Evaluate and Predict Concentration of Particulate Matter (PM10) Using Machine Learning Approach

http://dx.doi.org/10.9728/jcc.2019.12.1.1.11

Evaluate and Predict Concentration of Particulate Matter (PM10) Using Machine Learning Approach

M. F. Mridha[1], Md. Abdul Hamid[2], Shaon Hossain Sani[2], Akramkhan Rony[2], Seungmin Oh[3], Jinsul Kim[3]

[1]Department of CSE, Bangladesh University of Business & Technology, Dhaka, Bangladesh

froz@bubt.edu.bd[1]

[2]Department of Computer science, University of Asia Pacific, Dhaka, Bangladesh

{ahamid, akrakhanrony1997, akram}@gmail.com[2]

[3]School of Electronics and Computer Engineering, Chonnam National University, Gwangju, South Korea

osm5252kr@gmail.com, jsworld@jnu.ac.kr[3]

Abstract. Particulate matter (PM10) is a general term used for a mixture of solid particles and liquid droplets. PM10 is the most significant air pollutant associated with diseases and death compared to other measured criteria pollutants. In this paper, we have focused on PM10 concentration at Dhaka city in Bangladesh. With the help of our proposed predictive model to predict hourly criteria air pollutant concentrations. The ambient air quality data were collected from October 2016 to March 2019. We have used Artificial Neural Network (ANN) to fill the missing value of our Dataset. And we have used Ensemble model (StackNet) to predict PM10. The average correlation coefficient (R) and root-mean square error (RMSE) values when comparing predictions and measurements were 0.94 and 26.14, respectively.

Keywords: Particulate matter (PM10), ANN, StackNet

1 Introduction

Air pollution is one of the most worrying issues for Dhaka City in Bangladesh. Day by day Bangladesh is having developed rapidly. Because of developing mills,

---

Received 05 June
Revised 15 October 2019
Accepted 20 November 2019
***Corresponding Author;** M. F. Mridha
Tel: ※ 개인정보 표시제한
E-mail: froz@bubt.edu.bd

factories, industries, brick kilns, diesel generators are increasing gradually. In addition, the number of motor vehicles increased significantly in Dhaka, there has been a steep rise in a heterogeneous mixture of old technology vehicles despite that the road space is narrowing and the traffic congestion is reaching in unmanageable proportions. The main contributors of air pollution are motor vehicles, brick kilns, diesel generators and industries. It has become one of the most tackled issues for every citizen living in Dhaka city. In recent years much research interest has been shown on atmospheric particles as they influence on climate change and cause adverse health effects. Although importance of particulate matter in atmospheric and environmental process is pronounced, our knowledge, especially in Dhaka City, on their concentration and sources are inadequate. Bilkis et al. have studied the source identification of particulate matter during winter months in Dhaka city and at urban and semi-urban areas in Bangladesh by positive matrix factorization. They found the contribution from elemental carbon fraction at Farmgate which in comparison to Aminbazar is less. Because, at Farmgate, only the city vehicles ply on road and during the day time mostly 80 percent of the vehicles are of duel-fueled engine. Particle sources (from coal and biomass burning in brick field) impacts may be contributing haze at urban and semi-urban areas of Bangladesh. A numerical value of Air Quality Index (AQI) between 151 to 200 indicates that everyone may begin experience health effects and air is regarded as ”Unhealthy”. Members of sensitive groups said that, it’s may experience more serious health effects. AQI between 201 to 300 is classified as “very unhealthy”, if the score is between 301 to 500, then it is classified as “Extremely Unhealthy”. Dhaka is one of the most densely-populated cities in the world, it has been struggling with air pollution for a long time. Moreover, Dhaka continuously ranks in the world’s most polluted cities.

