International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-6, March 2020

Air Quality Measurement using Computer Vision and CCTV Footage of Road Traffic

Viral Tagdiwala, Muhammad Umair Siddiqui, Maithili Bhuta, Juhi Shah, Kriti Shrivastava

***Abstract*: Air Quality is at a steady state of decline throughout the world. While the Indian government, in particular, has been deploying monitoring stations across multiple cities to not only monitor but also establish a cause and effect relationship when it comes to air pollution, these monitoring stations clearly, don't suffice the actual demands for building a robust model for Air Quality Index.**

Our goal here is to reduce costs in terms of hardware deployment while, at the same time, provide a higher number of data points of collection on pre-existing infrastructure.

The project aims at calculating the air pollution factors at the suburban level using Vehicular Emissions. The idea is to identify the number and type of vehicles from a video feed and then estimate the vehicular pollution levels using the data collected.

***Keywords* : Computer Vision, Air Pollution, PM2.5, Air Quality Indices**

I. INTRODUCTION

In the course of the most recent couple of decades, many nations have endured sensational urbanization and industrialization forms on a phenomenal scale. In India, the population had expanded to more than one million in excess of 120 urban areas. This quick development in such a brief time frame has caused increased air contamination in India. Because of the costly expense of structure and maintenance, the air quality checking stations can't be put on each square in urban areas. Also, there are just 8 air quality checking stations in Mumbai, which is the biggest Indian city, by population. Air quality shifts non linearly, with the goal that the compelling scope of an air quality checking station is constrained. We scarcely know the accurate air quality on each square in the city by those scanty checking stations, so how to acquire the air quality quickly and advantageously will draw in much consideration.

Due to financial reasons, most existing techniques depend on satellite remote detecting innovations. In any case, these techniques just can mirror the air nature of the environment which is a long way starting from the ground stage quality. As of late, a few works concentrated on air quality have been introduced by the means of huge information capturing sensors. These works accomplish great outcomes at the expense of time utilization on the mind-boggling calculations. In addition, the gigantic infrastructure utilized in these works is hard to get.

With the advancement of the Internet of Things (IoT), different sensors, for example, PDAs and cameras assume significant jobs in sensing. There are a large number of traffic cameras in urban cities. In Mumbai (Maharashtra, India) for instance, there will be 10,342 traffic cameras by the end of 2019 (4717 pre existing + 5625 newly approved as of March 2019). Along these lines, we present an advantageous and effective air quality level deduction approach dependent on various highlights and different portions from single pictures through traffic cameras.

The data for the emission values of CO, CO2 and PM10 from different types of vehicles like car, motorcycle, truck and bus is collected from the Central Pollution Control Board (CPCB).

This video feed can be very easily collected by pre-existing infrastructure across the city, such as traffic cameras. This would allow us to interpolate the data points captured at various traffic cameras, for developing a much more robust estimate across the city.

To calculate the average air quality indices for a particular region ex. Vile Parle, CCTV feed from every traffic signal in Vile Parle will be used to calculate the total number of vehicles passing. The average value will be calculated by aggregating the estimates from each of these feeds. Images will be samples from the video feeds at specific intervals to make sure that we aren't overestimating the values of the indices.

Using TensorFlow \& OpenCV, we can perform the tasks of detecting and distinguishing various objects, such as cars, motorcycles, etc. Using the detections found by these models, we plan to combine inferences drawn from industry experts in this field to determine the pollutant exposure caused by every type of vehicle.

The scalability of this solution is extremely high, as cameras are being installed at an extremely high rate throughout the nation. This allows us to have a higher number of data collection points, giving better accuracy overall.

To outline, we build up a methodology for air quality level deduction from a solitary picture with the accompanying commitments:

Manuscript received on March 15, 2020.
Revised Manuscript received on March 24, 2020.
Manuscript published on March 30, 2020.

***** Correspondence Author

Viral Tagdiwala*, Computer Engineering, Dwarkadas Jivanlal Sanghvi College of Engineering, Mumbai, India. Email: tagdiwalaviral@gmail.com

Muhammad Umair Siddiqui, Computer Engineering, Dwarkadas Jivanlal Sanghvi College of Engineering, Mumbai, India. Email: umn2o2co2@gmail.com

Juhi Shah, Computer Engineering, Dwarkadas Jivanlal Sanghvi College of Engineering, Mumbai, India. Email: juhipshah12@gmail.com

Maithili Bhuta, Computer Engineering, Dwarkadas Jivanlal Sanghvi College of Engineering, Mumbai, India. Email: maithilibhuta@gmail.com

Kriti Shrivastava, Computer Engineering, Dwarkadas Jivanlal Sanghvi College of Engineering, Mumbai, India. Email: kriti.srivastava@djsce.ac.in.

