

Performance Evaluation on Applied Low-Cost Multi-Sensor Technology in Air Pollution Monitoring

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ABSTRACT

This research aims to discuss the application of multi-sensor network technology for the monitoring of indoor air pollution. Indoor air pollution has become a severe problem that affects public health, especially indoor parking. The indoor air pollution monitoring system will provide information about vehicle exhaust emission levels. We have improved the system to identify six parameters of the vehicles' gas emissions within a different location at once. This research aimed to measure the parameter of Carbon Monoxide (CO), Carbon Dioxide (CO₂), Hydro Carbon (HC), temperature and humidity, and levels of particulates in the air (PM₁₀). The performance of this system shows good ability to compare the results of measurements of air quality measuring professionals. In this study, we investigated the performance of a custom-built prototype developed under the android-based application to detect air pollution levels in the parking area. Our objective was to evaluate the suitability of a low-cost multi-sensor network for monitoring air pollution in parking and the other area. The benefit of our approach is that its time and space complexity make it valuable and efficient for real-time monitoring of air pollution.

Keywords: Air Pollution, Low-Cost, Multi-Cencor, Parking Indoor, Performance.

1. INTRODUCTION

Air pollution is a condition when air quality becomes damaged and contaminated by harmful substances. Several factors that caused air pollution are increasing infrastructure development, smoke factory, and vehicle exhaust gases [1][2][3]. It can cause various diseases, including eye irritation, upper respiratory tract infection, sore throat, even death [4][5].

Based on data from the World Health Organization (WHO), about 4.2 million people died from air pollution or about 5% of the 55 million people who died every year in the world 1500 million people who died prematurely occurred in Asian cities. The morbidity rate resulting from air pollution is much higher [6].

Air pollution has become a widespread concern in metropolitan areas. The quality of outdoor air has a considerable impact on indoor air quality. Consequently, we must look at both indoor and outdoor air quality [7]. According to the Environmental Protection Agency (EPA), indoor pollutant levels can be up to 100 times greater than outside pollutant levels and are one of the top five environmental dangers to the

public. [8][9]. Because the average person spends 90% of their time indoors, poor indoor air quality creates a severe threat to public health [10].

The increased health concerns caused by indoor air pollution are a serious topic of discussion for researchers all over the world. In indoor environment, Carbon monoxide (CO), particulate matter (PM), volatile organic compounds (VOCs), aerosol, biological pollutants, and other harmful pollutants can be found [11].

As the number of cars on the road increases, so does the number of underground parking garages. Currently, newly constructed commercial and residential districts are developed with underground parking garages that are supplied with ventilated parking spaces (including natural ventilation) [12]. But, traffic in these facilities impacts indoor air quality.

Car exhaust produces pollutants such as carbon carbon dioxide (CO₂), monoxide (CO), particulate matter (PM), nitrogen dioxide (NO₂), and volatile carbon (VOC). In parking indoor, the air pollution produced by motor vehicles has long-term and negative consequences for human health and the environment. Significantly, an increase in exhaust emission concentrations in closed locations and where adequate ventilation is not provided may have a negative impact on human health [13].

Recently, with the development of mobile technologies, IoT, and machine learning, big data, technologies have attracted attention as advanced technology for real-time indoor air quality monitoring. Indoor air quality can now be easily monitored and managed using Internet of Things-based portable indoor air quality monitoring devices. Several indoor air quality monitoring systems and Internet of Things-enabled devices are available, including open-source software for data processing and transmission [14][15].

The use of wireless sensor networks (WSN) has attracted substantial attention in a variety of monitoring applications [16][17]. WSN consists of nodes sensor with a vital role in gathering information from sensors in the environment and connecting with other nodes in the system. Most WSN systems have a dispersed sensor network connected to a cloud system. While optimizing the cloud computing systems, sensor network data gathering has also been done in some cases [18]. Additional processing includes applying artificial intelligence techniques to optimize pollution detection results.

New technology combines several sensors with a Wireless Sensor Network (WSN) in a device known as a Multi-Sensor Network (MSN) system [19]. The data acquired by these sensors is sent to a monitoring center via a smart device, which automatically manages distributed resources and optimizes tasks in real-time [20][21][22]. This system is capable of providing object data that is automatically detected by sensors. Sensor networks are made up of various small, low-cost devices that are dispersed throughout an environment.

