IoT-based AQI Estimation using Image Processing and Learning Methods

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Abstract

Air pollution is a concern for the health of all living beings. It is essential to check on the quality of air in the surroundings. This experiment was conducted to provide an IoT-based real-time air quality index (AQI) estimation technique using images and weather sensors in the Indian city of Hyderabad. A mixture of image features, i.e., traffic density, visibility, and sensor features, i.e., temperature and humidity, were used to predict the AQI. Object detection and localization-based Deep Learning (DL) methods, along with image processing techniques, were used to extract image features, while a Machine Learning (ML) model was trained on those features to estimate the AQI. In order to conduct this experiment, a dataset containing 5048 images along with co-located AQI values across different seasons was collected by driving on the roads of Hyderabad city in India. The experimental results report an overall accuracy of 82% for AQI prediction.

1 Introduction

1. What is the problem you are trying to solve?
   In recent times, Air pollution has been a significant concern for urban society. Air pollution consists of many hazardous chemicals and tiny particles in our daily air [1]. The sources of pollution can be stationary (chimneys, industry sites) and remote, such as vehicles. Many devices are available in the market that can monitor air quality and particulate matter (PM), from which Air Quality Index (AQI) can be calculated. The currently available solutions, mainly sensors, require maintenance with time due to their limited lifespan. For example, AQI sensor SDS011 by Nova Fitness works for only 10 to 12 months [2].

2. Why is this problem important, and to whom?
   The problem needs to be resolved because a massive amount of money and effort are being used yearly to maintain and service these air monitoring systems, as the sensors used are insufficient for the longer run.

3. What is your solution to this problem?
   Instead of using sensor- based pollution monitoring systems, the AQI can also be computed with the help of a novel image processing-based technique. Our solution is proposed to estimate the real-time AQI into five levels using traffic images and weather parameters instead of pollution monitoring sensors.

   The proposed method is a systematic yet cost-effective image-based AQI classification technique on an IoT device using a combination of ML and DL-based supervised learning algorithms. The primary motivation of this project is to have an image-based AQI estimator. We used the respective sensors to get the temperature and humidity of the given location. However, in the long-term goal, these two values can be achieved from the nearby weather stations. Hence, having an image-based AQI estimator can be used with smartphone cameras to get the AQI in real-time. In this way, the whole method is sensor free.

   We chose to show the AQI into levels instead of continuous numbers to make it more user-friendly. Showing a continuous value as AQI to the end user may need to be clarified and more informative.

Most users may need help understanding the technicalities behind a continuous number. On the other side, an AQI level is more understandable to all kinds of users.

Finally, the whole solution can be used as a mobile app. Images can be captured from the smartphone camera, and temperature and relative humidity can be obtained from the nearby weather station to estimate the AQI in real-time.

4. What are the supporting results you have to show that your solution can solve this problem?
Our proposed methodology has been tested on the testing dataset and we report overall 82% accuracy and 81% F1-Score while estimating the AQI for the images collected. In the case of monsoon images, the accuracy increases to 91% while in the case of winter images, we report 80% accuracy.

2 Goals

1. Deploy simple yet efficient image-based Air Quality Index (AQI) classification technique on an end to end IoT device using a mixture of ML and DL-based supervised learning algorithm.
2. A completely new traffic dataset is collected on Indian roads containing 5048 images and related weather data with co-located ground truth PM values.
3. The created dataset contains data points across the Indian city of Hyderabad in different seasons with precise GPS coordinates all along the city.
4. The proposed method achieved overall 82% accuracy considering PM variation due to season. authors show a significant improvement in the accuracy of AQI estimation using images when compared with existing work [3].

3 System Architecture and Design

3.1 Hardware

Fig. 1 shows the block architecture of the hardware developed and Table 1 shows the components used for this experiment. The Prana sensor which authors have used to measure the PM concentrations is a reliable PM sensor as per the study, also the BME280 sensor used for the Relative Humidity and Temperature values gives nearly accurate values. The PM values obtained by the PM sensor are used to calculate the AQI (Air Quality Index) which also served as a ground truth for the ML algorithm developed for this experiment. The hardware setup will send the processed data into a remote server, making it suitable for edge computing. A sample from each sensor was collected once in every 30s by the MCU. Cellular 4G-based Wi-Fi access point was used to send the data to the remote server and it is also get stored locally to avoid any kind of data loss. The device was placed on top of a car. With the help of the hardware setup mentioned, a traffic dataset was collected, containing images of traffic and the measurement of pollution levels. The car was driven on the streets of Hyderabad, India covering the routes shown in Fig. 2.

Models trained on this dataset may not work for other cities where the AQI level distribution is entirely different. We propose a methodology that works for one particular city. However, the same methodology can be used for other cities as well to estimate the AQI. We propose a methodology to predict the AQI using images for traffic and show that it performs up to the mark.