(i) We propose a novel air quality level derivation approach from a single picture dependent on numerous highlights and various bit learning.
(ii) We build a dataset of a variety of adjusted pictures, which covers a wide scope of light and air quality conditions.
It has the potential incentive for picture preparing and environmental sciences and can be utilized as a proving ground for some algorithms. We scarcely know the definite air quality on each square in the city by those meagre observing stations, so a method to acquire the air quality quickly will draw in much consideration.

II. LITERATURE SURVEY

There is developing proof that early-life introduction to surrounding air contamination may influence neurodevelopment in kids. Epidemiologic examinations have demonstrated that pre-birth and additionally early-life exposures to surrounding air poisons are related with a number of neurodevelopment issues and performance in newborn children and little youngsters. [1][2] autism diagnoses [9][10] and attention-deficit/hyperactivity disorder.

Based on the fuel consumed by automotive vehicles, they emit various pollutants. These pollutants also include transient emissions which rely on factors such as the vehicle type, its maintenance, etc. The prime pollutants released in the way of vehicle (fuel) emissions are, nitrogen oxides, carbon monoxide, photochemical oxidants, air toxics viz. aldehydes, benzene, 1-3 butadiene, particulate matter, lead, hydrocarbons, oxides of sulphur and polycyclic aromatic hydrocarbons. While hydrocarbons and carbon monoxide gas are the major pollutants in petrol/gasoline driven vehicles, the prevailing pollutants from the diesel based vehicles are oxides of nitrogen and particulates.

S.No.	Parameter	Delhi			Mumbai		
		Transport	Industrial	Domestic & other sources	Transport	Industrial	Domestic & other sources
1.	CO	76% to 90%	37% to 13%	10% to 16.3%	92%	8%	Nil
2.	NOx	66% to 74%	13% to 29%	1% to 2%	60%	40%	Nil
3.	SO_2	5% to 12%	84% to 95%	Nil to 4%	2% to 4%	82% to 98%	Nil to 16%
4.	PM	3% to 22%	74% to 16%	2% to 4%	Nil to 16%	34% to 96%	53% to 56%

Fig. 1. Summary of results of various studies performed by auto fuel policy

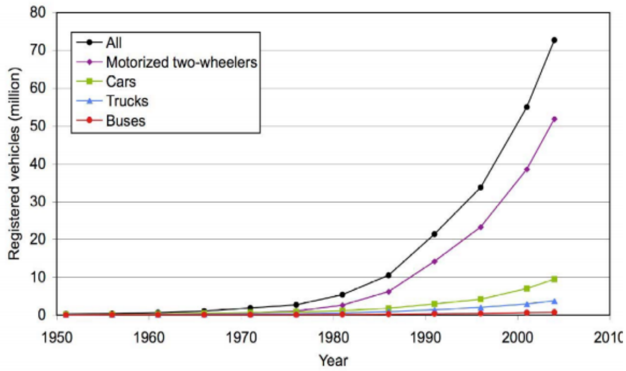

Fig. 2. Registered vehicles under various categories in India

The transport demand in the Asian subcontinent, India has been growing apace, that is the second largest patron of energy, next solely to Industry. Over time, according to the domestic and international demand, the installed capacity of Indian automobile industry is also growing.

The table reveals that personal mode (constituting primarily 2 wheelers and cars) accounted for over four-fifth of the motor vehicles within the country compared to their share of very little over three-fifths in 1950. Further classification of motor vehicle population reflects preponderance of 2 wheelers with a share of over seventy two percent in total vehicle population, followed by cars that can seat no more than 9 people (passenger cars) at thirteen percent and other vehicles (a heterogeneous category that includes 3 wheelers (LMV Passengers), trailers, tractors, etc.) around 9\%. Personalized mode juxtaposes the share of buses which in total registered vehicles has declined from 11.1\% in 1951 to 1.1\% during 2006. Also, the share of goods vehicles at about 5\% in vehicle population is modest in comparison to the size of the economy. The share of buses in the vehicle population at about 1 percent possibly indicates the slow growth in public transport.

