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IoT-based AI Methods for Indoor Air Quality Monitoring Systems: A Systematic Review

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Abstract

This exploratory disquisition delves into the world of Indoor Air Quality(IAQ) monitoring systems, using the solidarity of Artificial Intelligence(AI) and Internet of Effects (IoT) technologies. Its overarching thing is to check the efficacity of these structures in regulating IAQ within structures, with a specific focus on mollifying pollutant degrees and their dangerous results on inhabitants. The study undertakes a comprehensive review of present literature and exploration trials, which depend upon AI and IoT algorithms for border monitoring, records analysis, and contrivance evaluation. also, it delves into the complications of machine armature, deployment ways, and functional efficiency. Furthermore, the exploration attracts different instructional budgets, including clever detectors and IoT bias stationed within the ambient surroundings. It elucidates the functionality of those instruments to accumulate real-time statistics, encompassing variables together with unpredictable natural composites, temperature oscillations, and moisture ranges. A vital aspect of this study is the disquisition of AI, contrivance getting to know Machine Leanring (ML), and Deep Learning (DL) algorithms, showcasing their prophetic prowess within shadowing fabrics. also, they have a look at delving into the symbiotic dating among those algorithms, expounding their function in enhancing machine delicacy and optimizing energy intake. Moreover, the studies trials to delineate personalized health tips knitter- made to character inhabitants, decided from the wealth of records accrued through these structures. By integrating present-day technologies with empirical perceptivity, this takes a look at trials to pave the manner for better IAQ control strategies, fostering more healthy and lesser sustainable lodging surroundings.

Keywords: Sick building, Machine learning, IAQ Monitoring system

1. Introduction

The conception of Sick Building Syndrome(SBS) dates returned to 1791, characterized by way of a myriad of signs and symptoms endured employing people within unique structures, ranging from skin vexations to respiratory issues, which use up upon leaving the demesne. This underscores the imperative of administering IAQ monitoring structures inside enclosed areas. still, traditional monitoring widgets have lengthy grappled with challenges conforming to data availability, cost, and complexity[1]. The preface of low-cost detector generation has revolutionized the geography, easing real-time and figure-important evaluation of air nice. using IoT-primarily grounded detectors has further propelled our moxie of Indoor Air Pollution(IAP), challenging real-time manipulation mechanisms for fostering healthier inner surroundings[2]. The IoT atmosphere, acting as a conduit for statistics collection and analysis, has reshaped multitudinous aspects of mortal cultures, gauging safety, healthcare, consolation, and energy effectiveness[3]. Smart domestic structures, employing IoT chops, offer a lamp of want, turning by affordable and movable IAQ monitoring results. These systems check inner adulterants, temperature, and moisture degrees, issuing caution in the event of unsafe contaminant attention[4]. Integration with AI augments the delicacy and factual-time evaluation capabilities of similar structures, enabling knitter-made fitness suggestions primarily grounded on inhabitants' choices. As generation progresses, fortune duplications maintain a pledge for further suitable overall performance and flawless integration with AI ways[5][6].

While being literature abounds with the exploration of AI and IoT operations in IAQ shadowing, this observes trials to emphasize their myriad blessings, design complications, overall performance opinions, and data sources, at the side of their community with other AI technology[7]. AI and ML algorithms come potent gear for refining delicacy and factual-time analysis in IAQ shadowing, while IoT-primarily grounded answers offer a price-important means of measuring air adulterants, mollifying longstanding issues with conventional observers[8]. Looking beforehand, the paper delineates fortune targets and challenges, supplying a comprehensive assessment of current IAQ tracking systems employing clever IoT technology[9].

2. IAQ Monitoring Systems Design

2.1. Sensors Selections

The selection of sensors significantly influences the efficacity of IAQ monitoring systems, as it necessitates high perceptivity and delicacy in detecting colorful adulterants and pollutants present in inner surroundings. Among the array of sensors employed for this purpose are MQ3 and MQ135 detectors, designed to measure situations of adulterants affecting mortal health similar as carbon dioxide(CO2), dust, bank, alcohol, benzene, and NH3, quantified in corridor per million(PPM). These detectors operate in real-time, furnishing precise and dependable data pivotal for air quality analysis and informed decision-making to enhance inner air quality[10].

Also, real-time perceptivity can be enhanced by integrating low-cost sensors with AI methodologies similar to ML/DL ways. This integration empowers the system to fete patterns and trends in the data, thereby perfecting the perceptivity of analysis and delivering more accurate assessments of air quality. For this case, ML algorithms can dissect collected data to identify temporal and spatial patterns of air pollution, guiding posterior conduct to effectively and efficiently ameliorate air quality. This holistic approach combining sensors with AI enhances the system's capability to exhaustively and efficiently cover and manage air quality[11]. Likewise, the selection of sensors constitutes a vital step in the construction of accurate and effective IAQ covering systems. using slice-edge seeing technologies and integrating AI and IoT-enabled sensors enables point perceptivity in detecting and prognosticating dangerous adulterants in the air while furnishing real-time analytics and responses. This contributes to cultivating a comfortable and healthy inner terrain, constantly optimized to guard inhabitants against the mischievous goods of dangerous adulterants[12][13]. also, the presence of ray dust detectors graces attention for their capability to measure small patches ranging from 0.3 to 10 micrometers, with a dimension range gauging from 0 to 1000 micrograms per boxy cadence. Table 1 elucidates the specifications of the ray dust detector for patches within the 0.3 to 10-micrometer range, showcasing its dimension capabilities[14].

