



An AI-Enabled IoT Framework for Carbon Emission Monitoring and Sustainable Environmental Management

Dr Prathibha R D¹, Dr Vishruti Desai², Dr. N. Muguntha Manikandan³, Nagarajan Jeyaraman⁴, Dr. Shilpa Ghode⁵, Vogirala Nandini⁶

¹Assistant Professor, Department of Zoology, St Joseph's University, 36, Lalbagh Road, Bengaluru- 560027, India. Email: prathiba@sju.edu.in

²Assistant Professor, CKPCET, Surat, Gujarat, India – 395007, Email: vishruti.desai@ckpcet.ac.in

³Professor, Department of Physics, V.S.B.Engineering College Karur 639 111, Tamilnadu, India. Email: nsmugunth@hotmail.com

⁴Assistant Professor, Department of Electrical and Electronics Engineering, Dr. Mahalingam College of Engineering and Technology, Pollachi, Tamilnadu, India. Email: nagarajanjeyaraman636@gmail.com

⁵Assistant Professor, Department of Computer Science and Engineering, Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Pune, Nagpur, Maharashtra, India. Email: shilpa82.2009@gmail.com

⁶Assistant Professor, Department of Computer Science and Engineering, VFSTR, Vadlamudi, Guntur, Andhra Pradesh, India. Email: nandu.vogirala@gmail.com

Abstract

Rising carbon emissions and the increasing impact of climate change necessitate the development of intelligent and real-time environmental monitoring systems. The traditionally used methods for monitoring carbon emissions are mostly periodical, manual and fail to provide sufficient insights in fast changing environmental situations. For these reasons, an AI-supported Internet of Things (IoT) framework is proposed for real-time monitoring of carbon emissions and for sustainable environmental management in general. Distributed sensor networks of the IoT in industrial, urban and residential areas record environmental parameters like concentration of carbon dioxide (CO₂), temperature, humidity, as well as other emission indicators. Measured data is transmitted by reliable connections and, after processing by a structured data pipeline, analyzed by machine learning and deep learning networks for predicting emissions, for trend forecast, for detecting anomalies as well as for spatial clustering of pollution hotspots. The real-time registration of emission changes, the early detection of strong increases of emissions and a precise prognosis of future emission developments support the increased environmental awareness and facilitate fast decision making. In addition, the sustainable use of resources is promoted by the framework in the context of Smart City. It supports the implementation of environmental regulations and enables carbon management in line with global targets for net zero emissions.

Keywords: Carbon Emissions, IoT, Artificial Intelligence, Machine Learning, Sustainability, Environmental Monitoring, Smart Sensors, Edge Computing, Green Computing

1. Introduction

Increasing of global carbon emissions has turned to be one of serious problems of the contemporary world that causes the climate change and the global warming as well as leads to eco-system destruction. In the process of assimilation in the atmosphere of the planet of so-called green house gases, such as carbon dioxide, methane, nitrous oxide and others, mainly emitted by a person, appear serious negative impact on the environment[1]. For example, the increasing temperature of the Earth in global scale, frequency of extreme weather events, long-term negative impact on the environment – all of them do not leave any doubts that the problem of increasing volume of carbon emissions is of the global scale. More than that, there are some sources of emissions of so-called green house gases, and among them: the processes of industrial manufacturing, transportation, urban areas. Thus, for example, the industrial area at first sight does not cause any doubts that it is one of the largest consumers of energy. This is why there are large volume of emissions that are connected with the processes of production. Another significant source of emissions – the transportation[2]. The main feature of this type of emissions is the combustion of fuel in the vehicles of different types. Urban areas as well, cause the significant increase of the volume of emissions due to the large number of people living on the relatively small area, big need of different types of energy, as well as big number of infrastructure objects etc[3]. For these reasons in the modern world there are serious needs of application of the modern system of monitoring of the emissions in real time. Periodical reports on emissions in a traditional way do not allow to take into account the dynamics of the volume of negative impact on the environment in short period of time as well as to react on time in case of its sudden changes[4]. Therefore, in order to manage the environment in the proactive mode it is necessary to use the system of monitoring of the emissions of carbon dioxide in real time.

Current systems for monitoring environmental parameters have several shortcomings[5]. The foremost of these is the dependence on manual collection of data and subsequent delayed reporting. In most cases, fragmented and inconsistent systems are used to monitor emissions. Such systems lack real-time capabilities and hence are unable to provide up-to-the minute information required for making timely and informed decisions[6]. Moreover, these

systems lack an integrated framework that can harness information from sensing technologies and from data analytics. Thus, such systems are ineffective for the accurate and on-going assessment of emissions[7]. The information generated by such systems lacks real-time processing capabilities and hence are unable to identify hotspots of pollution or forecast future trends in emissions. Most existing systems do not employ advanced forms of AI and hence are unable to process large amounts of data generated from various environmental monitoring systems[8]. A more intelligent, automated, and scalable system is thus required for the monitoring of carbon emissions[9].