According to Air Visual, the air quality at Dhaka is too much “Very Unhealthy”. And It’s ranked top among all other cities in the world. Particulate matters are released directly into an atmosphere from sources such as cars, trucks, heavy equipment, forest fires, and other burning activities like burning wastes, wood stoves, wood-fired boilers. Primary particles also consist of crustal material from sources such as unpaved roads, stone crushing, construction sites, and metallurgical operations. But the major sources of air pollution are transportation engines, power and heat-generation, industrial processing and burning of solid waste. Air quality further declines during the dry months- from October to April- but improves during the monsoon because fine particles have seasonal patterns with impact most of the case for the concentration of Particulate matter. Particulate matter has two variety one PM10 and another PM2.5. Basically, PM10 consists of fine particles with aerodynamic diameters less than or equal to 10 µm. An extensive body of scientific evidence shows that short or long-term exposures to tiny particles can cause adverse cardiovascular effects, including heart attacks and strokes resulting in hospitalizations and in some cases premature death also. Recently, the number of air pollutants related disease patients increase dramatically because of detrimental air quality. In our proposed Machine learning approach we specially used an Ensemble model (Stacknet) that are based on GradientBoostingRegressor, ExtraTreesRegressor, MLPRegressor. Our proposed Machine learning Regression models work with some important air pollutants (SO2, NOx, CO, O3, PM10) and meteorological values (Solar Rad, BP, Rain, Temperature, Humidity) to predict Particulate matter(PM2.5). With the help of predicted values, we may evaluate our model that how much it learn from data accurately. Though our dataset has lots of missing values and it's quite impossible to predict accurately without doing some smart works on dataset. We use Artificial Neural Networks to fill missing values and probably it works better than any traditional methods.

The rest of the paper is organized as follows. In Section 2, we discuss some works related to the proposal in this paper. We present the Data Processing Analysis in section 3. Then in Section 4, we present the Methodology of this paper. In Section 5, we present the result analysis. Finally, in Section 6, we conclude our paper. This paper proposed a machine learning technique for analyzing air pollutant PM(10).

2 Related work

After many studies about PM10, We found some related paper that contains harmony to our propose methodology. But somehow, we are not satisfied with those methodology. Some related works use Machine learning classification algorithm to classify the pollutants class. Some are trying to reach very complicated approach that are totally un- usual to such kind of problems. In [2] this paper Bilkis, A.Begum analyzes the data over 15 years and observe the effects of PM10, Black carbon (Bc) and Lead(Pb). And she had an observation from this paper is, over long-term air quality of Dhaka has eventually stabled though industries like economical platform establish rapidly and passenger cars and brick kilns are increasing. [3] In this paper, they worked for collecting air quality data specially PM2.5, PM10, Black carbon to analyze and compare which area is most polluted in Pabna city located in Bangladesh, what are the main cause of high concentration of Particulate matter with their method Counter "repeat mode". [4] PM10 is the main issues, Data are sampled over 10 years for predicting PM10 factor in New Zealand. Multivariate Linear Regression (MLR), Artificial Neural Networks, and also varies alternating approach of Classification and Regression trees. [5]" Dixian Zhu" forecast PM2.5, Ozone, sulfur using several types of Regularization techniques like standard "Frobenius norm regularization", "Nuclear norm regularization", and l2,1 norm regularization. Their experiment showed that there proposed parameter-reduced formulations and consecutive-hour-related regularization achieve better performance than existing standard regression models and existing regularization. [6] "Heidar Malek" have used an artificial neural network (ANN) algorithm to predict air pollutant concentrations, air quality index (AQI) and air quality health index (AQHI), for Ahvaz, Iran. And they have obtained the correlation coefficient (R) and root-mean square error (RMSE) values when comparing predictions and measurements were 0.87 and 0.59.

3 Data processing and analysis

3.1 Data source

In Dhaka city, there are 3 stations for Measuring and collecting Air quality data on an hourly basis. Bangladesh government takes action for resolving air pollution and strictly monitor air quality. So, that purpose the Ministry of Environment Forests proposed a Project named Clean Air Sustainable Environment (CASE). Basically, we have collected data over 2.5 Years from October 2016 to March 2019 of 2 stations only. The Shangshad Bhaban and the Bangladesh Agricultural Research Council (BARC) are almost in same the location within 1km. So, we take only one station data which is BARC because BARC is located in Farmgate which have been concerned for the most polluted area in Dhaka city. Few surveys conducted between January 1990 and December1999 showed that the concentration of suspended particles goes up to as high as 3000 µgrams per cubic meter (Police Box, Farmgate, December 1999), although the allowable limit was 4000 µ per cubic meter. The Sulphur dioxide in the air near Farmgate as found to be 385 µgrams per cubic meter, whereas the maximum permissible limit is 1000 µgrams per cubic meter. All of those have happened because Tejgaon Industrial area brought the maximum concentration of Sulphur dioxide and Particulate matter. Another Station is Darussalam, Dhaka which is located at near Gabtoli, Dhaka. Near Darussalam within 5km, there are lots of Bricks kilns, Industries, one of the busiest Bus Station located, and most the other side of Darussalam there are so many Garments Factories located. So we clearly noticed that both stations have a strong correlation with air pollution and pollutants.