In India, the figure of motor vehicles has increased from 3 lakhs in 1951 to approximately 5 crores in 2000, of which, two wheelers (mainly driven by two stroke engines) accounts for 70\% of the total vehicular population. Two wheelers, combined with cars (four wheelers, excluding taxis) (personal mode of transportation) account for approximately four fifth of the total vehicular population. The problem has been additionally aggravated by steady increase in urban population (from close to seventeen percent to twenty-eight percent through the years 1951-2001; Sharma; 2001 and bigger concentration of vehicles in these urban cities especially in four major metros namely, Delhi, Mumbai, Chennai and Kolkata that account for over fifteen percent of the aggregate vehicular population of the whole country, whereas, more than 40 other metropolitan cities (with human population more than 1million) accounted for 35\% of the vehicular population of the country. Further, twenty-five percent of the entire energy (of what ninety-eight percent comes from oil) is consumed solely by the road sector.

Retrieval Number: F9454038620/2020©BEIESP
DOI:10.35940/ijrte.F9454.038620
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Vehicles in major metropolitan cities are calculated to account for 7 parts of CO, 5 parts of HC, 3-4 parts of NOx, 3 parts of SPM and 1 part of SO2 of the aggregate pollution load of the aforementioned cities. Of ths, two thirds is contributed by two wheelers alone. These high levels of pollutants are primarily liable for breathing and other air pollution induced problems not excluding lung cancer, asthma etc. that is considerably higher than the national average (CSE, 2001; CPCB, 2002).

Categories	CO_2	CO	NO_x	CH_4	SO_2	PM	HC
Bus	28748.16	207.26	679.73	5.02	79.24	31.36	51.72
Omni buses	8508.42	60.94	200.53	1.49	23.45	9.28	15.11
Two wheelers	8701.08	719.64	62.15	58.88	4.25	16.36	464.49
Light motor vehicles (Passenger)	4378.10	370.29	92.93	13.07	2.11	14.52	10.16
Cars and jeeps	23901.22	212.30	22.14	18.17	5.67	3.22	28.01
Taxi	2367.08	10.23	5.68	0.11	117.0	0.80	1.48
Trucks and lorries	70288.92	491.15	859.51	12.28	193.7	38.20	118.69
Light motor vehicles (Goods)	44654.58	442.04	110.94	7.80	123.0	17.33	12.13
Trailers and tractors	46563.85	460.94	115.69	8.13	128.3	18.08	12.65
Others	5705.22	57.41	64.54	1.83	32.19	3.98	8.96

Fig. 3. Emissions from different vehicle type of India (Gg)

Having acquired these values, we now move on to implement the system by analysing the localised value of CO2, CO, NO, SO2, PM values.

Apart from the above mentioned values, road dust also comes to play when it comes to determining the pollution levels. The total emission is a combination of two factors : Vehicular Emission and Road Dust [11].

We determine the factors on which vehicular emission depends upon and the values that we have obtained from the CPCB for each type of vehicle.

The PM2.5 value is a density measure which gives us an idea of how much Particulate Matter (PM2.5) is present per volume of space, thus having units ug/m3.

The factors on which it depends include:

1) Particulate matter emitted from each vehicle
2) Area covered by the cctv camera
3) Height of surrounding buildings. [11]

We essentially want to calculate the average density of PM2.5 for the volume seen by our cctv camera

The car emission values (x) received from the CPCB is the amount of PM2.5 matter released by the car if it travels a unit distance.

To calculate the PM2.5 matter emitted from a vehicle as seen by our camera, we must multiply this value by the distance (d) a vehicle travels while it is in the POV of our camera.

Thus x*d amount of PM2.5 matter will be suspended in the air.

We then calculate the density of this, for that we require volume which is the product of surface area and height.

