, prognoses, and predictions of future health outcomes, guiding clinicians and other stakeholders in doing what is best for their patients[10]. Therefore, this study aims to review Internet of things (IoT)-based Indoor Air Quality (IAQ) and health monitoring systems and AI analysis methods for environment and health prediction.

2. Indoor Air Quality Monitoring System (IAQMS)

It is a notable fact that air pollution directly affects human health in negative ways, and many studies have confirmed that indoor air is more fatal than outdoor air [11]. Indoor air pollution is a critical environmental health problem worldwide because the half of the world's population depends on biofuel for cooking and heating indoors [12]. For this reason, health problems caused by the increasing number of Indoor air pollution worldwide are an essential topic for discussion among researchers around the world. Many researchers have proposed an improved IAQMS by sensor development and verification. But it is difficult to review all existing and suggested IAQMS in this paper. Because researchers are actively working to improve air quality [13].

The most threatening air pollutants in global public health are considered PM. In order to monitor PM, a light scattering method capable of real-time measurement has been continuously studied [14]. Existing methods of measuring PM concentration include gravimetric and β-ray absorption methods, and light scattering method. The gravimetric and β-ray absorption method are difficult to measure in real time, and the equipment is large and heavy. In contrast, the light scattering sensor is small, light and inexpensive, and there is no need to collect dust with a filter, so data can be easily measured [15, 16]. However, there is a disadvantage to use the light scattering sensor because particle separation is difficult, error rate is high, and it is more severe when an amount of rainfall is low [17].

A miniaturized and low-cost light scattering sensing device was developed to enable separation by PM particle size. A semiconductor laser diode was used inside, and a voltage level signal was converted to a frequency level by applying a fast fourier transform algorithm, and a DSP function was added to the Digital CUP. As a result, the developed sensor overcame the difficulty of real-time measurement and miniaturization of the existing β-ray absorption method. In addition, by connecting smartphone through bluetooth, PM can be monitored in real time and the device can be controlled [18].

To evaluate the accuracy and precision of low-cost sensors, the standard device, metone Aerocet 531s which can calculate dust particles to 0.3μm to be controlled, was compared with three low-cost laser sensors. In the case of $PM_{1.0}$, the error range of all sensors is quite large [19]. This study shows that it is difficult to detect very small particles such as $PM_{1.0}$ with a commercially available inexpensive sensor. In the future, Research on the reliability of more precise and sensitive sensors is needed.

The most studied technology to detecting CO is the Metal-oxide semiconductor (MOS). MOS sensors are very sensitive, selective, robust, lightweight, long lasting, fast response and recovery time, stable and reversible, very low power consumption and low manufacturing costs. MOS has been used extensively to measure and monitor trace levels of important gases such as CO and NO_2 for environment [20, 21]. Both n-type and p-type MOSs are used for gas sensing, but n-type is more popular [22]. In n-type MOS, Tin dioxide(SnO_2) is the most widely utilized. because it provides a high sensitivity in the case of CO sensing [20].

For accurate IAQ evaluation, the interference gas effect of the electrochemical ammonia sensor and NO_2 sensor was studied. The sensor of ammonia is greatly affected by Hydrogen Sulfide (H_2S) and Hydrogen (H), and the presence of SO_2 and NO also affects the sensor operation. In addition, the operation of the NO_2 sensor is affected by all gases except Hydrogen Chloride (HCl). The H_2S was the highest at 14 ppm, and the remaining gas values did not exceed 1 ppm, but were still affected [23]. Therefore, the presence of the interference gas in the electrochemical sensor may cause an error.

The performance of electrochemical sensors of NO_2 and SO_2 was verified for accurate IAQ evaluation. The ppm/response time duration was calculated. In the NO_2 detection, hybrid material-based sensors had a high average ratio, and in SO_2 and H_2S, GaN and metal oxide-based sensors were the highest [24].

Ventilation is essential for indoor air quality measurements. IAQMS has been developed to find general IAQ with modern cooking stove and traditional cooking stove. In poorly ventilated kitchens, total suspended particles are more than 100 times higher than the standard due to excessive smoke generation [12].