Table 1: List of components

Component	Use
Raspberry Pi Zero W	It is connected to the MCU to capture and process the vehicle images.
Pi Camera	It is connected to the MCU to capture and process the vehicle images.
BME280 Sensor	It is interfaced with MCU to Relative Humidity and Temperature values.
Prana (PAS-OUT-01) PM Sensor	To measure the PM2.5 and PM10 Concentrations.

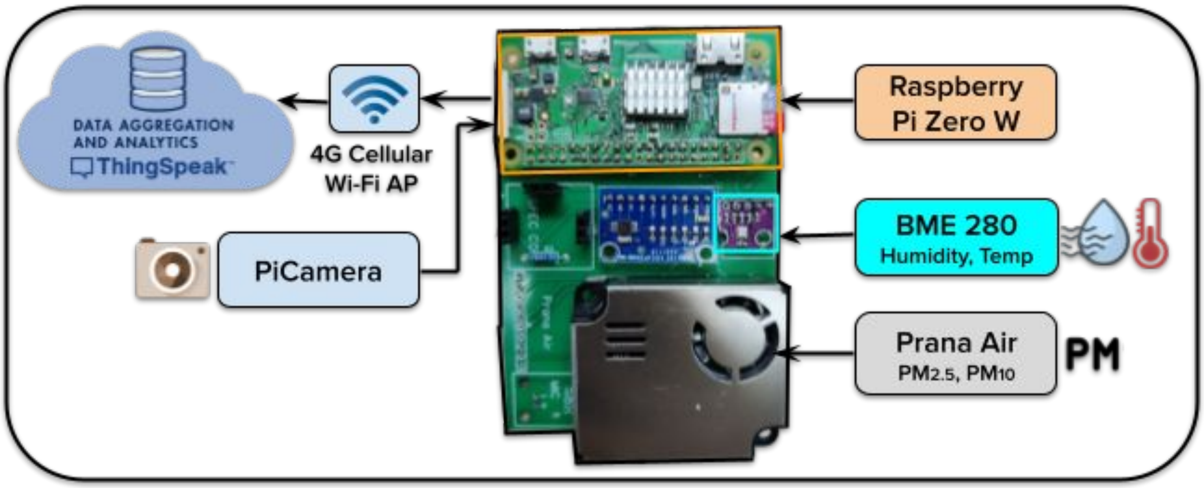

Figure 1: Hardware Setup

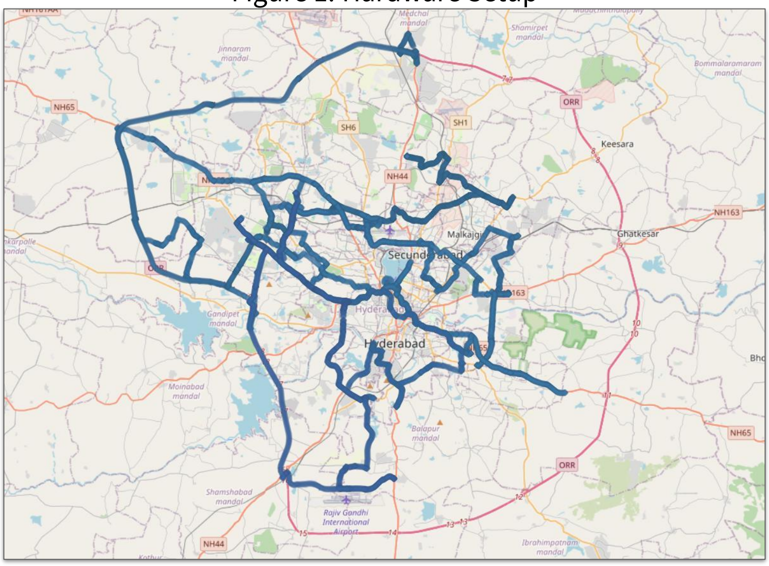

Figure 2: Street view of routes traveled during measurement campaign (Total distance = 1000 km)

3.2 Software

We propose a novel methodology to estimate AQI using traffic images for Indian roads. A pipeline for the same is shown in Fig. 3. Firstly, the image features are extracted using DL and image processing methods and concatenated with sensor features to generate a feature dataset. Further, an ML model is trained [4]on the feature dataset to estimate the AQI level.

Image Feature Extraction - From the given image, all the pollution-emitting vehicles were detected and their respective count was used as an image feature. We are only detecting vehicles that contribute to air pollution. To quantify the vehicles (motorcycle, car, truck, bus, autorickshaw) present in the image, YOLOv5 algorithm was used. The output of YOLOv5 for a single image is: detected objects (classification) and their bounding box (regression). YOLOv5 was trained on the Indian Driving Dataset.

