Comparative Analysis of different Statistical Methods for Prediction of $PM_{2.5}$ and PM_{10} Concentrations in Advance for Several Hours

Sharjil Saeed[1], Lal Hussain[1, 2*], Imtiaz Ahmed Awan[1], Adnan Idris[3]
1 Department of Computer Science & IT, The University of Azad Jammu and Kashmir, City Campus, 13100, Muzaffarabad,
*2 Correspondence Author, Quality Enhancement Cell, The University of Azad Jammu and Kashmir, City Campus, 13100, Muzaffarabad, Pakistan

Pakistan
[3] Department of Computer Science & IT, University of Poonch Rawalakot, Rawalakot, Azad Kashmir, Pakistan

Summary
Atmospheric particulate matter (APM) is harmful for living being due to their small size which is ranging from ultra-fine particles up to particles with aerodynamic diameter up to 10 micrometers and hence because of their ability to penetrate deeper into human respiratory system. Particulates less than 2.5 micrometer ($PM_{2.5}$) are more hazardous as compared to coarse particles of size 10 micrometer (PM_{10}). The damage due to APM can be minimized through appropriate preventive measures. In order to gage the sway of air on the health and welfare of every living being it is necessary to perform an analysis of air quality for accurate decisions about preventive measures. Different machine learning methods including Support Vector Machines, Decision Trees, Neural Networks and Linear Discriminant analysis have been proposed for robust forecasting and prediction. This work is aimed at analyzing and benchmarking different methods for the prediction of average $PM_{2.5}$ concentrations. For this purpose, data was acquired during the hours of the day from the ambient air and indoor environment in the suburb of Muzaffarabad (Azad Jammu and Kashmir, Pakistan). Linear and Radial Support Vector Regressors and RF algorithm were used for model generation and prediction. Results from these methods are then compared using root mean squared error (RMSE) for accurate predictions. The finding indicated that RF method and Radial Support Vector Regressor provided better prediction with RMSE as compared to Linear Support Vector Regressor.
Key words:
Atmospheric particulate matter, forecasting, PM2.5, Machine Learning, Support Vector Regressor

1. Introduction

The atmospheric aerosol or particulate matter (PM) is one of the major factors that distort the urban air quality and affect human and ecosystem wellbeing across the globe. It is highlighted topic of research to know the effects of particulates that are present in the indoor environment especially those which are located near the roadways. It has been found by many studies that indoor particulates were associated with many human diseases like asthma, rise in blood pressure, respiratory and cardiovascular diseases [1]; [2]. The lifetime of any pollutant from its origination to removal is the critical component of the forecasting. Transportation, dispersion or concentration of originated pollutant depends on many factors including its physics, sources, composition topography and meteorology of the region [3]. The airborne cycle ends when a pollutant deposit on surfaces, is washed out from the atmosphere or escape into the space [3]. The lifetime of PM2.5 varies from a few seconds to weeks.
The activities that we carry out in indoor environment reasoned deposited particles on the surface of the room to become re-suspended in indoor air [4]. APM consists of numerous particles of different sizes, ranging from ultra-fine particles up to particles with an aerodynamic diameter up to 10μm (PM10 also known as coarse particulates) or larger. It has been reported that particulates less than 2.5μm (PM2.5) are more hazardous due to their ability to penetrate deeper into human lungs and blood and hence become a major cause of increase in respiratory and cardiovascular morbidity compared to coarse particulates. Increased mortality from long-term air pollution exposure is caused by cardiopulmonary diseases or from lung cancer [5]. Short-term exposure generally corresponds with higher concentrations of air pollutants and this exposure has been linked to several health problems. Correlations between asthma and interim exposure to air pollution, unrelieved bronchitis, and ischemic heart diseases have also been established [6] ; [7]. Time series analyses (compares short-term changes in particulate matter and death counts on daily basis) have established a link between exposure and increased mortality. Exposure to particulate matter has also been connected to increased rates of hospitalization. The impact of particle size on human health is of increasing interest [8]. Small particles with diameters less than 10μm can bypass mechanisms within the nasal passage that prevent unwanted material from entering the body and depositing in the lungs. The