3.1.1 Analyze Data set and Missing Data

After a deep observation of the dataset, we have found that there are lots of missing values among both of the dataset. So, we have to use the right technique to filling the missing values for getting better results and prediction. Because if we rigorously understand every key feature of data set then we easily do the rest of the part through that level of understanding.

Both BARC and Darussalam data sets show that One value missing or Series of values are missing. So we proposed a technique that is, we split Date into Year, Month, Week, Day. And then we have used interpolation method for Temperature, Humidity, Solar Radiate, Barometric pressure columns because of those value are always maintaining an upward or downward trend. So if any value is missing, then interpolation method can guess data between them.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Date	Time	SO2	NO	NO2	NOX	CO	O3	PM25	PM10	Temperature	RH	Solar Rad	BP	Rain
2	2016-10-01	1	3.98					0.8		55.13	26.59	84.03			1.2
3	2016-10-01	2	2.83					1.23		34.41	26.61	86.57			2.3
4	2016-10-01	3	1.79					0.95		19.04	27.15	88.1			1.61
5	2016-10-01	4	0.83					0.78		12.59	27.05	89.71			
6	2016-10-01	5	0.36					0.92		9.2	26.45	91.11			1.44
7	2016-10-01	6	0.11					0.62		13.42	26.51	87.56			1.97
8	2016-10-01	7						0.63		19.85	26.61	88.33			1.35
9	2016-10-01	8	3.41					0.72		17.52	26.54	91.88			0.75
10	2016-10-01	9	6.27					1.02		34.47	27.16	88.68			1.68
11	2016-10-01	10	5.02					0.55		74.13	26.67	85.05			0.84
12	2016-10-01	11	7.5					1.88		114.12	26.74	76.43			0.32
13	2016-10-01	12	3.05					0.95		141.83	26.72	65.41			1.02
14	2016-10-01	13	0.52				0.34	1.24		145.12	26.47	64.32			1.5
15	2016-10-01	14	0.13				0.94	1.4		122.42	26.45	65.05			
16	2016-10-01	15	0.44				0.82	1.27		117.16	26.98	72.67			1.2
17	2016-10-01	16	1.09				0.6	0.82		108.26	26.4	72.05			2.46
18	2016-10-01	17	2.02				1.1	0.66		84.82	26.63	67.01			0.67
19	2016-10-01	18	1.81				1.32	0.8		81.2	26.49	66.62			1.02
20	2016-10-01	19	3.28				1.23	1.07		93.71	26.62	69.56			1.22
21	2016-10-01	20	4.49				1.92	0.98		94.78	26.59	72.45			0.29
22	2016-10-01	21	7.89				3.24	0.62		107.69	26.4	73.67			1.2
23	2016-10-01	22	14.51				3.84	0.92		127.53	26.57	73.51			
24	2016-10-01	23	20.8				1.1	0.86		106.95	26.57	77.38			1.46
25	2016-10-01	0	7.33				0.25	1.1		78.96	26.59	86.48			0.64
26	2016-10-02	1	0.45				0.09	0.45		58.87	26.35	90.07			2.66
27	2016-10-02	2					0.1	0.74		41.82	26.45	92.38			1.16
28	2016-10-02	3						0.97		39.88	26.64	94.98			1.41