	Specification	Range
1.	particle size Measurement	0.3 - 10 μm
2.	Measurement range	0 -1000 μg/m^3
3.	Time to first reading	≤8 s
4.	Working temperature	-10 - 50 Celsius
5.	Working humidity	0 - 95% RH (non-condensing)
6.	Signal output	UART-TTL, PWM, IIC

Table 1: Laser dust sensor specifications [13].

2.2. Placement of Sensors in Indoor Environments

Effective data collection is consummate for real-time monitoring and analysis of IAQ, emphasizing the strategic placement of sensors. icing spatial content of air quality parameters aids in carrying a comprehensive understanding of inner environmental conditions. During the placement of sensors, careful consideration must be given to the types of adulterants being targeted. For case, installations of particulate matter and unpredictable organic emulsion sensors may be necessary to give detailed analyses of contaminant situations forming from different sources such as hotting systems, manufacturing processes, or kitchen areas. This strategic positioning of sensors enhances the efficacity of data collection and analysis, enabling the identification of factors impacting IAQ and easing remedial conduct[15] Also, the installation of sensors should align with the operation and layout of inner spaces. For case, locales with high mortal residency similar to promenades and gymnasiums may bear smaller specialized sensors for monitoring, recording, and assaying air quality oscillations. also, tailwind patterns and dissipation mechanisms told by ventilation systems, doors, and windows can affect the rates of cross-ventilation and the rotation of adulterants within structures. thus, it's prudent to consider these dynamics when sticking sensors to ensure accurate monitoring of IAQ [16]. Figure 1 illustrates a Scenario of the system Placement of Sensors in Indoor Environments [17].

likewise, the communication capabilities of sensors are essential considerations when determining their placement. exercising wireless communication technologies like Low Power Wide Area Networks(LPWAN) or Wi-Fi enables flexible placement of sensors across colorful structures, easing dependable and secure data transmission to central monitoring systems[18]. similar communication structure enhances the scalability and rigidity of IAQ monitoring systems, icing flawless integration into different inner surroundings.

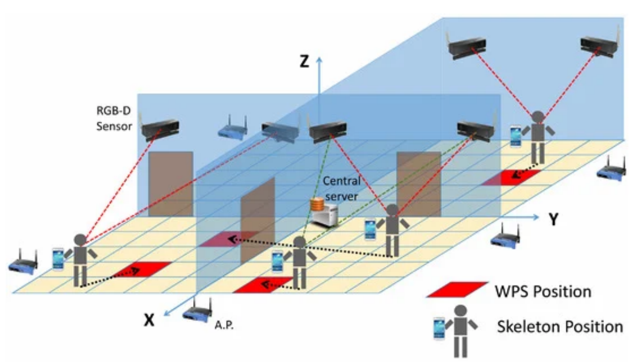

Figure 1: Scenario of the system[17].

2.3. Data Collection and Storage Methods for Monitoring Systems

Effective IAQ systems influence advanced AI and IoT technologies to gather real-time data, employing wireless sensors equipped with colorful detectors to cover air quality parameters. These IoT-enabled air quality sensors continuously cover particulate matter, unpredictable organic composites, moisture, and temperature, transmitting this data to a central mecca for remote monitoring[19]. to manage the large volumes of data generated, ways similar to data contraction, loss minimization, and prioritization are proposed, icing the effective running of data aqueducts.

A unified data management service facilitates periodic storehouse and ingestion of detector data into pall-grounded software factors. Platforms like knot-RED and InfluxDB support low-law sluice-ground programming, enabling the composition of data aqueducts from different sources. InfluxDB, chosen as the time series database platform, efficiently analyzes and captures real-time data, relating it with specific temporal patterns. This enables rapid-fire filtering and sorting through automated query processes, indexing markers for each record alongside temporal patterns[20]. The integration of AI algorithms and IoT technology offers significant advantages, including scalability, real-time environmental monitoring, remote monitoring capabilities, and mobility, contributing to prophetic analysis models similar to LSTM structures. These models can directly read environmental parameters with a high degree of perfection. Figure 2 illustrates how high-resolution environmental information forms the base of decision-making processes. Collecting comprehensive environmental data is essential for robust environmental analysis systems. It's pivotal to separate between sensors stationed at specific locales and the monitoring range of videotape displays, as well as to discern whether environmental variations stem from natural conditions or artificial sources[21].