The motivation for the development of carbon emission monitoring systems stems from smart city projects as well as from the increasing importance of Environmental, Social, and Governance (ESG) factors for organizations. Smart cities use digital technologies to manage urban life in a sustainable manner and to efficiently use available resources. In order to achieve these goals, monitoring of environmental parameters in real time is fundamental for optimizing processes and for improving air quality[10]. Organizations are forced by governments to respect environmental rules and consequently carbon emissions need to be measured, reported and reduced in order to comply with regulations, such as carbon taxes or with targets, such as net zero emissions. Thus, organizations need support systems that enable them to comply with rules, to be transparent and to implement effective carbon emission reduction strategies in line with global sustainability targets.

2. Literature Review

The use of Internet of Things (IoT) technologies for monitoring the environment has grown considerably in recent years. This growth stems from an ever-increasing need for continuous and real-time environmental monitoring to assess the quality of air we breathe. By leveraging a network of distributed environmental monitoring sensors installed within a variety of environmental settings (e.g. industrial areas, busy urban traffic routes and residential sites) it is possible to measure a variety of air pollutants continuously. Such include carbon dioxide (CO₂) and other gaseous pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x) and particulate matter (PM_{2.5})[11]. The incorporation of IoT technologies into Smart City frameworks have become increasingly relevant as real-time data from a variety of sources (e.g. environmental, traffic management, health services) are required on an on-going basis to continuously monitor a number of criteria such as pollution[12], traffic management and public health. This data can then be used by urban decision-makers on an on-going basis to create and manage sustainable environments that are ‘Smart’ by nature and become ever more environmentally aware and resilient as time progresses[13].

Various climate analytics utilizing large datasets generated by IoT systems have recently come into focus using artificial intelligence. Machine learning (ML) models such as linear regression, random forest and gradient boosting have been utilized for the regression and prediction of the amount of carbon emissions, using historical data as well as real-time data[14]. For complex time series such as those for climate analysis, deep learning models, including recurrent neural networks (RNN) such as long short-term memory (LSTM) networks, have also been utilized to forecast[15]. These models are particularly good at learning non-linear relationships between input variables and time series output variables and for identifying long-term dependencies within data.

The current systems of carbon accounting for and monitoring of greenhouse gases are generally limited to the measurement and reporting of emissions by means of structured frameworks, such as the carbon footprint calculators as well as the emission reporting systems of industry. These carbon footprints can be calculated for individuals, organizations and processes by means of pre-defined factors for emissions and by the input of data with respect to activities and other relevant parameters[16]. The emission reporting systems of industry are generally used by large companies for the purposes of environmental reporting in accordance with statutory requirements, and the data are reported on a periodic basis to relevant authorities. The systems of carbon accounting have an important function for the assessment of the environmental impact of human activities and for the creation of and management of carbon markets[17]. However, the systems are generally of a static nature and are based on data, which are therefore not in a position to provide a continuous monitoring and of real-time analysis of emissions.

Although significant advances have been made in recent years, the integration of sensing provided by IoT technologies and analysis performed by AI into a real-time carbon emission monitoring framework is still an open field of research. The vast majority of currently available solutions have been implemented so that sensing is used primarily for data collection, and then analysis is performed on the collected data, normally by means of AI[18]. A major limitation of such isolated approaches is that they are unable to support predictive real-time analytics and automatically provide decisions[19]. In addition to this limitation, most currently available solutions for monitoring air quality are not designed to be scalable, and therefore they are normally used in small geographical areas (such as within a city or even within a single neighbourhood[20]). They also present a number of limitations caused by the lack of interoperability between the different sensing devices, communication protocols, and data formats used within environmental monitoring systems. Clearly, there is a need for a unified, intelligent, and scalable monitoring framework, which makes effective use of sensing, analysis provided by AI, and predictive monitoring capabilities, and in real time.

3. System Architecture

The proposed system in this work is enabled by an innovative IoT framework that supports Carbon emissions Monitoring & tracking using AI for Environment & climate change. The Framework is a 6-layer architecture comprising – a) IoT Sensing layer, b) Edge layer, c) Communication layer, d) Cloud layer, e) AI / Analytics layer and, f) Application layer. Each of the six modules play a critical role and help the entire system perform in real

time with scalable support to grow large & serve diverse set of sensing, monitoring & tracking uses cases – across Industrial sites, Urban monitoring, Large Transport networks etc. within multiple geospatial locations. The system thus is able to be designed & implemented to support large variety of diverse physical sensing agents and corresponding large scale computing and storage facilities – over wide geospatial coverage with support to large-scale, dynamic, distributed real-time monitoring and related multiagency decision-making for all timely, environment & climate change management actions.