Fig. 1 BARC Dataset (Farmgate, Dhaka)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Date	Time	SO2	NO	NO2	NOX	CO	O3	PM25	PM10	Temperature	RH	Solar Rad	BP	Rain
2	2016-10-01	1	0.57	13.84	9.22	23.06	1.76	1.12		124.34	29.48	80.56	7.99	1006.15	
3	2016-10-01	2	0.29	17.45	11.89	29.34	1.67	1.03		69.42	29.01	82.86	8.06	1006.05	
4	2016-10-01	3	0.07	12.93	6.2	19.13	1.6	1.13		83.36	28.84	83.68	8.19	1006.01	0.02
5	2016-10-01	4	0.08	9.69	0.92	10.61	1.54	1.05		60.51	28.75	84.18	8.18	1006.14	
6	2016-10-01	5	0.07			1.97	1.48	0.99		43.51	28.53	85.12	8.2	1006.36	
7	2016-10-01	6	1.08				1.44	1.2		26.87	27.98	83.48	8.35	1006.71	
8	2016-10-01	7	0.2		2.09		1.66	1.24		23.5	27.01	82.81	13.69	1007.36	0.08
9	2016-10-01	8	0.12		3.23	2.62	2.05	0.97		41.22	26.87	85.8	48.36	1007.73	
10	2016-10-01	9	0.27	39.83	10.66	50.49	2.33	1.09		49.47	28.33	83.92	211.88	1008.16	
11	2016-10-01	10	0.28	36.28	20.22	56.51	2.07	1.1		66.98	30.46	76.01	550.7	1008.35	
12	2016-10-01	11	0.33	46.5	30.39	76.89	2.2	0.82		101.93	31.19	71.77	459.63	1008.26	
13	2016-10-01	12		24.95	46.87	71.82	1.91	1.54		183.43	32.32	65.36	758.1	1007.83	
14	2016-10-01	13		13.4	52.31	65.7	1.73	1.61		157.72	32.91	62.56	522.61	1006.78	
15	2016-10-01	14	0.11	38.27	49.8	88.07	1.81	0.9		115.92	31.74	68.13	151.19	1005.8	0.02
16	2016-10-01	15	0.34	18.06	30.54	48.6	1.79	1.62		148.36	29.9	74.41	68.21	1005.17	0.02
17	2016-10-01	16	0.7	22.11	21.19	43.3	1.87	1.25		162.42	29.47	72.87	79.13	1004.81	
18	2016-10-01	17	0.96	28.06	20.64	48.7	1.99	1.22		210.87	30.31	70.26	76.61	1004.59	
19	2016-10-01	18	1.29	42.79	22.71	65.5	2.28	0.91		242.56	30.63	69.72	31.46	1004.99	
20	2016-10-01	19	1.14	86.99	20.98	107.96	2.68	0.91		328.14	30.28	72.06	7.95	1005.9	
21	2016-10-01	20	3.09	118.69	22.27	140.96	3.27	1.18		168.67	30.1	74.34	8.24	1006.92	
22	2016-10-01	21	3.39	89.24	20.04	109.28	3.6	1.26		257.17	30.26	74.23	8.04	1007.67	
23	2016-10-01	22	3.75	190.42	21.88	212.31	4.3	1.24		232.92	30.32	75.2	8.43	1008.04	
24	2016-10-01	23	1.19	85.29	16.72	102.02	2.98	1.19		400.6	30.15	76.16	8.19	1008.28	0.02
25	2016-10-01	0	0.42	34.82	9.01	43.83	2.11	1.08		256.81	29.23	82.45	8.07	1008.54	
26	2016-10-02	1	0.35	35.26	6.61	41.87	1.91	1.02		163.81	28.74	85.87	8.16	1008.24	
27	2016-10-02	2	0.57	27.74	4.53	32.27	1.89	1.09		124.74	28.56	87.28	7.97	1008.29	

Fig. 2 Darussalam Dataset (Darussalam, Dhaka)

