AirNet: Air Quality Level Predictor

A Project Work Report

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Abstract

Our project is to monitor the pollution using image processing technology. Image processing obtains the polluted parts of the image using edge detection and depth estimation technique. Thus air pollution monitoring is done through the image processing.

It detects and quantifies PM pollution by extracting a combination of image features, including transmission, depth, RGB channel, local image contrast, and image entropy.

We further consider the time, date and weather condition of each photo, to determine the correlation between PM level and various factors. Based on these features, we build a deep learning model to predict PM level using photos collected.

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<u>*List of Symbols*</u>

I	*Haze-free scene image*
J	*Sky Luminance*
A	*Transmission matrix that describes the portion of the light that*
t	*reaches camera*
d(x)	*Scene depth map*
β	*Atmosphere scattering coefficient*
SGD	*Stochastic Gradient Descent*

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1.INTRODUCTION

1.1 Problem Definition

In India, we have seen a tremendous increase in the air pollution over a past few years. In some of the large cities such as Delhi the concentrations of the pollutants have risen about 5.5 percent since 2016. It has become an alarming environmental issue due to rapid urbanization and industrialization. Among different air pollutants particulate matter less than 2.5 micrometer has severe harmful effects on the human body. They are capable of transmitting chemicals into the human lung causing major respiratory diseases. The crucial first step to solve the problem of air pollution is to enable citizens to gauge the quality of air they breathe.

This could be done by using pollution sensors but they are expensive to deploy at scale. Our goal is to design a reliable and inexpensive air quality solution which could be accessible to everyone with just a smartphone.

1.2 Project Overview

The objective of our project is to monitor the environment pollution using image processing technology. We will train the model by given data and test the model with a real time image. Image processing obtains the polluted parts of the image using edge detection and depth estimation technique. With the increasing availability of smartphones, images can be really useful in information representation and description. For these techniques to work efficiently we have to avoid using it for night time images, or images with no sky in it. It detects and quantifies PM (particulate matter) pollution by extracting a combination of image features, including transmission, depth, RGB channel, local image contrast, and image entropy. General observation that we made, the images with high AQI are much misty and bright, and the structural objects are blurred without clear boundaries. We further consider the time, date and weather condition of each photo, to determine the correlation between PM level and various factors. Based on these features, we build a model to predict PM level using photos collected. Output is the real-time PM level with the Air Quality Level Indicator.

2. Hardware and Software Specifications

Laptop/PC with

- Python3 installed
- Internet connectivity
- Python3 Libraries- Tensorflow, Torch, numpy, Matplotlib, Sklearn
- V.S Code for API development
- Kotlin Installed
- Android Studio fox

Android phone with

- Minimum android 7
- Active Internet Connectivity
- Min 8mp Camera
- minimum Snapdragon 435 Processor

2 LITERATURE SURVEY

2.1Existing System

As proposed by X Chen, Yaru Li, D Li [5] the histogram features and edge extraction of the input image can be considered for making a model of back-propagation neural network (BPNN) that can be trained with the collected data comprising of photos and AQI values. While in evaluation stage, the BPNN model takes the feature vector computed from the image as input, and conducts forward computation to produce the AQI prediction.

Here, what was observed is, due to serious diffuse reflection caused by the large number of particles, the images with high AQI are much misty and bright, and the structural objects are blurred without clear boundaries. On the contrary, due to good air quality and light environment, the images with low AQI are much clear and have uniform brightness, and the objects also have clear structures.

Histograms are approximate distribution of data, moreover it is not able to distinguish between fog and high pollution level, the histogram outputs for both of these kinds of images are same.

As proposed by He, K., and Fattal, R. [2,3] the current image based haze level analysis methods are mainly inspired by the dehazing algorithms [2, 3]. The haze image can be modeled as:

$$I(x) = J(x)t(x) + A(1-t(x))$$

The transmission matrix t(x) can be expressed as:

$$t(x) = e^{-\beta d(x)}$$

Transmission matrix t(x) and depth map d(x) are quantities related to haze level hence they are important features for air quality analysis.

Li [3] proposed a method to estimate the haze level using different pooling and transformation functions based on depth and transmission information extracted from haze images.