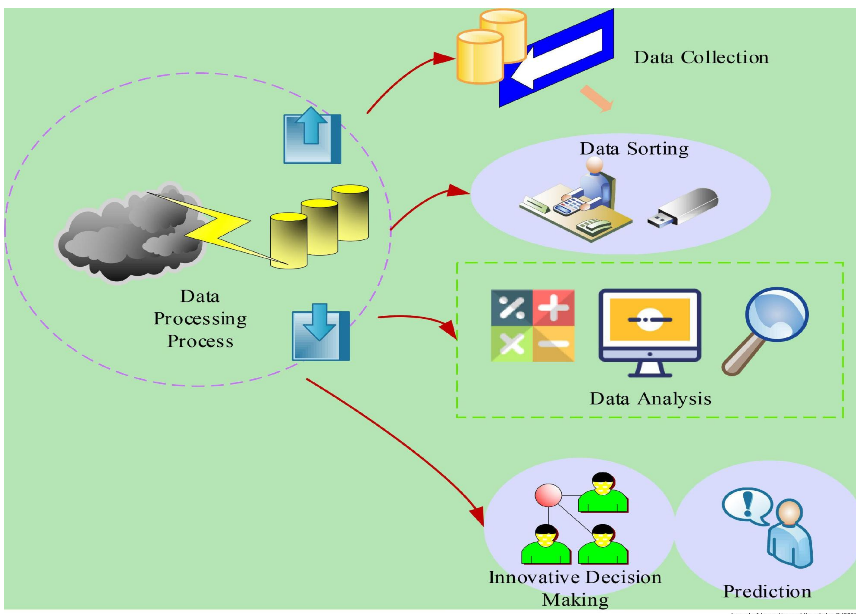

Figure 2: Environmental monitoring information procedures[22].

3. Implementation of IAQ Monitoring Systems

3.1. Hardware Components and Connectivity Requirements

Indoor air quality monitoring systems calculate intertwined device connectivity and communication to ensure their effectiveness. The selection of sensors plays a pivotal part in directly measuring parameters similar to temperature, unpredictable organic composites(VOCs), carbon dioxide(CO_2), and humidity situations. A strategic sensor placement strategy is essential for comprehensive data collection. Energy consumption is a primary concern for real-time monitoring systems, driving the hunt for energy-effective druthers similar to Bluetooth and ZigBee platforms[23]. Low Power Wide Area(LPWA) transmission technology offers a feasible result for transmitting limited data loads, enhancing spatial and temporal resolution. Scalability and effective data processing are critical considerations, with Software Defined Radio(SDR) technology contributing to achieving these pretensions and ensuring accurate air quality data collection[24].

Integration with the pall enables real-time visibility into a structure's IAQ, easing communication with Building Management Systems (BMS) equipped with automatic control mechanisms grounded on IAQ situations[25]. Designing ultramodern Heating, ventilation, and Air Conditioning (HVAC) systems grounded on IAQ considerations is essential for creating healthier inner surroundings. Careful attention to communication conditions and tackling factors is necessary for the successful perpetration of IAQ monitoring systems[26][27]. Table 2 provides detailed specifications of the CO2 seeing module.

Operating voltage	4–6 V
Operating current	Mean 50 mA
Detection accuracy	± 50 ppm
Detection range	0–5000 ppm
Operating temperature	0–60 °C
Service life	5 years
Size	57 mm × 35 mm × 15 mm
Operating humidity	0–90%RH

Table 2: Detailed specifications of CO 2 sensing module[24]

3.2. Software Development for Real-Time Data Processing

Advanced computing and communication technologies are seamlessly integrated into IAQ systems to give robust monitoring results. using IoT bias, AI algorithms, and ML ways ensures the achievement of real-time monitoring, analysis, and control of air quality. When developing software for IAQ monitoring bias, careful consideration of AI ways for data analysis is consummated. With the support of IoT bias, AI ways grounded on ML styles empower the identification of pollution situations by assaying vast datasets, landing structure structural trends, and relating patterns associated with anomalies[28].ML ways similar to Linear Retrogression(LR), Random Forests(RF), Autoregressive Integrated Moving Average (ARIMA), and other models play an effective part in detecting adulterants and prognosticating their situations in the air. also, intelligent AI vaticination ways enable the early identification of implicit outfit failures before they do[29]. The integration of AI algorithms into monitoring bias enables the provision of substantiated health recommendations acclimatized to the preferences of the inhabitants. By assaying sensor data using AI technologies, personalized recommendations can be made to enhance the IAQ of structures grounded on the specific requirements and preferences of the inhabitants[30].

3.3. Integration with Existing Building Management Systems

The integration of IoT bias into structure operation systems(OS) has the implicit to revise the assiduity. Smart detectors able to measure and assess outfit performance, IAQ, energy consumption, and residency situations in real- time can empower structure operation professionals to make informed opinions aimed at enhancing quality and effectiveness. Prophetic conservation, for case, plays a pivotal part in relating cost-saving openings by proactively detecting implicit issues before they escalate into major problems. Energy operation is also optimized through IoT detectors, leading to reduced costs and environmental impact[31].

Monitoring IAQ in structures using IoT bias is necessary for maintaining a healthy terrain for inhabitants. likewise, the integration of IoT security systems, residency shadowing for space optimization, perpetration of smart lighting results, waste operation through packing position monitoring, and deployment of immediate exigency response systems further enhance the overall functionality and safety of structures[32]. IoT platforms grease the collection and analysis of data, enabling the generation of practicable perceptivity and reports to support decision-making processes. In summary, the integration of IoT bias into structure operation systems not only enhances functional effectiveness and cost savings but also promotes better IAQ and sustainability, thereby perfecting overall structure security and efficiency.

4. Performance Evaluation of IAQ Monitoring Systems

4.1. Accuracy Assessment of Sensor Readings

Experimenters have conducted limited studies on the delicacy of detector readings in IAQ control systems for structures, particularly those using ML and IoT technologies. Accurate detector readings are pivotal for real-time data processing and prophetic analysis. Some studies have demonstrated emotional discovery and vaticination rates for IAQ. For case, results from developed models have shown remarkable delicacy in classifying air quality in apartments, particularly with the use of neural networks(NN). also, LSTM networks have displayed significant success in prognosticating air contaminant attention. Accordingly, AI systems for IAQ monitoring offer superior capabilities in furnishing dependable and accurate real-time data for analysis[33].