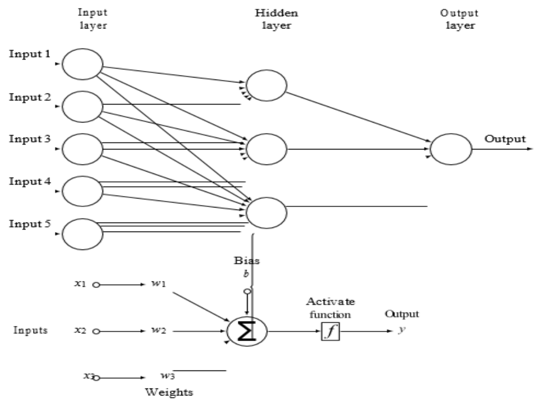


Fig. 3 Artificial Neural Networks

After that, we have used Artificial Neural Networks for predicting PM10 with respect to Year, Month, Week, Day, Hour, Temperature, Humidity, Barometric pressure, Solar Radiate, and guess the missing value and filled those. For predicting PM10 with respect to Year, Month, Week, Day, Hour, Temperature, Humidity, Barometric pressure, Solar radiate, PM2.5 and guess the missing value and filled those. Then for predicting O3 and CO, we have comprised Year, Month, Week, Day, Hour, Temperature, Humidity, Barometric pressure, Solar Radiate and fill their missing values. After that to fill the missing value of NOx, we have comprised Year, Month, Week, Day, Hour, Temperature, Humidity, Barometric pressure, Solar radiate, O3 and fill their missing values. Finally we have used Year, Month, Week, Day, Hour, Temperature, Humidity, Barometric pressure, Solar radiate, PM2.5, PM10, CO, NOx, O3 for filling the missing values of SO2 with the help of Artificial Neural networks model. We select different input parameter based on relation between data.

Table 1. ANN model input parameter for missing values prediction

Input Params for PM_{10}	Input Params for $PM_{2.5}$	Input Params for O_3	Input Params for CO	Input Params for NO_x	Input Param for SO_2
Date	Date	Date	Date	Date	Date
Month	Mont	Month	Mont	Month	Mont
Week	Week	Week	Week	Week	Week
Day	Day	Day	Day	Day	Day
Time	Time	Time	Time	Time	Time
Temp	Temp	Temp	Temp	Temp	Temp
Hum	Hum	Hum	Hum	Hum	Hum
BP	BP	BP	BP	BP	BP
Solar Rad	Solar Rad	Solar Rad	Solar Rad	Solar Rad	Solar Rad
–	PM_{10}	–	–	NO_x	PM_{10}
–	–	–	–	–	$PM_{2.5}$
–	–	–	–	–	CO
–	–	–	–	–	NO_x
–	–	–	–	–	O_3

3.1.2 Visualizing PM 10 Concentration over Time

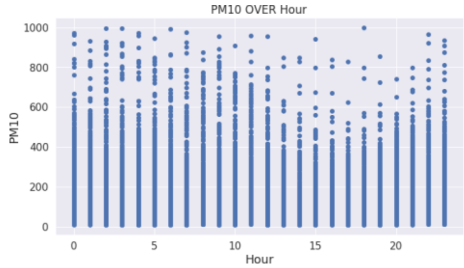


Fig. 4 PM10 Concentration on different Hour of a day shows variation over Time (BARC Dataset)

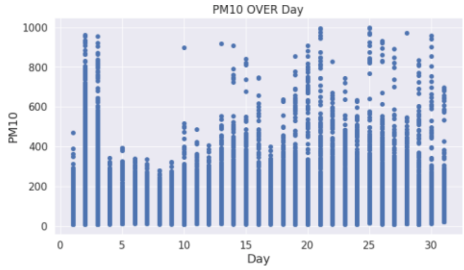
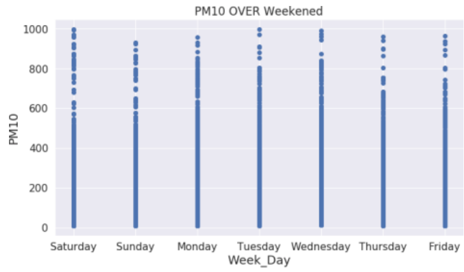


Fig. 5 PM10 Concentration on different Day of a Month shows variation over Day (BARC Dataset)

Fig. 6 PM10 Concentration on different Week Day of a Week shows variation over Week



Day (BARC Dataset)

