CHAPTER 2

REVIEW OF LITERATURE

2.1 Introduction

The global network of intelligent devices known as the Internet of Things (IoT) is capable of detecting and connecting to its surroundings as well as exchanging data with other systems and people. The most important concern of all is air pollution, which is exacerbated over time by a number of variables such as urbanization, industrialization, population growth, and greater automobile use. These factors have a negative impact on human well-being by adversely affecting the health of those who are exposed to the pollution. Air pollution monitoring for IoT networks were introduced in numerous research papers. Many research investigations have been carried out for various air quality samples in order to produce efficient air pollution forecasts with higher air pollution forecasting accuracy, as well as the lowest possible air pollution forecasting time and error rate.

2.2 Deep Learning based Air Pollution Monitoring Methods

The forecasting modeling approach was developed by Abdelkader Dairi et al. (2021) using an inventive Integrated Multiple Directe Attention Deep Learning architecture (IMDA) and the Variational AutoEncoder (VAE) based on it. It also showed how well the suggested approach worked for forecasting data on air pollution over time, both univariate and multivariate. It was necessary to create a method for early detection of abnormal pollutants with high concentrations.

A lasting time series pollution prediction utilizing an autoregressive deep learning technique was designed by Prithijit Nath et al. (2021) to ensure accuracy with a minimal error rate. In recent years, there has been a unique cause of air pollution in metropolitan areas: the extensive use of motorized transportation for travel has resulted in harmful pollution of the environment. However, the designed method did not analyze changes like the pollution data through and after the lockdown.

An advanced deep convolutional network was developed by Gao Huang et al. (2021) for the purpose of large-scale air pollution prediction. It is well known that convolutional networks can assess spatial relationships in visual data with effectiveness. The created model carried out simultaneous spatial and temporal modeling in an end-to-end manner, resulting in a simple and accurate technique for AQP. To improve prediction accuracy, though, various elements should have been taken into account.

A CNN-LSTM deep learning system for an hourly forecast of PM2.5 concentration was presented by Abdellatif Bekkar et al. (2021). During the proposed model, the Spatiotemporal data characteristics were extracted. By fusing the benefits of the CNN model, it effectually filters out the spatial characteristics that comprise pollutant components and Weather between adjacent stations. However, it needed to have applied the long-term prediction model to develop the precision.

A deep-learning system that enhances run-time for air pollution monitoring and forecasting was developed by Philipp Hahnel et al. (2020). Additionally, it offers a unique approach that fuses deep learning with domain decomposition. The difficulty of time and space usage, however, was not studied.

For the purpose of forecasting air quality, Ekta Sharma et al. (2020) created a deep learning hybrid convolutional neural network (CNN) and LSTM network. Whereas the CNN model emphasizes important precursor-lagged predictor elements, the LSTM model uses a novel feature mapping technique to anticipate the forthcoming hourly Total Suspended Particulate (TSP) value. However, the generated ensemble empirical mode decomposition model was not applied using the suggested way to separate the noisy air pollution data from the temporal information.

In order to accurately estimate air quality, Ning Jin et al. (2021) proposed a new DL architecture that included multiple nested LSTM networks. Data-driven prediction performance is enhanced via a novel multi-task multi-channel (MTMC) learning approach that considers the contemporaneous internal connection among multiple AQI components. Using the discrete stationary wavelet transform, the unique data was split into several sub-signals according to frequency. The temporal complexity analysis performance, however, could have been focused more.

Three parts of a hierarchical deep learning model were introduced by S Abirami and P Chitra in 2021 for forecasting air quality. The data's whole spatial relations are encoded by the first component, the encoder. The next one was called Spatiotemporal relationship Analysis LSTM (STAA-LSTM), and it can identify any type of time-based relationship as well as the degree of association between the detected spatiotemporal relation and the predicted value. The decoder, the final one, appropriately decodes these relationships to produce a precise forecast. To improve prediction performance, however, the ensemble-based techniques needed to be merged.

Urban environmental monitoring was concentrated on DL to increase air pollution predicting in Jun He Yang et al. (2022) study. Machine learning was used to learn representations of the pertinent data while considering the various urban big data connected to air quality. But precision in air quality monitoring must be improved.

Yuting Yang et al. (2022) proposed an explainable deep learning method to increase the precision of air quality forecasts. Using LSTM and GRU models for air quality prediction under different conditions yielded good results. The SHapley Additive exPlanation (SHAP) approach was used to show how meteorological circumstances affected air quality forecast. The forecast of how climatic conditions affect air quality could have enhanced computing efficiency and was not done.

Considering convolutional LSTM for the extensive random nature of air quality predicting, Ichrak Mokhtari et al. (2021) developed a multi-point deep learning approach. As a result, despite the significant climate variation, even accuracy was reached. Regarding the meteorological prediction and air control, air quality forecast was regarded as the most important source of information. Prediction algorithms based on a single model, however, also become more complex as a result of overfitting.

A denoising autoencoder deep network model was developed by Jianxian Cai et al. (2020) in order to lower noise and boost the accuracy of air quality predictions. The LSTM network structure of the DAEDN model was designed as a bidirectional LSTM in order to address the problem of a lag in the unidirectional LSTM prediction findings. The designed paradigm, however, was ineffective in bringing down the space complexity of processing a significant amount of data.

Manal Alghieth et al. (2021) created an air pollution forecast system using deep learning. The method's goal was to use LSTM to anticipate harmful pollution concentrations. Additionally, it produces reliable results with a lower mistake rate. Deep learning-based multi-target regression was developed by Taofeek Dolapo Akinosho et al. (2023) to provide remarkably accurate predictions of traffic-related air pollution. The intended performance assessment employed the incorporation of roadway information, weather data, and pollutant data. But it didn't look into other pollutants.

The Artificial Flora Optimization method (AFODL) model was developed by Mr. K. Azhahudurai and Dr. V. Veeramanikandan (2023) to evaluate the value of an air contaminant using a hyperparameter-optimized deep learning model. The pre-processed input data was utilized to train it, and DBN is used to perform the predictive analytics. The hyperparameters value optimization performed with the AFO method enhanced the prediction performance of the DBN model. However, the feature selection technique was not incorporated into the prediction network to increase the AFODL model's overall efficacy.