It developed an overall air quality alarm system by detecting the levels of seven gases, including O_3, PM, CO, NO_2, SO_2, VOCs, and CO_2. To test the effects of various IAQ factors, the experiment was conducted by dividing the size of the space into church(big), class room(medium), and living room(small). Wind, location, airflow, human density, and room size were found to affect the quality of indoor notice [25].

AirCloud, a cloud system for extensive, low-cost personal air quality monitoring, has been developed. Based on the fusion of sensor data, we invented an air quality analysis engine which learns and generates air quality models. On the cloud-side, this study creates an air-quality analytics engine that learns and creates air-quality models based on a combination of sensor data. This engine is used to calibrate Air Quality Monitoring (AQM) and mini-AQMs in real-time, and predict $PM_{2.5}$ concentrations. AirCloud can achieve superior accuracies at much lower cost than previous solutions [26].

A web-based system for indoor air quality monitoring was presented by applying four types of sensors: gas, PM, temperature, and humidity. The data measured by each sensor is sent to the base station via the WSN node and stores the data collected using a self-developed server program that can be accessed via the web [27].

To develop IoT-based indoor air pollution monitoring, CO_2, NO_2, and CO are monitored using the low-cost gas sensors, and the obtained values were treated with Raspberry Pi. The system is designed using the python coding language. The monitored values can be accessed from the IoT platform. When each sensor interfaces with the Raspberry-Pi module through a different channel, it is output in ppm. A threshold value was set so that when the emission gas concentration is high, an alarm is generated [28].

To test the applicability of the comprehensive Air Quality Index (AQI), a widely used indoor air quality indicator,

Comprehensive Air Quality Indicator, A small air quality monitoring system, has been developed. It responds well to real-time dynamic changes in VOCs, CO, and PM_{10}, and is suitable as an IoT-based small-sized air quality monitoring system with low memory usage [29].

According to the developing trend of IAQMS, over the past few years, most researchers conducted Wireless Sensor Network (WSN)-based designs with Zigbee as the most reliable communication protocol. Given battery life expectancy and stable single-hop communication capabilities, IoT monitoring systems are considered the most reliable solutions for IAQ measurement. With lower latencies and lesser power consumption, these systems also demand lesser efforts for maintenance [13].

3. Health monitoring System

There is an increasing interest in person-generated wearable device data for research purposes.

With the recent movement toward people(patient)-centered care and the widespread routine use of devices and technologies, person-generated health data have emerged as a promising data source for biomedical research [30].

Also, there is an increasing interest in reusing person-generated wearable device data for research purposes, which raises concerns about data quality. However, the amount of literature on data quality challenges, specifically those for person-generated wearable device data, is just few. [31]

Therefore, this paper reviews the health data collection and utilization method by classifying it into wearable device types.

Technological development in the wearable market is increasing exponentially. Personal health monitoring and Physical Activity (PA) are popular across all ages and clinical communities [32]. In addition, routine PA is also effective in preventing and managing chronic diseases such as cardiovascular disease, hypertension, diabetes, and obesity [33]. Among them, the type worn on the wrist is the biggest growth.

A remote health monitoring and support system using information and communication technology was developed to evaluate and manage the physical condition and PA level of home-care patients with COPD. The study using an iPad as a system device, and a developed application that handles input and transfer of the following data and six evaluation items related to symptom (cough, phlegm, breathing, sleep, appetite, vitality), number of steps per day, and energy consumption. This application enables remote monitoring to medical personnel such as doctors and nurses, preventing acute exacerbation of COPD and enabling early detection and treatment of acute exacerbation. In addition, the system can provide lifestyle guides that fit individual lifestyles and medical conditions [34].

