Review

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Review of Internet of Things-Based Artificial Intelligence 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 examined the correlation between environmental and health information have been conducted with public data targeting large cohorts, and studies with real-time data analysis are insufficient. Therefore, this research explores the research with an indoor air quality monitoring (AQM) system based on developing environmental detection sensors and the internet of things to collect, monitor, and analyze environmental and health data from various data sources in real-time. It explores the usage of wearable devices for health monitoring systems. In addition, the availability of big data and artificial intelligence analysis and prediction has increased, investigating algorithmic studies for accurate prediction of hazardous environments and health impacts. Regarding health effects, techniques to prevent respiratory and related diseases were reviewed.

Keywords: Air Pollution; Artificial Intelligence; Health Effect; Air Pollution, Indoor; Internet of Things; Respiratory Tract Disease

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 adversely impact health. Pollutants with the most substantial 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 significant source of health risks, as these very tiny 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 the chronic obstructive pulmonary disease (COPD). COPD is an incurable, progressive life-threatening chronic condition that restricts airflow in the lungs and causes dysfunction and severe 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 cooking and heating industries. The main sources of indoor pollution are cooking inefficient stoves, or burning fuels such as wood and coal in open ovens, resulting in various pollutants, including PM and volatile organic compounds (VOCs)[3]. Indoor air pollution induces significant early impairment of airway function and subclinical cardiovascular damage. A long term PM and black carbon (BC) exposure were associated with a significant burden of COPD and cardiovascular dysfunction in the case of the older participants[4]. Exposure to these environmental pollutants causes wide range of adverse health effects in adults and children[5] and even fetal[1], from respiratory diseases to cancer[6], stroke[7], cardiovascular disease[8], and premature death, and cognitive ability[9]. Many studies have been conducted comparing exposure between cities by collecting information from cohort and public environment sites, and empirical studies with experimental data are insufficient. Because of these data restrictions, there is a lack of explanation for individual-level heterogeneity. The fields of artificial intelligence (AI), such as machine learning (ML), deep learning (DL) are rapidly expanding and impacting wide ranges of industries. Recently AI has been revolutionizing health care. With the development of electronic health records, growth in computing power, continuous monitoring systems, and the availability of big data, AI technologies have the perfect platform to flourish and mature. Personalized diagnoses, solutions, prognoses, and predictions of future health outcomes have become crucial clinical decision-making tool that guides physicians 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 the environment and health prediction.

Indoor Air Quality Monitoring System

Air pollution negatively affects human health, and several studies have confirmed that indoor air is more dangerous than outdoor air[11]. Indoor air pollution is a critical environmental health problem worldwide because 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 pollutants worldwide are an essential topic for discussion among researchers worldwide. Many researchers have proposed an improved indoor air quality monitoring system (IAQMS) by sensor development and verification. However, reviewing all existing and suggested IAQMS in this paper is difficulty because researchers actively working to improve air quality[13].

Air pollutants are considered the prime threat to global public health. A light scattering method capable of real-time measurement was continuously studied for monitoring PM[14]. Existing methods of measuring PM concentration include gravimetric and β-ray absorption methods and light scattering methods. The gravimetric and β-ray absorption methods are challenging 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 that data can be easily measured[15,16]. However, there is a disadvantage to using the light scattering sensor because particle separation is complex, the error rate is high, and it is more severe when rainfall is low[17].

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

To evaluate the accuracy and precision of the low-cost sensors, a standard device, metone Aerocet 531s (NaraeTek, Busan, Korea), which can count dust particles down to 0.3 μm, was compared with three low-cost laser sensors. In the case of $PM_{1.0}$, the error range of all sensors is very large[19]. This study shows that detecting small particles such as $PM_{1.0}$ with an inexpensive sensor is difficult. In the future research on the reliability of more accurate and sensitive sensors is needed.

Metal oxide semiconductor (MOS) is the most studied technology for CO detection. MOS sensors are susceptible, selective, robust, lightweight, and durable, and they have a fast response and recovery time, are stable and reversible, have low power consumption and have low manufacturing costs. MOS is widely used to measure and monitor trace amounts of environmentally essential gases 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]. Among the n-type MOS, tin dioxide (SnO_2) is the most widely used because it provides high sensitivity in the case of CO sensitivity[20].