Yongliang Feng (2022) created a DL based spatial-temporal AQI prediction model to efficiently abstract the features from the sample data. Next, forecast and analyze AQI data appropriately with an extreme learning machine model. It was unable to offer more accurate air quality forecasts. To estimate air quality, Chi-Yeh Lin et al. (2021) developed ensemble multifeatured DL models. With this strategy, multiple linear regression integrates with several features via various intercepts and successfully predicts PM2.5. However, this technique did not predict the concentration of other air contaminants.

An ideal model tailored to air pollutants was developed by Middya et al. (2022) in order to perform long-term forecasting. Additionally, it investigates several statistical and deep learning methods for forecasting different air contaminants. To improve missingness-recoverability, a combination of univariate and multivariate techniques was used. employing LSTM deep learning and metaheuristic algorithms, predict air pollution The LSTM deep learning algorithm is based on the Genetic Algorithm (GA) technique. To forecast air quality, Ghufran Isam Drewil et al. (2022) created an air pollution prediction algorithm. In contrast to other methods, this methodology was intended to provide more accurate results.

2.3 Air Pollution Forecasting with ML Techniques

Nabil Mohamed Eldakhly, Magdy Aboul-Ela, and Areeg Abdalla (2016) introduced a probability weight variable to a typical machine learning SVM model in order to forecast the amount of air pollution in Egypt. This increased accuracy while reducing error. The results of this study showed that SVM algorithms outperformed other contemporary ensemble learning algorithms when they were modified and fused with the right theory, particularly the chance theory. The prediction time was still somewhat long, though.

Amina Nazif et al. (2017) used multiple linear regression (MLR), stepwise regression (SR), and principle component regression (PCR) to examine the daily mean particulate matter (PM10) concentration levels. Data on average PM10 concentration, temperature, humidity, wind direction, and wind speed were used in the experiments. The data came from a Malaysian industrial air quality monitoring station. The SR analysis's findings showed a lower coefficient of determination (R2) and a less significant effect on PM10 concentration levels. The results of the prediction analysis also demonstrated that MLR methods and PCR models had lower R2 values. Furthermore, the results of the prediction analysis showed that, in terms of R2, PCR models performed better than MLR approaches. But the error rate persisted.

An inexpensive Internet of Things system for monitoring traffic flow and the AQI was presented by José Angel Martn-Baos et al. (2022). The computation of the traffic flows was based on the processing of compressed video. Using dissimilar feature data acquired from the sensors, ML regression methods were used to support an AQI assessment. It did not, however, specify the elapsed times or the locations where the measures should be put into effect.

K. Kumar and B. P. Pande (2022) conducted a thorough investigation into a case study of air pollution forecast using ML. Following the dataset's preparation, significant features were chosen for the correlation study. In order to determine the air quality index and uncover other hidden patterns within the dataset, an exploratory data analysis was carried out. The most accurate model is the Gaussian Naive Bayes model. However, the performance time did not change.

To forecast the atmospheric air matter concentration and reduce the mean square error, Doreswamy et al. (2020) developed a machine learning prediction technique. The created technique was also used to estimate PM2.5. The method for air pollution and meteorological information gathered from Taiwan is trained by the Taiwan Air Quality Monitoring Network (TAQMN). To cut down on time consumption, the dataset must still go through data pre-processing.

Mauro Castelli et al. (2020) utilized Support Vector Regression (SVR), a state-of-the-art machine learning technique, to estimate both pollution and particle levels and thereby significantly predict the Air Quality Index. RBF was the tested alternative's kernel that allowed SVR to produce the best accurate forecasts. Instead of choosing features using Principal Component Analysis, a more effective strategy. However, it was necessary to investigate how SVR could be used to predict air quality.

Adaptive machine-learning techniques were created by Saverio De Vito et al. (2020) for the purpose of network standardization of Internet of Things smart air quality monitoring sensors. In order to use online machine learning components, they tested with different combinations of updates periodicity and quantity of received labeled samples. It might have, however, increased the performance's precision.

T. Mandava et al. (2022) created a middleware architecture based on machine learning techniques for monitoring pollution in South Africa. This method aids in assessing the degree of air pollution and its impact on public health. It also promotes creation of sustainable air quality regulations that advance the welfare of the general public. The processing accuracy, however, could have been improved.

Mohammed Rakib et al. (2022) developed an IoT and Machine Learning technique to precisely monitor pollution levels and anticipate forthcoming pollution levels. Focused on the interior monitoring in this solution. The surrounding AQI could be tracked accurately by an IoT device. However, it was unable to make use of built sensors and an enhanced hyper parameter adjusted model. Gokulan Ravindiran et al. (2023) generated an accurate prediction of AQI utilizing machine learning models with Random Forest and Catboost algorithms. Additionally, it predicted different air quality circumstances. However, the amount of prediction skill was not evaluated.

Supervised machine learning and a proxy were created by Mohammad A. Alolayana et al. (2023) in order to better predict air pollution and look into its main causes. This forecast was enhanced by employing a modeling proxy for emission rate. Using the planned methodology, it was exactly confirmed if a source was substantial or not. However, it did not account for how long the process was. methods that use machine learning Air pollution prediction was created by A. Samad et al. (2023) to replace physical monitoring stations with virtual ones. It also evaluates the expanded methodology's effectiveness in different contexts.

An advanced technique for monitoring and forecasting air pollution was developed by Amisha Gangwar et al. (2023) in order to advance the various components of air polluting models. The optimal location for sensors was highlighted, and real-time Internet of Things-based air monitoring devices were also investigated. Models derived from big data and machine learning were critically examined. It also discusses problems and difficulties with the intended method. The data-driven models, however, were not created to account for changing climate.

Hemanth Karnati et al. (2023) introduced the IoT-Based AQI Monitoring System with ML technique for Exact as well as Real-time Data Investigation. It creates a transportable air quality recognition tool that can be used in any place. The information is visualized and gathered via a cloud-based web app. The gadget sensors were used to calculate air quality in parts per million (PPM) and identify harmful gases. Additionally, machine learning analysis was used to the data acquiring procedure.

IoT technology and machine learning approaches were used by V. N. Kukre et al. (2023) to enhance the monitoring of several environmental parameters including air quality. Limited data from air quality samples are predicted more accurately using this method. More air quality sample data, however, were not anticipated. N. Srinivasa Gupta et al. (2023) discussed a comparative analysis of the AQI forecast using ML methods. They were examined using regression models for accuracy. However, more comprehensive information did not provide evaluations for specific city locations.