Fractional Exhaled Nitric Oxide (FeNO) is a non-invasive indicator of airway inflammation in asthma. Recent studies have shown that FeNO is a potential outcome of COPD. Recently, a new hand-held FeNO analyzer (NIOX MINO) has been developed. The level of FeNO in short time was compared using NIOX MINO and stationary chemiluminescence analysis (NOA, Sensormedics) in COPD patients and healthy people. There was no significant difference in the short period, COPD patients show high variability for a long period. it was significantly associated with exacerbation rate. Also, The FeNO electrochemical hand-held analyzer is available in the COPD showing positive consistency with the stationary chemiluminescence analyzer [35].

Data was monitored by wearing Basis Peak for 5 months for 43 patients. As a result, it was possible to identify physiological differences between the condition of health among individuals [36].

The system was proposed to measure environmental factors and notify workers with alarms and vibrations to protect safety in case of danger to workers, and to transmit situation information to the control center to take immediate action. It was combined Galaxy Watch' Biosensor, Apple Watch(electrocardiogram(ECG), Heart Rate, Saturation of Percutaneous Oxygen(SpO_2)), Gas Sensor(CO_2, VOCs), and wireless communication technology. For accurate measurement and analysis, multiple levels of risk setting and ML techniques must be added [37].

A Surface Electromyogram(sEMG) electrode with a diameter of 10 and 24 mm was developed by screen printing PEDOT:PSS ink on 100% cotton fabric. The larger the diameter, the lower the resistance value(38).

A wireless patch-type wearable pulse oximeter has been developed to measure the heart rate and SpO_2 by reflecting light sources of two wavelengths(red 625nm, infrared 865nm) in a person's forehead. The size of the flexible circuit is 7cm×2cm, interfaced with an 8.5cm×3.5cm wireless system board. It weighs only 15g, it is an elastic band that can be easily wearable on the forehead. By detecting and measuring the change in amplitude of photoplethysmographic (PPG) signals for red and infrared light due to changes in blood oxygen saturation, SpO_2 is calculable from the infrared and red PPG signals' amplitude ratio. SpO_2 values measured using our system were consistent with commercial non-abrasion pulse oximeters in both normal and inhale/exhale conditions [39].

These wearable biosignal monitoring sensors are used by adhering to the human body, so it is important to surface-treat materials that are harmless to skin contact. If the surface is treated with a flexible polymer material such as PDMS, as the electrode does not directly adhere to the skin, it can safely sense a bio-signal. However, PDMS has a high moisture permeation rate, so when adhered for a long time, there is a risk that body fluids such as human sweat penetrate and the sensor is oxidized [40].

COPD is one of most common diseases related to breathing. A new diagnostic method is developed to detect the COPD parameters by using a Microelectromechanical System (MEMS) based acceleration sensor. It records the data of acceleration that occur the movements of the diaphragm in three axes during breathing. With the proposed device in this work, the parameters such as tidal volume capacity, forced vital capacity and respiratory rate which are commonly associated with COPD are successfully measured. The measurement results were very similar to spirometer and can be considered as an alternative instrument for spirometer [41].

There is a study on wearable devices with clothing type. Typical clothing is soft and flexible and can be draped to our bodies [42]. It must be washable for reuse, but there are technical difficulties due to the fiber material with hard and non-washable electronic products and electrical materials [43].

All smart electro-clothing systems consisted of hardware and software, are mostly electronic and non-fiber materials with sensing subsystem, action subsystem, control subsystem, communications subsystem, location subsystem, power subsystem, storage subsystem, and display subsystem as a common component [43, 44]

A smart jacket is designed for securing the coal miners' life. This prototype senses the various health related parameters i.e. the presence of hazardous gas, pulse rate of miner, updated temperature/humidity, exact depth and geographical location of miner. All of these parameters are transmitted through Wi-Fi to the internet protocol. All miners were monitored. In addition, in the event of a disaster, the miners' lives can be secured immediately. This designed wearable embedded system will send the last GPS location to a specific IP as well as continuous updates of the miner' pulse rate detected by the pulse sensor to the control system [45].

