

Determination of PM2.5 from distant views: Across the miles with machine learning

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Abstract. Monitoring of air quality and especially the level of PM 2.5 (particulate matter of size $2.5 \mu m$ or less) is of great importance as it poses a serious health hazard. As monitoring stations are expensive to set up and maintain, image-based approaches have gained popularity on account of their cost-effectiveness and versatility. However, the current image-based approaches usually compute a single PM2.5 level from an input image making an underlying assumption of a constant level of PM2.5 across the entire distance captured by the image. This work proposes a novel approach which, for the first time, attempts to determine the PM2.5 level at different depths or distances from the camera. This is achieved by making a judicious choice of two different Regions of Interest (ROI) from different views captured by the camera. Such an approach is consistent with the physical phenomenon of visibility degradation with distance. Extensive experiments to assess the viability of the proposed approach have been presented with initial results being extremely promising. It may be emphasized in no uncertain times that this work is unique in that it is able to correctly capture the different PM2.5 concentrations at two different locations using a single camera and multiple views. The use of a simple machine learning model makes the approach computationally simple yet able to make accurate predictions.

Keywords: Image · Particulate Matter · Region of Interest.

1 Introduction

The presence of fine, suspended particulate matter in the atmosphere is considered to be a major pollutant apart from oxides of sulphur and nitrogen. The smaller components *viz.* PM2.5, of size less than or equalling $2.5 \mu m$ bypass the filtration system of the nose and penetrate deep into our lungs paving the way for respiratory disorders [1]. In the face of increasing development, which is one of

the major culprits causing such pollution, monitoring the air quality is of prime importance across the world. Sophisticated monitoring stations do the job well but are unfortunately usually located sparsely, only at key locations, due to their prohibitive cost and also logistical issues. Consequently, image-based strategies form an attractive solution and have become an important area of research in recent times.

The phenomenon of haze in the atmosphere caused by the presence of PM_{2.5} and its various aspects have been studied as in [2]. They explored the use of convolutional neural networks to grading haze concentration using satellite images and thereby PM_{2.5}. An ROI based approach was proposed in [3], making use of contrast transmittance and entropy of the image. The use of naturalness statistics models employing entropy features in time and spatial domains was proposed in [4]. Deep learning based approaches have made their way in due course. A Vision Transformer based architecture incorporating a Double Layered LSTM and Multi Head Self Attention in order to harness temporal properties as well as global dependencies was proposed in [5]. An approach especially designed to estimate night-time PM_{2.5} was proposed in [6] making use of a depth mapping technique.

A smartphone image based approach, able to make use of different views and extracting features such as colour and sky patterns for use by a machine learning model was proposed in [7]. The use of Deep Convolutional Neural Networks on smartphone images was explored in [8] for a number of locations around Dhaka, Bangladesh. Use of Convolutional Networks was again applied to satellite images in [9] to estimate PM_{2.5} concentration on the Earth. Some benchmark datasets have been created for research in this area as in [8, 10].

An approach based on the dependence of visibility on the level of PM_{2.5} followed by the quantification of the degradation using the Structural Similarity Index Measure (SSIM) was proposed in [11]. Computation of the SSIM of a selected ROI was performed using a clear reference image obtained from the hazy image by dehazing. Moreover, it made use of 2 ROIs, one close to the camera and one far away. The differential change in the SSIMs was used as an indicator of the PM_{2.5} level – higher the level, more the difference in the SSIMs.

The proposed approach further builds on this by focussing on the fact that though the level of PM_{2.5} remains fairly constant over an area of about 2 km, it does change with distance. Hence, the image captured by a camera would be the result of light travelling through a non-uniform medium and consequently be affected by multiple levels of PM_{2.5}. Alternatively, a nearby ROI would yield information regarding the local level of PM_{2.5}. A distant ROI on the other hand would carry PM_{2.5} information of both the distant area as well as that of the local area.