Despite the advancements in IAQ monitoring exercising sensors and ML ways, there remains a critical need for further exploration concentrated on assessing and homogenizing sensor performance evaluation. A scientific review stressed the inadequate substantiation supporting the validity of low-cost sensors for IAQ monitoring in structures. It's essential to estimate the cost-effectiveness of enforcing these systems and emphasize the significance of homogenizing sensor performance evaluation to ensure accurate and dependable readings. Addressing these issues will enhance the robustness of IAQ monitoring systems and ameliorate the quality of data used in decision-making processes[34].

In conclusion, achieving accurate detector readings is essential for the successful perpetration of smart technology-grounded IAQ covering systems. While recent studies have shown promising results with ML ways and IoT sensors, there's a critical need for further exploration concentrated on assessing and homogenizing sensor performance. Emphasizing the refinement of detector delicacy will enhance the effectiveness of these systems and inseminate confidence in the data used for decision-making in the field of IAQ operation[35].

4.2. Comparison of Different AI Algorithms for Data Analysis

Within IAQ systems, data collected from different detectors suffer critical analysis and exploration using AI technologies. The effective application of both ML and DL ways has led to bettered structure performance and fortified environmental quality. For illustration, the AI- AI-grounded multiple Linear Retrogression algorithm is considerably employed in prognosticating periodic heating and cooling energy conditions. Retrogression ways, artificial neural networks(ANNs), decision trees, and residency styles have also been necessary for soothsaying thermal loads and civic electric power demand, as well as creating thermal comfort models. These ways grease comprehensive data analysis, enabling informed opinions to enhance IAQ and overall structure performance[36]. Figure 3: provides a neural network with three layers: the input layer, the hidden layer, and the output layer.

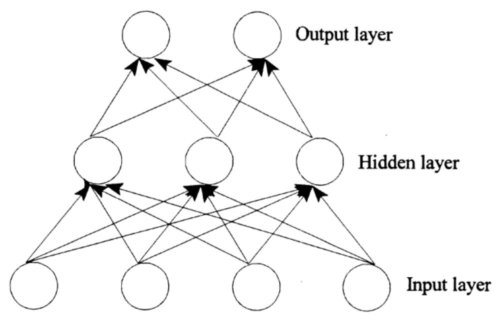

Figure 3: neural network with three layers [37].

IoT detectors play a pivotal part in studying real-time data for IAQ monitoring systems, as emphasized by recent studies and exploration. ML styles, similar to Linear Retrogression, are generally used for assaying IAQ data. Integrating particular health information with air quality data allows for the assessment of implicit goods of the inner terrain on health, enabling applicable conduct to be taken consequently[38]. The combination of IoT detectors and ML capabilities for real-time IAQ monitoring and vaticination is a notable point stressed in important exploration. ML ways like LSTM infrastructures and NN algorithms have demonstrated high delicacy in detecting adulterants and prognosticating their attention[39]. Figure 4 There are three cell gates of the LSTM architecture: the forget gate, the input gate, and the output gate.

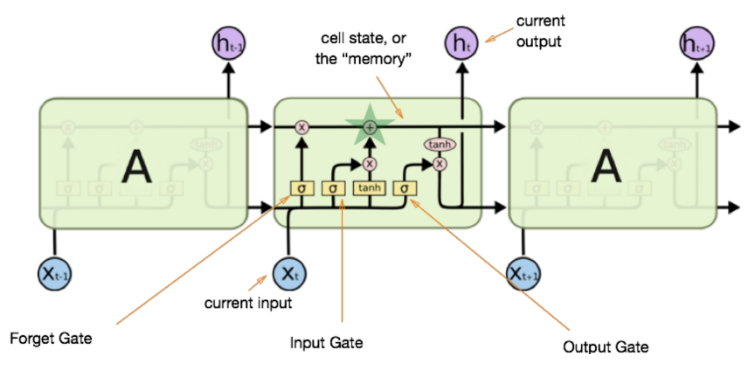

Figure 4: The structure of an LSTM [40]

4.3. User Feedback and Satisfaction Surveys

Stoner feedback and occupant satisfaction checks play a pivotal part in assessing the effectiveness of IAQ monitoring systems. These perceptivity are essential for perfecting the air quality of structures by furnishing precious information about the performance and usability of covering outfits [41]. In a recent study, an IAQ monitoring system was enforced, and a questionnaire was distributed among scholars to estimate their thermal comfort and air quality satisfaction. The results indicated advanced satisfaction situations among druggies, pressing the effectiveness of the enforced classroom monitoring systems in enhancing air quality[42].

Numerous companies prioritize investing in significant coffers to ameliorate the air quality for their workers, particularly in areas with known air pollution pitfalls[43]. workers themselves are decreasingly apprehensive of the significance of air quality detectors in colorful settings similar to medical conventions, services, and seminaries. Understanding the specific requirements and preferences of workers regarding IAQ detectors is pivotal for acclimatizing effective results[44].In conclusion, gathering stoner feedback will be essential for the continued development and improvement of IAQ monitoring systems to ensure their effectiveness in perfecting the structure of IAQ[45].