For accessory types, Photonic textiles that can measure pulse oximetry were sewed on gloves. SpO_2 is measured in accordance with a change with the amount of light transmitted by mounting an optical sensor at the finger' tip. By measuring the amount of light transmitted by two different wavelengths (HeNe laser, Halogen lamp) with an optical sensor, oxygen-reduced and deoxygenated hemoglobin can be calculated to obtain oxygen saturation in body. Using photonic textiles is feasible for pulse oximetry [46].

4. AI analysis for Air Quality Prediction

Research for air quality prediction has been conducted on the basis of various algorithm models. Most of studies' settings are largely divided into comparison of artificial intelligence analysis techniques and developing new algorithms. Therefore, this paper reviews it in two ways.

First, it reviews comparison of artificial intelligence analysis techniques for air quality prediction.

The study was conducted to determine a predictive model for determining air pollution based on PM_{10} and $PM_{2.5}$ pollution concentrations in Tehran. As a ML methods for air pollution prediction were used by Support Vector Regression (SVR), geographically weighted regression, Artificial Neural Networks (ANN), and autoregressive nonlinear neural networks using external inputs. The most reliable algorithm for air pollution prediction is an autoregressive nonlinear neural network with external input using the proposed prediction model, with a one day prediction error of 1.79μg/m^3 [47].

To predict PM and BC, a transportation-related air pollution factor, ML model performance was compared. This study investigates the Land Use Regression (LUR)' boundaries approaches and the potential of two different ML models: ANN and gradient boost. Models was developed for PM performing better than those for BC. For the same contaminants, ANN and eXtreme Gradient Boosting (XGBoost) models showed better performance than LUR [48].

To assess PM prediction performance, it was compared ANN with MLR models. The model's input data was PM_{10} concentration and variables for weather. As a result of comparing the two models, the nonlinear ANN method showed better performance for prediction of PM_{10}(49).

The PM_{10} concentration in seoul was predicted using weather factors as an input dataset of MLR, Support Vector Machine (SVM), and Random Forest (RF) models, and the performance of the model was compared and evaluated. The model's input dataset was composed by nine meteorological factors obtained by Automatic Weather System (AWS): temperatures, precipitation, wind speeds, wind direction, yellow dust, and relative humidity. The prediction performance of the ensemble model RF was the highest followed by the relative humidity and yellow dust which contributed greatly to the predictive performance of all models, and the maximum temperature and average wind speed showed relatively low. In case of Gwanak-gu and Gangnam-daero which are relatively close to Air quality monitorimg sites (AQMS) and AWS, SVM and RF models were highly accurate according to the model validations. By contrast, Yongsan-gu which is relatively far from AQMS and AWS, both models didn't perform well. The results indicate that AQMS and AWS adjacencies have a very significant effect on PM10 concentration prediction [50].

In order to compare the performance of the PM concentration prediction algorithm, the performance of MLR, SVR, Auto-regressive integrated moving average(ARIMA), and Autoregressive integrated moving average with explanatory variable(ARIMAX) was compared. It was evaluated with Root Mean Square Error(RMSE) using air quality information and weather information. In the integrated concentration prediction, the performance of SVR was superior to that of MLR, and in the time series prediction by location, the performance of ARIMAX was superior to that of ARIMA [51].

The study performs a traditional model k-Nearest Neighbors(k-NN) and Logistic Regression (LR) and a non-traditional Long-Short Term Memory (LSTM) network-based DL algorithm for the creation of alert messages regarding to bin status and predicting the amount of air pollutant CO presence in the air at a specific instance. The recalls of LR and k-NN is 79% and 83% respectively, in a real-time testing for predicting bin status. The accuracy of modified LSTM and simple LSTM models is 90% and 88%, respectively, to predict the future gases concentration presence in the air. The system provided real-time monitoring of garbage levels along with notifications from alert mechanism and improved accuracy by utilizing ML [52].

Second, it is a review on the development of algorithms for prediction of air quality.

A data mining algorithm was developed by inter-applying ANN and k-NN to implement accurate PM prediction models. For ANN operation, a network, consisting of 13nodes in the input layer, 15nodes in the hidden layer, and 1node in the output layer was constructed. Output was classified using the k-NN algorithm and had the highest accuracy when K=9. The proposed model showed an improved prediction rate than ANN and k-NN [53].