The IoT sensing layer is the initial component of the framework for monitoring carbon emission. It gathers a variety of data that enables the system for monitoring environmental conditions. They are deployed on a large number of locations across different environments such as industries, transportation, urban and environmental settings. Sensing nodes record a variety of environmental parameters that include temperature, humidity, traffic flow as well as concentrations of gases and in particular of carbon dioxide. In the context of industries, there are specialized emission monitoring sensors. They are used to monitor emissions discharged by various industries. These emissions can stem from processes as well as from energy generation systems. The variety of sensed environmental data is used by subsequent layers of the framework for monitoring environmental conditions and for processing sensed data in various forms. This Edge layer is primarily used for initial processing of data collected from various sources around the monitoring environment, thus facilitating better quality data before it is actually sent to the Cloud for further use by AI systems or by Decision makers. A number of processing functions are supported by this layer, namely Data Pre-processing and noise reduction and also anomaly detection for any abnormal local emissions. By offloading part of the processing near to where data is the data source, the system can significantly reduce latency, preserve available bandwidth and above all of course provide timely information to all stakeholders involved.

In terms of data transfer between IoT Sensors and / or Edge Devices and the Cloud Layer, within this Communication Layer, various standard communication protocols may be utilized.

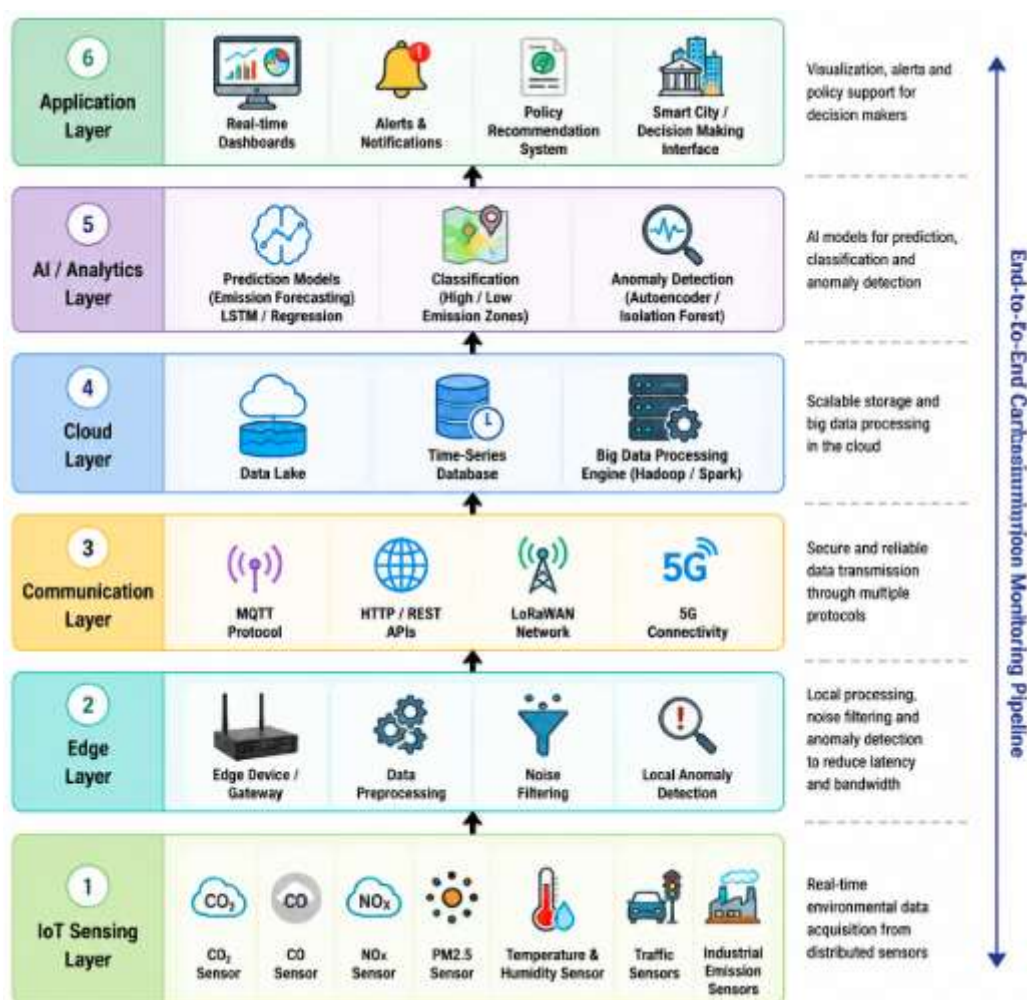


Figure.1: System Architecture of AI-Enabled IoT Framework for Carbon Emission Monitoring

Figure.1. presents a multi-layered AI-enabled IoT framework that is instrumental for the continuous real-time monitoring of the carbon emissions and for environmental sustainability. The proposed IoT framework uses an array of sensing devices in the IoT layer that are able to collect large amounts of data from environment and send the collected data to cloud layer via edge layer and communication layer. The collected data in the cloud layer is then analyzed using AI-based algorithms to predict the emissions, to classify emission zones, and to detect abnormal situations. Finally, the application layer of the framework displays the collected data in real time via a number of dashboards, and issues alerts and suggests measures via various policies in order to provide intelligent decision making for the environmentally sustainable development of urban and industrial environments. These

would typically include MQTT, HTTP and support for sensors / nodes operating over LoRaWAN or other 5G networks. MQTT being suited to situations that involve very light data communication between / and from Sensors / and to and from IoT Sensing and / or Edge Devices, within a framework that is required to operate on a real-time basis, for instance, in monitoring environmental phenomena, for example, within an industrial setting. In this scenario, using a protocol such as LoRaWAN would allow for extended range monitoring of environmental metrics with very low power consumption. The use of 5G within this layer would then enable very fast real-time transfer of very large amounts of time-stamped data between nodes, within a very large area (city or region) in real or near real-time. The cloud layer of the carbon monitoring framework consists of a large-scale data repository, storing the stream of sensor readings in so-called data lakes and time-series databases, in order to process it using big data methods for analysis. For that end, the cloud framework uses scalable computing resources in order to be able to process the huge amounts of data, generated by various distributed sensor networks from all parts of the globe.