Manuscript received November 5, 2017
Manuscript revised November 20, 2017

deposited particles then pass through the alveolar membrane of the lungs into the blood stream. Studies have found that PM2.5 can be associated with increase of stroke, MI (cardiac infarction), arrhythmia and heart failure [8]. Ultrafine particles and gaseous co-pollutants (e.g. ozone and nitrogen oxides) have also been implicated in the effects of particulate matter on the human body. However, few studies have analyzed the effects of ultrafine particles because of the challenges involved in conducting the research [8]. To issue warning about air pollution episodes in a region, the air quality predictions is of main concern. Recent technological developments and research have shown that finer particles (particles produced by chemical reactions in the atmosphere are mostly PM2.5) have the adverse impact on human's health. The major sources of PM2.5 in the urban areas are vehicle exhaust emissions and suspended surface dusts containing carbon, ammonium sulphate and nitrate [9]. Generally, the concentrations of APM remain high in ambient environment due to direct exposure to the sources of APM as compared to indoor environment where individuals are less prone to the dangers of APM. In countries like Pakistan, sources of air pollution are diverse and also the geographical pattern varies from city to city. Particularly in some areas meteorological and geographical conditions do not allow good air circulation and there exists large population not in well-designed cities. City Muzaffarabad, Azad Jammu & Kashmir, Pakistan is one of such cities. In such conditions, episodes of high atmospheric pollution demand to take some extreme actions to limit the potential damages of atmospheric pollution. If such episodes are predicted one or two days in advance, more efficient actions could be taken and advisory to take necessary preventive measures may be issued in order to protect the citizens.

It is widely accepted that prediction based on single scalar time series assuming that, all the information regarding the external factors is contained in that single time series of the system, is possible [10]. Moreover, in literature different algorithms have been proposed to build predictive models using single time series data including Support Vector Regressors.

In present study, the mass concentrations of atmospheric particulates are predicted using linear and radial Support Vector Regressors and data collected from ambient air and indoor environment in the suburb of the city Muzaffarabad (Azad Jammu and Kashmir, Pakistan). The data of consecutive ten days was used to build the predictive model, which was later on used to predict mass concentration of six consecutive hours of next day.

2. Related Work

Prediction of atmospheric particulate matter is of great importance and researchers have investigated the methods for early prediction of the APM concentrations. [11] perform experiments and compare SVM and RBF (Radial basis function) and demonstrated that SVM is the best classifier for air quality prediction than RBF network having better generalization performance when compared to RBF.[12] chooses Aviles urban area (Spain) at local scale and generates a model of regression for air quality prediction using the support vector machine (SVM) technique. [13] performed experiments using ELM (Extended Machine Learning) and SVM for the prediction of Minority Class for suspended particulate matters. [14] used Principal Components Analysis to identify the air pollution and predicted the air quality using ensemble learning and using a tree based classifier. [15] collected and analyzed the sensor information in smart environments using tree base classifier and also found the association between air quality and resident actions.

For PM10 forecasting various techniques have been employed such as ARMA (Auto Regressive Integrated Moving Average) and ARIMA (Auto Regressive Integrated Moving Average) [16]. On the other hand, because for a representation of a system that is non-linear and we represent it by some linear representation, and not able to incarcerate intense concentrations [17]. Besides, these methods require continuous historical data [18]. ARIMA and ARMA models have the ability to take in external explanatory variables and in this case, they are named ARIMAX and ARMAX, correspondingly. In some studies, hybrid models are developed by coupling the ARMA or ARIMA with other methods (ANNs for example). [19] evaluated the performance of ARMAX, ANNs, MLR and hybrid ARIMAX-ANN for the forecasting of daily maximum PM10 moving average values in one station in Temuco, Chile. The foundation of Support Vector Machines (SVM) is a machine learning technique that was initially developed for classification problems by Cortes and Vapnik [20]. A regression technique based upon SVM was then developed [21]. SVM is able to perform linear and non-linear regressions. The advantages of SVM, compared with MLP, are its better generalization ability and its capability for learning, using a small number of training data and huge number of input variables [12]. Researchers [12] employed SVM for simulation of PM10 in Avilés, Spain and they showed that SVM with different Kernel function performs better than MLP. [22] compared SVM and ANN for temporal Prediction of PM10 in a station in Goteborg, Sweden, and they found that the SVM produced better hourly PM10 forecasting results than an ANN. [23] demonstrated that CART technique outperforms than linear regression techniques.

In this work, linear and radial Support Vector Regressors and RF algorithm are used for the prediction of atmospheric particulate matter concentration on the basis of the data collected from the said study area.