A separation prediction model for each concentration of PM based on Deep neural network (DNN) was designed to improve PM_{10} prediction accuracy. In order to select the optimal hyperparameter, a total of 3,600candidate parameters were set for each model through the grid search technique. In this process, in order to select a hyperparameter value with a high generalization performance, the hyperparameter search was performed by setting the number of folds of k-fold, which is one of the cross-validation methods, to 3. In addition, for performance comparison with the proposed concentration-specific separation prediction model, the hyperparameter optimization of the DNN based model was performed [54].

Predictive models were designed through MLR and ANN and the suitability of algorithms for PM prediction was evaluated through comparison with real data. To evaluate the suitability of algorithms for PM prediction, MLR and ANN were compared with real-world data. In the case of the algorithm PM prediction, ANN was better in performance, and the composition of the hidden layer to which the appropriate number of neurons was applied was important when designing the PM prediction model using ANN [55].

The PM_{10} concentration prediction algorithm was modeled using variables of weather and traffic-related air pollutant concentration such as CO, Nitric Oxide (NO), Nitrogen (N) data. A Generalized Additive Model was developed and evaluated. Through this study, weather variables such as temperature and wind speed were identified as major control factors for PM_{10} concentration, but traffic-related air pollutants and PM_{10} concentrations showed a weak relationship. Therefore Road traffic is not the main cause of PM [56].

Despite the abundance of studies on $PM_{2.5}$ and PM_{10} estimations from satellite remote sensing, only a few studies have been conducted on $PM_{1.0}$ by using satellite observations. Thus, this study estimated hourly $PM_{1.0}$ oncentrations in China by using an integrated Principal Component Analysis (PCA) and hybrid Generalized Regression Neural Network (GRNN) model that combines ground-based observations of $PM_{2.5}$ with a geostationary satellite Himawari-8 Aerosol optical depth data. Fusing $PM_{2.5}$ data was advantageous for the continuous spatiotemporal estimation of $PM_{1.0}$, and the estimation accuracy of each model was significantly improved. Specifically, the R^2 of MLR increased from 0.21 to 0.38, and the GRNN and PCA-integrated GRNN models improved by 8% and 6%, respectively. Comparison of the linear regression model and GRNN model(including PCA-integrated GRNN) showed that the nonlinear model can determine the potential relationship between PM and predictors [57]. Due to the absence of low-cost, high-quality $PM_{1.0}$ sensors, prediction of $PM_{1.0}$ AI analysis is an important research topic.

There is a study that proposes an air quality prediction system 'Gated Recurrent Units (GRU)' using six atmospheric sensor data(VOCs, CO_2, PM, temperature, humidity, and light quantity) and DL models. The predictive accuracy performance of the proposed GRU model was compared to other models such as LSTM networks and linear regression. The proposed system showed better performance with 85% higher accuracy for various parameters [58].

5. AI analysis for Health Effect Prediction

Research for health effect prediction has been conducted on the basis of various algorithm models. The settings of most studies are largely divided into comparison of artificial intelligence analysis techniques and developing new algorithms. Therefore, this paper reviews it in two ways.

First, it reviews comparison of artificial intelligence analysis techniques for health effect prediction.

To predict sepsis mortality, there is a study comparing conventional context-based logistic regression approaches with four ML techniques: Least absolute shrinkage and selection operator Regularization, RF, XGbost and DNN. All four ML models showed higher sensitivity, specificity, positive prediction, and negative prediction values compared to the logistic regression model [59].

When the most accurate predicted model is the goal, ML algorithms are more advantageous than conventional regression methods. When using ML methods, special attention is required in the form of model validation, and the usefulness of solving individual problems varies, so comparison with multiple approaches is required, and the criterion for how much flexibility can be allowed becomes the ultimate modeling technique [60].