Surface are will be the area covered by our cctv camera (A) and since the Emission factor also depends on the height of the surrounding buildings (h), we can calculate Volume as A * h and out Vehicular Emission factor as:

$$E_{fe} = \frac{x * d}{A * h}$$

We can easily quantify road dust emission levels using the following formulae:

$$E = E_{fe} + E_{fd}$$

$$E_{fe} = \frac{x * d}{A * h}$$

$$\frac{E_{fd}}{E_{fe}} = K$$

$$E = K * E_{fe} + E_{fe}$$

$$E = (K + 1) * E_{fe}$$

$$E_{fd} \rightarrow Road\ Dust\ Emission$$

$$E_{fe} \rightarrow Vehicle\ Exhaust\ Emission$$

$$x \rightarrow Average\ Emission$$

$$d \rightarrow Average\ distance\ travelled$$

$$A \rightarrow Ground\ surface\ area\ covered\ by\ camera$$

$$h \rightarrow Average\ height\ of\ surrounding\ buildings$$

Thus, the value of K needs to be determined separately in every location and for various time periods because it is time variant and location dependent.

III. IMPLEMENTATION

R-CNN, or Region-based Convolutional Neural Network, consisted of 3 simple steps:

1. Scan the input image for possible objects using an algorithm called Selective Search, generating say ~1000 region proposals
2. Run a convolutional neural net (CNN) on top of each of these region proposals
3. Take the output of each CNN and feed it into
   - an SVM to classify the region and
   - a linear regressor to tighten the bounding box of the object, if such an object exists.

So, on a high level, we first propose regions, then extract features, and then classify those regions based on their features. R-CNN is very intuitive, but very slow.

So, Faster R-CNN resembled the original R-CNN in many ways, but improved on its detection speed through two main augmentations. First, being performing feature extraction over the image before proposing regions, thus only running one CNN over the entire image instead of 1000 CNN's over 1000 overlapping regions. Secondly, we can replace the SVM with a softmax layer, thus extending the neural network for predictions instead of creating a new model.

IV. TESTING AND RESULTS

Developing a testing methodology for the same proves to be challenging because of the fact that traffic camera feeds tend not to have public accessible APIs, resulting in a lack of high number of data points which is essential for the development of our system.

We chose a single data collection point which had a hardware monitoring station at a proximity of roughly 50 meters. We recorded 5 videos of length one minute for a week from a constant angle from an elevation of 15 meters above the road. These videos were then used to determine the count and type of vehicles in the region. This data, along with constants:

- d (Average distance traveled by a vehicle as seen by our camera)
- A (Ground surface area covered by our camera)
- h (Average height of surrounding buildings)

we calculated a value for the Vehicular Exhaust Emission.

Fig. 4. Sample frame from our traffic recording showing identified vehicles and their types

A Linear Regression Model was created with inputs being the Vehicle Exhaust Emission and was trained with actual PM2.5 values that we obtained from the hardware monitoring station's output using the OpenAQ API.

We followed this by recording 5 videos per day for the following week with the same timeframe and maintaining the same angles. Now, using the regression model we calculated the PM2.5 values. These predictions were then compared against the hardware monitoring station's output using the OpenAQ API.

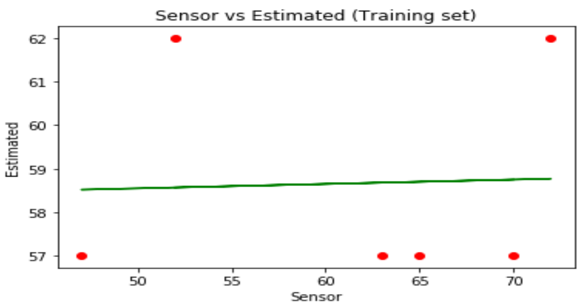

Fig. 5. Output of linear regression performed on the sensor readings & the actual estimations

The Linear Regression model gave a Root Mean Square Error value of 2.56 on our test data. This error is acceptable and well within range. Considering an average value of 60mg/m3 for Vile Parle, the RMS error value is only 4.27%.

V. CONCLUSION

The suggested method encapsulates a cost-effective strategy to tackle air pollution monitoring in growing economies where investment towards specialized hardware can be met with resistance. While our work focused on a single video capture and physical monitoring station, a comprehensive review is required which would study the effect on a larger area, encompassing multiple video streams and aggregating those values.