First, d(x) and t(x) of the haze image are generated by a Deep Convolutional Neural Fields based approach proposed in [4] and a Dark Channel Prior based dehazing algorithm proposed in [2]. Followed by different transformation, bivariate, and pooling functions that are applied on both transmission and depth matrices to estimate haze level in a statistical manner. The performance is evaluated using absolute Spearman correlation coefficients. Although this method performs well with synthetic images, the correlation on a real image dataset with thousands of images is 40.83%.

This method failed in prediction of $PM_{2.5}$ values for locations other than the locations present in the training images, which we intend to change using convolutional neural networks.

2.2 Proposed System

Instead of analyzing weather conditions, the sky region's color and the location of sun during the image taken [2,3], we input RGB color channels [6] of the image to the deep learning network to estimate $PM_{2.5}$ concentration directly, which overcomes the restrictions of having sensors, auxiliary data, fixed location, or sophisticated image features. This also reduces the computational complexity and requires lesser depth information and transmission.

We are using a dataset of 327 images from Beijing city with associated $PM_{2.5}$ data.

The range of $PM_{2.5}$ concentrations is from 2 to 634 and we separated the images into three class: Good (<75), Moderate (75~115), and Severe (>115)

The input to the CNN is the RGB three color channels of an image with size 224×224.

Table 2.1: Literature Review Summary

Year and Citation	Purpose of Study	Intermediate Representation	Granularity Level	Type of vulnerabilities	Data set	Evaluation Parameters
2015 [1]	Estimation of haze level	Considering t(x) as the perceived depth of hazy pictures	Estimate haze level using t(x), d(x), transformation and pooling functions	Not optimal for Particulate Matter 2.5 levels detection	FRIDA (90 synthetic images of 18 urban scenes)	Spearman Correlation Coefficients, no cross-validation methods needed
2016 [5]	Histograms and Edge Detection	RGB to YCbCr Conversion	Ratio between high-brightness pixels to overall image pixels increases as AQI increases	Histogram giving same output for cloudy scenes and high pollution level	SINA Weibo (1 year time lapse of same scene)	Comparison of predicted AQI with the actual Air Quality Index

Year and Citation	Purpose of Study	Intermediate Representation	Granularity Level	Type of vulnerabilities	Data set	Evaluation Parameters
2017 [6]	RGB Channels of image relation with AQI	During the training, the parameters of all fully connected layers are adjusted by the back-propagation algorithm with batch SGD	Feature extraction using random forest classifier, fine tuning the CNN	PM 2.5 levels detection is challenging with shortage of relevant dataset	591 images of Beijing City with associated AQI data	Accuracy, defined as the number of correctly classified images divided by the number of all images.

3 PROBLEM FORMULATION

During the existing image-based haze level analysis methods usually need to use sophisticated algorithms to extract the transmission matrix and the depth map from the single input image for haze level estimation, which not only increases the computation complexity but also requires accurate transmission and depth information. As a simple and explicit end-to-end architecture, the CNN can extract both low-level and high-level image features automatically and greatly simplify image analysis process.

Hardware also plays an important role in the same as low quality images can affect the output of the result.

There are a lot of remote area and cities whose past pollution index is not present which can affect the efficiency of the prediction model.

We live in a society in which everybody has internet access and the processing speed of the task is quite fast but in some area net connectivity is slow or not available, in such area this application can't work as it requires internet connectivity for sending the image and receiving the result from the API. It can also happen the API goes down because of any reason.

So we need a method in which the application should have everything compiled in itself. Next problem is low accuracy in live location. The model uses the live location of the user toimprove the accuracy of the result. It can happen that the GPS in the device does not providethe correct location of the person which can affect the result.

3. RESEARCH OBJECTIVES

The proposed research is aimed to carry out work leading to the development of an approach for the prediction of the air quality level in a specific area. The proposed aim will be achieved by dividing the work into following objectives:

1. Possible external factors that affect the concentration of the pollution and the prediction of AQI.
2. The model performance when noise is present or induced during and after data collection.
3. Feature extraction using different image recognition objectives.
4. The existing learning algorithms used for forecasting the air quality level.
5. To understand the link between air quality and its affects.

4. METHODOLOGY

Generally, feature extraction is a key step for most image recognition algorithms. To imitate the ability of human visual perception, we choose some typical images with different AQI values to observe, as shown in Figure III. Given close observation, we find that the following results. Due to serious diffuse reflection caused by the large number of particles, the images with high AQI are much misty and bright, and the structural objects are blurred without clear boundaries. On the contrary, due to good air quality and light environment, the images with low AQI are much clear and have uniform brightness, and the objects also have clear structures. Therefore, we are inspired to evaluation the AQI based on the proportions of bright pixels and the edge pixels in the whole image.