In order to predict the frequency of asthma, it was analyzed through three predictive models: SVM, Neural Net, and DL based on asthma-causing lifestyle, eating habits, environmental characteristics, and basic characteristics. The predictive ability of the model was compared on the basis of the accuracy of the model, RMSE, and Mean Absolute Error (MAE). SVM has a significant accuracy of 93.19%, but RMSE 0.320 and MAE 0.300 indicators are not good. The evaluation results of the DL are accuracy 74.78%, RMSE 0.252, and MAE 0.120, which are generally good. In contrast, Neural net model is quite good with an accuracy of 93.19%, and RMSE 0.251 and MAE 0.124 indicators are also quite good. The neural net model is the best prediction model for asthma. Because the model is learned by feedforward neural networks learned by backpropagation algorithm [61].

Second, it is a review on the development of algorithms for prediction of health effect.

The automated device for asthma monitoring and management, a wearable IoT sensor smart device, was used to collect general conditions such as the patient's physical condition, body temperature, emotion, heart rate, respiratory status, and behavior. A patient monitoring system based on Iterative Golden section optimized Deep Belief neural Network (IGDBN) using MATLAB for the collected data is developed. The developed IGDBN guarantees a higher precision and a higher MCC value with a lower error rate than DNN, Hybrid random forest with linear model, Long short-term neural network, Fuzzy rule-based neural classifier [62].

An electronic stethoscope was developed through artificial intelligence analysis of medical acoustic data by measuring lung sound. The device is divided into three parts including Sounds Collection Module (SCM), e-healthcare Home Gateway (eHG), and smartphone. SCM records heart and lung sounds, eHG communicates with data translation and cloud servers, and mobile devices interface. For lung sound analysis, firstly perform a Short-Time Fourier Transformation (STFT) of the sound file and output signals for further classification. Use Convolutional neural network (CNN) and k-NN models for classification. After the STFT image is loaded, it is first converted into a gray-tone image, and then used CNN model. The last extracted features are used as input to the k-NN model for the final classification [63].

The existing auscultation through the stethoscope may cause interpretation errors due to the subjective approach from a doctor. Therefore, objective evaluation is required using ML to detect wheezing. This study proposed an LSTM-based neural network, a novel wheezing detection model that distinguishes normal and wheezing. Mel-Frequency Cepstral Coefficients (MFCC) were used as the feature extraction method. A simulation was performed through MATLAB R2020a. The performance of the proposed model was evaluated and compared with the existing Multilayer Perceptron (MLP), a widely used neural network that has proven efficiency in traditional respiratory sound classification. LSTMs are an up-and-coming alternative to feedforward networks since they provide relatively better results [64].

It is a difficult task for human listeners because some lung sound events have a frequencies's spectrum that is beyond human hearing ability. Thus, this paper proposed a system capable of detecting and classifying abnormal lung sounds, such as crackle or wheeze sounds. CNN was used to successfully detect and classify adventitious sounds in lung sound signals. various functions(Power Spectrum Density (PSD), Mel Spectrum (MS), MFCC) for converting lung sound signals into 2D images were presented. MS when feed into CNN, achieves results in line with the current cutting-edge technology and followed by PSD, MFCC [65].

6. Conclusion

The reliability of IAQ and health effect sensors has been demonstrated through many studies. However, in the case of $PM_{1.0}$ with small particles, large equipment must be used, and real-time prediction is difficult through small and portable sensors. Although it is possible to predict $PM_{1.0}$ through artificial intelligence analysis of $PM_{2.5}$ data with large particles, more research on precise sensors that can be directly measured is needed. In addition, the reliability of electrochemical sensors should be studied in the future by overcoming the interference gas effect. IoT-based real-time monitoring is efficient to monitor, collect, and analyze more accurate air quality, and in the future, AI analysis needs to improve precision and accuracy.

In addition, research on the convergence of medical and artificial intelligence has recently continued. This is because a doctor's subjective judgment increases the demand for accurate analysis and predictive power of artificial intelligence. Many AI-based studies have been conducted to predict lung disease from health effect data, and mortality from lung disease. In addition, a recent increase in demand for telemedicine has led to an increase in research on a development of remote healthcare services.

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