REFERENCES

1. Edwards SC, Jedrychowski W, Butscher M, Camann D, Kieltyka A,Mroz E, Flak E, Li Z, Wang S, Rauh V, Perera F. Prenatal exposure to airborne polycyclic aromatic hydrocarbons and children's intelligence at5 years of age in a prospective cohort study in Poland. Environ Health Perspect. 2010;118:1326–1331.
2. Guxens M, Aguilera I, Ballester F, Estarlich M, Fernandez-SomoanoA, Lertxundi A, Lertxundi N, Mendez MA, Tardon A, Vrijheid M,Sunyer J. Prenatal exposure to residential air pollution and infant mental development: modulation by antioxidants and detoxification factors. Environ Health Perspect. 2012;120:144–149.
3. Kinickmeyer RC, Gouttard S, Kang C, Evans D, Wilber K, SmithJK, Hamer RM, Lin W, Gerig G, Gilmore JH. A structural MRI study of human brain development from birth to 2 years. J Neurosci.2008;28:12176–12182.
4. Perera FP, Rauh V, Whyatt RM, Tsai WY, Tang D, Diaz D, Hoepner L,Barr D, Tu YH, Camann D, Kinney P. Effect of prenatal exposure to airborne polycyclic aromatic hydrocarbons on neurodevelopment in the first 3 years of life among inner-city children. Environ Health Perspect.2006;114:1287–1292.
5. Jung CR, Lin YT, Hwang BF. Air pollution and newly diagnostic autisms pectrum disorders: a population-based cohort study in Taiwan. PLoSOne. 2013;8:e75510.
6. Kalkbrenner AE, Daniels JL, Chen JC, Poole C, Emch M, MorrisseyJ. Perinatal exposure to hazardous air pollutants and autism spectrum disorders at age 8. Epidemiology. 2010;21:631–641.
7. Roberts AL, Lyall K, Hart JE, Laden F, Just AC, Bobb JF, Koenen KC,Ascherio A, Weisskopf MG. Perinatal air pollutant exposures and autismspectrum disorder in the children of nurses' health study II participants.Environ Health Perspect. 2013;121:978–98.
8. Roberts G, Bryant D. Early Mathematics Achievement Trajectories:English-Language Learner and Native English-Speaker Estimates, Usingthe Early Childhood Longitudinal Survey. Developmental Psychology.2011;47:916–930.
9. Volk HE, Kerin T, Lurmann F, Hertz-Picciotto I, McConnell R, CampbellDB. Autism spectrum disorder: interaction of air pollution with the METreceptor tyrosine kinase gene. Epidemiology. 2014;25:44–47.
10. Volk HE, Lurmann F, Penfold B, Hertz-Picciotto I, McConnell R.Traffic-related air pollution, particulate matter, and autism. JAMA Psy-chiatry. 2013;70:71–77
11. Wang, Yuan, Huang, Zihan, Liu, Yujie, Yu, Qi, Ma, and Weichun,"Back-Calculation of Traffic-Related PM10 Emission Factors Based on Roadside Concentration Measurements," MDPI, 02-Jun-2017. [Online].Available: https://www.mdpi.com/2073-4433/8/6/99/htm. [Accessed: 16-Mar-2020]
12. M.FermandK.Sj¨oberg,"Concentrations and emissionfactors for PM2.5 and PM10 from road traffic in Sweden,"AtmosphericEnvironment,15-Aug-2015.[Online].Available:https://www.sciencedirect.com/science/article/pii/S135223101530282X.[Accessed: 16-Mar-2020].
13. W.-Y.Pan1andH.-Y.Shen1,"IOPscience,"IOPscience.[Online].Available:https://iopscience.iop.org/article/10.1088/1755-1315/153/6/062005. [Accessed: 16-Mar-2020

AUTHORS PROFILE

Viral Tagdiwala is a final year computer engineering undergraduate with keen interests in cyber security and embedded devices. He has worked in esteemed organizations like the Indian Institute of technology, Bombay (IIT B), MNCs and startups across the globe.

Muhammad Umair Siddiqui is currently a Computer Engineering student. He has interests in the fields of Machine Learning, Deep Learning & Computer Vision. He has worked on several projects & will soon begin working as an Analyst in COE Assurance at Ernst & Young. He has published two research papers in the field of Deep Learning.

Maithili Bhuta is a final year computer engineering undergraduate with interests in management of information & data analytics.

Juhi Shah is a final year Computer Engineering student. She is a learner who is exploring different fields to find her area of interest. She has worked on several projects and also with the American financial services organization- TIAA as an intern.

Kriti Shrivastava Assistant Professor (Computer Engg). Dwarkadas J Sanghvi College of Engineering Mumbai Qualification: M. Tech (Computer Engg). Area of Interest: Artificial Intelligence and Machine Learning Email: kriti.srivastava@djsce.ac.in.