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Air Quality Prediction and Monitoring using Machine Learning Algorithm and Sensors

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Abstract: High amounts of harmful chemicals & particles in the atmosphere create health problems. They influence the planet's ecosystems, making air pollution the critical problem in human development in the previous century. As technology improves, scientists and environmental associations examine new ways to fight and control air pollution, resulting in new resolutions. Over the final decade, devices that can monitor and control pollution classes have evolved more accessible and small expensive. The Internet of Things (IoT) has spawned new approaches to pollution management. The purpose of the research described in this article was to apply machine learning to predict the behaviour of the air quality index. To test our model, they collected data from one of the IoT sensors. To explore temperature growth about pollution levels and other pollution sources, there provided Q-Learning and Fuzzy logic approaches. Finally, the results of the algorithms are displayed in terms of accuracy and error rate for two different methods. Finally, we find that the proposed Q-Learning method outperforms existing state-of-the-art classification algorithms in terms of accuracy.

Keywords: Air quality monitoring, MQ6, IoT, Machine learning, Data processing, Supervised learning, Classification

1. Introduction

Due to the obvious detrimental impact it may have on the health, air pollution has been one of the most concerning topics in recent decades. According to Gupta et al. [1,] it may cause a variety of health issues in people, including stroke, heart disease, lung cancer, and respiratory illnesses. The issue is also becoming more important as a result of WHO pronouncements, which claim that more than 80% of people live in metropolitan regions where air quality routinely exceeds WHO guidelines, as stated by Becnel et al. [2]. As a result, as proven by Spandana et al. [3], the scientific community's interest in monitoring environmental factors in contemporary cities has expanded significantly, and novel methods have been presented to prevent or remedy the resulting concerns. One of the most important creative ideas driving and supporting such an endeavour to monitor and decrease pollution impacts in cities is the IoT idea [4]. Because of its vast network of sensors, it is altering nearly every aspect of our daily life (such as linked thermometers, weather stations, and security cameras). A "Smart City" environment is defined as the application of information and communication technologies (ICT) and, in particular, Internet of Things (IoT) solutions in a city context [5]. The purpose of this concept is to "use ICT to better employ public resources, enhance the quality of services offered to people, and, as a consequence, improve the quality of life in metropolitan regions, while cutting public administration operational expenditures" [6]. Several research papers (e.g., [7] and [8]) have used IoT to

improve various circumstances, and it has also been used to monitor city air pollution, as indicated by other studies & literature reviews [9,10].

Nonetheless, owing to many circumstances and events, the degree of pollution in a country or a particular sector of a city may drastically change over time. For example, Boso et al. [11] observed an increase in pollution in the city of Temuco, Chile, over a period of time. In reality, due to the

COVID-19 pandemic's limitations, residents who were obliged to stay at houses increased their use of wood-burning stoves to heat their homes, resulting in more significant pollution. As a result, government organizations must use real-time systems and platforms to enable immediate and timely actions under challenging circumstances and precise assessments of observed data to plan long-term functions to enhance citizen grade of life. Both automated identification of environmental factors data and community benefit might be beneficial. As suggested by Doran et al. [12], crowd sensing systems "involve people in the planning process" [13] by gathering their input and informing municipal authorities, which might subsequently act to monitor or alleviate issues in the short, medium, and long term. Consequently, the present study suggests a solution for municipal authorities and residents to facilitate (a) the collecting of user complaints regarding perceived rising pollution levels. (b) Real-time mobile device re-location, based on state-of-the-art research. That found no way to help local governments monitor city conditions using a combination of user input & real-time data acquired by specialized mobile IoT sensors. City authorities may use the established system to access a centralised interface on which all data and comments are gathered, and by consulting it, they can get a quick and easy overview of the city's present status and link, for example, traffic statistics with pollution information. Furthermore, the ability to receive alerts and dynamically re-locate transportable sensors to analyze noted anomalous situations allow them to act sooner rather than later.