Image Visibility Score Calculation - To capture the essence of pollution caused by other sources, the visibility of the image is computed using Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) which is a no-reference Image Quality Assessment (IQA) metric. The output of BRISQUE algorithm for a given image is a number between 0 to 100, where 0 signifies the best, and 100 signifies the worst visibility.

Feature Vector Generation - A feature vector is generated corresponding to each sample defined in the dataset collected. The feature vector comprises of image features (types of the vehicles and their count alongside visibility score) [5], sensor features (temperature and humidity), and the associated AQI level for

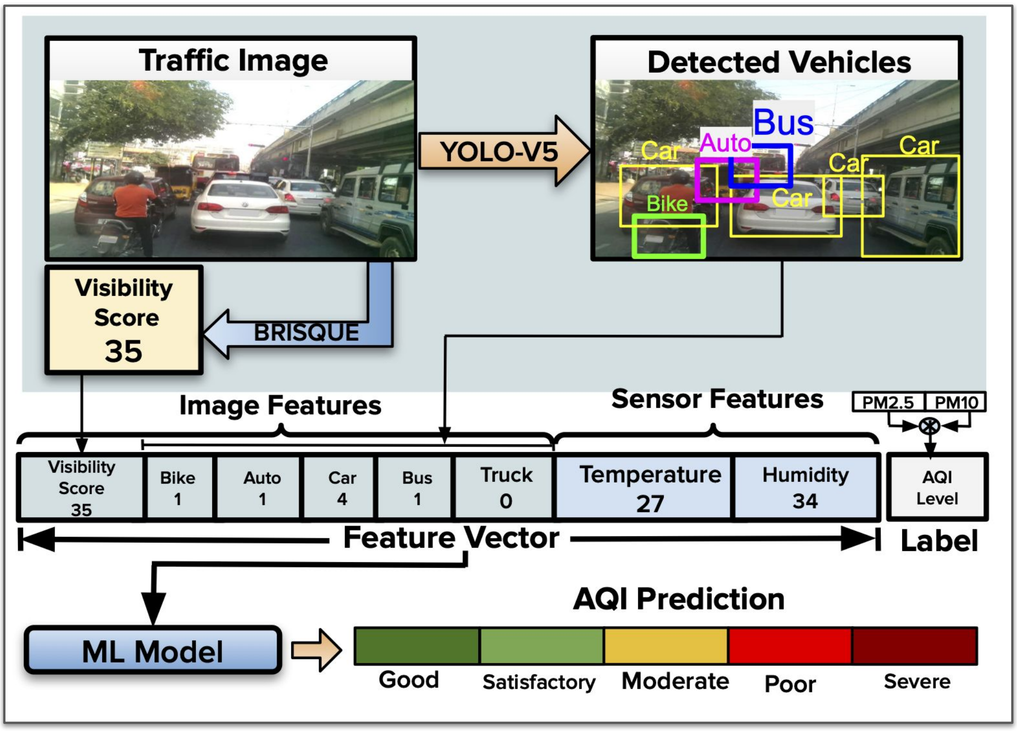

Figure 3: Algorithmic pipeline of the proposed method. Firstly, the image is passed to the trained YOLOv5 and BRISQUE algorithm to generate the image features. Then it is concatenated with corresponding sensor features to generate a complete feature vector with the corresponding label. Finally, an ML model is used to train and detect the AQI into five categories.

it computed using $PM_{2.5}$ and PM_{10} score. After generating the feature vector for all the samples in the dataset, a $m \times 8$ sized data matrix M is obtained, where m is the total number of samples present in the dataset. A $m \times 1$ sized vector y containing the corresponding labels is also obtained.

Training - With the help of the dataset M, and the corresponding label vector y, an ML model was trained to classify the samples into five different AQI levels. A classification-based ML model was trained to predict the AQI for a given sample. To choose the best performing ML model, three different ML models that best suit the data were experimented: 1. RF 2. SVM and 3. MLP. Each of the models has five classes (AQI levels) as output.

Detection - To compute the AQI for a given traffic location, the PiCamera captured the image, which is passed to the YOLOv5 and BRISQUE algorithm to compute the count of each type of vehicle and image visibility score respectively. The sensors provided the corresponding temperature and humidity values. A feature vector of size 8×1 was created and passed to the trained ML model to detect the AQI level. All the computation related to AQI estimation (YOLOv5, BRISQUE and ML model) are performed on Rpi0 itself and only the estimated AQI is sent to the remote server, thus making it suitable for edge-computation.

4 Addressing Challenges

1. Training the YOLOv5 model to detect the autorickshaws.
   Detecting the autorickshaws was a key challenge, as India is among the countries where autorickshaws are vogued. Therefore, the YOLOv5 model was trained on Indian Driving Dataset(IDD) [6], which had better results for detecting the autorickshaw.