5. Data Sources for IAQ Monitoring Systems

5.1. External Data Sources (e.g., Weather, Pollution Levels)

Likewise, integrating external data sources is essential for directly assessing the effectiveness of structure IAQ systems. Research has demonstrated the mischievous health goods of civic air pollution, including disinclinations, neurological diseases, respiratory conditions, and cardiovascular conditions. Particularly by low-and low-middle-income countries, being environmental monitoring systems may not be as robust as demanded. To enhance IAQ, associations can integrate out-of-door air quality monitoring networks and public rainfall data into their IAQ covering systems. By using these fresh data sources, associations can track how out-of-door pollution infiltrates inner spaces and take visionary measures to address IAQ issues and promote plant health[46].still, the high cost associated with approved air quality monitoring systems limits their vacuity, especially in resource-constrained areas. thus, integrating different data sources into IAQ monitoring systems is pivotal to gaining a comprehensive understanding of inner air conditions. Real-time data on temperature and moisture can illuminate the impact of out-of-door environmental factors on IAQ[47].

A comprehensive evaluation of inner environmental air quality relies on the integration of external data sources with monitoring systems grounded on AI algorithms and IoT bias. These external data sources generally correspond to real-time data that can be seamlessly integrated into IAQ covering systems for nonstop monitoring and analysis of air quality. using AI technology within IAQ monitoring systems enables the provision of substantiated health recommendations acclimatized to both the terrain and inhabitants. This mode of communication is anticipated to establish a more robust communication channel with governmental authorities, informing them about implicit adulterants and enhancing their environmental monitoring capabilities in the future[48].

5.2. Internal Data Sources

The significance of inner data sources in assessing the IAQ of structures lies in their vital part in perfecting air quality and the overall inner terrain. Inner sources, along with mortal conditioning and HVAC systems, are primary contributors to state quality improvement. The World Health Organization(WHO) identifies several dangerous adulterants, including sulfur dioxide, carbon monoxide, particulate matter, ozone, and nitrogen dioxide, which radiate from colorful inner sources similar to energy combustion, primitive cuisine ranges, and precious presence[49].thus, using IoT detectors to collect data on parameters like temperature, moisture, and air movement in real-time, while covering heating, ventilation, and air exertion HVAC systems, is pivotal. This information is essential for relating implicit problem areas and assessing inner air quality situations. also, mortal conditioning and the presence of faves can complicate inner pollution situations, further impacting IAQ. Monitoring these conditions using IoT detectors provides precious perceptivity into the overall state of IAQ [50]. likewise, recycling this internal data using AI technologies helps identify patterns and trends that, when employed in prophetic analytics, can significantly impact air quality operations. AI algorithms can effectively gauge IAQ situations, prognosticate unborn patterns, and cast trends grounded on data from HVAC systems juxtaposed with inhabitant conditioning. The integration of AI algorithms and IoT technologies grounded on internal data sources facilitates ongoing assessment and monitoring of IAQ[51].

6. Integration of AI Techniques in Monitoring Systems

6.1. Machine Learning Algorithms

Machine Learning styles are necessary for prognosticating internal quality control systems, particularly in relating air quality trends and patterns that are pivotal, especially for individuals with respiratory issues[52]. using ML and IoT detectors enables largely accurate dimension and vaticination of air adulterants and inner contaminant attention. Models similar to NN and LSTM networks have demonstrated remarkable delicacy in classifying and prognosticating IAQ parameters. mongrel models, created by combining ML algorithms, have shown superior soothsaying performance compared to individual models. likewise, ML ways can prop in diagnosing respiratory ails stemming from air pollution[53].

By assaying real-time IAQ data from multiple sources using ML algorithms and IoT detectors, issues can be instantly linked, and necessary preventives can be communicated effectively. Wearable detectors enable druggies to conduct prophetic data analysis, easing informed opinions to ameliorate IAQ. ML technologies and IoT detectors are vital in enhancing the real-time logical delicacy of IAQ monitoring systems in structures. also, these technologies offer substantiated health and medical recommendations acclimatized to individualities' requirements and preferences, representing a significant advancement in air quality monitoring capabilities[54]. Table 3 provides a summary of exploration findings where ML models were employed.

No.	Dataset	Approach	Evaluation Criteria	Results	Year	
1	Energy load dataset	SVM	RMSE, MRE	The SVM achieved a better accuracy and generalization in compared with the evaluated neural network techniques.	2010	[55]
2	Historical data	Fuzzy C-mean clustering algorithm	MAPE, RMSE	The clustering technique used to decrease the number of data required for training purposes and to avoid noisy data.	2010	[56]
3	Central Pollution Control Board (CPCB)/ India	ANNs, SVM	Accuracy	The results show improvement in the prediction accuracy	2019	[57]
4	Simulation	Support vector regression (SVR), Ensemble, General linear regression, Classification and regression tree, ANN	R^2, MSE, RMSE, MAE, MAPE	The results show that (SVR +ANN) and SVR are the best models for heating and cooling load prediction purposes.	2019	[58]
5	Experiment	Nonlinear ML algorithms, SVR with nonlinear radial basis function (RBF) kernel, and neural networks	MAE, R^2, Time	The result indicates that the nonlinear models have better performance than the linear models. However, the neural network(NN) had significantly recorded the best performance.	2018	[59]
6	Simulation	Multivariate regression model	R2, Fisher's criterion	The result shows that the high accuracy predictions are provided with R2 of 0.981 model	2018	[60]
7	Simulation	Combined ANN with an ensemble approach	R^2	The ANN combined with an ensemble approach model significantly improved the prediction accuracy.	2018	[61]
8	Experiment	Ensemble method	R^2, RMSE, MAE, r	The proposed model results show better performance than ANN and SVM.	2018	[62]