Hongmin Lia et al. (2019) created a multi-objective optimization-based innovative analysis-forecast method for the air quality index. The input structure was enhanced and noise was decreased by using the feature selection model. The optimize-forecast module executed a modified LSSVM with parameters improved via multi-objective multi-verse optimization with accuracy and efficiency.

2.4 Novel Methods Employed in Air Pollution Forecast

A Multi-output and Multi-index of Supervised Learning for Air Quality Prediction was presented by Dewen Seng et al. in 2021. The model was updated with information on airborne gaseous pollution, weather, and particle pollution. The complete set of data was standardized and translated to the supervised learning format. The statistics on performance inaccuracy from the air quality prediction, however, remained rather high.

WenTsai Sung and SungJung Hsiao (2021) developed an interior air quality monitoring method based on Internet of Things architecture to investigate individuals who reside in areas with superior air quality. Fuzzy control was taken into consideration when creating the foundation for fuzzy rule-based modeling of the environment elements for effective load. Decision logic was employed as a temporary replacement for the indoor air quality (IAQ) threshold regulation. A Wi-Fi wireless transmission module and Arduino Uno expansion board were used to create a comfortable quality air monitoring system. It did not, however, attain a true ideal home environment because it needs to consider a number of aspects, including temperature, humidity, home safety, and hygiene.

Koel Datta Purkayastha et al. (2021) created a server on a cloud platform for processing and storing data gathered by an air quality monitoring system (AQMS). Rapid industrialization and urbanization policies led to an evaluation dilemma of air pollution in many countries. IoT has been used to regularly monitor vehicle emissions in a manner similar to this. It was asserted that the automated approach was required to reduce pollution. Though further investigation revealed a plethora of potential uses, the server and mobile app were never developed.

Ahmed Samy Moursi et al. (2021) recommended an IoT-enabled system that practices nonlinear auto regression with exogenous input to guarantee speed and accuracy. This system makes use of a hybrid prediction architecture supported by Nonlinear Auto Regression with Exogenous Input (NARX) and other Machine Learning (ML) methods. A PC was used to test the planned system's cloud forecast, and a Raspberry Pi was used to test its edge device forecast. It was essential to have a system like this that could react quickly to air pollution in places where there was little or no internet access. However, the conventional method of using stationary sensors is unable to provide a comprehensive overview of air pollution because nearby sensors may be kilometers apart.

In order to provide effective air quality monitoring, Dan Zhang et al. (2020) presented a concentric focus on modeling air quality in a specific area using both static and dynamic IoT sensors installed on vehicles patrolling the area. Additionally, it illustrated the viability and efficacy of the planned strategy by using several machine learning models to analyze the prediction outcome. To improve predicting performance, it did, however, need to incorporate additional characteristics.

D. Hepsiba et al. (2021) created an autonomous detection and pollution control method emitting from the vehicle. According to reports, air pollution that has been specifically established in urban areas has been a common problem recently. Due to the expanding urban population and increased motorization brought on by the increased traffic volume, there were significant gas emissions. However, it was unable to accurately monitor automobiles.

Raquel Espinosa et al. (2021) provided a method for comparing numerous contaminant-predicting methodologies and their features that is based on the two unique criteria of precision and robustness. LSTM and one-dimensional CNN with various window widths were some of the approaches used. However, it was necessary to create new methods for calculating step-ahead prediction.

Time series analysis and predictions were based on the particulate matter utilizing a hybrid single particle lagrangian integrated trajectory in Uzair Aslam Bhatti et al. (2021). This research methodology provides a thorough examination of the primary causes of air pollution. The Prediction method made use of the SARIMA model. The focus should have been more on the various urban areas with a detailed comparison of health aspects with particulate matter development.

Isura Sumeda Priyadarshana Nagahage et al. (2021) suggested a continuous evaluation of an inexpensive sensor for a continuous multichannel specimen monitoring system. To avoid inaccurate gas discovery, the system applies substantial dilution when the concentration surpasses the detection limit. It was notable for using an automated gas sampling technique for vacuum chamber measurements. The method employed for gas sampling improved the sensor's robustness and measurement precision. However, predicting sensor values detection time was not reduced.

An elaborative analysis and association between transport-related air pollutant concentrations and effortlessly accessible descriptive variables were presented in Mario Catalanoa et al. (2016). The novel techniques were incorporated with conventional traffic management to ease road vehicle mobility in urban areas. However, it could have low forecast frequency concentration peaks and higher levels of pollution deriving.

Regression techniques were utilized in A. Aarthi et al. (2020) to predict carbon monoxide concentration in the environment gathered for one year. However, the prediction time remained the same.

Anikender et al. (2011) proposed a study to examine the various seasons of seven years to analyze the air quality index using principal component regression. The covariance of the input data matrix was used to compute the principal components using the Principle Component Regression method. The developed strategy did not alter consumption time, even if it reduced mistake efficiently.

In R. Smit et al. (2019), the air quality of the road was observed in order to calculate vehicle emissions using remote sensing in an urban setting. The measurements of volatile hydrocarbons (VOC) in the road match the findings of a previous tunnel study by revealing significant differences with vehicle emission variables. The precision of motor vehicle emission estimation can still be improved.

An Autoregressive Integrated Moving Average (AIMA) was employed by Tong Liu et al. (2018). It was applied to Hong Kong monitoring stations, where RMSE was significantly decreased as a result of accurate and consistent air quality predictions. However, the performance's intricacy was overlooked.

Jennifer L. Moutinho et al. (2020) evaluated traffic-related air pollutants by analyzing vehicle emissions air quality monitoring with temporal influences, which increased their accuracy. In order to quantify an individual's exposure to the local road environment, epidemiological health evaluations typically rely on a limited number of monitoring sites. Air contaminants from traffic have been related to detrimental health effects. The planned strategy, however, was distinct from typical vehicle emission hotspots and their effects on exposures.

In order to forecast and evaluate air pollution, Azim Heydari et al. (2022) initially introduced a novel hybrid intelligence technique based on LSTM and

MVO algorithm. The proposed model estimated the amount of NO2 and SO2 that the combined cycle power plant will produce using the LSTM model. The MVO approach was used to optimize the LSTM parameters in order to lower prediction error. However, it was unable to provide accurate forecasts.