The AI/analytics layer represents the intelligence or smart component of the framework. It comprises a range of advanced machine learning or deep learning techniques and is used for a variety of functions including the prediction of future emissions. Additionally the AI can be used to classify regions of the world into high-emitting or low-emitting 'Carbon-emissions-monitoring-with-IoT-and-AI regions and thus identify areas that would most benefit from green initiatives. Moreover, this layer of the framework is also used to identify abnormal emissions. The identification of such emissions can indicate a number of issues including equipment failure, potential environmental hazards or even instances where companies are breaching environmental regulations. The use of AI in this fashion allows the system to create vast amounts of intelligence that can be used by environmental decision-makers to make environmentally-sustainable decisions.

The application layer provides a means to present the information, alerts and notifications to the appropriate decision maker(s) via an interface or a collection of interfaces. Real time monitoring of current levels, and trends of past levels, of emissions, in addition to predictions made via the analytics layer, will aid decision makers in determining optimal emission reduction methods to comply with the knowledge of current and past policies, i.e. to assist in developing future green policies and in ensuring compliance with current regulations. Alerts and notifications can be issued in real time to notify staff of sudden spikes in emission(s) and/or any environmental abnormalities that may pose a risk to the environment.

4. Methodology

For environmental monitoring, implementing an end-to-end IoT solution that integrates real-time environmental monitoring using a range of low cost sensors with AI algorithms for predictive analytics provides a systematic approach to transform raw monitoring data into real time monitoring and useful insights that can be used for environmental management. Such a framework must be capable of dealing with large volumes of disparate data, must support real time processing, and must have the ability to continuously adapt and learn as more data becomes available from a range of monitoring locations. The solution can therefore be used in any location, and can deal with large amounts of monitoring data from around the world.

Data Collection

For the IoT part of the environment monitoring framework, we developed a distributed environmental monitoring system consisting of different sensing modules and a sophisticated back-end system. The framework currently monitors industrial areas, urban traffic areas, as well as residential areas. Environmental parameters such as the carbon dioxide concentration in the air, temperature and relative air humidity as well as the amount of fuel are recorded. In addition to these environmental parameters, indicators for the industrial activity as well as for the transportation systems are monitored, in order to be able to analyze also the influencing factors for the environmental pollution. Heterogeneous sensors are used to record the relevant environmental data. While some of course also direct emission values are recorded, also so-called indirect emission causes are detected and logged. These environmental data are collected continuously and in real-time, so that fast changes in the emission profile are registered and analyzed in due time. Figure 2 presents a complete machine learning pipeline for the AI-enabled IoT carbon emission monitoring system, illustrating the sequential flow from data acquisition to decision support. Regressions, time-series analysis, anomaly detection and clustering are the 4 types of AI/ML analysis that will be conducted on the data that has gone through the proper preprocess of filling missing values, removal of noise and normalization. The predictions of the amount of emissions produced by the sources of emissions (air-conditioners, generator-sets, etc.), the classes of emissions produced by the same sources of emissions (very toxic, toxic, slightly toxic), the flags of anomalies in the emissions produced by the same sources of emissions and the hotspots of emissions produced by the same sources of emissions will be generated as a result of the analysis conducted on the data. Application layer will transform the information generated from the previous layer into real-life decisions through dashboards, alerts, decision support systems and policy recommendations for optimum and effective environmental management system.



Figure.2: Data Flow and Machine Learning Pipeline for AI-Enabled IoT Carbon Emission Monitoring System

Data Preprocessing

Data collected from various sources often contain many inconsistencies and even may include missing values or noise, which need to be handled before analysis can be conducted. A number of different techniques can be used for handling missing values, and each of them needs to be chosen on a case-by-case basis. When it comes to noise, it can be reduced with the help of a variety of statistical and signal processing methods, such as the Kalman filter or moving average methods. As mentioned above, a large number of different sensors and even different measurement units are used in IoT systems, and this is why all of the collected data needs to be normalized in order to be able to effectively feed it into machine learning models. In the context of the environmental monitoring framework proposed in this paper, this stage plays a very important role, because it ensures that all of the input data for the subsequent analysis is clean and consistent. As a result, the various machine learning models that are used for prediction or for classification in environmental monitoring systems become much more stable and much more accurate.