9	Experiment	Decision Tree	RMSE	The results indicate that the decision tree model was able to estimate the occupancy situation.	2016	[63]
10	Malaysia Air Pollution dataset	(MLP), and Random Forest	Accuracy Precision recall	According to the results, Random Forest performed better than MLP with 97% and 92% accuracy, respectively.	2021	[64]
11	Simulation	K-Means algorithm	CV, STDV	The result shows that the k-means algorithm helped optimize the HVAC system to reduce energy consumption.	2018	[65]
12	Energy load dataset	Random Forest Regressor, k-nearest Neighbour Regressor, and Linear Regressor	MAPE	The results illustrate that the Random Forest Regressor provides better short-term load prediction, while the KNN provides much better long-term load prediction.	2019	[66]
13	the data collected through real-time measurements of indoor CO_2, number of occupants, area per person, outdoor temperature, outer wind speed, relative humidity, and air quality index	ANN, SVM, DT, GPR, LR, EL, optimized GPR, optimized EL, optimized DT, and optimized SVM	R, RMSE, MAE, NS	The mentioned ML models have been used to predict the intensity of CO_2 inside the buildings.	2023	[67]
14	Simulation	Random Forest	R2, RMSE	Compared to SVM, the Random Forest model reduced the energy consumption in the buildings.	2021	[68]
15	Energy and Occupancy dataset	K-means for building energy prediction. ANN for end-user group prediction.	CV-RMSE	The prediction accuracy is improved while dealing with diverse occupancy and their correlation with energy consumption by using K-means for building energy prediction and ANN for end-user group prediction.	2017	[69]
16	Experiment	ANN	Correlation coefficient and mean square error were used to validate the model.	Geographical data in the ANN module was trained using the Leverberg Marquardt (LM) Algorithm.	2019	[70]
17	Experiment	K-nearest neighbor	Accuracy	The K nearest neighbor-based thermal comfort model can achieve an accuracy of 88.31% using 1000 sets of training	2021	[71]

				data.		
18	Experiment	Decision Tree	Confusion matrix	The results indicate that the ratio of Sick Building Syndrome (SBS) symptoms was 74.4% among women and 68.5% among men.	2021	[72]
19	Simulation	Random Forest	R^2, RMSE	Compared with SVM, the Random Forest model shows significant advantages in constructing energy consumption forecasting.	2022	[73]