An intelligent hybrid air-quality forecasting system was developed by Jianzhou Wang et al. (2021). it employs climate-influencing variables to produce precise air-quality prediction data. The feature-selection model was used to determine the best input structure for the developed model since it is highly efficient at extracting the influencing variables and eliminating unnecessary data. Additionally, the evolving interval type-2 quantum fuzzy neural network (eIT2QFNN) was designed using the chaotic Bonobo optimizer approach. By considering the importance of influencing variables that control the uncertainty and fuzziness in the forecasting process, the upgraded eIT2QFNN achieves AQI prediction. But the technique for anticipating air quality was badly designed.

Long short-term memory (LSTM) based on a spatiotemporal attention approach was used by Xiangyu Zou et al. (2021) to construct an air quality prediction model. To maintain the relative influence of neighboring sites on the prediction region, a spatial attention mechanism was integrated into the encoder. On the other hand, less time was required to make the quality prediction.

To lessen the complexity of air quality prediction, Hongqian Chen, Mengxi Guan, and Hui Li (2021) developed an integrated dual LSTM prediction technique. A single-factor prediction model was created using the Sequence to Sequence (Seq2Seq) approach, which takes the air quality data and extracts the expected value for each component. During the forecasting method, each aspect of air quality was treated as a time series of data. The second multi-factor prediction model to be used was the LSTM model with concentration method. However, there was no change in the various data forecasts' accuracy.

Using the time series of components made up of the Hong Kong monitoring network, Shan Jiang et al. (2021) investigated the possibility of long-term prediction and produced short-term predictions by combining a multiscale framework with non-stationary oscillation resampling (NSOR) and empirical mode decomposition (EMD). Finding the relevant elements was essential to progress the development of air quality prediction.

Qi Zhang et al. (2022) presented a method called Deep-AIR employing CNN and LSTM framework in order to close the gap in delivering fine-grained city-wide air pollution assessment by domain-specific features which then take spatiotemporal input. A 1-to-1 convolution layer was also developed to support the learning of temporal and spatial relationships. As a result, air pollution forecasts were more accurate. It might have, however, increased the designed framework's correctness.

By combining different ML models, Ying Zhang et al. (2020) presented a method for predicting air quality based on multiple features. The historical meteorological data are part of the focus feature group, and there are also statistical data, date data, and polynomial variations. Air pollution forecasting ensured accuracy and decreased the associated loss. The investigation of the pollutant propagation effects did not, however, pay attention to the spatial component.

An aggregated LSTM model (ALSTM) was proposed by Yue-Shan Chang et al. (2020) to incorporate external pollution sources and local air quality observation stations, i.e., the station in nearby regions. An aggregation of the LSTM models was used to make premature projections based on external sources of pollution obtained from industrial air quality monitoring. The required model's forecast accuracy was enhanced. However, the prediction time decrease was overlooked.

An indoor air quality detector (IAQD) that measures temperature, humidity, CO2, and PM2.5 in residential buildings was developed by Zhibin Liu et al. (2021).

For comparison, the parameters of the outside world were also quantified. In winter, it was able to see how the outside environment affected the air within by opening and closing doors and windows. The indoor penetration of the wireless signal was not, however, improved.

R. Senthilkumar et al. (2020) created a unique way to implement the IoT-based fog computing air quality monitoring system. Sensors gather air quality data over time and send it amongst fog nodes inside an embedded system. Each fog node might be a completely virtualized software program running on a different computational node that has a communication interface. The computational time was maintained, nevertheless.

JunHo Jo et al. (2022) introduced a platform for monitoring indoor AQI with sensors. This software tracks indoor air quality anywhere by utilizing IoT and cloud computing technologies. in order to efficiently track the quality of the air and send the information in real time via Long-Term Evolution (LTE) to a web server. Smart-Air was developed based on IoT technology. It did not succeed in creating autonomously operated air quality states, though.

A fuzzy inference technique was used by Liang Zhao et al. (2022) to evaluate the environment indoor air quality (EIAQ). a method of monitoring and managing air quality that computes and identifies EIAQI values represented in many categories using fuzzy logic controllers (FLC). EIAQI data served as index references for the control system's automatic setup. The control system was used to notify the status level and to lessen pollutants that affect indoor air quality and thermal comfort. However, there was still room for improvement in performance accuracy.

Jing Huang et al. (2018) conducted an examination of mortality statistics and data from national air quality monitoring. The intended method assessed how the Air Pollution Prevention and Control Action Plan will impact long-term air quality management and public health implications. Due to the significant collinearity of air pollutants, it was unable to evaluate the health impacts of every air pollutant.

Qing Zhou et al. (2022) developed a cloud-edge collaboration framework for agricultural environment monitoring and the use of LSTM-based agricultural environment prediction functions. It accomplishes cooperative computing and unified management of IoT resources for environmental monitoring activities. However, it might have improved the prediction model's training performance and forecast accuracy.

The inventors of the IoT-Based Intelligent Smart Home Control System (2021) are Olutosin Taiwo and Absalom E. Ezugwu. The sensor-based automation system's installation made it possible to detect movement and intruders within the home. A machine learning technique was used to distinguish between the pictures in the house to avoid the security system sending out erroneous alarms. The mobile application may have been expanded to include the iOS platform, though.

Yu-Lin Zhao et al. (2020) created a reliable and effective method for gathering data on air monitoring from various IoT devices and carrying out large-scale cloud-based calculations. The system monitors and controls ambient air quality, and the maintainability of the code allows for highly extendable connectivity between hardware and software. Still, it was important to identify low-cost strategies.

An adaptive IoT node was developed by Reginald Ekene Ogu et al. (2022) for AQ monitoring. Specifically, a prototype was created for an Air Quality (AQ) node that can be connected to the Internet over Bluetooth, Wi-Fi, and mobile networks. In addition, the online dashboard's web user interface was enhanced. On the other hand, the rate at which energy is consumed must accelerate.

By adjusting the ventilation speed, Anas Bushnag (2022) developed fuzzy logic based on an enhanced air quality and weather control monitoring system for the surrounding areas. This speed is determined by the system's three inputs: temperature, humidity, and air quality. These sensors gather data from the environment, which is then processed to choose the appropriate ventilation speed. The suggested approach reduces power usage, but more sensors must be developed in order to collect more accurate measurements of the environmental conditions.

