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Research Article

Internet of Things Based Data Acquisition Module Design for Air Quality in Public Transport Vehicles

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Abstract

In this study, an ARM-based data acquisition module is designed with the Internet of Things in public transportation vehicles for air quality analysis. The designed module communicates with the driver's computer in the vehicle. TEMPerHUM USB Thermometer Hygrometer Sensor is used to collect temperature and humidity data and a dust sensor is used as PM2.5 and PM10 sensors. The data obtained from these sensors are sent to the microprocessor with the RS-485 port. Microsoft Azure Hub is used to save all data from the microprocessor in real-time. Machine learning algorithms are used to evaluate regression models constituting the temperature, humidity, and PM data. Regression models are generated in the Python Language. Results of the R^2 score and RMSE are found for the different regression models. The results are assessed and represented.

Keywords: Air Quality Analysis, Internet of Things, Machine Learning.

Toplu Taşıma Araçlarında Hava Kalitesi İçin Nesnelerin İnterneti Tabanlı Veri Toplama Modülü Tasarımı

Öz

Bu çalışmada, toplu taşıma araçlarında hava kalitesi analizi için Nesnelerin İnterneti ile kullanılarak ARM tabanlı bir veri toplama modülü tasarlanmaktadır. Tasarlanan modül, araçtaki sürücü bilgisayarı ile haberleşmektedir. Sıcaklık ve nem verilerini toplamak için TEMPerHUM USB Termometre Higrometre Sensörü ve PM2.5 ve PM10 sensörü olarak Dust Sensörü kullanılmaktadır. Bu sensörlerden elde edilen veriler RS-485 portu ile mikroişlemciye gönderilmketedir. Microsoft Azure Hub, mikroişlemciden gelen tüm verileri gerçek zamanlı olarak kaydetmek için kullanılmaktadır. Sıcaklık, nem ve PM verilerini oluşturan regresyon modellerini değerlendirmek için makine öğrenme algoritmaları kullanılmaktadır. Regresyon modelleri Python dilinde üretilmektedir. Farklı regresyon modelleri için R^2 puanı ve RMSE sonuçları bulunmaktadır. Sonuçlar değerlendirilmekte ve temsil edilmektedir.

Anahtar Kelimeler: Hava Kalitesi Analizi, Nesnelerin İnterneti, Makine Öğrenmesi.

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1. Introduction

Air pollution continues to be a major problem in industrialized cities and causes deaths by threatening the health of millions of people (Bowdalo, D., 2022). PM2.5 and PM10 are among the harmful particles to human health (Pandey, P., 2013). Observation of harmful particles in the air in real-time is significant to prevent possible negative effects. Objective and more sensitive results for air pollution can be obtained by machine learning. Determination of the level of pollution is substantial. Fixed points and mobile stations in the city are used to determine air pollution (Mihăiţă, A. S., 2019). Air quality data from the fixed points are measured and transmitted in real-time by wireless sensor networks (Kingsy Grace, R., 2019). Air quality data in a great number of cities is limited and only taken from a fixed point by the reason of cost. The collection of measurements from a single region makes it difficult to interpret the effect of global warming (Kumar, P., 2015). In mobile stations, measurements are taken with sensor models placed in the vehicle (Devarakonda, S., 2013). Data is transferred in real-time by the Internet of Things. Regression models have been proposed for the relation between airborne PM2.5 and PM10 particles and humidity and temperature (Peci, A., 2019).

An air quality module is created by using a 32-bit microcontroller to measure PM2.5 and PM10 particles and humidity and temperature variables. In the study, data is transmitted in real-time with the Internet of Things by placing the designed module on public transportation vehicles. The effect of air quality on global warming is observed by the regression models. R^2 and Root Mean Square Error (RMSE) are used to analyze the performance of models.

An ARM-based module for public transportation vehicles is designed. The design of the system is presented in section 2. Internet of Things is real-timely used to analyze the impact of PM2.5 and PM10 particles in the air. The impact of temperature and humidity on airborne PM2.5 and PM10 is mentioned in section 3. The air pollution identity of the city is observed from the data obtained from the sensors. In section 4, the conclusion is described.

2. Material and Method

STM32L4 is used as a microprocessor. The Dust Sensor is used to collect PM2.5 and PM10 in the air. TEMPerHUM USB Thermometer Hygrometer Sensor is used to collect temperature and humidity variables. i.MX6UL card is used for transmission of the sensor variables through the Microsoft Azure Hub. In Fig. 1., the module of the proposed system is shown.

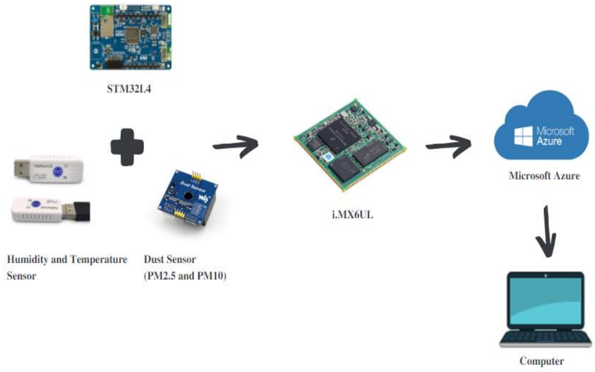

Fig1: The system for real-time monitoring

2.1. Transmission of Data

I2C and UART are used to connect data from the sensors by STM32L4. The microcontroller sends the data to the i.MX6UL by the RS-485 communication protocol. The data is deleted in case the data is corrupted in the course of sending over the RS-485 protocol. Message Queuing Telemetry Transport (MQTT) protocol is used to send the transmitted data to the cloud by i.MX6U. Regression models are observed by the data in the cloud.