The interference gas effect of the electrochemical ammonia sensor and NO_2 sensor was studied for accurate IAQ evaluation. The ammonia's sensor is greatly affected by hydrogen sulfide (H_2S) and hydrogen (H), and SO_2 and nitric oxide (NO) also affects sensor performance. In addition, the operation of the NO_2 sensor is affected by all gases except hydrogen chloride (HCl). The H_2S was maximal at 14 ppm, while the remaining gas values did not exceed 1 ppm, but were still affected[23]. Therefore, interference gas in the electrochemical sensor may cause an error.

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

Ventilation is essential for measuring IAQ. The IAQMS has been developed to identify common IAQ with modern and traditional cooking stoves. In poorly ventilated kitchens, total suspended PM is 100 times higher than the standard due to excessive smoke generation[12].

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

AirCloud, is a cloud system developed for comprehensive, low-cost personal air quality monitoring (AQM). Based on the combination of sensor data, we invented an air quality analysis engine that learns and generates air quality models. On the cloud-side, this study develops an air quality analysis engine that learns and creates air quality models based on a combination of sensor data. This engine calibrates AQM and mini-AQMs in real-time, and predicts $PM_{2.5}$ concentrations. AirCloud can achieve higher accuracy at a much lower cost than previous solutions[26].

A web-based system IAQMS presents by using four sensors: gas, PM, temperature, and humidity. The data measured by each sensor transmits to the base station via the wireless sensor network (WSN) node, and a self-developed server program accessible via the internet stores the collected data[27].

To develop IoT-based indoor air pollution monitoring, CO_2, NO_2, and CO are monitored using low-cost gas sensors, and Raspberry-Pi processed the obtained values. The system is designed using the python coding language. The monitored values are accessible from the IoT platform. As each sensor interfaces with the Raspberry-Pi module through a different channel, it outputs in ppm. A threshold value was sets such that an alarm generates when the emission gas concentration is high[28].

To test the applicability of the comprehensive Air Quality Index (AQI), a widely used IAQ indicator.

A comprehensive air quality indicator and a close monitoring system have 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 AQM system with low memory usage[29].

According to the developing trend of IAQMS, in the past few years, most researchers have conducted WSN-based designs with Zigbee as the most reliable communication protocol. IoT monitoring systems are considered highly reliable solutions for IAQ measurement with long battery life stable single-hop communication capabilities. Along with low delays and low power consumption, these systems also demand less effort for maintenance[13].

Health Monitoring System

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

Also, there is growing interest in reusing person-generated wearable device data for research purposes, raising concerns about data quality. However, the literatures on data quality challenges need to be improved, specifically for person-generated wearable device data[31]. Therefore, this paper reviews the health data collection and usage patterns by categorizing wearable device types.

Technological development in the wearable's market is increasing exponentially. Personal health monitoring and physical activity (PA) are popular among all age groups and medical communities[32]. In addition, regular PA is effective in preventing and managing chronic diseases such as cardiovascular disease, hypertension, diabetes, and obesity[33]. Among them, the wrist-worn type is the most significant development.

A remote health monitoring and support system was developed using information and communication technology to access and manage physical status and PA levels in home-care patients with COPD. A study using an iPad (Apple, Cupertino, CA, USA) as a computing device and a developed utility dealing with the input and transfer of the following data and six assessment items related to the symptom (cough, phlegm, breathing, sleep, appetite, vitality), number of steps per day, and energy consumption. This application enables remote monitoring for medical personnel such as doctors and nurses, prevents exacerbations. Of COPD and helps with early detection and treatment of acute exacerbations. In addition, the system can provide lifestyle guides tailored to 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 consequence of COPD. Recently, a new portable FeNO analyzer (NIOX MINO, Aerocrine, Solna, Sweden) has been developed. Qualification of FeNO was compared in COPD patient's and healthy subjects over a short period using NIOX MINO and standard chemiluminescence analysis (NOA, Sensormedics, Yorba Linda, CA, USA) in COPD patients and healthy people. While there was no significant difference in the short period, COPD patients showed greater variability in the long term. This is associated with a significantly exacerbation rate. Also, a FeNO electrochemical portable analyzer is available in COPD, which shows positive consistency with a stationary chemiluminescence analyzer[35].