High-Density Real-Time Air Quality Derived Services as of IoT Networks was developed by Claudio Badii et al. (2020). Utilizing the services and information available, city authorities helped citizens make decisions by using them. The distributed data was utilized to generate dense grid values for contaminants and give users broad information through mobile apps and dashboards. There was still no change in the error rate.

Komal Dahekar and Prof. Rahul Dhuture (2022) created systems for monitoring and controlling industrial air pollution using the Internet of Things. The developed method was crucial for modeling in situations when the government needs comprehensive pollution monitoring and the populace wants to continue to be concerned about the quality of the air. Precision monitoring is possible, and pollution is also avoided. However, it overlooked the impacted area and did not mitigate the harm to the next generation.

Aman Kataria and Vikram Puri (2022) developed a real-time air quality monitoring system based on the Internet of Things. In addition to building the sensor node with the intention of monitoring AQI data, a local smart gateway was also created with data security in mind. A Kalman filter was employed to eliminate noise from the data that the sensor node was gathering during the data collection process. However, the created AI techniques were not assessing the performance during the statistical parameters.

In order to monitor air quality, Mohd Tahseenul Hasan et al. (2019) developed a forecasting tool. based on cloud and IoT technologies. Furthermore, the user built and downloaded an Android application. The user receives access to the application's data upon registration, allowing them to view sensor data along with the air quality index (AQI) and receive alarm messages on the AQI and likely concentration of pollutants. However, more accurate pollutant forecasting may have been achieved with improved data analytics.

An Internet of Things-based system for tracking particulate matter concentration and air quality was developed by Puneet Kalia and Mamtaz Alam Ansari in 2020. This monitoring device gives access to a digital dashboard on smartphone that shows you the most recent data on air quality in your immediate area. The system was deployed anyplace needed in the city, neighborhood market, or industrial thanks to its portability. But the planned strategy required extending nanotechnology to measure nanoparticles.

Martin M. Soto-Cordova et al. (2020) developed an IoT-based Urban Areas Air Quality Monitoring Prototype with the goal of improving societal health. This device seeks to monitor the air quality continually while harmful gasses are present. However, it was necessary to set up a sensor network in various locations to promote environmental and medical care.

Haolin Ma et al. (2021) carried out a field test for a solid fumigant sterilizer in addition to developing an accurate control and monitoring system. A linear equation was developed between the rotational speed and the amount of fumigant allotted per shaft revolution in order to calculate the shaft's rotating speed for the control system. However, it might have lessened the amount of effort required and stopped drivers from ingesting solid fumigants.

The authors of the survey, Mannam Veera Narayana et al. (2022), focused on developing a low-cost, sustainable setup for air quality monitoring. There were separate stages for the sensor selection, evaluation, and end user-specific applications in the Low-cost Sensors (LCS)-based AQM system. Though, data on air quality could have been more easily accessible.

An Internet of Things-based air quality system was created by T Dinesh kumar et al. (2021) to evaluate the air quality in a particular area. The device uses sensors to track the concentrations of several compounds in the air, including particulate matter. An Arduino WIFI module is used to send the data to the cloud system and retrieve it. One may view the tracking effects on a cloud site page. The existing model was applied to the actual system implementation with efficiency. But, the developed system assessment accuracy needed to be enhanced.

Silvia Liberata Ullo et al. (2020) created improved intelligent environment monitoring systems for use with IoT and sensors. The utilization of various environment monitoring systems for various objectives was thoroughly examined. Big and noisy data challenges were handled by the designed system, and a reliable classification strategy was produced. However, the created system needs to learn about additional environmental elements like noise pollution and natural calamities.

A multi-step, multi-output multivariate model was developed by Rajnish Rakholia et al. (2023) for the purpose of forecasting air quality. To offer helpful insights, investigational data analysis, correlation analysis, and factors influencing urban air quality were all conducted. A low-power wide area network (LPWA)-based Internet of Things method that made use of an air quality monitoring system was presented by Deepak Narayan Paithankar et al. in 2023. The portable sensors broadcast data and gather LPWA at the same time. Any information about air quality that was examined and processed by the IoT. However, it fell short of minimizing the problem of more extensive air contamination monitoring.

Kirti Vaidya et al. (2023) used IOT to create a simple and affordable air pollution monitoring system. The intended method computed, displayed, and used for future analytics was the environment's temperature and humidity level. The sensed data was shown on the LCD display panel. To track pollution levels, Uddesh U. Naik et al. (2023) developed an IoT-based air pollution monitoring system. The approach was designed to characterize air quality levels and also to identify excessive amounts of contamination. Additionally, a specific region's air quality is monitored. However, it did not include additional multiple sensors to calculate various types of contaminants.

Using Internet of Things technology, Akhil Mathew Mohan et al. (2023) developed a Real-time Air Quality Index Monitoring and Alert System. the specially designed system device that measures and continually monitors the air quality inside a building using sensors and networked technologies. The cost was greater in terms of energy use and performance, though. Using univariate time-series analysis, Manzoor Ansari and Mansaf Alam (2023) created an intelligent IoT-cloud-based air pollution forecasting algorithm. The developed prediction model considers both current and historical air pollution levels, enabling better forecasting of future levels. However, it was unable to create a more reliable model for in-the-moment observation.

IoT-based intelligence Tarun Kumara & Amulya Doss (2023) designed AQM Solution to quickly screen the air quality for any site. A hybrid DL model was created to predict future AQI and air pollutant absorptions. During monitoring air pollution, the developed solution was to diminish respiratory diseases risk. But, hybrid DL model was not prolonged to additional urban by means of the transfer learning approach**.** LSTM encoder-decoder architecture basis of air pollution forecasting models were designed by Jovan Kalajdjieski et al. (2023) to lessen the issue of missing sensor information. But, it failed to consider other time-series related complications inside diverse domains.

A hybrid learning approach was developed by K. Sridhar et al. (2023) for air quality prediction in modular IOT sensing platform. The platform was appropriate for applications involving Big Data analysis, such as traffic and weather forecasts. The improvement of distributed field, less expensive sensing devices for environment intelligence applications was the goal of this approach. Mohamed Fahim et al. (2023) created a fuzzy inference model and a robust, low-cost modular weather station platform for the Internet of Things in order to effectively determine the state of the air quality for a specific place. Air pollutant data concentrations depend on air pollutant data concentrations. But, the measured environmental parameter of precision was not amplified.