Researchers in environmental science has recently become interested in low-cost sensors that monitor air pollution with a high degree of temporal and spatial resolution. Even though the sensors' accuracy, precision, sensitivity, and specificity are higher than those of more expensive sensors, the sensors are less expensive [23]. Sensors can solve some of the limitations of traditional techniques due to their inexpensive cost, compact size, high temporal resolution, portability, and low power consumption [24][25]. On the other hand, sensors have several disadvantages, including the need for significant laboratory and field calibration, lesser accuracy, precision, sensitivity, and long-term stability as compared to conventional techniques, and a lower level of precision and sensitivity [26][27].

In this research, we investigated the performance of a prototype developed under the android-based application to detect air pollution levels in the parking area. Our objective was to evaluate the compatibility of a multi-sensor network for monitoring the low cost of air pollution in parking and other areas.

2. METHODS

This section describes the network of the multi-sensor system for detecting particles in the environment and monitor air pollution. A multi-sensor network of gas sensors has been constructed to achieve this aim. The many components of the system are investigated thoroughly in this section. The developed multi-sensor network, which is responsible for wirelessly measuring and transmitting data, is presented first. The data is received by a server, which is the network's central node. As a result, the user can control the network, preprocess data, and connect to the webserver. The second subsection used sensor response measurements for data validation, comparison, and data processing. Sensors that performed best were selected based on high sensitivity with high resolution and short response time.

2.1 DESCRIPTION OF MULTI-SENSOR NETWORK

Multi-sensor nodes that have been developed are low-cost, small-sized devices that can receive and communicate information about gases air pollution in the environment. Each node can have up to five gas sensors linked to it for this function. Furthermore, Wi-Fi technology is used for wireless connectivity servers. Figure 1 depicts a multi-sensor network technology-based air pollution monitoring system.

Multi-sensor network consists of several sensors, including the Tgs2442 as CO sensor, the MG811 as CO₂ sensor, the Tgs2611 as Hydrocarbon sensor, the Sharp GP2Y1010 as particle and dust sensor, the DHT11 as temperature and humidity sensor, and the Neo-6M as GPS module to determine location, as show in Figure 2. The Raspberry Pi node can only read the output value digitally, while each sensor's output value is analogous. An ADC or Analog to Digital Converter module is needed in getting the output value reading, namely ADS1115 as a sensor reading value converter. The Raspberry Pi can process it, which functions as a gateway. The voltage source used in the device is a 12V battery.

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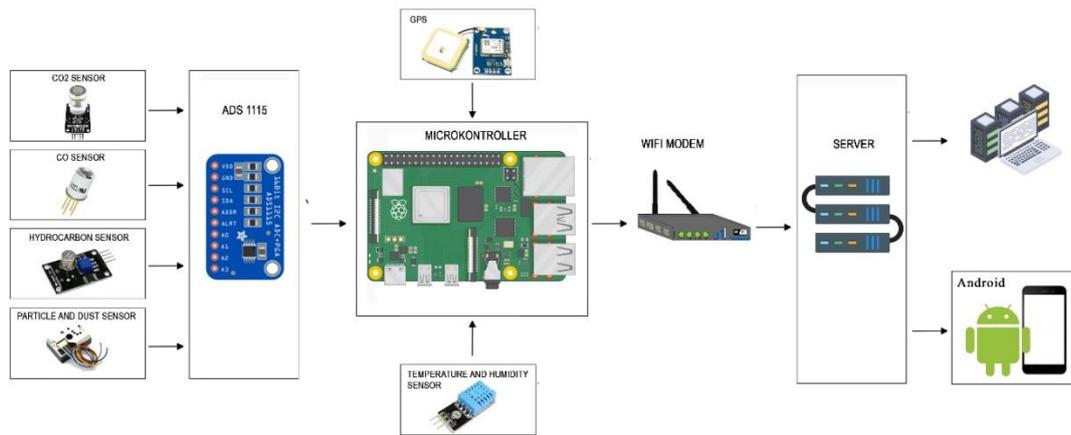