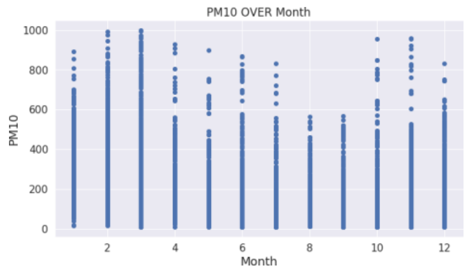


Fig.7 PM10 Concentration on different month of a year shows variation over month (BARC Dataset)

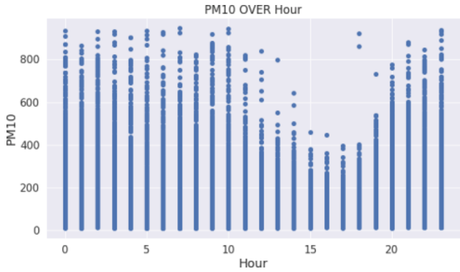


Fig. 8 PM10 Concentration on different Hour of a day shows variation over Time (Darussalam Dataset)

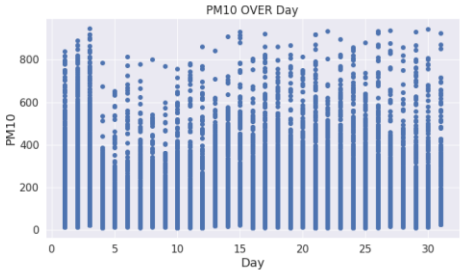


Fig. 9 PM10 Concentration on different day of a month shows variation over Day (Darussalam Dataset)

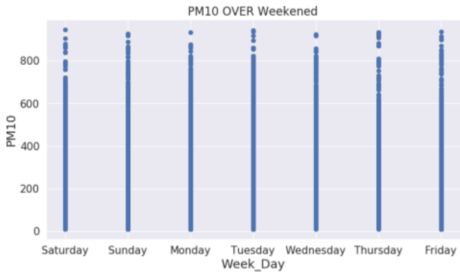


Fig. 10 PM10 Concentration on different day of a week shows variation over week (Darussalam Dataset).

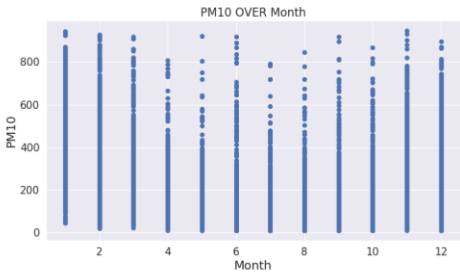


Fig. 11 PM10 Concentration on different month of a year shows variation over month (Darussalam Dataset)

After Visualization of both BARC Darussalam Dataset, We have noticed that there are many variation over month, week, hour basis PM10 Concentration.

4 Methodology

StackNet[13] is a computational, scalable and analytical framework implemented with a software implementation in Java that resembles a feedforward neural network and uses Wolpert's stacked generalization in multiple levels to improve accuracy in machine learning problems. In contrast to feedforward neural networks, rather than being trained through back propagation, the network is built iteratively one layer at a time (using stacked generalization), each of which uses the final target as its target.

1. Stacknet Design
2. Flow Chart

In this paper, we especially focused on GradientBoostingRegressor,ExtraTreesRegressor, RandomForestRegressor and Bayesian Ridge. With the help of Root Mean Squared Error RMSE we evaluate our proposed model.

4.1 Stacknet Design

There are two different forms of StackNet: one is every layer outright uses the predictions from only one previous layer, and another is every layer uses the predictions from all previous layers including the input layer that is regarded as restacking. StackNet is ordinarily better than the best single model which is contained in every first layer. However, its ability to perform well still count on a mix of robust and various single models for the purpose of getting the best out of this meta-modelling methodology. We design the StackNet architecture for our problem based on the following concepts : (a) including more models which have similar prediction performance, (b) having a linear model in each layer (c) placing models with better performance on a higher layer, and (d) increasing the diversity in each layer. The resulting StackNet, shown in Fig. 11, consists of three layers and 4 models. These models include Bayesian ridge regressor, random forest regressors, extra-trees regressors, gradient boosting regressor and ridge regressor. The first layer has one linear regressor and three ensemble-based regressors, the second layer contains one linear regressor and two ensemble-based regressors, and the third layer only has one linear regressor. Each layer uses the predictions from all previous layers including the input layer.