2. Literature Review

According to numerous study evaluations [8–10], there are many studies in the literature to address the need to monitor the environmental indicators in modern cities utilizing IoT technology. They are, however, primarily focused on the technologies' advantages, with just a handful combining dispersed remote monitoring sensors & systems with public opinions/feedback inside the detection and response procedures. Spandana et Shanmugha sundram [3] provide a fascinating initial contribution that employs distributed mobile sensors but excludes user input. The authors adopt a low-cost and successful way to monitor air pollution levels in particular locations, focusing on low-power systems and wireless devices that they can transport to specific areas to monitor the environment. Preliminary data demonstrated the system's practicality and usefulness in specialist care the environment using low-cost equipment. Furthermore, Becnel et al. [2] propose a system that collects airborne pollution data regularly using a network of low-cost pollution monitoring sites that act as single nodes. The technique is a little different in this situation than it was in our previous work. In reality, rather than dynamically relocating sensors in interesting zones and/or using end-user input in the selection of the regions to be watched, as we suggest in this paper, the authors decided to spread different sensors around the city. Patil et al. [14] provide a wireless sensor network (WSN)-based environmental monitoring system that captures air pollution data in numerous zones of a monitored city utilizing low-cost sensors. The gathered data is transferred to a cloud backend. It is analyzed and made accessible to the end customer through an Android app that can report pollution levels in various city areas. On the other hand, Garzon et al. [15] work on the assumption that the city can be separated into multiple zones, each with a distinct level of pollution. As a result, the authors devised a system that alerts users when they enter an area with high pollution levels (i.e., with a dangerous pollution rate). On the other hand, other initiatives take the opposite approach, concentrating on exploiting human "inputs" for city monitoring rather than IoT-aware systems. All of the achievements mentioned above, on the other hand, are focused on the usage of dispersed mobile sensors in various sections of the city for element in the world monitoring without making use of user input. Others tend to take the opposite strategy, emphasizing the utilization of "inputs" from users for city monitoring rather than detecting IoT-aware approaches. For example, White et al. [16] suggest an urban digital twin that enables people to provide comment on proposed city modifications. Their study provides a virtual public model of a Dublin neighbourhood & shows how this model may be used to create skylines and green areas. Instead, R. Cecconi and his associates propose a method that employs a streamlined system to incorporate citizens in the urban degradation research survey and back up the government's strategic decisions. A scalable web-based decision-making system based on community interaction was developed, which included technical studies on the urban physical decline and public evaluations of perceived urban deterioration. The outputs are thematic maps, which the government uses to make strategic decisions on spending cash on repairing urban flaws. Ertiö et al. [18] investigate 3 citizen-initiated online platforms in order to learn more about what occurs when communities employ technology in particular geographic locations. The authors are interested in learning how individuals might utilise technology to actively engage in community planning and design. The study is based on secondary data gathered from the three case studies' web and social media sites. The technique suggested by Rinaldi et al. [19] of the few studies that combine dispersed mobile monitoring sensors with user input is similar to ours. The authors discuss the early stages of a system's installation that relies on communication between the building and its users. Sensors are installed in the Smart Campus Demonstrator to monitor and adjust comfort, indoor air quality, and HVAC factors. It also includes a behavioural approach, which connects the framework to the users' mobile application to provide bidirectional interaction between the constructed environment and the social landscape. Users' input was exclusively connected to data acquired by the sensors on their smartphones, and it was utilised to trigger actuators to alleviate unpleasant conditions. On the other hand, in our work, we take into account actual user input in the form of responses to planned surveys and utilise it to recommend new actions to local authorities. Tagliabue et al. [20] present a system for evaluating and controlling a broad variety of sustainability parameters in real time inside a building. The research uses a hybrid technique that combines Digital Twin (DT) and the Internet of Things (IoT) to adopt a user-centred approach (IoT). The framework enables the observation of building status through specialized sensors and the assessment of user input to find the best techniques for optimizing a trade-off with renewable energy generation. They tested the framework in a prototype building at the University of Brescia with various uses (Italy). By interacting with the sensorized asset, which monitored interior comfort & air quality levels and the building's energy behaviour, the building was able to adapt to the student's daily activities. Tagliabue et al. propose an approach similar to the one described in this article. Still, it concentrates on interior building monitoring but does not utilize moveable sensors that they may move if municipal authorities need it.