2. Deploying the YOLOv5 model on Rpi0 microcontroller for edge computing.
   Rpi0 microcontroller was unable to run the YOLOv5 object detection model at the first hand, then authors have to quantize the model and convert it to TensorFlow Lite model [7]for the better outcomes.

The YOLOv5 model was trained for 25 epochs and converted into a TensorFlow Lite model to run on Rpi0.

3. Finding the accurate and robust sensors for the PM 2.5, PM 10, Temperature and Humidity.
   While conducting the experiment, it was difficult to decide which sensors should be used for more reliable results as there are many sensors present in the market for the measurement of parameters like PM 2.5, PM 10, Temperature, and Humidity. After comparing three main sensors for Particulate matter [8], authors have decided to use the Prana (PAS-OUT-01) PM Sensor.

4. Cleaning the collected dataset.
   The collected dataset has a significant amount of data points. Where the quality of data was hampered because the data contains inaccurate, inconsistent, missing, duplicate values, and outliers, in this case, data cleaning is necessary.

5. Finding the best suitable way to calibrate the collected sensor data with a reference sensor including timestamp.
   Calibration verifies the precision and reproducibility of sensors. Sensors that are calibrated are the prerequisite for precise, reliable, and reproducible measurement results. Calibration is one of the key prerequisites for effective quality assurance. Our approach to calibrate the sensors was simple as authors have compared two different sensor values by fitting a simple linear regression line, and then use the model fit to achieve the better results.

6. Camera resolution and change of the camera at detection
   The camera used in the proposed methodology is of 5MP resolution. Images captured through this camera are used to count the vehicles and visibility. For vehicle detection, the YOLO-v5 algorithm is used, which is trained on highly variant data distribution. Hence, images taken through the 5MP resolution camera or better than that will fetch the vehicle counts needed for feature generation. The same case is applicable for visibility detection using the BRISQUE algorithm.

7. The YOLOv5 object detection model was unable to detect the vehicles in the heavy traffic area.
   While collecting the image data there were few images which contains heavy traffic area and in that case our object detection model's accuracy was compromised, this issue was resolved by relaxing the Intersection over Union(IoU) thresholds.

8. Tuning the ML model for quality results.
   The process of tuning a model involves finding the optimal values of hyperparameters so that it performs as well as possible. Hyperparameters are variables whose values cannot be estimated by the model using the training data.

5 Performance Evaluation and Testing Results

The ML models were trained and validated for the dataset mentioned above. As there are seasonal variations in PM values [9], we trained three different models each for:

- **Monsoon dataset** (samples collected between Sep'21 - Oct'21)
- **Winter dataset** (samples collected between Nov'21 - Dec'21)
- **Overall dataset** (combining Monsoon and Winter dataset)

The results obtained for all three datasets are presented in Table 2.

For the overall dataset, the RF model achieved an accuracy of 82% and an F1-score of 81%. For the data points of monsoon season, it is observed that the RF classifier performs the best with an accuracy of 90.32%. The main reason for this relatively high accuracy is better training of the model as there are significantly high number of data points with low AQI values in monsoon season. Hence, most of the data points belong to

Table 2: Performance of various methods on overall and season-wise data.

Method	**Monsoon**		**Winter**		**Overall**	
	Acc	F1	Acc	F1	Acc	F1
SVM	0.86	0.85	0.74	0.72	0.77	0.76
MLP	0.90	0.89	0.78	0.74	0.79	0.78
RF	**0.91**	**0.90**	**0.80**	**0.78**	**0.82**	**0.81**

the first two categories. On the other hand, RF is the best performing model for Winter dataset as well, with an accuracy of 80.14%. It is relatively low as compared to the monsoon season as the data is spread over all categories of AQI, which also increases the chance of misclassification.

6 Concluding Remarks and Avenues for Future Work

The experiment is conducted to provide an simple yet efficient image-based AQI classification technique on an IoT device using a mixture of ML and DL-based supervised learning algorithm. Experimental results show accuracy up to 90% for the AQI classification. Additionally, a feature-rich dataset was created to be released in the public domain to promote further research. Currently, the work is limited to predicting the AQI only under daylight setting (from morning to evening). The authors plan to scale it to nighttime as well as to collect data for the all season. The proposed methodology is used to estimate the AQI for traffic scenarios only. We have yet to test it for other scenarios. Currently, the method is limited to pollution-emitting vehicles and does not differentiate between the type of cars (electric/non-electric) or other vehicles.

This method can also be used for AQI surveillance purposes. The proposed technique is edge-computation enabled, which allows all the computations at the device itself. As a part of the process, the image captured by the camera is processed at the device and the AQI is estimated. After the estimated AQI is sent to the cloud, the image captured is deleted from the device. Hence, no user/image information is compromised, making the whole process secure and private.

7 Availability

1. Demonstration video
2. Source code

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