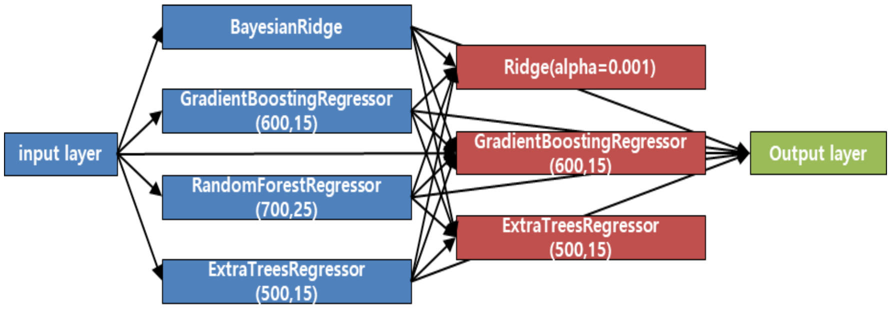


Fig. 12 StackNet framework architecture for the ensemble-based regressor, the number of trees and the maximum depth of each tree which are indicated in the first and second number, respectively

4.2 Flow chart

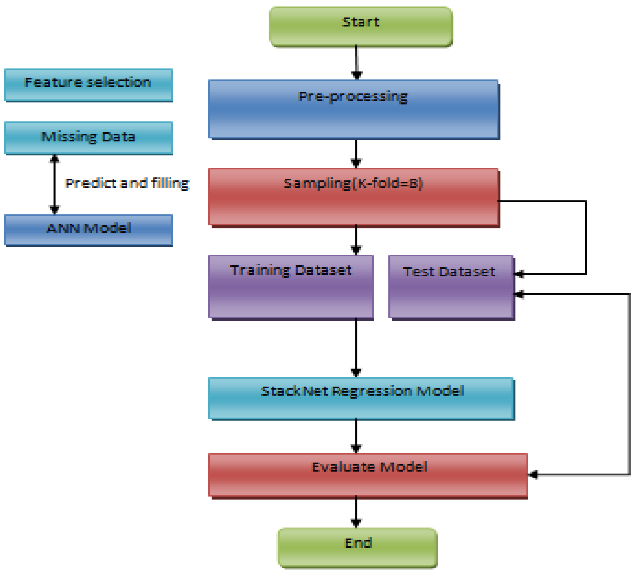


Fig.13 Flowchart of Whole process for predicting PM10

Here we draw our overall working procedure that graphically describes how our propose model work. First of all, we process our raw dataset with feature selection and missing values filling. For filling the missing values, we have applied Artificial Neural networks. After that, We split our preprocessed dataset into 8- folds for the k-fold cross-validation. Then fit every training data and evaluate every test data with our proposed method.

5 Result Analysis

Fig.14 Scatter plot of Test data and Predicted data for PM10 (Darussalam Dataset)

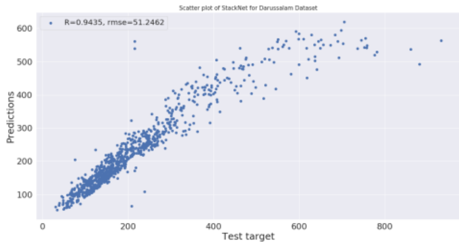
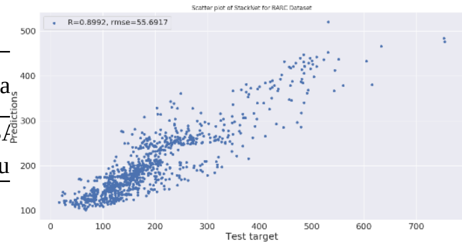


Fig. 15 Scatter plot of Test data and Predicted data for PM10 (BARC Dataset)



Da	RMSE
B	55.6917
Daru	51.2462

Table 4. Performance Measurement

Performance evaluation by RMSE value. We know that the Root Mean Square Error (RMSE) value sometimes better than the Mean Squared Error (MSE). For considering a model performance, the RMSE value helps us.