We consider an area in the northern part of the city of Kolkata, India shown in Figure 1. The site of data acquisition is the terrace of Indian Statistical Institute (ISI), is shown with a green dot. The location of three monitoring stations at Rabindra Bharati University (RBU), Belur and Ghusuri (referred to as Howrah in this work) are marked with red dots and corresponding Air Quality Index

(AQI) values marked to give an idea of the variation in their values. The distance from ISI to RBU is about 2.6 km while Belur and Howrah are about 4 km and 8 km from ISI, respectively.



Fig. 1. Location of the monitoring stations and image acquisition Courtesy:Harsh Bhandari [6]

The variation in PM2.5 among RBU, Belur and Howrah are shown in Figures 2 and 3 during March-April, 2026. As already mentioned, the monitoring station at RBU is closest to ISI. Hence, an image acquired from a camera focussed on this region would correspond to a nearby area while an image acquired from a camera focussed on Belur or Howrah would correspond to a distant region for the present work. The PM2.5 values obtained from the corresponding monitoring stations would be used as the ground truths for training and verification of performance.

The most significant contributions of the present work can be summarized as:

- Establishing the relative contribution of SSIM and other factors such as date and time as well as meteorological ones, towards the prediction model.
- The formulation of two different image based approaches employing machine learning incorporating the effect of distance. The two approaches differ in their modes of integrating this into the framework for PM2.5 determination.
- Exploring the effect of the distance parameter on PM2.5 estimation.

The rest of the paper is structured as follows. Section 2 gives a description of how the data was acquired and lays down the basic tenets of the image-based approach adopted. The proposed algorithms are described in Section 3 while results of the different experiments performed are presented in Section 4. Section 5 highlights interesting inferences and ensuing discussions. The article is concluded in Section 6.

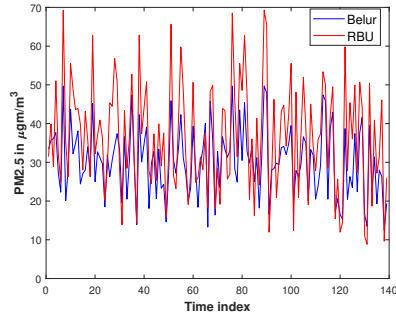


Fig. 2. A comparison of PM2.5 measured at Belur and RBU

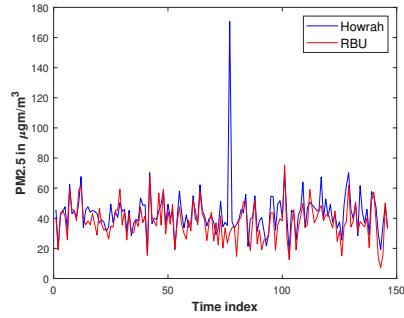


Fig. 3. A comparison of PM2.5 measured at Howrah and RBU

2 The Basic Principles

2.1 Data acquisition

All images were acquired using a Dahua 4 MP 32X Network PTZ camera. The camera was set up so that it continuously captured images corresponding to six different viewing directions over a span of fifteen minutes. Three such views are shown in Figure 4 (RBU - near view), Figure 8 (Belur - distant view) and Figure 9 (Howrah - distant view). The quarter-hourly data for PM2.5 and other pollutants as well as atmospheric parameters are obtained from the website of the Central Pollution Control Board upon selection of the location of the monitoring station. Data curation was a non-trivial task as it sometimes required averaging the PM2.5 values for two successive 15-min slots if the captured views of the distant and nearby views happened to belong to two different (albeit successive) slots. Proper temporal alignment of all the views is crucial to the performance of the proposed algorithms. Besides, data imputation was performed for isolated missing values while extended periods for which data was missing in part or totally, had to be deleted. Though this resulted in loss of data samples and an irregularly spaced dataset, it did not pose a problem as the approach does not follow a time series paradigm where the temporal relationship between the samples is exploited.

2.2 Formulation of the strategy

The basic approach for setting up a regression model for estimating the PM2.5 level from an image adopts a slightly modified version of the procedure laid down in [11] and is briefly outlined here for convenience:

1. Select a suitable Region of Interest (ROI) in the input image which is located close to the monitoring station.
2. Perform dehazing of the input images as in [12] to obtain a reference image set for computing the SSIM of the ROIs.