2.2. Sensors

TEMPerHUM USB Thermometer Hygrometer Sensor is used to measure the humidity and temperature. PM2.5 and PM10 are measured by the SDS011 sensor. SDS011 can detect particle concentrations between 0.3µm to 10µm by the principle of laser scattering (Budde, M., 2018). SDS011 is a low-cost dust sensor. The ideal range for temperature and humidity sensor TEMPerHUM USB Thermometer Hygrometer can operate between -40 and 85 degrees Celsius with a maximum accuracy of ±1°C. The calculation of the temperature and humidity sensor is shown in Eq1and Eq2.

$$Temperature\ (°C) = \frac{175.72 \times CodeTemp}{65536} - 4 \qquad \text{(Eq1)}$$

$$\%RH = \frac{125 \times CodeRH}{65536} - 6 \qquad \text{(Eq2)}$$

where %RH is the Humidity, CodeTemp, and CodeRH are the 16-bit words returned by the temperature and humidity sensor.

2.3. Internet of Things

The i.MX6UL operates on Linux Operating System and the Python programming language is used on it. Transmission of the data determining air quality to the cloud is operated by i.MX6UL real-timely. The processor is used for internet connection. In Fig. 2, transmitted data on the local computer is shown. Data from the sensors is stored in .csv format. The machine learning algorithm is used in the .csv format data.

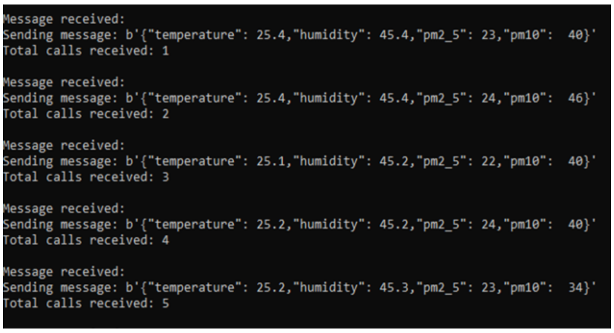

Fig2. Real-Time Monitoring on Computer

2.4. Machine Learning

Regression is the analysis of the process of statistical methods used to estimate the relationship between variables. In the study, various supervised learning methods are used. Data set has been tested with multiple linear regression, polynomial regression, random forest, decision tree and K- NN. Regression models are used to determine the effect of airborne PM2.5 and PM10 particles on temperature and humidity.

3. Results and Discussion

In the dataset, variables are humidity, temperature, airborne PM2.5, and PM10 particles. Data is obtained from various points in the city. Regression models are observed by machine learning algorithms. Regression models are modeled from the data to realize the effect of global warming. R^2 and RMSE are used for the performance testing of the regression models of the system.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{k}(y_i - x_i)^2}{k}} \qquad \text{(Eq3)}$$

where y_i is the output, x_i is the value of the estimated output.

$$R^2 = 1 - \frac{\sum_{i=1}^{k}(y_i - x_i)^2}{\sum_{i=1}^{k}(y_i - x_i)^2} \qquad \text{(Eq4)}$$

4. Conclusions and Recommendations

Air pollution is becoming increasingly important with the increase in population. The harmful effects of air pollutants show complex distribution patterns. The complexity means that modeling and estimating exposure levels are difficult. Determination of the pollution level of the area is possible by measuring air quality frequently. Airborne PM2.5 and PM10 particles, temperature, and humidity variables have been collected by the Internet of Things in real-time. The effect of PM2.5 and PM10 on the temperature and humidity has been modeled. The effect of global warming on air pollution has been observed from the regression models by the obtained data. The regression model that shows a more valid distribution has been determined by testing the regression models with R^2 and RMSE. Random Forest is the more accurate model to analyze the data obtained in terms of R^2 and RMSE than the others. In Table 1 results are shown for different machine learning algorithms. The relation between airborne PM2.5 and PM10 particles with temperature and humidity is shown in Fig. 3 and Fig. 4 respectively. Air pollution causes an increase in temperature and humidity is observed. Appropriate precautions can be taken for the future with the pollutant and concentration data of air pollution as a conclusion.

Table 1. R^2 Score and RMSE of Regression Models

Regression Models	**RMSE**	**R^2**
Linear Regression	5.18	0.1974
Polynomial Regression	4.07	0.4927
Random Forest Regression	2.83	0.7268
Decision Tree Regression	3.57	0.6019
KNN Regression	3.26	0.6782

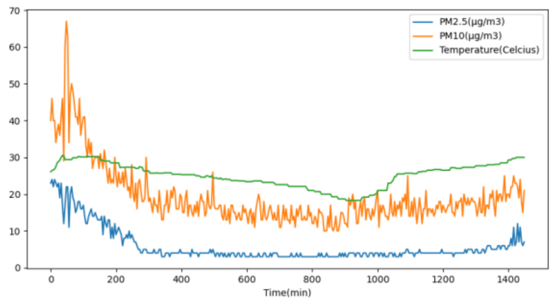

Fig3. Regression Model of PM2.5, PM10 vs Temperature

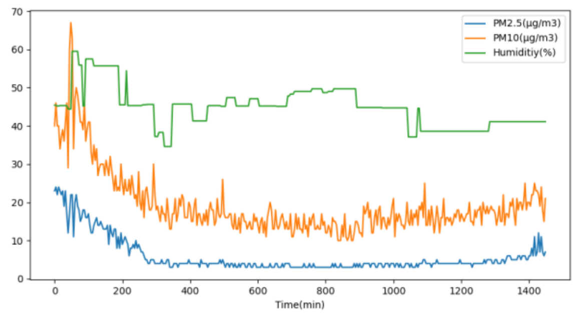

Fig4. Regression Model of PM2.5, PM10 vs Temperature

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