AI/ML Models

The processed data can now be analyzed by using various combinations of Machine Learning (ML) models and Deep Learning (DL) models. This enables the system to generate valuable insights and also predict the future emissions. It is able to detect abnormal environmental behavior, that could indicate a fault in the system or even a pollution event. Additionally, it is also possible to group various geographic locations into groups of similar emission intensity using clustering techniques, such as K-Means. These groups of locations with highest emission intensity can be marked as carbon emission ‘hotspots’ that need to be monitored and managed. Thus, the proposed framework will not only aid in the effective environmental management, but also enable the end users to predict, detect and classify the carbon emissions.

5. Results and Discussion

The performance evaluation of the proposed AI-enabled IoT framework is conducted by employing a suite of standard regression, classification, and system efficiency metrics to measure and compare the capabilities of the framework to realize real-time environmental monitoring and its enablement of predictive environmental analytics for Carbon emission. Results obtained via the aforementioned performance evaluation indicate significant upshot in the monitoring of Carbon emissions on real-time, and aid in improving the sustainability of industrial processes (in Carbon terms) via the successful deployment of the framework across a diverse set of monitoring environments ranging from industrial and urban scenarios in real-time, to residential monitoring, on a predictive analytics basis. The performance metrics for the prediction models were calculated using error-based metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as well as classification-based metrics such as accuracy. The ability of the emission prediction models such as Linear Regression, Random Forest, XGBoost, LSTM, and GRU to predict future emissions were evaluated based on their MAE and RMSE values. The performance of the zone classification models were evaluated based on their ability to accurately classify a region

into a high-emission zone or a low-emission zone. Classification accuracy is an essential factor that determines the effectiveness of a zone classification model. The model can effectively assist environmental interventions in areas with high levels of pollution only if it is able to accurately identify such pollution-intensive zones. Additionally, the latency of the system, which is defined as the time taken from the moment data is sensed from the various IoT sensors to the moment the system generates the necessary analysis, was another key factor that determined the performance of the system as a whole. The system's ability to process data in real-time and provide the necessary outputs in an efficient manner is crucial. This is only possible if the system is able to process data in real-time at the edge of the network and also transfer data to the cloud in an efficient manner.

These predicted results and real-time measurement data enable various functionalities. Firstly, early detection and timely alerts of emission peaks can enable prompt counter measures to prevent a sharp increase in carbon emissions. The framework is also able to identify the locations of emission 'hot spots' by means of spatial clustering of measurement data and AI-driven analysis thereof. This supports the effective designation of locations with very high emissions for focused implementation of environmental protection measures. In addition, the system facilitates the prediction of trends in emissions over time by analyzing historical as well as real-time measurement data. These predictions in turn enable proactive environmental management and help to develop sustainable policies in advance. This in turn is expected to enhance the degree of awareness regarding the environment and increase compliance with environmental regulations as well as contribute to sustainable development by enabling implementation of smart cities.

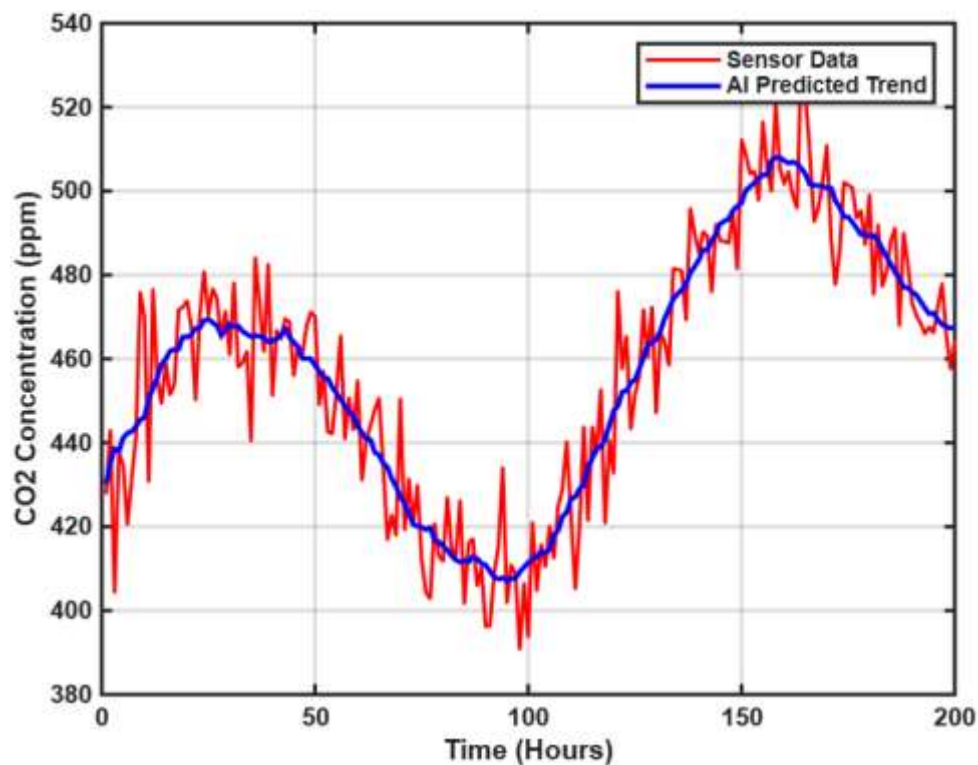


Figure.3: Real-Time CO₂ Emission vs Time (IoT Sensor Stream + Prediction Curve)