Real-time air pollution monitoring was performed Sami Kaivonen & Edith C.-H. Ngai (2020) with sensors on urban vehicle. An air quality monitoring system improvement as well as deployment of with movable sensors was conducted in Sweden. But, it failed to analyze sensor data quality. Waheb A. Jabbar et al. (2022) devised the long-range wide area network (LoRaWAN) based Internet of Things air quality monitoring system for long-range outdoor air quality monitoring. Using the Arduino Uno microcontroller, collected data was combined into a single packet with several payloads, which was then sent via a LoRaWAN gateway while using the least amount of energy possible. Next, on the IoT server of The Thing Network (TTN), the data was in real time. However, it was unable to provide a sufficient number of fake nodes for the LoRaWAN network and did not allow the public to access a greater amount of data.

An incorporated air quality monitoring network inside Sheffield by means of a multi-use as well as more robust method was developed by Said Munira et al. (2019) to offer maximum value from a sensors network. This network comprises diverse layers of AQ monitoring methods contains reference sensors with high accurately. A Review of the Protocols as well as Enabling Technologies was developed by Zeba Idrees et al. (2019) with minimum Cost Air Pollution Monitoring. But, the performance of system efficiency was not boosted.

S. Chenchu Jyoshna et al. (2021) created an IOT-based air pollution monitoring system that uses an Arduino microcontroller to screen the air and improve air quality. Sensing Data Fusion approach was developed Q. P. Ha et al. (2020) for enhanced Indoor Air Quality Monitoring. Here, waspmote sensors were to calculate indoor air pollutant levels. An extended fractional-order Kalman filter employed for combining IAQI as well as humidex information. As well, it attains precise prediction with better performance against computation noise as well as nonlinearity. But, the performance efficiency was not better.

Shajulin Benedict et al. (2020) created an IoT Blockchain enabled Air Quality Monitoring System (IB-AQMS) for smart cities. This technology was meant to record industry air pollution data in the form of untampered blocks in smart cities. An IoT device gathers sensor data as well as blockchains underlying peers' basis that information was validated. Air Quality Prediction was performed by Himawan Nurcahyanto et al. (2022) for IoT Applications depend on real-time data. But, it failed to apply machine learning as well as deep learning techniques for IAQP.

A remote sensor network system was designed by Zhihe Zhao et al. (2018) to monitor Real-Time Air Quality on Green Roof. In order to enable data analysis as well as remote sensor control, graphical user interface (GUI) was developed. UAV-Basis Air Pollution Monitoring Systems was developed by Oscar Alvear et al. (2017) and employed for automatic monitoring of a particular area. The designed UAV was guided through chemotaxis metaheuristic as well as local particle swarm optimization method basis Pollution-driven UAV Control process.

Wenjing Mao et al. (2021) developed a graph convolutional temporal sliding long short-term memory (GT-LSTM) model for air pollution prediction. In this case, neighbor data is gathered by graph convolution networks in order to simulate spatial dependency. Temporal sliding technique LSTM networks were utilized to learn dynamic air pollution alterations. Kan Zheng et al. (2016) created a low power wide area (LPWA) networks-based air quality monitoring system to collect data on air quality using portable sensors. Inside the IoT cloud, the entire air quality information was processed as well as analyzed.

Julio H. Buelvas et al. (2023) developed Internet of Things-based air quality monitoring systems for multi-dimensional data quality analysis. It also identifies the majority of linked DQ characteristics considered when designing the monitoring system. Also, integration of the related DQ dimensions basis unified DQ index was computed by multi-dimensional model. Moreover, it enhances in general DQ index assessment and also implements it to the low-cost sensor network specific case. But, the data quality does not frequently monitor.

The Water as well as Air Monitoring scheme was developed by Aditya Agarwal et al. (2021) to find out contamination of water and air using IoT. But, it failed to preserve the delicate ecosystem. Jagriti Saini et al. (2020) conducted a thorough study of indoor air quality monitoring devices based on the Internet of Things. As well, it emphasizes design features with sensor, microcontrollers, and structural design along with execution problems. But, the designed system was applied in the outdoor air pollution field.

A Spark Big Data Framework was designed by Dong-Her Shih et al. (2021) for PM2.5 Air Pollution prediction. The designed structure was splits into three modules were to gather real time PM2.5 data and the PM2.5 concentration value was forecasted by ensemble learning approach. However, it did not focus on image-based convolutional deep learning neural network air quality prediction.

Intelligent air pollution visualization as well as prediction system was developed by Mladen Korunoski et al. (2019). In this method, the rapid performance was measured and it comprises web service as well as a client that runs inside a browser. IoT basis air pollution effect on the lung's visualization approach was developed by Calorine Katushabe et al. (2023) employing HEPA filters to monitor AQI in real-time. The designed filter was effectively decrease risky factors of air pollution on human lungs.

Financial analysts looked into Rui Dong et al. (2021) Evidence for Air Pollution, Effect and Forecasting Bias. Julio Buelvas et al. (2023) created IoT-based air quality monitoring systems with the goal of improving data quality. Inside an IoT context, data-quality dimensions general overview was detected. Also, systematic mapping was developed to find out the relation amid these concepts. But, in the evaluation of air quality low-cost sensor measurements were not carried out.

A review of air pollution monitoring system was developed by S.M.S.D. Malleswari et al. (2022) using IoT devices. The intention of designed method was to understand data on environmental variables. As well, internet-basis architecture that gathers sensors data related to smart city environment computations. IoT embedded systems rely on Yanghao Ye et al.'s work on architectural digital art design and green city air monitoring (2021). Both a software and hardware system are part of the designed system.

A modular end-to-end IAQM system was designed by Mohieddine Benammar et al. (2019) for Real-Time applications. It was also developed Gateways that ensure transmission from the sensor’s nodes into IoT servers. As well, it contains transmission error detection mechanism as well as incase happen temporary interruption of communication, packet resubmission. In order to improve system performance and prevent data loss, Santanu Metia et al. (2021) integrated the extended fractional order Kalman filtering (EFKF) approach with the wireless dependable control (W-DepC) scheme. Also, it offers reliable as well as accurate solution for air quality monitoring issue. But, it failed to consider combination the existing models for air pollution prediction.

Distributed Ledger Technology Basis Decentralized Pollution-Monitoring System benefits were described by Markus Lücking et al. (2020). Different consensus techniques and digital signature strategies were used to appropriately construct the PMS and meet the specified needs. Graph Learning Techniques were introduced by Pau Ferrer-Cid et al. (2021) to explain the air pollution monitoring network topology. But, signal reconstruction techniques were not employed to minimize the error rate. As well, it failed to analyze data missing during air pollution monitoring.