Table 3: Summary of research papers

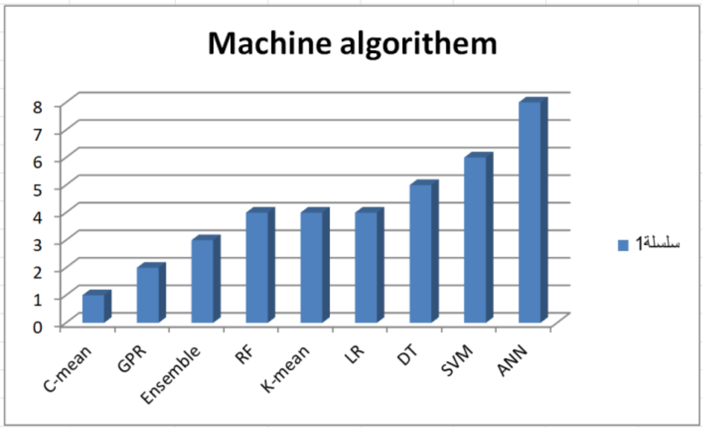

Figure 5: Machine Learning Algorithms

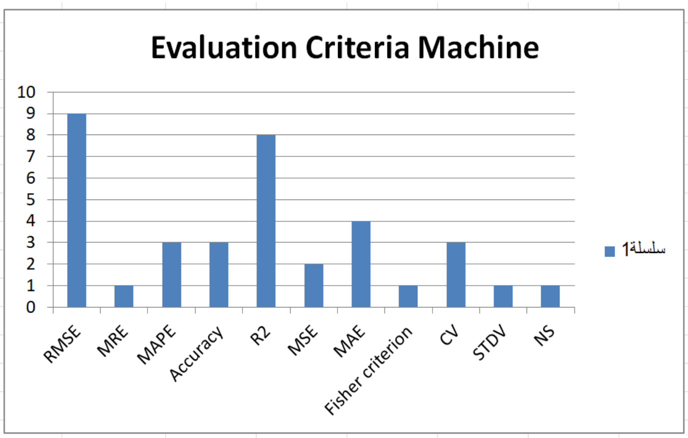

Figure 6: Evaluation Criteria in Machine Learning

6.2. Deep Learning Algorithms

Indoor air quality monitoring systems equipped with erected-in DL algorithms have the capability to describe patterns and cast air quality situations. These systems can reuse vast quantities of data collected from multiple detectors, enabling the discovery of anomalies, patterns, and trends in real-time. This real-time discovery allows for nippy action to maintain IAQ in optimal situations. also, DL algorithms aren't limited to prognosticating current conditions but can also read unborn scripts related to air quality, including relating outfit malfunctions, anticipating the need for repairs, and optimizing energy operation[74].In a recent study, a model was developed to exhaustively cover, describe, and prognosticate air pollution situations across different civic areas. The model LSTM with Convolutional Neural Networks(CNN) and Deep Neural Network(DNN) models to measure air adulterants. Both univariate and multivariate models were employed, incorporating data on individual adulterants as well as fresh environmental factors similar to downfall compliances. The study employed expansive datasets collected from metropolises like Istanbul, Kocaeli, and Barcelona[75]. The community between AI and IoT technologies facilitates a deeper understanding of environmental conditions and enables prompt responses, leading to enhanced artificial effectiveness and bettered stoner gets across colorful sectors. also, DL algorithms can be abused to develop IAQ labeling systems that give accurate assessments of impurity situations and enable real-time monitoring of IAQ- related issues. By assaying patterns and changes in IAQ data, DL ways contribute to visionary problem-working and nonstop enhancement[76][77]. Table 4 summarizes exploration findings where machine literacy algorithms were employed.

No.	Dataset	Approach	Evaluation Criteria	Results	Year	Ref.
1	Kaggle website	GA -LSTM	Root Mean Squared Error (RMSE)	Results were accurate with less experience and faster than ML and LSTM models	2022	[78]
2	Experiment	three LSTM models	MSE, RMSE, R2, MAE	The CO2 modification level is much higher Electronics 2023, 12, 107 4 of 12 that of PM	2021	[79]
3	Electricity dataset	CNN-Long short-term memory (LSTM)	RMSE, MAPE, MAE, MSE	In residential houses, The CNN-LSTM network estimated the real-time consumption of electric energy with a stable performance of 0.37 MSE	2019	[80]
4	Experiment, Video, Simulation	Faster region-based convolution al neural network (RCNN)	IoU, Accuracy, Precision, Recall, F1 score,	RCNN provides customized ventilation control data on the dynamic changes of occupancy to enhance IAQ.	2022	[81]
5	UCI Machine Learning Repository	LSTM, GRU, Bi-LSTM, Bi-GRU, CNN, CNN-LSTM, and CNN-GRU	g the mean absolute error (MAE), the mean squared error (RMSE), and the coefficient of determination (R2).	The presented approach can extract the important features of the training data using CNN and LSTM, with high accuracy and stability.	2021	[82]
6	Smart meter dataset	Recurrent neural network (RNN), recurrent inception convolution neural network (RICNN)	RMSE, MAPE	RICNN model outperforms the RNN and 1-D CNN	2020	[83]
7	Energy consumption data	CNN-LSTM	RMSE, MAPE, MAE, MSE	The proposed model captured the spatiotemporal features in constructing energy consumption data	2021	[84]
8	Electricity dataset	Gated RNN, CNN	CV, MAPE, Computational efficiency	The results show that the 24-hour gated RNN model performed better than CNN.	2019	[85]
9	The 2018–2021 hourly data in Guilin	MLP(1D-CNN)	RMSE, MAE, and SMAPE.	The predictive performance of the presented model was better than (MLP), (1D-CNN), (GRU), (LSTM) and Transformer, at	2023	[86]

				all time steps (1, 4, 8, 24 and 48 h		
10	Building operational data	Recurrent neural network (RNN)	RMSE, MAE, CV-RMSE	The results indicate that RNN models achieved the most accurate predictions without increasing computational load.	2019	[87]
11	Experiment, Video, Simulation	Faster region-based convolution al neural network (RCNN)	Accuracy, Precision, Recall, F1 score,	In comparison to the use of static office occupancy profiles, the results illustrate that the residents' heat gains could be represented more accurately using the deep learning algorithms	2021	[88]
12	HVAC dataset	Deep belief network	Correct rate (CR), Hit rate (HR)	The correct fault diagnosis rate of the optimized model was around 97.7%,	2018	[89]
13	China Platforms	GT-LSTM	Accuracy, root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R2), and normalized root mean square error (NRMSE).	The proposed model could achieve higher accuracy and stability compared to the state-of-the-art baselines	2021	[90]
14	Human action dataset	Deep neural network	Accuracy	Using a multi-stream fusion network for activity recognition, the model achieved 84% accuracy.	2019	[91]
15	Beijing Multi-Site Air-Quality Data Set	CNN-LSTM	(MAE), (RMSE) and coefficient of determination (R^2)	The results indicate that the advantages of including spatial information on many surrounding stations, as well as using as much historical information as possible.	2022	[92]
16	Experiment	ANN	Pearson’s correlation coefficient R2	The result shows that the forecast for comfort conditions is excellent,	2021	[93]
17	Thermal comfort dataset	CNN-LSTM	Accuracy, Precision, Recall, F1 score, MCC	The proposed model gives accurate forecasting and overcomes the challenges related to the inadequacy of data.	2021	[94]
18	Experiment, Video, Simulation	Faster region-based convolution al neural network (RCNN)	Accuracy, Precision, Recall, F1 score,	The initial results illustrate the method's ability to identify opened windows with an average accuracy of 97.29%.	2021	[95]
19	(Pollutant and meteorological information)colle cted manually for three years in Shanghai city	CNN-LSTM	RMSE, correlation coefficient	By improving the performance, CNN-LSTM can predict future concentrations of particulate matter (PM2.5) as a time series.	2019	[96]

20	Video	Faster region-based convolutional neural network (RCNN)	Accuracy, Precision, Recall, F1 score,	Results showed the accurate detection of fire detection while smoke detection did not perform well.	2022	[97]