3. Form a feature set consisting of the SSIMs (of the ROIs) and cyclically encoded date and time information regarding acquisition of the input image.
4. Train the model with the feature set as input and the corresponding PM2.5 values obtained from the nearest monitoring station, as the target output. We use the ExtraTrees Regressor which was reported in [11] to perform the best.

In order to assess the contribution of the features towards the model, an ablation study was carried out using a dataset of 4525 samples acquired during July, 2021–January, 2023, of the view (and ROI) presented in Figure 4. The corresponding dehazed image is presented in Figure 5. It may be noted that short length of the data set (s compared to the time period of acquisition) is entirely due to non-availability of the data from the monitoring station. Further, the inclusion of meteorological variables could not be performed due to very limited availability during this time.



Fig. 4. The ROI in the vicinity of RBU



Fig. 5. The dehazed image

The results of the ablation study are summarized in Table 1.

Table 1. Ablation Study

Input Feature(s)	R^2 ($\uparrow$)	MSE($\downarrow$)	RMSE($\downarrow$)	MAE($\downarrow$)	Mean($\downarrow$)	Standard Dev($\downarrow$)
SSIM+Date&Time	0.93	156.61	12.51	5.85	-0.94	12.49
Date & Time	0.85	327.38	18.09	8.37	-0.95	18.08
SSIM	0.66	764.64	27.65	19.48	-0.6	27.67

Figure 6 shows the prediction performance with all inputs while the corresponding scatter plot is shown alongside. The metrics vindicate the use of both features for the model.

We next consider the focus of the current work - the task of estimating the PM2.5 values of distant views *viz.* that of Belur and Howrah using image datasets acquired by the camera positioned on the terrace of ISI. It may be pointed out that since the camera is programmed to capture six different views in 15 minutes'

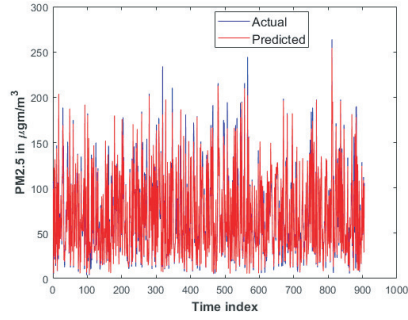


Fig. 6. PM2.5 prediction using SSIM& Date/Time

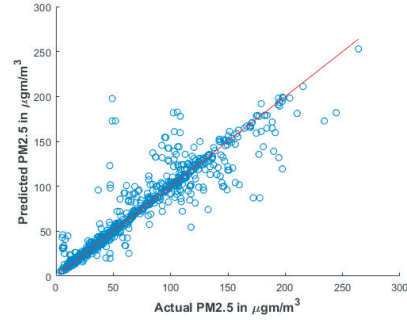


Fig. 7. Scatter plot of PM2.5 prediction using SSIM & Date/Time

time, the time lapsed between two consecutive views of the same location is 15 minutes as well. Figures 8 and 9 show examples of the images captured with ROIs marked.



Fig. 8. The ROI in the vicinity of Belur



Fig. 9. The ROI in the Howrah region

3 Methodology

Two different approaches are considered for the task at hand.

3.1 Algorithm I: A far-near view integrated approach

An outline of the proposed method is presented in Figure 10.

The nearby and distant views are checked for proper time alignment and then subjected to ROI selection. They are then dehazed and respective SSIMs calculated using the selected ROIs. These, along with the cyclically encoded date and time information form the inputs to the regression model. As already mentioned, the ExtraTrees regressor is used.