FIGURE 1. Multi-Sensor Network Scheme

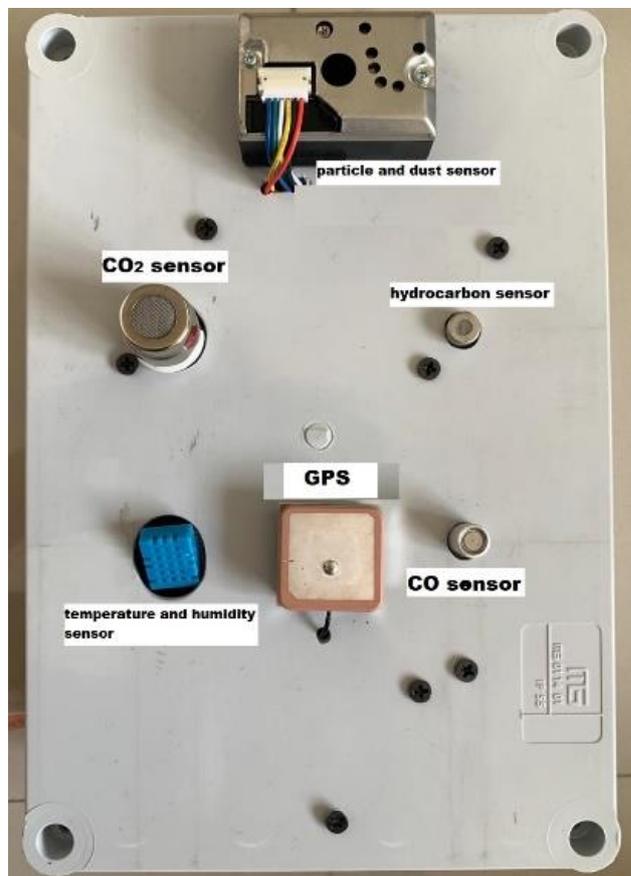


FIGURE 2. Closed Views Of The Air Pollution Sensor Box

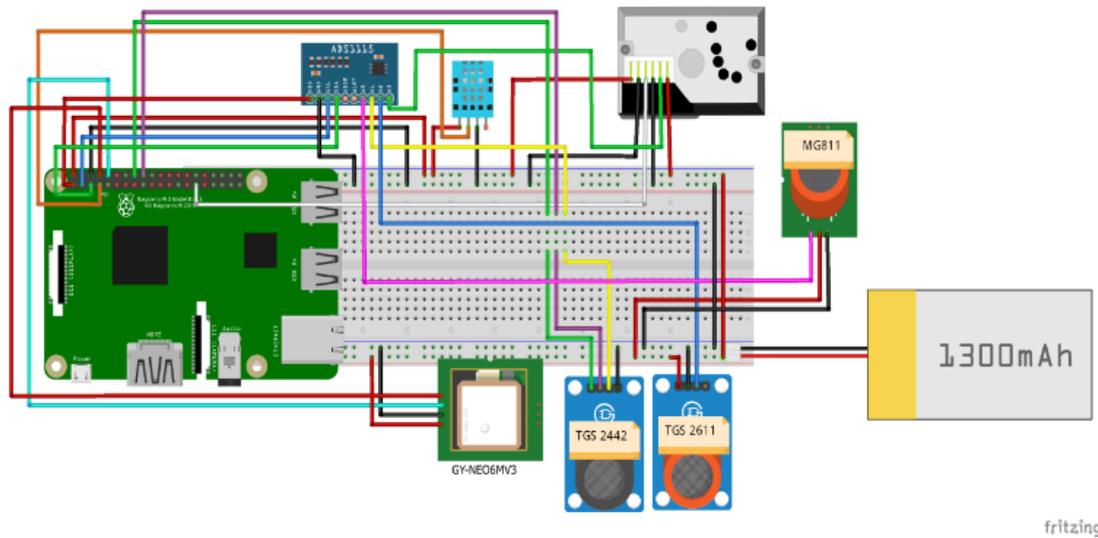


FIGURE 3. Electric Circuit

The Raspberry Pi is connected to an available Wi-Fi network from the gateway to the database server during the communication procedure. With a dual-band wireless connection that supports 802.11ac, the Raspberry Pi has enhanced network capabilities. As an internet service provider, the Wi-Fi network in this test uses a Wi-Fi modem. In this experiment, sensor nodes will automatically detect air quality levels in a location and send temperature, humidity, and gas content information to the server in real-time while the device is still on. The data is then entered into a database table that has already been created. The data is utilized as a caller to display air quality monitoring data and send emergency air quality notifications. The air quality is divided into three categories: normal, moderate, and hazardous.