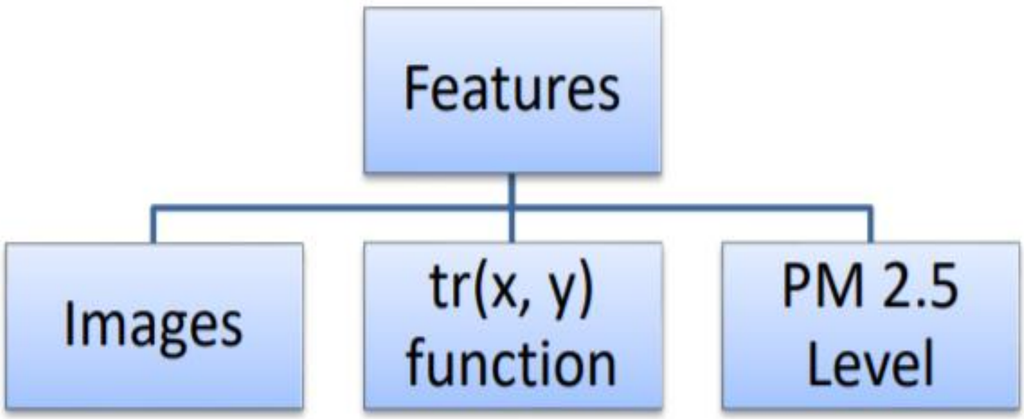


Figure 1: Project overview

• The dataset consists of 327 images of a fixed scene, featuring Beijing Television Tower, captured at almost the same time every morning in 2014.

Figure 2: Dataset

- The transmission function is calculated using above mathematical modeling.

• The last feature consists of PM level used for training and prediction.

We created the dataset using tr (x, y) values for each image captured and respective PM level for each image. As tr(x, y) is a matrix representation so we took the average of it and created a dataset. This dataset consists only of training data from which we trained our regression

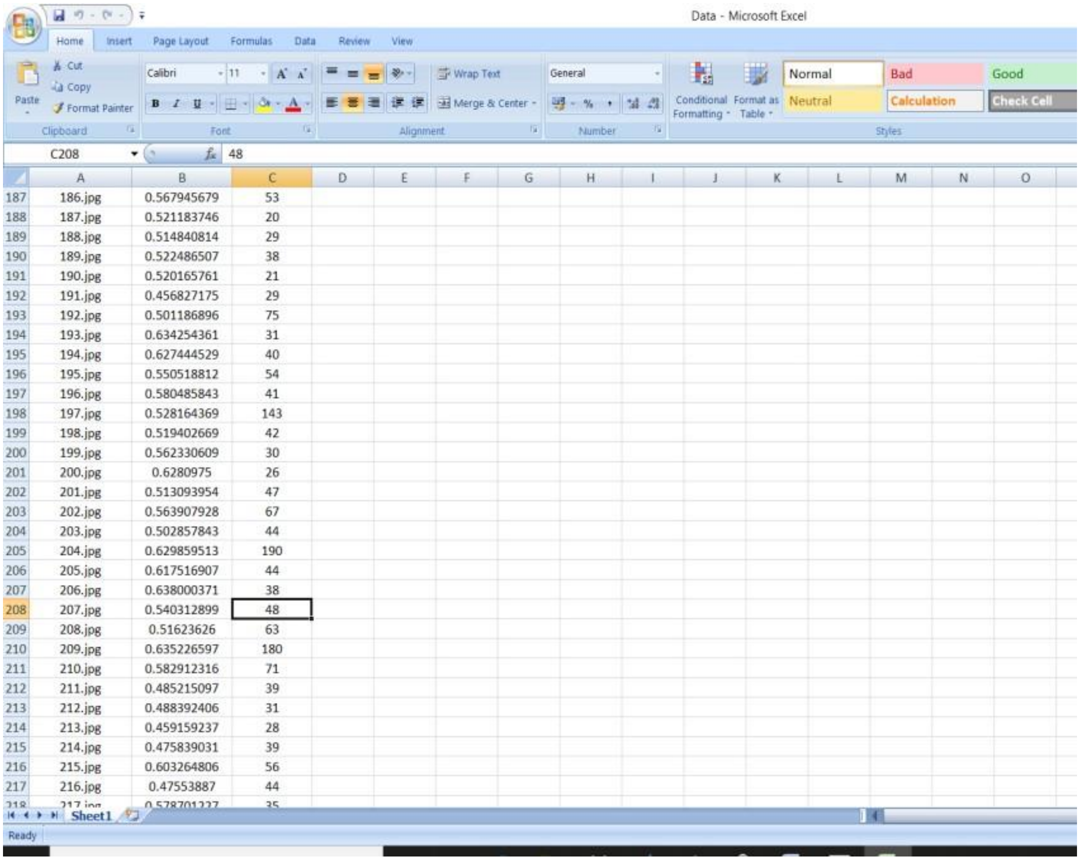
model and used it for prediction of PM level (pollution level) in the images captured at real time.