Anurag Barthwal et al. (2021) developed an Internet of Things (IoT) based sensing system for modeling and forecasting urban air quality. The sensor device was intended to gather data on air quality as the car was traveling along the road. Next, using statistical and stochastic forecasting models—quantile regression—the collected data was used to forecast the quality of the air. A review of UAV-basis air quality monitoring system was developed by Naser Hossein Motlagh et al. (2023) to emphasize as well as explore technical solutions in addition to detecting challenges.

Air pollution control algorithms were developed Jovan Pantelic et al. (2023) for smart and healthy homes. However, it was unable to enhance a more advanced closed-loop control method for air quality. Prashant Kumar et al. (2023) created an improved air pollution forecasting model for the school site. The method was put into practice to comprehend how weather conditions affected the movement of pollutants.

An investigation of PM2.5 dominant spatiotemporal difference patterns linked with severe pollution occurrences in South Korea Subin Han et al. (2023). The pollution events were assisting to find out locations for additional air quality monitoring stations. Fine-tune the CAMS European multi-model air quality predicts was carried out by Gabriele Casciaro et al. (2022) for area air pollution monitoring. But, the designed approach was not applied in the higher-resolution forecast.

A new volcanic emission as well as air pollution prediction from time series models was carried out by Gordon Reikard (2019). The predictive accuracy was enhanced by means of failure of volcanic emissions. Air Quality forecast method basis of Predictive Data Feature investigation was performed by Ying Zhang et al. (2019). The primary modules within the weather prediction data were extracted using the PCA dimension reduction method, which also minimized the detrimental impact of redundant features.

Kun Gao et al. (2021) presented a regional AQI based on web-text analysis to enhance AQI monitoring. By contrasting immersive web-text analysis approaches with conventional monitoring methods across many user domains, the benefits of the designed methodology were illustrated. Ayaz Hussain Bukhari et al. (2022) devised an effective, reliable and stable technique to accurately monitor and control air pollution in megacities. Better performance is provided by the created model, which extracts the seasonal difference in fractional order. Furthermore, controlling rules and principles of physics helped to improve the generalization of the modeling process. However, the developed model was not used as a substitute method to address the application of some other systems based on nonlinear modeling.

Data pre-processing as well as Multi-Objective Dragonfly Optimization Algorithm depends Air Pollution Interval Prediction was performed by Jiyang Wang et al. (2022). It effectively analyzes the instability as well as uncertainty of pollution. But, it failed to lessen the cost as well as risk of air pollution system. S. Metia et al. (2020) created the Chemical Transport Model (TAPM-CTM) and Air Pollution Model to improve forecast performance. It could not, however, address the inherent ambiguities of the method.

A computational intelligence optimization algorithm was designed by Ranran Li et al. (2019) for air pollution monitoring. The entropy weighing method basis fuzzy synthetic estimation model was to construct upcoming air quality condition data. But, system error was not detected. A new spatio-temporal effect basis AQI prediction model was designed by Zixi Zhao et al. (2022). It comprises spatial auto-correlation analysis as well as trait selection. To improve the prediction accuracy, a feature selection technique that combines a heuristic algorithm with reinforcement learning was used.

Air quality prediction with AI approaches content was investigated by Yanzhao Li et al. (2022). But, the performance error was not reduced. Learning-basis CO2 concentration prediction was performed by Saman Taheri et al. (2021) across various forecasting horizons with less energy consumption. But, the designed system validation process was not precise.

A smart mobile pollution monitoring as well as data-driven modeling approaches were developed by Adriana Simona et al. (2019) to assess air quality as well as detect air monitoring patterns. But it failed to develop Data-driven modeling for real-time operations. Ho-Yong Jin et al. (2020) examined a case study of air pollution in order to increase learning speed and make real-time predictions. However, it was unable to describe how to handle the data in a way that is adaptively consistent with both its quantity and its pace.

2.5 Neural Network Based Air Pollution Prediction

Using spatiotemporal dynamic correlations, Yu Huang et al. (2021) developed a spatial attention integrated recurrent neural network for air quality forecasting. An adjacency matrix based on graphs was incorporated into the attention cells in order to examine the connections between the monitoring stations. While lowering the error, the designed model cannot lower the program's complexity.

To improve air quality forecast accuracy, Yuan Huang et al. (2020) developed an optimizing Back Propagation (BP) neural network based on an enhanced Particle Swarm Optimization (PSO). The dissimilarity inertia weight approach and the learning factor are optimized by the PSO algorithm. Additionally, it ensures early-stage global search capabilities and later facilitates rapid convergence to the ideal answer. The complexity analysis, however, should have been more narrowly focused.

A convolutional-based bidirectional gated recurrent unit (CBGRU) is used in a short-term forecasting model proposed by Qing Tao et al. (2019) to reduce forecasting error. Even though the temporal complexity cannot be overcome, the designed CBGRU model significantly improves prediction performance.

Recurrent neural networks and long short-term memory (LSTM) were combined by Saba Gul et al. (2022), which significantly decreased error and increased forecasting accuracy. In order to replicate the particle material pattern, a multi-step multivariate LSTM model was developed that precisely records past events and measures the air quality in a given region. On the other hand, the performance might have been less difficult.

To lessen overfitting, Canyang Guo et al. (2020) created an ensemble network (EN) that consists of a recurrent neural network (RNN), a gated recurrent unit (GRU) network, and an LSTM network. a technique to increase prediction accuracy by categorizing according to wind direction. Unfortunately, because topography and human activity data are lacking, the planned approach only looks at how meteorological data affects PM 2.5.

A bidirectional RNN by D. Saravanan et al. (2021) was incorporated with temporal factors that monitored the air quality in a timely method. This designed model hardware cost was lessened as the system monitored the area using sensors. Furthermore, air pollution quality was monitored by predicting status frequently in a temporal way using neural network technology on a perception system. Also, neurons found to be self-connected were utilized for performing cyclic formation in the network. Due to this, the bidirectional RNN controlled current and historical input for air pollution quality monitoring, thus enhancing pollution detection accuracy. However, immense and complicated data collection requires numerous exploration levels, thus compromising accuracy and error.