Figure 3 demonstrates a real-time monitoring of the Carbon Dioxide (CO₂) emissions, utilizing the IoT sensor data that has been integrated with a real-time AI powered prediction system. A simple line of the smoothed AI predicted trend on top of the raw sensor data readings for the varying CO₂ concentrations over time has been graphed. This simple graph shows the ability to track and predict the emission of atmospheric CO₂ in real time, providing near accurate real time data, which can be utilized for the early detection of increase in the emissions and for the subsequent green environment management. The results illustrate the accuracy of the emission monitoring by utilizing the real-time sensor data and the emission's data-driven AI prediction. Figure.4 compares the carbon emissions of industrial, urban (of traffic) and residential areas for a particular time frame. The graph indicates that especially industries produce high amounts of emissions by reason of very energy-consuming production processes and permanent emission. Urban traffic also generates a certain amount of emissions, which in a temporary way can even increase because of the high traffic volume. By contrast the emission of residential locations is small and fluctuates only slightly. The emission distributions in different parts of the world clearly differ and are inhomogeneous. This comparison of emission can identify highly polluting sources and thereby support the sustainable environmental management by adequate measures.

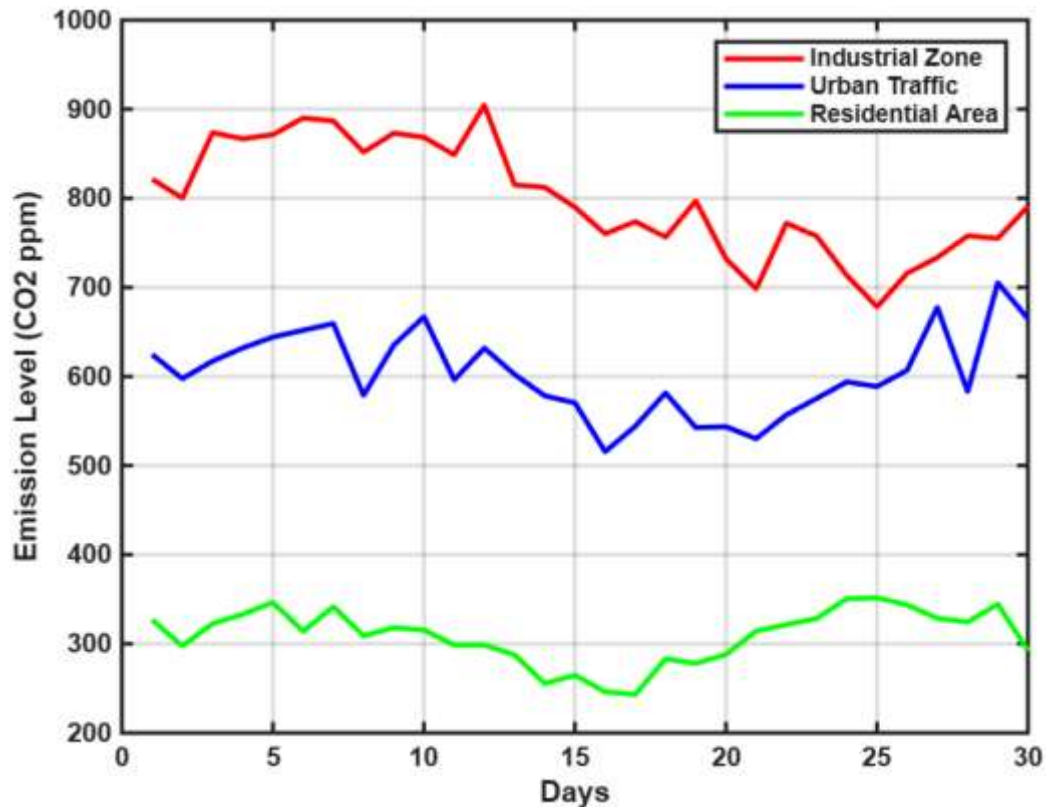


Figure.4: Multi-Region Carbon Emission Comparison (Industrial vs Urban vs Residential)

Figure 5 demonstrates AI-based carbon emission hotspot detection by using the K-means clustering algorithm on geospatial emission data. The emission data, that includes information about the emission intensity, are grouped by their latitude and longitude. The high-density areas of the resulting groups of emission data points of a cluster indicate high carbon emission of the corresponding region that is spanned by the respective cluster. Consequently, the areas of low-density indicate low carbon emission. In the visualization, the respective cluster centroids mark the locations of the highest emission intensity of the respective region. As a result, by using K-means clustering on geospatial emission data, emission hotspots can be automatically detected by the system, thus supporting the intelligent decision of the environmental authorities for taking actions. These actions could include the regulation of emission sources and the implementation of pollution control measures in high-emission areas.