Our data is a excel file having data in 3 columns: Image tr(x, y) PM conc.

Image	Tr(x,y)	PM Value
1.jpg	0.057981	0.71
2.jpg	0.724369	0.45

Table2: Sample of Dataset

Based on this data we train our model. An application is also created which captures image at real time and predicts its PM level.



	A	B	C
187	186.jpg	0.567945679	53
188	187.jpg	0.521183746	20
189	188.jpg	0.514840814	29
190	189.jpg	0.522486507	38
191	190.jpg	0.520165761	21
192	191.jpg	0.456827175	29
193	192.jpg	0.501186896	75
194	193.jpg	0.634254361	31
195	194.jpg	0.627444529	40
196	195.jpg	0.550518812	54
197	196.jpg	0.580485843	41
198	197.jpg	0.528164369	143
199	198.jpg	0.519402669	42
200	199.jpg	0.562330609	30
201	200.jpg	0.6280975	26
202	201.jpg	0.513093954	47
203	202.jpg	0.563907928	67
204	203.jpg	0.502857843	44
205	204.jpg	0.629859513	190
206	205.jpg	0.617516907	44
207	206.jpg	0.638000371	38
208	207.jpg	0.540312899	48
209	208.jpg	0.51623626	63
210	209.jpg	0.635226597	180
211	210.jpg	0.582912316	71
212	211.jpg	0.485215097	39
213	212.jpg	0.488392406	31
214	213.jpg	0.459159237	28
215	214.jpg	0.475839031	39
216	215.jpg	0.603264806	56
217	216.jpg	0.47553887	44

Figure 3: TR value datset

Here we take:

I = the observed hazy image

Our model is based on the principle equation:

*I (x, y) = J (x, y) * tr (x , y) + A (1 – tr (x, y))* .. (1)

Where,tr (x, y) = Transmission from scene to camera

A = Air light colour vector

J(x, y) = Scene radiance

The first term of eq(1) is the direct transmission of the scene radiance into the camera, which is light reflected by the object surfaces in the scene and attenuated by air before entering the camera. The second term (1-t(x, y))A is called air light, which is the ambient light scattered by air molecules and PM into the camera.

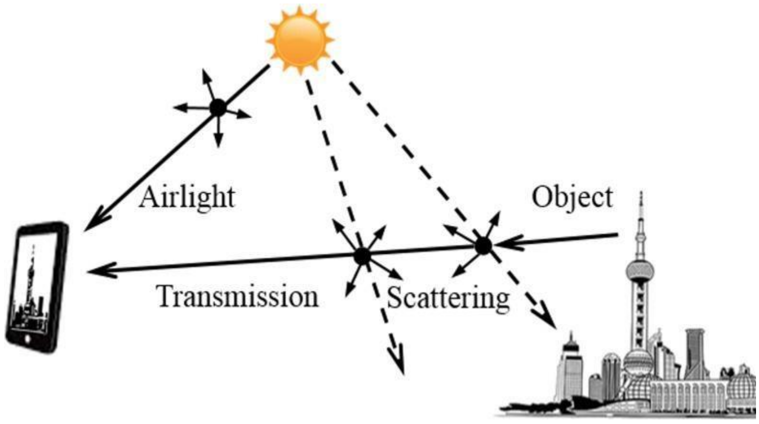


Figure 4: Appearance of real time object into image

Assumptions:

- $\beta=1$ where β=scattering coefficient
- $\min(J(x, y)^c) \simeq \min[J(x , y)^R , J(x, y)^G , J(x, y)^B] \simeq 0$
- A=1

Computations:

- tr (x, y)
- tr (x, y) as X

PM level as Y

- Y = mX + c
- Input Image = X

$I (x, y) = J (x, y) * tr (x , y) + A (1 - tr (x, y))$ ...eq(1)

As our main aim is to calculate tr(x, y) i.e. transmission function of our image pixels, so that we can calculate I(x, y) i.e. pollution level in our image. As value of tr(x, y) goes from 1 to 0, pollution level increases.