K. Krishna Rani Samal et al. (2021) created a Convolutional Neural Network - Long Short-Term Memory, Sparse Denoising Autoencoder (CNN-LSTM-SDAE) (CLS) model to improve air pollution forecasting. The developed architecture used the k-closest neighbor (KNN) imputation technique to recover the missing values from the air quality dataset. Through temporally modeling pollutants, the CNN-LSTM unit extracts information from the large dataset on hidden features. Additionally, the CNN-LSTM model's output is reconstructed at the dynamic fine-tuning layer by the Sparse Denoising Autoencoder, which uses the Bidirectional Gated Recurrent Unit (BIGRU) as both an encoder and a decoder to produce accurate prediction results. The intended CLS model, however, was not improving its multivariate prediction capabilities.

The combined weight forecasting model (CWFM), developed by Bingchun Liu et al. (2021), and allows for accurate prediction of air pollutants. The discrete wavelet transform was used to partition the input data in order to improve the dimensionality of the data. Then, the bi-directional long-short term memory neural network (Bi-LSTM), gated recurrent units (GRU), and long short-term memory neural network (LSTM) were built using the wavelet decomposition results. Owing to temporal and individual capability constraints, the estimation of exact contamination was not limited.

One-dimensional convolutional neural networks (1D-CNNs) and bi-LSTM were developed by Shengdong Du et al. (2021) to mine spatial correlation data for air quality prediction. Based on pre-determined methods for distribution representation, a hybrid deep learning framework is constructed that includes learning of multivariate air quality related time series data. However, the multi-step forecasting capabilities and better results were not achieved under different forecasting conditions.

A two-layer model prediction technique called LSTM&GRU was created by Baowei Wang et al. (2019) and is based on a long short-term memory neural network and a gated recurrent unit. A double-layer recurrent neural network method was created to forecast the PM2.5 level. The prediction rate was increased by this two-layer model. But it could have done a better job of keeping an eye on the surroundings.

For air pollution forecasting, Qingchun Guo et al. (2020) used wavelet neural networks with meteorological conditions to find nonlinear relationships between input and output variables. During the forecasting stage, the wavelet artificial neural network (WANN) and ANN models produced the APIs with accuracy, and Bayesian regularization was employed as a nonlinear model. On the other hand, it might have handled meteorological aspects and anticipated the API in other places.

A new Sodar-based meteorological sensor network (SMSN) with IoT capabilities was developed by P. Chourey et al. in 2022. The SMSN had seven distinct sites with sodar-integrated temperature, relative humidity, and wind sensors. The Internet of Things-supporting SMSN demonstrated enforcing standard uncertainty for data packet losses across all parameters and sites. The integration of IoT with meteorological and sodar elements has greatly benefited in the development of overall air quality planning and decision-making. However, the rate of data packet loss did not change.

In order to improve the accuracy of PM2.5 concentration predictions, WeilinWan et al. (2021) created a spatiotemporal convolutional recursive LSTM

(CR-LSTM) neural network model. The developed model was intended to forecast PM2.5 concentrations in the future for the purpose of air quality monitoring. Bidirectional long short-term memory (BiLSTM) neural networks and empirical mode decomposition (EMD) have been used by Luo Zhanga et al. (2021) to estimate PM2.5 concentrations. This method enhanced short-term trend predictions as well.

Back-propagation neural network (BPNN) was developed by Xu Fenga et al. (2019) to forecast the daily fire pollution in Southern China. Every day, the suggested model was employed to predict variations in PM2.5 concentrations brought on by emissions of pollutants from burning biomass. In order to deal with overfitting problems, Yanlai Zhou et al. (2019) created a Deep Multi-output LSTM (DM-LSTM) neural network model. Additionally, it more accurately spreads within multi-step air quality forecast and extracts complicated spatiotemporal related critical elements.

Rodrigo de Medrano et al. (2021) developed a novel forecasting and monitoring operating system to forecast the major pollutant concentration. The devised strategy made it possible to incorporate the varied data associated with air quality into the model by relying on an ensemble of statistical as well as neural models. However, it did not undertake a cost-effectiveness analysis that took the likelihood of the NO2 protocol activation into account.

2.6 Research Gap

A deep learning method based on Integrated Multiple Directed Attention to create a malleable and significant solution for ambient pollution forecasting was created. But the multi-resolution function was not confirmed the goal by ensuring accuracy and timeliness for monitoring and air quality control. Forecasting of air pollution was being developed using the CNN-LSTM-SDAE model. The CLS model that was created did not enhance multivariate prediction performance.

Another cutting-edge hybrid intelligence technique based on LSTM and MVO made unsatisfactory predictions and analyses on air pollution. For the less accurate prediction of extensive air pollution, an enhanced deep convolutional network was used.

CNN-LSTM is a deep learning solution with an hourly forecast of PM2.5 concentration. It should have applied the long-term prediction model to enhance precision. The CWFM attains accurate air pollutants prediction. The time and personal capacity constraints were included in the estimation process. A deep-learning framework was forecasting the ability with lesser run-time. However, the time and space consumption rates still need to be examined. An intelligent hybrid air-quality forecasting system uses climate-influencing factors. But the designed system could have improved the forecasting of air quality.

2.7 Contributions

The following is the research's primary contribution:

The AQI measurement is the initial step toward making an important forecast about air pollution and it is followed by a new model called LR-MSV classification for an improved prediction. The suggested approach uses an IoT enabled system to forecast air pollution in a cloud computing environment. As a result, risk reduction necessitates innovative methods of air pollution prediction.

Next, a novel BTBSR-QWEBC model is presented for highly accurate and quickly computed IoT-based air pollution forecasts. The input data is pre-processed using a BDZWT technique to eliminate the noise. Next, OIBR uses relevant feature selection to shorten the air pollution forecasting time. Lastly, the data is classified using the selected features for air pollution forecasting using the weighted emphasis boost technique. Weak learners are turned into strong learners through the use of an ensemble classification method called quadratic weighted attention boost.

Finally, a novel air pollution monitoring and prediction model for Internet of Things networks termed DR-LSSV is developed. India's air quality data is initially made available as input in the input layer. Second, a DHT-based pre-processing model is used to eliminate the noise in the first hidden layer by converting actual inputs to real outputs. The CMLLR Feature Selection model is used to choose the more pertinent features based on the significance of the correlated feature in the second hidden layer. In the third hidden layer, the results of the air pollution prediction are obtained, and the output is given.