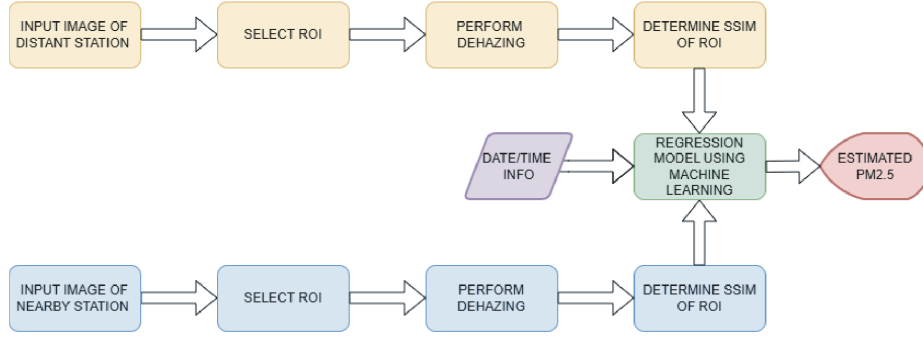


Fig. 10. Block diagram of the far-near view integrated approach

3.2 Algorithm II: A residual prediction based approach

The workflow is illustrated in Figure 11.

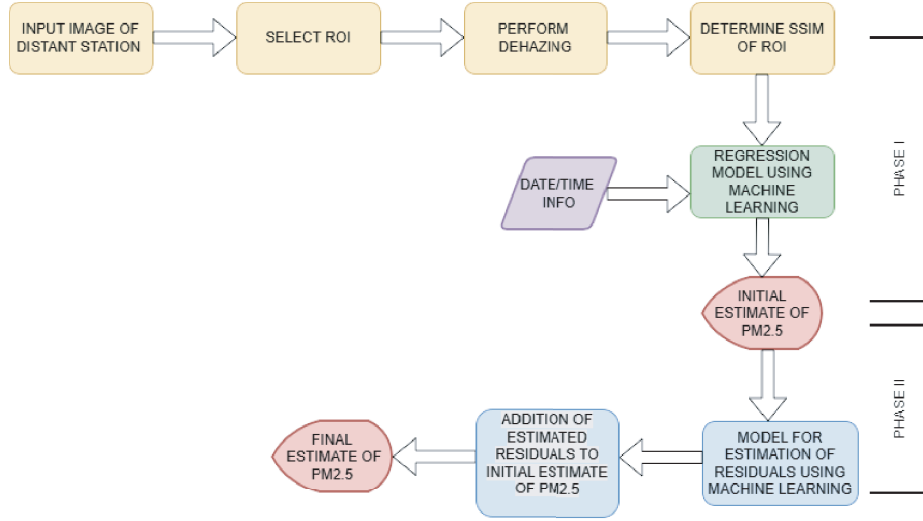


Fig. 11. Block diagram of the Residual prediction based approach

- Phase I: This pipeline takes as input the distant view from which the ROI is extracted and SSIM computed after dehazing the image. The model is trained with ground truth PM2.5 data corresponding to the near view. Its output serves as the initial estimate of PM2.5 which then forms the input to Phase II.

- Phase II: This module performs the task of residual prediction. The model is trained with its target output as the difference between the ground truth PM2.5 data of the distant station and the initial PM2.5 estimate which is termed the residual. The output is the final estimate of PM2.5 for the distant station/view.

4 Results

In order to examine the performance of the proposed algorithms, eight experiments were conducted. In each case, the Date and Time information was provided to the model. For each experiment, the training was conducted on 80% of the input dataset while the rest were used for testing the performance. Since forecasting of PM2.5, which is an objective of time-series data analysis, was not attempted, the data split was not performed chronologically.

All the plots and figures reported, pertain to the test set. The data set consisted of about 2500 samples (exact length depending on the alignment between the stations) collected during March-April, 2026. The experiments performed are described as follows:

1. Algorithm I with images of Belur and RBU as inputs and PM2.5 of Belur as the predicted output. Figure 12 presents the prediction while Figure 13 gives the scatter plot.