2.2 LOW-COST MULTI-SENSOR NETWORK

Low-Cost sensor networks are more compact, more portable, and powerless as compared to reference instruments. Field testing against reference equipment in various environmental conditions was done to characterize low-cost air pollution control and monitoring systems. The field testing was intended to identify faults induced by real-world settings that could not be tested in the laboratory.

This research is to obtain data or parameters from sensors at each node. This is useful for measuring and calculating the results of processing readers to detect the quality of air in the environment. The measurement test is the air quality of 3 nodes, namely Node 1, Node 2, and Node 3, (display in Figure 4) which is carried out in three different locations. Research data is obtained by collecting parameter values from multiple sensors and displaying information on air quality conditions (normal, moderate, and hazardous) and then analyzed.



FIGURE 4. Node Sensor Network Device

The output is the result of measuring data for each node in pollution values from air quality. The overall measurement of data is used to determine the success rate of data accuracy on the system. The results are presented in this report of data collected. In this study, the measurement parameters used in measuring air quality with a multi-sensor network system at a location are used in Table 1.

TABLE 1.
Air Pollution Parameter

Air Pollution Parameter	Air Quality		
	Normal	Moderate	Hazardous
CO	200-400 ppm	400-600 ppm	800-1600 ppm
CO ₂	350-550 ppm	600-2500 ppm	2500-5000 ppm
HC	0-5000 ppm	5000-9000 ppm	9000-10000 ppm
Dust	0-50 µg/m ³	51-100 µg/m ³	301-400µg/m ³
Temperature	20°-30° C	30°-40° C	40°-50° C

3. RESULTS AND DISCUSSION

This study aims to obtain the accuracy value, precision, and recall from each node. At each node, the air quality parameters are measured from multiple sensors with different measurement locations. The data is helpful to know which node has a level of accuracy values, the value of precision, and a high recall value. The results can be used to determine how polluted the air is in some areas.

3.1 EVALUATION OF MULTI-SENSOR NETWORK QUALITY

From the experiment on the outdoor parking area, Figure 5 (a) shows the input value of the multi-sensor node 1. Data collection was performed from 9:30 to 11:30 am. The results obtained are 56.638091202451186 ppm CO, the readings for 377.9368542998419 ppm CO₂, and HC is 349.39987425649383 ppm, and dust is 22.395761458846724 g/m³, and temperature is 31°C with a humidity level of 72%. The air pollution monitoring results for multi-sensor are categorized as normal classification.

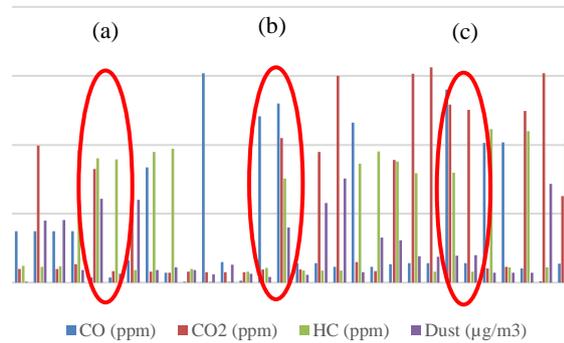


FIGURE 5. Parameter Values From Node 1

Experiment at 12.30 – 14.30 at the parking area, in Fig. 5 (b) shows parameter air pollution is CO 52.954789921444636 ppm, CO2 689.73027054129005 ppm, parameter HC 347,19426281804994 ppm, and dust is 30.605413807483792 g/m3. The temperature is 33°C with a humidity of 66%. Sensor readings are categorized as moderate classification. With is an increase in temperature and a significant increase in CO2. This situation is due to the hot and sunny sky conditions, increasing temperature. In addition, the rise in CO2 occurred at 13:32:13, which was a break time so that many vehicles are active, which causes air pollution in the area.