In this paper, we have used Fig-1 and Fig-2 for Data sets which we collect from the Environment Department(CASE project) in Bangladesh. Fig-1 is for BARC data set (Farmgate, Dhaka) and Fig-2 is for Darussalam dataset(Darussalam, Dhaka).

Though our both dataset contains a huge amount of missing values. So, it's quite impossible to work with those datasets. But Using Neural Networks for predicting missing values and make our both dataset usable is a huge success for us. Because we have obtained a very accurate result for both datasets with the help of StackNet that combined 8 fold cross validation. And for Darussalam dataset, we have acquired 0.96 for the Pearson correlation coefficient (R) and RMSE 0.25. On the other hand, For BARC dataset we have acquired R equal 0.93 and RMSE 0.26.

6 Conclusion

In this paper, our main goal is to predict the Particulate Matter (PM10). Our data sets have a significant number of missing values because of a technical problem in the Data Center. We have overcome this problem by using Artificial Neural Network. Then, we have used the GradientBoosting Regressor, Random forest Regressor, and ExtraTrees Regressor within StackNet model to predict PM10. And our proposed model has learned from data along with minimum error which indicates that our missing value filling method is quite real for our datasets. So we ensure that for further work about these datasets, anyone may apply our approach.

Acknowledgements

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2018-2016-0-00314) supervised by the IITP (Institute for Information & communications Technology Promotion).

References

[1] (2011) Clean Air & Sustainable Environment. http:/0/case.doe.gov.bd. Accessed 2011
[2] Begum BA, Hopke PK (2018) Ambient Air Quality in Dhaka Bangladesh over Two Decades: Impacts of Policy on Air Quality. Aerosol and Air Quality Research 18: 1910-1920
[3] Hasan MR, Hossain MA, Sarjana U (2016) Status of Air Quality and Survey of Particulate Matter Pollution in Pabna City, Bangladesh. American Journal of Engineering Research (AJER) 5(11):18-22
[4] Whalley J, Zandi S (2016) Air Quality-Measurement and Modeling. In:Particulate Matter Sampling Techniques and Data Modelling Methods, INTECH, Croatia
[5] Zhu D, Cai C, Yang T, Zhou X (2018) A Machine Learning Approach for Air Quality Prediction: Model Regularization and Optimization. Big data and cognitive computing 2(1):5
[6] Maleki H et al (2019) Air pollution prediction by using an artificial neural network model. Clean Technologies and Environmental Policy 21(6):1341-1352
[7] Roy S (2012) Prediction of Particulate Matter Concentrations Using Artificial Neural Network. Resour. Environ 2(2):30-36

[8] Chen MJ et al (2018) Machine learning to relate PM2.5 and PM10 concentrations to outpatient visits for upper respiratory tract infections in Taiwan: A nationwide analysis. World journal of clinical cases 6(8):200
[9] Xiao D et al (2019) Machine learning-based rapid response tools for regional air pollution modelling. Atmospheric Environment 199:463-473
[10]Gore R, Deshpande D (2018) Air Data Analysis for Predicting Health Risks. International Journal of Computer Science and Network (IJCSN) 7(1):36-39
[11]Deters JK, Zalakeviciute R, Gonzalez M, Rybarczyk Y (2017) Modeling PM2.5 Urban Pollution Using Machine Learning and Selected Meteorological Parameters. Journal of Electrical and Computer Engineering 2017. https://doi.org/10.1155/2017/5106045
[12]Aditya CR et al (2018) Detection and Prediction of Air Pollution using Machine Learning Models. International Journal of Engineering Trends and Technology (IJETT). https://doi.org/10.14445/22315381/ijett-v59p238
[13] Marios M (2018) meta modelling framework. https://github.com/kaz-Anova/StackNet. Accessed 20 Sep 2018
[14] Hoque MM et al (2015) Particulate Matter Concentrations in the Air of Dhaka and Gazipur City During Winter: A comparative study. Paper presented at the International Conference on Physics Sustainable Development Technology (ICPSDT-2015), Chattogram, Bangladesh, 140-149, 19-20 Aug 2015