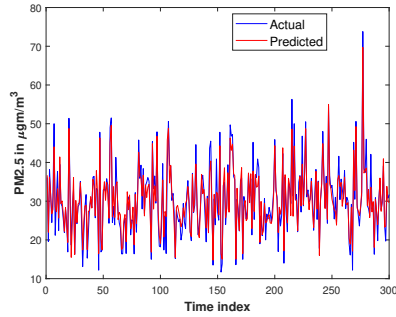


Fig. 12. PM2.5 prediction of Belur with Belur and RBU ROI SSIMs

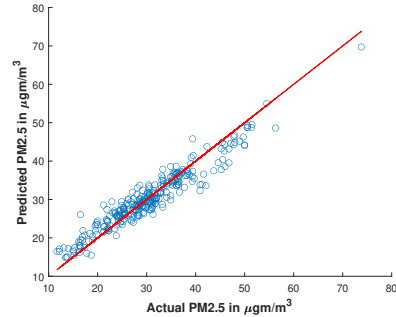


Fig. 13. Scatter plot of PM2.5 prediction of Belur with Belur and RBU ROI SSIMs

The effect of including meteorological variables Relative Humidity (RH), Wind Speed (WS), Air Temperature (AT) was also examined.

2. Algorithm I with images of Howrah and RBU as inputs and PM2.5 of Howrah as the predicted output. Prediction and scatter plots were similar to the above plots and hence not reported.
3. Algorithm II with the image of Belur as the input, PM2.5 of RBU as input of Phase I and PM2.5 of Belur as output of Phase II. Figure 14 shows the initial prediction output of Phase I while Figure 15 shows the scatter plot.

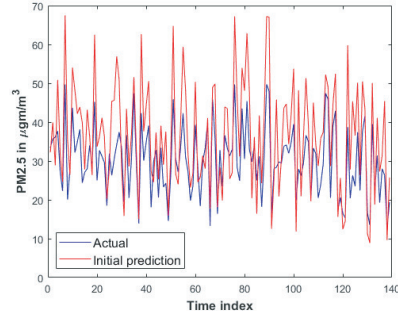


Fig. 14. Initial PM2.5 prediction of Belur

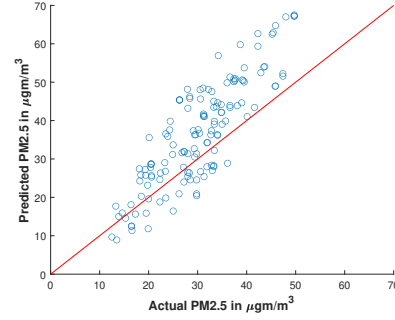


Fig. 15. Scatter plot of initial PM2.5 prediction of Belur

Figure 16 shows the final prediction output for PM2.5 of Belur of Phase II while Figure 17 shows the scatter plot.

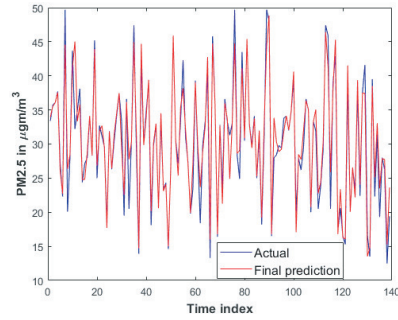


Fig. 16. Final PM2.5 prediction of Belur

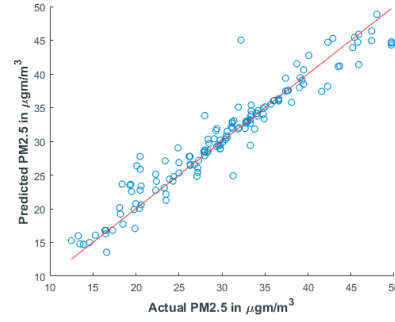


Fig. 17. Scatter plot of final PM2.5 prediction of Belur

It may be observed that the final prediction improves significantly over the initial estimate as evident from the plot of the prediction as well as the scatter plot.

4. Algorithm II with the image of Howrah as the input, PM2.5 of RBU as input of Phase I and PM2.5 of Howrah as output of Phase II. Figure 18 shows the initial prediction output of Phase I while Figure 19 shows the scatter plot. Figure 20 shows the final prediction output for PM2.5 of Howrah of Phase II while Figure 21 shows the scatter plot.

Once again, the final prediction clearly scores over the initial one, as observed from both the sets of plots.