3. Methodology

Various sensors were utilised in the current project to monitor air pollution and traffic in a particular region of the town. These sensors and devices utilized were

chosen from the list of the most often used in the literature. As a result, the following paragraph highlights the works that influenced the decision. Environmental contamination is often monitored using sophisticated and well-known sensors, which are generally huge and expensive. Tan et al. [21] employed several electrochemical sensors to detect different gases present in the air, and the average cost of these sensors is rather expensive. Due to the continual repair of the treated themes or the subsequent renovation ofthe repair material, researchers often choose to use less expensive sensors that can be replicated or readily changed if necessary, despite such sensors' excellent quality and dependability. To this end, Yi et al. [22] give technologically sophisticated, low-cost and small-scale choices for air pollution monitoring in their research. Even though the quality of the measures isn't as excellent as the more costly ones, their usage allows both cost savings or, as the document needs, the expansion of the monitored zone.

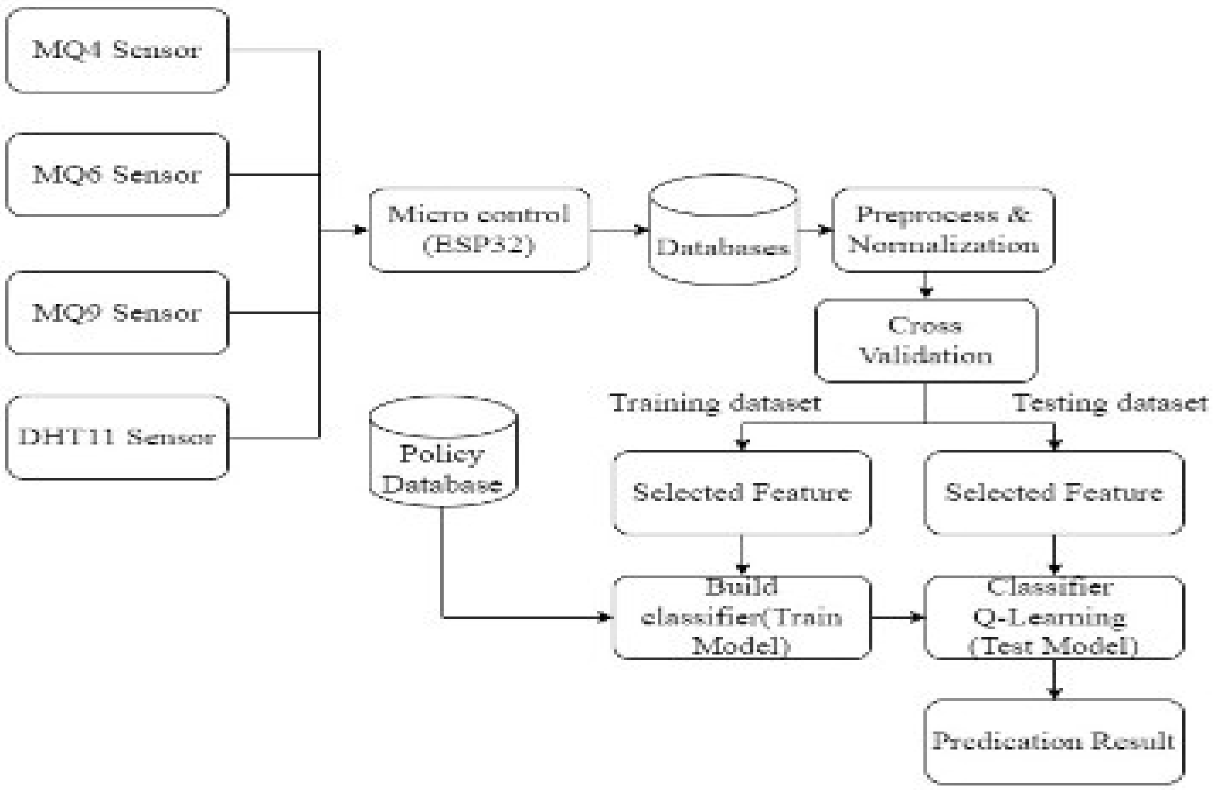

Figure 1 : Proposed system design

We picked low-cost sensors despite their reliability in this project due to the requirement to choose sensors to be spread around the city and the extra need to offer as many Smart Monitoring Devices as possible. Temperature, humidity, and gas values were measured using the sensors MQ135, MQ7, and DHT11, in particular as shown in Figure 1.