Data were monitored for 43 patients wearing basis peak for 5 months. As a result, it was possible to identify physiological differences between health conditions among individuals[36].

The system is proposed to measure environmental factors, notify workers with warnings and vibrations to protect safety in case of danger to danger, and send situational information to the control center to take immediate action. It integrated the Galaxy Watch' Biosensor (Samsung, Seoul, Korea), Apple Watch (electrocardiogram, heart rate, saturation of percutaneous oxygen [SpO_2]), gas sensor (CO_2, VOCs), and wireless communication technology. For accurate measurement and analysis, multi-level risk modeling and ML techniques must be included[37].

A surface electromyogram electrode with 10 and 24 mm diameters was developed by screen printing poly(3,4-ethylenedioxythiophene) polystyrene sulfonate (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 heart rate and SpO_2 by reflecting light sources of two wavelengths (red 625 nm, infrared 865 nm) on a person's forehead. The size of the flexible circuit is 7 cm×2 cm, interfaced with an 8.5 cm×3.5 cm wireless system board. Weighing only 15 g, it is an elastic band that can be easily wearable on the forehead. The SpO_2 calculates the ratio of the amplitude of the infrared and red photoluminescence (PPG) signals by detecting and measuring the amplitude change of the PPG signals to red and infrared light due to changes in blood oxygen saturation. 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 bio-signal monitoring sensors are used by adhering to the human body, so it is essential to surface-treat materials that are harmless to skin contact. If the surface is treated with a flexible polymer material such as polydimethylsiloxane (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 to 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 respiratory diseases. A new diagnostic method is developed to detect COPD parameters using a microelectromechanical system based acceleration sensor. It records the acceleration data of the movements of the diaphragm in three axes during breathing. With the proposed device in this work, parameters such as tidal volume capacity, forced vital capacity, and respiratory rate commonly associated with COPD are successfully measured. The measurement results were similar to the spirometer and can be considered as an alternative instrument for the spirometer[41].

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

All smart electro-clothing systems consist of hardware and software, primarily electronic, and non-fiber materials such as sensing subsystem, action subsystem, control subsystem, communications subsystem, location subsystem, power subsystem, storage subsystem, and display subsystem and common elements[43,44].

A smart jacket is designed to secure 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 the miner. All of these parameters transmit 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 global positioning system location to a specific internet protocol and continuously update the miner' pulse rate detected by the pulse sensor to the control system[45].

Photonic textiles that can measure pulse oximetry are sewn into gloves for subtypes. SpO_2 is measured to change the amount of transmitted light by placing an optical sensor on the fingertip. By measuring the amount of light transmitted by two different wavelengths (HeNe laser, halogen lamp) with an optical sensor, oxygenated and deoxygenated hemoglobin can be calculated to obtain oxygen saturation in the body. Using photonic textiles is feasible for pulse oximetry[46].

AI Analysis for Air Quality Prediction

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

First, it reviews the comparison of AI 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 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 have been used. The most reliable algorithm for air pollution prediction is an autoregressive nonlinear neural network with external input using the proposed prediction model, which has a one day prediction error of 1.79 $\mu g/m^3$[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 were 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].

In order to assess PM prediction performance, it was compared ANN with multiple linear regression (MLR) models. The model's input data was PM_{10} concentration and variables for the weather. As a result of comparing the two models, the nonlinear ANN method showed better performance for predicting 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 comprised nine meteorological factors from the 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 significantly 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 monitoring sites (AQMS) and AWS, SVM, and RF models were highly accurate according to the model validations. By contrast, both models could have performed better in Yongsan-gu, which is relatively far from AQMS and AWS. The results indicate that AQMS and AWS adjacencies significantly affect PM_{10} concentration prediction[50].

To compare the performance of the PM concentration prediction algorithm, MLR, SVR, autoregressive integrated moving average (ARIMA), and autoregressive integrated moving average with explanatory variable (ARIMAX) was compared. It was evaluated by root mean square error (RMSE) using air quality data and meteorological data. In the integrated concentration prediction, the performance of SVR was superior to MLR, and in the time series prediction, 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. In real-time testing for predicting bin status, LR and k-NN are 79% and 83%, respectively. The accuracy of modified LSTM and simple LSTM models is 90% and 88%, respectively, to predict the future gas concentration in the air. The system provided real-time monitoring of garbage levels along with notifications from an alert mechanism and improved accuracy by utilizing ML[52].