Experiment on multi-sensor node 1 shows that the air quality conditions at that location are classified as moderate and hazardous because the parking lot area is the main access point for vehicles to enter and exit. The frequent activity of vehicles at the location causes air quality to be polluted. The device accuracy is 95.02% based on the test data, with a classification error of 4.98%. Classification errors are caused by the results of sensor readings classified as not according to the data range.

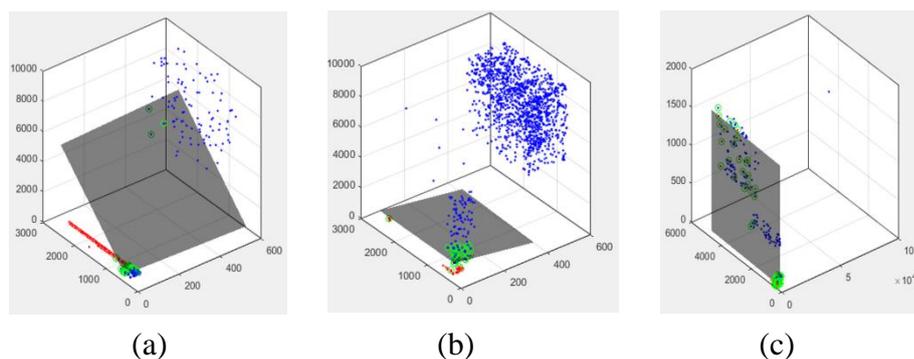


FIGURE 6. (a) Classification Normal, (b) Classification Moderate, (c) Classification Hazardous

The graph shown in Figure 6 shows that the measured data can separate two classes, namely normal data and unnormal data. Misclassification or error is evidenced by normal data in the area of unnormal data and vice versa. In multi-sensor node 1, the dominant data is classified as moderate and hazardous in Fig. 6 (b) and (c). The amount of data classified as moderate and hazardous is marked in blue.

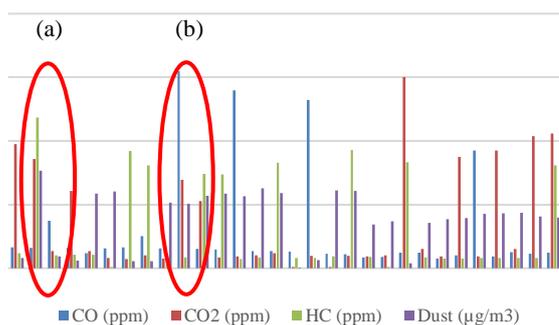


FIGURE 7. Parameter Values From Node 2

In Fig. 7 (a), shown the input value of the multi-sensor node 2. In the experiment at 09.30 – 11.30 am, the parameters' values detected were CO of 44,453860947227746 ppm, CO2 of 439,530934559465 ppm, HC of 350.059142167823 ppm, and dust of 11.331855666742724 g/m3. The temperature is 32°C, and the humidity is 71%. The sensor detection results were categorized as normal classification.

The experiment of a device at 12.30 - 2.30 pm; the detection results obtained CO of 43.361908797548814 ppm, CO2 of 647.35091191427847 ppm, HC of 375.280315962129 ppm, the dust of 12.218455621108903 g/m3. The temperature is 32°C, with a humidity level of 68% display in Fig. 6 (b). The detection results of multi-sensor node 3 are categorized as moderate classification. Parameter CO2 increase causes many activities that occur on that day, and that time is a break time which allows many vehicles to pass by in that location. The device accuracy is 99,33% based on the test data, with minimal classification error.

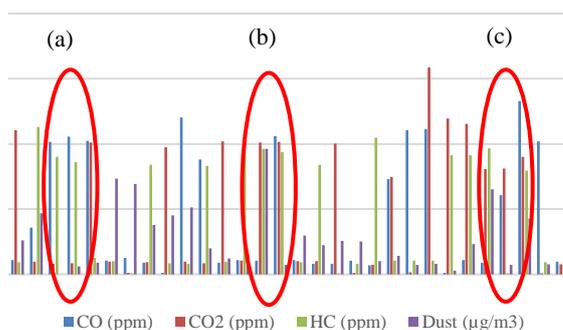


FIGURE 8. Parameter Values From Node 3

Figure 8 (a) shows the input value of the multi-sensor node 3; experiments were simultaneous with multi-sensor nodes 1 and 2, i.e., 09.30 – 11.30. Parameter values detected were CO 65.05427165161836 ppm, CO2 at 389.7864495358114 ppm, HC at 477.6918101185048 ppm, dust at 32.45577586533722 g/m3, and temperature 33°C and humidity 66%. The sensor detection results were categorized as normal classification.