Light scattering causes an attenuation of light transmission in air, which can be expressed by the Beer-Lambert law,

tr (x, y) = $e^{-Qd(x,y)}$

(β = scattering coefficient)

(d(x, y) = depth of scene)

Here, if value of β=0 then tr(x, y) = 1. This will make our eq(1) as

*I (x, y) = J (x, y) * 1 + 0*

Hence,

I (x, y) = J (x, y)

Pollution function = function that radiant 0 pollution

Hence, our image has no pollution

But here we take our assumption 1 i.e. β=1:

So our tr(x, y) value becomes,

tr(x, y)= $e^{-d(x,y)}$

As depth of an image is never zero, so,

d(x,y)⟶ ∞

which makes value of tr(x, y) as,

tr(x, y)= 0

This will make our eq(1)

as**I (x, y) = 0 + A (1– 0)**

$$\boxed{\mathbf{I\ (x, y) = A}}$$

Here, A is assumed to be 1 so,

$I(x, y) = 1$

i.e. highly polluted image.

As we all know there are 3 channels of color from which our image is made of i.e. Red, Green, Blue (RGB). So, we take the minimum of the I(x, y) function we calculated of all the 3 colours which together form the RGB channel.

Hence, $min(I(x, y)^c) = min(J(x, y)^c)tr(x, y)+A(1 - tr(x, y))$

c € {RGB}

As min($J(x, y)^c$) is very small so it tends to 0:

$$min(I(x, y)^c) = A - A\ tr(x, y)$$

$$tr(x, y) = \frac{A - \min(I(x, y))}{A}$$

RESULTS AND DISCUSSION

The result of proposed technique will be the prediction of the air quality levels using CNN based method to estimate $PM_{2.5}$. The model will be connected to the android application through API which further can be easily used to predict the air quality using real time smartphone camera.