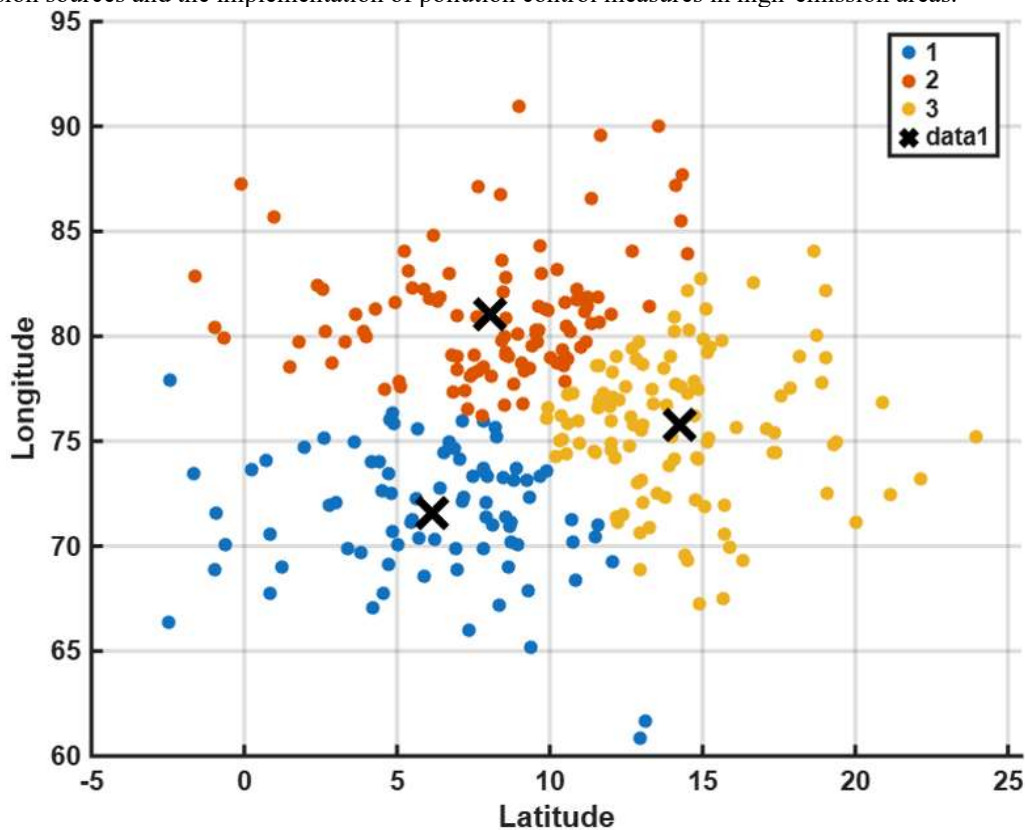


Figure.5: AI-Based Emission Hotspot Detection (Clustering Simulation - K-Means)

Figure 6 plots RMSE values for the predictions made by the most prominent models for predicting emissions. These models for carbon emission prediction include Linear Regression, Random Forest, XGBoost, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The trends show that the performance of predictions, especially in terms of errors, increase with regards to traditional machine learning models. On the other hand, deep learning models have superior performance and present the lowest values of errors for all the models as depicted by the graph. For example, the hybrid approach comprising of LSTM network presents the lowest values for errors in comparison to other models of prediction for emissions and, therefore, offers the highest accuracy of prediction as indicated by the lowest values for RMSE in the graph.

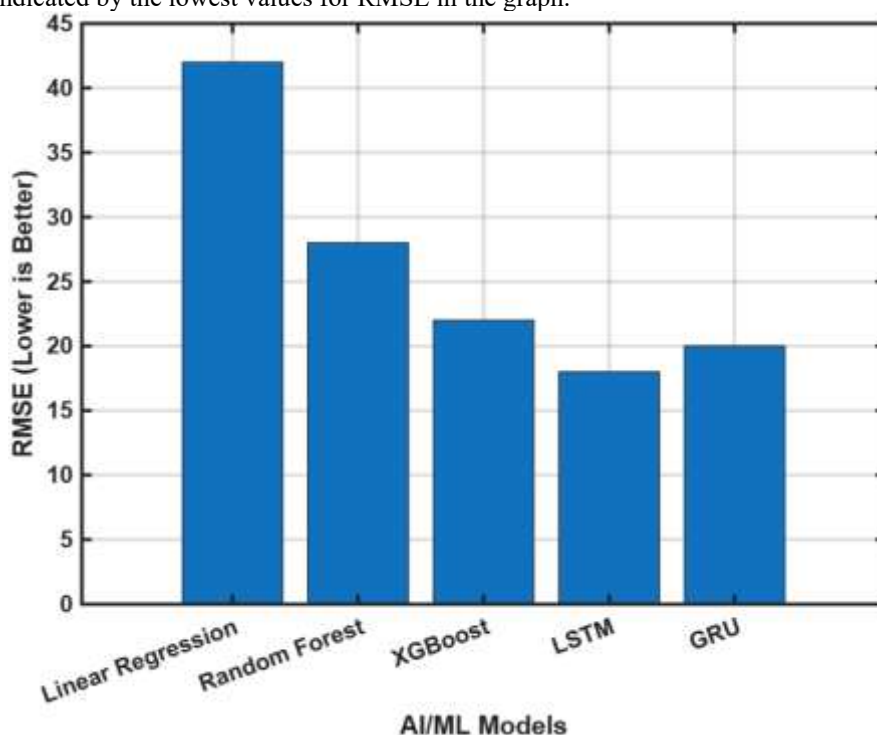


Figure.6: AI Model Performance Comparison (RMSE of Different Models)