The next 4 experiments can be considered as implementations of Algorithm I but without the additional image input *i.e.* the lower 'arm' of Figure 10.

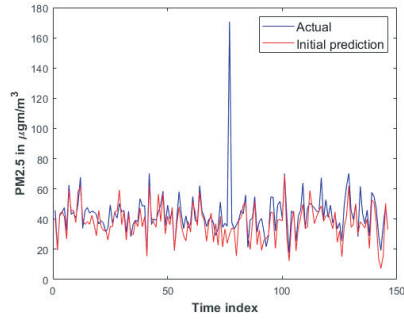


Fig. 18. Initial PM2.5 prediction of Howrah

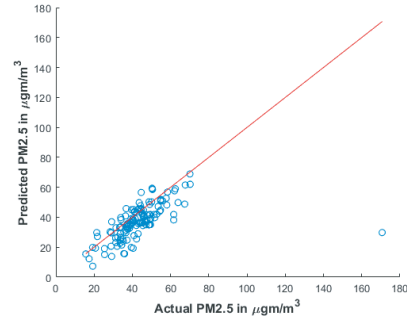


Fig. 19. Scatter plot of initial PM2.5 prediction of Howrah

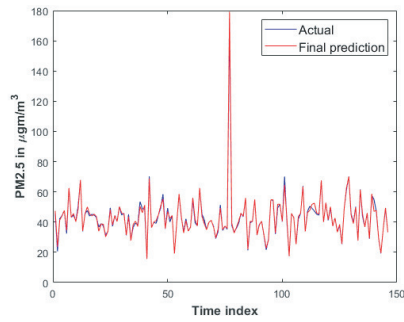


Fig. 20. Final PM2.5 prediction of Howrah

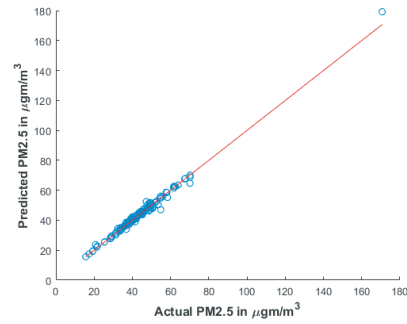


Fig. 21. Scatter plot of final PM2.5 prediction of Howrah

These were carried out to serve as baselines for Algorithms I and II against which their performances can be assessed.