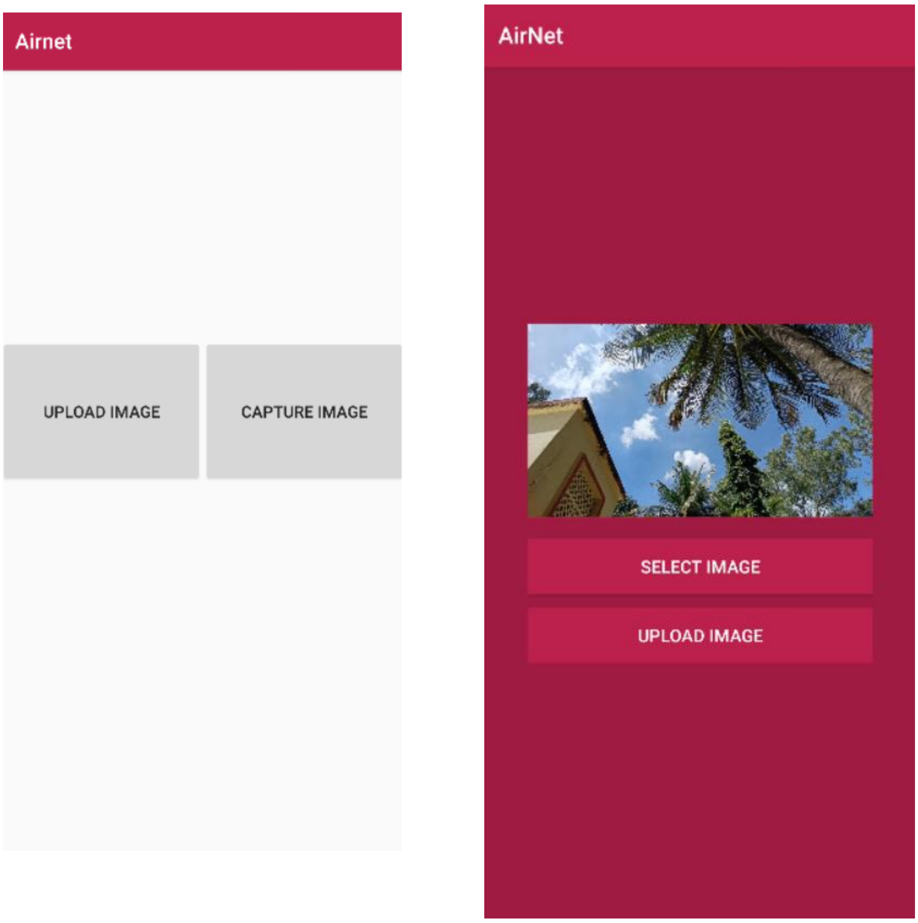


Figure 5: Results

Air Quality Index - Particulate Matter	
301 – 500	Hazardous
201 – 300	Very Unhealthy
151 – 200	Unhealthy
101 – 150	Unhealthy for Sensitive Groups
51 – 100	Moderate
0 – 50	Good

Figure 6: Air quality index table

CHALLENGES

- Quality of the image can affect the output of the model to some extent but most of the error in the low quality image will be corrected using CNN.
- There are a lot of remote area and cities whose past pollution index is not present which can affect the efficiency of the prediction model.
- In some areas net connectivity is slow or not available, in such area this application can't work as it requires internet connectivity for sending the image and receiving the result from the API.
- The sky part should be come in an image otherwise, wrong prediction of PM level will occur.
- Image captured in the dark(night time) also gives poor results.
- Model prepared is limited to location, that is Beijing but can be extended to the other locations too.
- Weather conditions over the area affect the prediction which includes the haziness and other factors.

FUTURE SCOPE

In large cities of India such as Delhi, the concentrations of the pollutants have been rising at an alarming rate. Among different air pollutants particulate matter less than 2.5 micrometer has severe harmful effects on the human body.

They are capable of transmitting chemicals into the human lung causing major respiratory diseases. The crucial first step to solve the problem of airpollution is to enable citizens to gauge the quality of air they breathe.

This could be done by using pollution sensors, but they are expensive and requires a very high cost for their deployment.

So, our goal is to design a reliable and inexpensive air quality solution which could be accessible to everyone with just a smartphone so that people can use it to predict the air quality in their area with zero cost.

4 REFERENCES

[1] Li, Y., Huang, J., & Luo, J. (2015, August). Using user generated online photos to estimate and monitor air pollution in major cities. (p. 79).

[2] He, K., Sun, J., & Tang, X. (2011). Single image haze removal using dark channel. (p. 2)

[3] Fattal, R. (2008). Single image dehazing (p. 3)

[4] Liu, F., Shen, C., & Lin, G. (2015). Deep convolutional neural fields for depth estimation from a single image.

[5] X Chen, Yaru Li & D Li (2016) An efficient method for air quality evaluation via ANN-based image recognition

[6] Avijoy Chakma, Ben Vizena, Tingting Cao, Jerry Lin, Jing Zhang (2017) Image Based Air Quality Analysis using deep learning convolutional network

[7] Elhoseiny, M., Huang, S., & Elgammal, A (2015) Weather classification with deep convolutional neural networks

[8] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional models for semantic segmentation

[9] Nallakaruppan, M. K., and Harun Surej Ilango (2017). "Location Aware Climate Sensing and Real Time Data Analysis."

[10] Li, X., Peng, L., Hu, Y., Shao, J., & Chi, T. (2016). Environmental science and pollution research

[11] D. Eigen, C. Puhrsch, and R. Fergus (2014), “Depth map prediction from a single image using a multi-scale deep network,”

[12] Joans. S. M and Pavithra. M, (2017) Air Pollution Monitoring through Image Processing

[13] C R. A, Deshmukh C. R., D K. N and Vidyavastu P. G (2018) Detection and Prediction of Air pollution using Machine Learning Models

[14] Ayturan Y. A, Ayturan Z. C and Altun H. O (2017) Air Pollution Modeling with Deep Learning: A Review

[15] Prochdxka. A, Kolinovd. M, Fiala. J, Hampl. P and Hlavaty. k (2019), Satellite image processing and air pollution detection