The proposed approach to enable carbon emission monitoring has several advantages. First, real time monitoring is performed to provide a continuously updated view of the environment, as opposed to periodic measurement. Hence, decision makers are able to respond quickly, thanks to the automated analysis, prediction and anomaly detection enabled by AI. In addition, by relying on IoT technology, it is possible to set up a system of distributed sensors that continuously supply the system with a fine-grained and complete view of emission sources. This enables the creation of a monitoring system that is scalable, distributed, and intelligent, supporting the sustainability of human activities and the development of smart cities. Despite the clear advantages of such a system, there are, however, also several constraints on the monitoring system. Sensor values can only be correct if the individual sensors are calibrated correctly, which can be affected by the environment, by aging of the hardware, and by variations inhomogeneities in manufacturing. Since the entire system is built on top of a network, there is also a high degree of dependency on the latter. For a monitoring system, it is therefore crucial to use communication protocols such as MQTT in combination with 5G or LoRaWAN for real-time monitoring, and to develop stable applications. Also, the energy consumption of the individual sensors and of the devices used in the IoT for sensing and data transmission in large-scale monitoring systems is critical. This means that a further optimization of the sensors as well as of energy-efficient communication solutions and robust failure-tolerant architectures for the monitoring system is necessary.

6. Applications

The proposed framework of AI-enabled IoT for carbon emissions monitoring and environmental management can be applied in a variety of fields. The smart cities emission control is one of the areas where the framework can be applied. The framework can support real-time monitoring of air quality and of the concentrations of greenhouse gases in urban environment. It can be integrated with sensor networks and with the AI-based analytics. Such a system would be able to dynamically control the pollution in urban environment by identifying areas of high emissions and by optimizing urban infrastructure, traffic flow and energy consumption. This would result in better air quality, reduced impact on the environment and more sustainable urban development.

The proposed framework shall play a pivotal role in the industrial compliance monitoring, which would enable tracking of the environment emitted by factories, power houses and industrial processing units. This would ensure that the monitored CO₂ along with other Greenhouse gases and pollutants are being compliant with the Environmental laws and regulations. The automated alert system and prediction algorithms in the framework would enable the industries to identify anomalies in their emission levels and in time take measures to rectify them to avoid any non-compliance penalties. This framework would also enhance transparency in environmental issues of industrial units.

The framework supports emission-optimized transportation by analyzing and monitoring real-time emissions and traffic-related pollution. This information is derived from various roadside sensors as well as from the traffic management system. Based on the derived AI results, the most efficient traffic management, the best routes as well as environmentally friendly mobility solutions can be developed with the goal of reducing the carbon emissions in the transportation sector. Environmental policy enforcement is also supported by monitoring and analyzing of data collected by the AI-powered system to help governments and environmental bodies develop effective policies. The system provides real-time information and historical trends and forecasting to support the evidence-based decision making required for effective environmental policies and to monitor their impact. The framework for carbon emission monitoring and management can also be utilized to accurately measure and verify the emissions by organizations and projects that are engaged in reducing their emissions and wish to receive carbon credits for such activities within a carbon trading system. Such a system enables organizations to sell any excess of carbon credits that they have not utilized and thus gain a financial return on their investment in emission reduction projects and activities.

7. Conclusion

The proposed framework in this article presents an innovative AI-enabled IoT framework for carbon emissions monitoring and green environmental management. The innovative framework provides a unique combination of distributed environmental sensing, intelligent green environmental data analytics and real-time decision support systems. The environmental sensing system was able to track and measure real-time monitoring of CO₂ emissions variances in real-time using simulated environmental sensors data. The generated CO₂ emission data fluctuated around the baseline of 420 ppm. The implemented AI-based environmental pollution predictors significantly minimized the prediction errors by employing the feature of smoothing in the generated data. The article presented a comparative study between various machine learning predictors. The results indicated that the performance of LSTM and GRU-based predictors provided the minimum prediction errors measured in terms of root mean square error (RMSE) and amounted to 18–20. These results outperformed the results of traditional environmental pollution predictors such as Linear Regression, which provided high prediction errors, measured in terms of RMSE, of approximately 42. On the other hand, the implemented clustering-based approach successfully identified the environmental pollution hotspots by classifying emissions into different categories of sources. The approach provided high accuracy in classifying the emissions from various environmental zones such as industrial, urban and residential zones. The framework also presented a high-performance environmental monitoring system capable of processing the large generated environmental big data in near real-time.

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