5. Image of Belur as input and PM2.5 of Belur as output

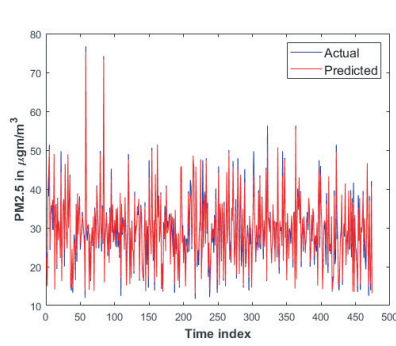


Fig. 22. PM2.5 prediction of Belur

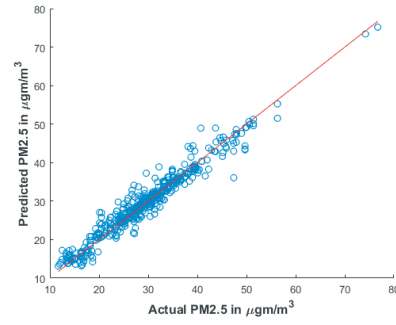


Fig. 23. Scatter plot of final PM2.5 prediction of Belur

6. Image of Belur as input and PM2.5 of RBU as output

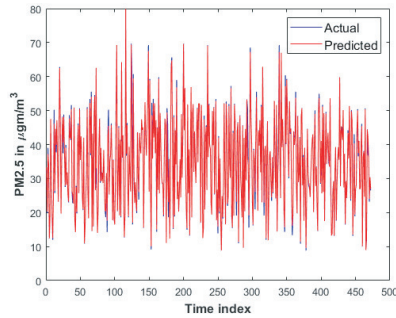


Fig. 24. PM2.5 prediction of RBU with SSIM of Belur ROI as input

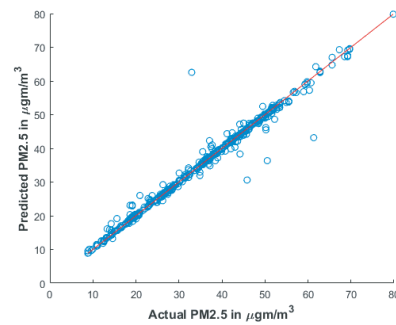


Fig. 25. Scatter plot of PM2.5 prediction of RBU

7. Image of Howrah as input and PM2.5 of Howrah as output

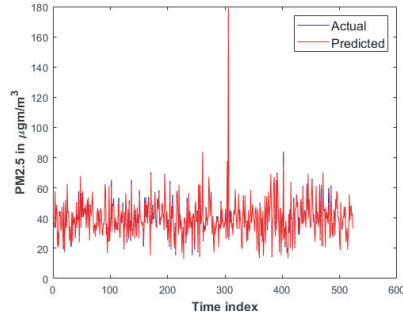


Fig. 26. PM2.5 prediction of Howrah with SSIM of Howrah ROI as input

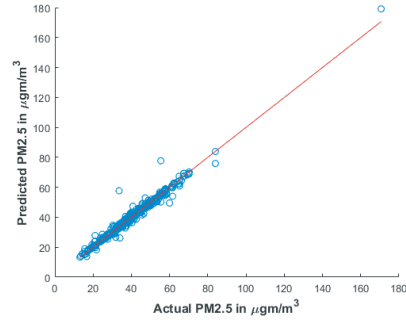


Fig. 27. Scatter plot of PM2.5 prediction of Howrah

8. Image of Howrah as input and PM2.5 of RBU as output

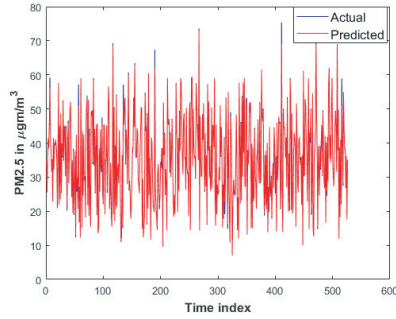


Fig. 28. PM2.5 prediction of RBU with SSIM of Howrah ROI as input

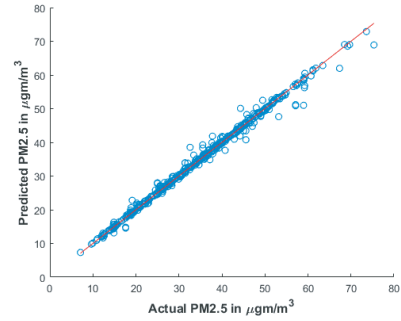


Fig. 29. Scatter plot of PM2.5 prediction of RBU

Figure 24 and Figure 25 exhibit overall better performance than Figure 22 and Figure 23. A similar observation holds for the Figure 28 and Figure 29 as compared to Figure 26 and Figure 27.

The results of the experiments, in the order that they were enumerated, are summarized in Table 2 in terms of standard performance metrics. Sl nos. 1 and 2 are implementations of Algorithm I while Sl nos. 3 and 4 represent implementations of Algorithm II.

5 Inferences and Discussions

Some important inferences drawn based on the outcomes of the experiments, are noted below:

1. Estimating PM2.5 with *only* a distant image, gives results close to the local PM2.5 value. The metrics corresponding to Experiment 6 (using Belur ROI and RBU PM2.5 for training) and Experiment 8 (using Howrah ROI and RBU PM2.5 for training) corroborate this observation. This indicates that the local PM2.5 is likely to cause more degradation than the PM2.5 level closer to the distant image.
2. The inclusion of Relative Humidity as an additional input led to an improvement in PM2.5 prediction of Howrah (Serial no.2 of Table 2) while it did not have an appreciable effect on the prediction of PM2.5 of Belur (Serial No.1). These findings need to be further validated on longer datasets.
3. Performances of Algorithm I and II are comparable, taking into account the two separate cases i.e. comparing Serial numbers 1 and 3 of Table 2 or Serial numbers 2 and 4.
4. The prediction plots indicate 'misses' when there are sharp changes in the PM2.5 levels. Capturing data over at least one year and ideally several years, is expected to enhance performance.