4 Algorithm design

1. Algorithm : Policy based Q- Learning Algorithm

Input : Total input parameters created by distinct input objects (Input[1.......n]), a collection of Threshold values Threshold_Min[1.....j] and Threshold _Max[1. j] for all inputs.

Output Start the transmission depending on whether the node is a straggler or not.

Step-1: They excerpt all parameters model from Databases (Row from Database)

Step-2: Param_Parts [] ← Splitting (Row) using the formula below

Step-3: $Par_{Parts}[\,]=\sum_{k=0}^{n} Col[k]$

Step-4: Validate (Current val against a collection of thresholds Thresholds_Min [1…..n] to Thresholds_Max [1…..n] **)**

If (true)

Start the appropriate output equipment..
Else Continue;
Step-5: Time_stamp(tm) ← Extract current VM time.

Step-6: if (Time_stamp_tm > Bount_Time)

All events should be penalty for FalseN++ is rewarded for TrueP++.
Else

Continue. Total++

Step-7: calculate penalty score = (TrueP *100 / Total)

Step-8: if (score >= Thval)
Predict straggler event

Results and Discussions

The system, which has four data nodes and a single master node, is based on an open-source local distribution system. Using a random task creation and dynamic job ordering approach, the workload was produced dynamically for each data node. All data nodes have identical configuration settings. Supervised machine learning classifiers are used to read and train each node's various attributes, such as Cpu usage, memory load, or data locality features. The system has also been verified using a proposed supervised learning technique, as shown in Figure 2.

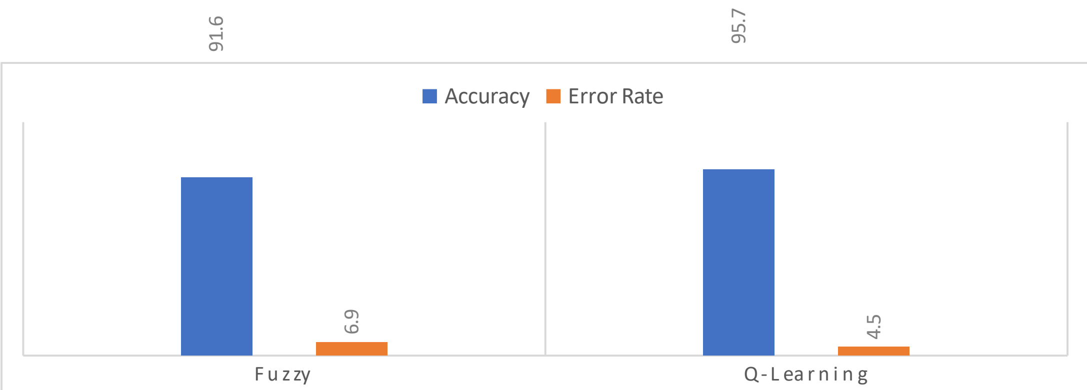

Figure 2: With different cross-validation, data is separated for training and testing.

We utilised another dataset as test cases produced by different log data sources to assess the efficacy of such classification techniques. The performance research was carried out on a number of existing systems that used comparable machine learning methods to build similar strategies. The Q-learning provides better accuracy for air quality prediction over the exiting fuzzy logic classification.

5. Conclusion

This research aimed to use numerous ML algorithms to predict temperature changes in a heavily populated region in Mumbai. They employed a variety of methodologies to anticipate how different pollution sources would affect temperature levels. They used data from one of the six atmospheric sensors placed strategically across Bucharest to test the model. For a system that can manage a vast quantity of data and create predictions, utilizing sensors for data collection is essential. Although the data processing procedure was the same, they noticed that particular complete results were not attained when comparing the graphs made utilizing data from two time periods. Researchers will combine present data with camera photographs in the future to study and predict air pollution in several metropolitan cities. The construction of a system that will give solutions for traffic recommendations based on air pollution projections is one of the future research goals.

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