Second, it is a review of developing algorithms for quality air prediction. A data mining algorithm was developed using ANN and k-NN to implement accurate PM prediction models. For ANN operation, a network, constructs with 13 nodes in the input layer, 15 nodes in the hidden layer, and one node in the output layer. The output was classified using the k-NN algorithm and had high accuracy when K=9. The proposed model showed a better prediction rate than ANN and k-NN[53].

A separation prediction model for PM based on a deep neural network (DNN) was designed to improve PM_{10} prediction accuracy. In order to select the optimal hyperparameters, 3,600 candidate parameters were set for each model through the grid search technique. In this process, 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].

MLR and ANN designed prediction models, and the suitability of algorithms for PM prediction was evaluated by comparison with real data. MLR and ANN were compared with real-world data to access algorithm's suitability for PM prediction. In the case of algorithm PM prediction, ANN was superior in performance. When designing a PM prediction model using ANN, the composition of a hidden layer with an appropriate number of neurons is essential[55].

The PM_{10} concentration prediction algorithm was modeled using weather and traffic-related air pollutants concentration variables such as CO, NO, and nitrogen (N) data. A generalized additive model was developed and evaluated. This study, identified weather variables such as temperature and wind speed 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 leading 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 $PM_{1.0}$ concentrations in China 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 (Mitsubishi Electric, Tokyo, Japan) 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. A comparison of the linear regression model and GRNN models (including PCA-integrated GRNN) showed that the nonlinear model could 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.

A study 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 compared to other models, such as LSTM networks and linear regression. The proposed system performed better with 85% higher accuracy for various parameters[58].

AI Analysis for Health Effect Prediction

Research for health effect prediction has been conducted based on various algorithm models. The settings of most studies are divided mainly into a comparison of AI analysis techniques and the development of new algorithms. Therefore, this paper reviews it in two ways.

First, it reviews a comparison of AI analysis techniques for health effect prediction. In order to predict sepsis mortality, a study compares conventional context-based LR 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 than the LR model[59].

When the most accurate predicted model is the goal, ML algorithms are more advantageous than conventional regression methods when the most accurate predicted model is the goal. When using ML methods, special attention requires in the form of model validation. 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 essential characteristics. The model's predictive ability was compared based on the model's accuracy, RMSE, and mean absolute error (MAE). SVM has a significant accuracy of 93.19%, but RMSE 0.320 and MAE 0.300 indicators could be better. The DL's evaluation results are an accuracy of 74.78%, RMSE 0.252, and MAE 0.120, which are generally good. In contrast, the 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 the backpropagation algorithm[61].

Second, it is a review of the development of algorithms for the prediction of health effects. 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, a hybrid RF with a linear model, a long-short term neural network, and a fuzzy rule-based neural classifier[62].

An electronic stethoscope was developed through AI analysis of acoustic medical data by measuring lung sound. The device divides into three parts: sounds collection module (SCM), e-healthcare home gateway (eHG), and smartphone. SCM records heart and lung sounds, and eHG communicates with data translation, cloud servers, and mobile devices interface. For lung sound analysis, first 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 use 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 of 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) uses as the feature extraction method. A simulation performs through MATLAB R2020a. The performance of the proposed model was evaluated and compared with the existing multilayer perceptron, 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 difficult for human listeners because some lung sound events have a frequency spectrum beyond human hearing ability. Thus, this paper proposed a system capable of detecting and classifying abnormal lung sounds, such as crackles or wheezes. CNN was used to detect and classify adventitious sounds in lung sound signals successfully. Various functions (power spectrum density [PSD], mel spectrum [MS], and MFCC) for converting lung sound signals into 2D images were presented. MS, when fed into CNN, achieves results in line with the current cutting-edge technology and is followed by PSD and MFCC[65].

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 AI 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, collecting, and analyzing 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 AI has recently continued. This is because a doctor’s subjective judgment increases the demand for accurate analysis and the predictive power of AI. 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 the development of remote healthcare services.

Authors’ Contributions

Conception or design of the work: Mun E, Cho J. Writing and/or reviewing the preliminary and definitive versions: Mun E. Approved the final version: all authors.

Conflicts of Interest

No potential conflict of interest relevant to this article was reported.

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