The train-test split in all the experiments reported has not been done chronologically. In a time-series forecasting problem this would inevitably lead to data leakage. For the problem at hand, the model has the task of building a relationship between the image features and the target PM2.5. In order for the model to perform well for an "unseen" period or "day held out" period, it is imperative for it to have adequate exposure during training to all seasons for at least over a year. This was verified by running some of the experiments using a chronological split of the data including a day-held out setting - the models failed badly.

6 Conclusion and Scope for Future Work

Two machine learning based strategies were proposed for estimating the level of PM 2.5 from views of distant scenes. Preliminary results indicate these to be very promising with comparable performances. The initial results firmly establish that the PM 2.5 levels of both the distant and near locations need to be factored into the estimation procedure. The designs are computationally simple and fast thus making them suitable for eventual deployment in smartphones. However, datasets covering at least an entire year need to be acquired. This would make it possible to undertake more rigorous and exhaustive testing including testing over unseen periods.

Data collection for images captured on a mobile phone is ongoing. Necessary adaptation and calibration issues are being investigated. The use of deep learning techniques, especially the use of vision transformers are being explored to further improve the performance. Further extension of the approaches for more than two different views at different distances from the camera are also planned to be undertaken.

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Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

Code and Data Availability All code and data will be made available upon reasonable request at palitsarbani@gmail.com.

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Table 2. Performance Metrics

Sl. No.	Setup	R^2 ↑	MSE ↓	RMSE ↓	MAE ↓	Mean error ↓	Std. Dev ↓
1.	ALG.I , <i>Input</i> : SSIM of Belur ROI <i>Input</i> : SSIM of RBU ROI <i>Output</i> : PM2.5 of Belur	0.93	5.89	2.43	1.75	0.09	2.43
	with addl. input RH	0.93	5.42	2.33	1.68	0.07	2.33
	with addl.input RH+WS	0.93	5.64	2.37	1.72	0.07	2.38
	with addl.input RH+WS+AT	0.92	6.18	2.48	1.77	0.07	2.49
2.	ALG.I , <i>Input</i> : SSIM of Howrah ROI <i>Input</i> : SSIM of RBU ROI <i>Output</i> : PM2.5 of Howrah	0.95	14.36	3.79	1.575	0.31	3.78
	with addl. input RH	0.97	10.15	3.19	1.63	0.21	3.18
3.	ALG.II , <i>PhaseI</i> : <i>Input</i> : SSIM of Belur ROI <i>Output</i> : PM2.5 of RBU <i>PhaseII</i> : <i>Input</i> : Estimated PM2.5 of RBU <i>Output</i> : PM2.5 of Belur	0.92	5.92	2.43	1.55	0.37	2.41
4.	ALG.II , <i>PhaseI</i> : <i>Input</i> : SSIM of Howrah ROI <i>Output</i> : PM2.5 of RBU <i>PhaseII</i> : <i>Input</i> : Estimated PM2.5 of RBU <i>Output</i> : PM2.5 of Howrah	0.98	2.48	1.57	0.92	-0.12	1.57
5.	<i>Input</i> : SSIM of Belur ROI <i>Output</i> : PM2.5 of Belur	0.94	4.52	2.12	1.46	-0.16	2.12
6.	<i>Input</i> : SSIM of Belur ROI <i>Output</i> : PM2.5 of RBU	0.97	4.54	2.13	0.70	0.02	2.13
7.	<i>Input</i> : SSIM of Howrah ROI <i>Output</i> : PM2.5 of Howrah	0.97	4.57	2.13	0.97	0.01	2.14
8.	<i>Input</i> : SSIM of Howrah ROI <i>Output</i> : PM2.5 of RBU	0.99	1.18	1.09	0.51	0.0	1.09