Table 4: Summary of research papers

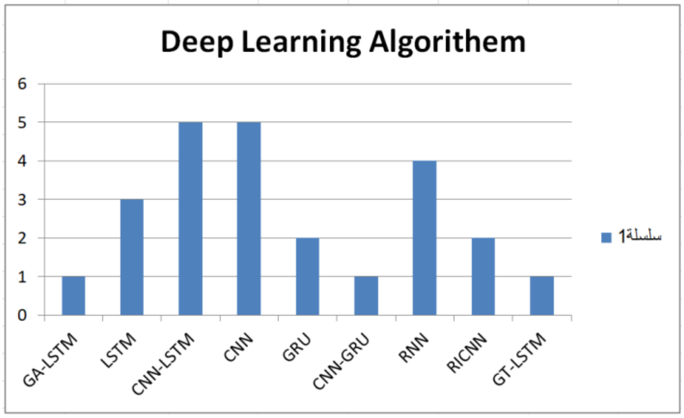

Figure 7: Deep Learning Algorithms

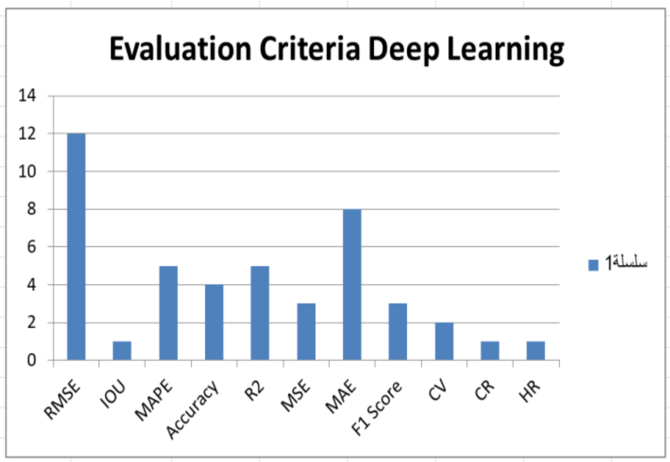

Figure 8: Evaluation Criteria in Deep Learning

7. Benefits of AI and IoT Integration in IAQ Monitoring Systems

7.1. Improved Accuracy and Real-Time Analysis

The strategic integration of DL patterns with IoT operations has revolutionized the delicacy and real-time analysis of air quality data. This integration facilitates the generation of large volumes of data from detectors and cold chain systems, allowing for the identification of consumption patterns and the vaticination of unborn trends. This information empowers structure and installation directors to make informed opinions regarding consumption optimization. also, AI models have demonstrated remarkable delicacy in prognosticating situations of colorful air adulterants, furnishing pivotal perceptivity necessary for addressing public health enterprises[98]. The combination of DL and sensitive-specific responses has further enhanced the capabilities of air quality monitoring systems. By integrating AI into the structure, a wealth of data collected from sensors is reused and interpreted by AI algorithms, furnishing precious perceptivity into consumption patterns. This enables directors to gain a clear understanding of power consumption trends, empowering them to make visionary opinions and optimize energy operations. also, AI models play a vital part in prognosticating air quality situations and furnishing essential data for addressing public health challenges[99].

7.2. Personalized Health Recommendations Based on Occupant Preferences

Thanks to advancements in technology, detectors, and AI networks, it's now possible to directly measure colorful aspects of structures to ensure a healthy terrain. These systems can dissect air quality pointers similar to temperature, moisture, CO2 situations, and unpredictable organic composites, allowing AI algorithms to give customized recommendations for perfecting IAQ. By considering individual preferences for heating, ventilation, and air exertion, these systems can suggest applicable treatment results to alleviate air adulterants and enhance comfort for residents. also, druggies can pierce structure operation services that incorporate rainfall conditions, allowing for dynamic adaptations to erecting criteria grounded on external factors[100]. By integrating data sources to assess the inner quality and accommodate specific preferences, AI-driven systems can deliver substantiated health recommendations in real time. This capability has the implicit to significantly ameliorate public health issues by using AI and IoT algorithms to optimize air quality operation according to individual conditions and preferences[101].

8. Conclusion and Future Developments and Challenges in AI-powered IAQ Monitoring

The integration of AI and IoT technologies in air quality monitoring systems allows for the delivery of substantiated health advice acclimatized to individual requirements. These systems calculate on real-time data collected from detectors to give up-to-date information on inner air quality. In addition to personalized services, automated recommendations grounded on real-time intelligent algorithms play a pivotal part in enhancing overall health and well-being. exercising AI styles during data analysis enables the system to offer targeted advice and suggestions to optimize air quality. Incorporating public data sources similar to pollution situations and rainfall conditions further enhances the system's capability to deliver applicable health advice. The collaboration between AI and IoT facilitates real-time data collection and analysis, furnishing nonstop assessment of IAQ. In the short term, fastening to the near future, we propose the design of a smart air monitoring system along with its digital twin. This system would allow for diurnal data updates and flawless integration with IoT platforms through the application of data-driven technologies. It should feature stoner-friendly controls, be operationally effective, and be cost-effective in addressing air pollution enterprises. By using smart technologies and air quality monitoring systems, we can respond more effectively to critical moments and address serious pollution issues. This requires combined trouble to prioritize and allocate coffers to these enterprises, icing a visionary approach to perfecting inner air quality and securing public health.

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