In Figure 8. (b), the detected parameter values are CO of 43.95514847289677 ppm, CO2 of 428.44144180750584 ppm, HC of 330.6506593298363 ppm, the dust of

23.62936164082343 g/m³, and a temperature of 32°C with a humidity level of 67%. The sensor detection results were categorized as normal classification. Experiment at 12.30 – 14.30 at the parking area is a rush hour/rest time, but the air quality at that location is normal. The cause is due to not much activity, so the area's air quality is not polluted.

Experiments at 15.30 – 17.00 pm shown Figure 8 (c), the detected air quality parameter values are CO at 63.94276215000489 ppm, CO₂ at 342.61239668414873 ppm, HC at 474.28549645179424 ppm, dust at 30.66921995685634 g/m³, and a temperature of 33°C with a humidity level of 66%. The category is normal, the same as the last time. Because there are few activities in this area, there is no pollution. With a categorization error of 4.97 %, the device accuracy is 95.03 %.

3.2 COMPARATIVE NODE MULTI-SENSOR OF A LOCATION RESULT

The basis for location is range measurement, and precise range measurement provides the certainty of accurate location [28]. As a result, knowing the exact internode distance is critical. In Table II. The location estimation error for all unknown nodes ranges from 0.007 m to 6,205 m. The approximate location estimation error is reduced by placing the node can toward the center of the area. The best position can conclude that the anchor node density in a central area is more significant than at the edge of the location.

TABLE 2.
The Location of The Nodes

Node	The estimated coordinate	The actual coordinate
	Latitude, Longitude	Latitude, Longitude
1	-2.99, 104.90	-2.983316667, 104.7328375
2	-3.00, 104.99	-2.983295934, 104.7338968
3	-2.99, 104.77	-2.982304732, 104.7343524

Precision is more of a concept than a measurable measure. The majority of precision evaluations have the purpose of characterizing the performance of most measurements. The homogeneity of precision over the measurement range, the normality of the difference distribution, and the desired objective of the precision estimate should be considered when selecting a method for estimating accuracy.

In paper [29], we refer to nondimensional precision estimates based on relative differences in data frequently used in the air quality field. However, if recorded concentrations do not consistently surpass 5–10 times the detection limit, they may not appropriately characterize the data.

We apply an approach using other air monitoring tools (by comparing one parameter) simultaneously and in the exact location. To compare competing systems effectively, we refer to the following performance metric [30], Recall is the ratio of correctly detected air quality to actual detected air quality. The ratio of incorrectly detected air quality to the number of false air quality detections is the False Positive Rate (FPR) (False Positive and True negative air quality TN).

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Table III is a recapitulation of the experimental results of our approach, showing that our approach is to achieve Recall = 96% with FPR = 4%. for node 1, node 2 is 98.78%, with 1.22% , and Recall = 99% with FPR = 1% at node 3.

TABLE 3.
The Metric

Node	Recall	False Positive Rate
1	96 %	4 %
2	98,78 %	1,22 %
3	99 %	1 %

4. CONCLUSION

This work addressed the concept of a real-time multi-sensor network of monitoring indoor parking areas. The main goal of our approach is to create a prototype that has the least amount of influence on the public parking infrastructure. Carbon Monoxide (CO), Carbon Dioxide (CO₂), Hydro Carbon (HC), temperature and humidity, and levels of particles in the air (PM₁₀) concentration are all reported in real-time by the system. Furthermore, the air quality sensor data will be processed to become information used by users or the general public. The proposed system performs better than a simple monitoring system.

We also aim to improve experimental designs of the sensor network. This sensor technologies should be tested, as well as innovative calibration methodologies, in order to achieve higher performance in the future.

Although a few models have established sufficient correlations between sensors and reference instruments, it is commonly accepted that the current generation of low-cost sensors requires further development to achieve the accuracy of reference monitors. Additionally, all data to be acquired can be used as information for the general public and government as policymakers dealing with air pollution.

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