3. Study Area

Muzaffarabad is the capital city of Pakistani administered Kashmir commonly known as the state of Azad Jammu & Kashmir (AJ&K). It is a beautiful cup shaped valley; the land of velvet green plateaus, charming lakes and waterfalls. At the conflux of Jhelum river and Neelum river (old names were Hydaspes and Kishan-Ganga respectively), the city is located at 73.47˚E (Longitude) and 34.37˚N (Latitude). Arrogant mountains bordered the city and weather conditions are almost same as Islamabad, the capital city of Pakistan. Muzaffarabad district is adjacent to the Khyber Pakhtunkhwa province of Pakistan in the west, Indian held Kashmir in the east and Chinese area in the North [24]. The infrastructure of Muzaffarabad was badly affected in 08th Oct. 2005 horrible earthquake with intensity of 7.6 on Richter scale [25]. Almost fifty percent of buildings were destroyed in the said event. Rehabilitation process started soon after the earthquake happening. Government of Pakistan, in addition with International aid, started to build destroyed roads, buildings. Re-construction process severely deteriorated environmental conditions in the area. During re-construction process, small roads were flooded with huge number of vehicles. The atmosphere was affected with different type of pollutants. The concentrations of Particulate Matters increased drastically due to closed (cup shaped) environment of Muzaffarabad City. Therefore, there is a need to study the environmental pollutants after the devastating event of earthquake. APM concentrations depend on direct and indirect exposure to its sources. Therefore, particulate matter time series concentrations were monitored from six sites near the road sides using portable air sampling instrument, EPAM-5000, both for ambient and indoor settings. The sites were selected on the basis of traffic flow, number of vehicles crossings, weather conditions, and number of people around the selected site. The monitor is installed for the period of continuously six hours at each site. PM (1.0), PM (2.5) and PM (10) filters were used to get the particulates at each site. Justifications of the monitoring sites are available in the following table 1 below.

Table 1: Justification of particulate sites in examination

Site Index	Site	Land Use	Road Grade	Type
A	Bank Road	Residential/Commercial	Flat	High traffic density
B	Bus Stand	Residential/Commercial	Flat	High traffic density
C	Chattar Chowk	Residential/Commercial	Flat	High traffic density
D	Chehla Bridge	Commercial	Flat with potholes	High traffic density
E	CMH Chowk	Commercial	Flat	High traffic density
F	Old Secretariat	Commercial/ Government offices	Flat	High traffic density

3. Predictions of Indoor Particulates

Predictions on the basis of historical data is important in several fields of life and it becomes utmost important when human health related matters are involved. Increased mass concentration affects respiratory track and lungs and hence causes serious health problems. Therefore, prediction of mass concentration may be advantageous to take precautionary measures in order to void or minimize the effects of increased concentrations. In this section simulation settings will be presented first and then obtained results will be discussed.

4. Simulation Setting

In machine learning literature, different supervised learning algorithms have been proposed for building predictive models [41]. Each algorithm has its own method for learning different parameters from provided data. Performance of a learned predictive model depends on learning algorithm also on data used for building predictive model [42]. In this work, mass concentrations for both indoor and outdoor environments have been predicted using linear, radial SVRs and RF methods. For this purpose, data collected for consecutive ten days has been used for training purposes and the mass concentration for six hours of next day have been predicted. For evaluation of prediction models Root Mean Squared Error (RMSE) was computed for each of the Predictive Models. This procedure is illustrated in figure 1.

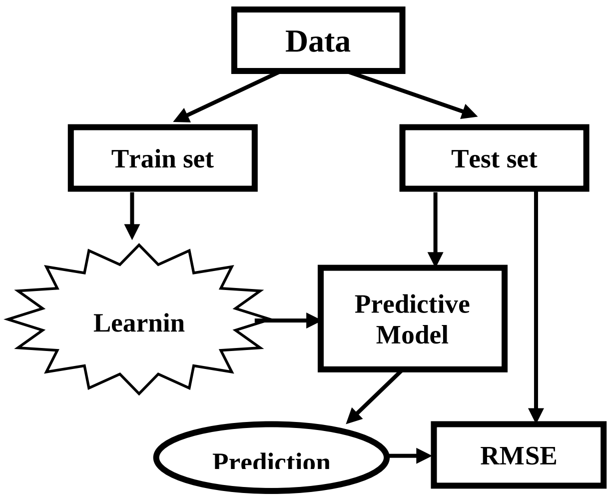

Figure 1: Simulation plan for indoor and outdoor mass concentration predictions

5. Prediction of Indoor Mass Concentrations

Results of indoor mass concentration predictions computed by using simulation plan presented in figure 2 and indoor data are illustrated in figure 1. Data collected for consecutive ten days has been used for training purposes while test set is further divided into six different test sets on the basis of time (hour-wise data) to represent the predicted results in more visible manner. In the figure 3 actual mass concentrations from test set are plotted in red color lines, predicted mass concentrations by linear SVRs in green color, radial SVRs in blue color and RF in brown color. Presented results show that predictions based on RF based model are closest to actual mass concentrations for all six hours data of test set which shows that RF method is more efficient and accurate for indoor mass concentration predictions compared to results of other two predictions models used in this work.

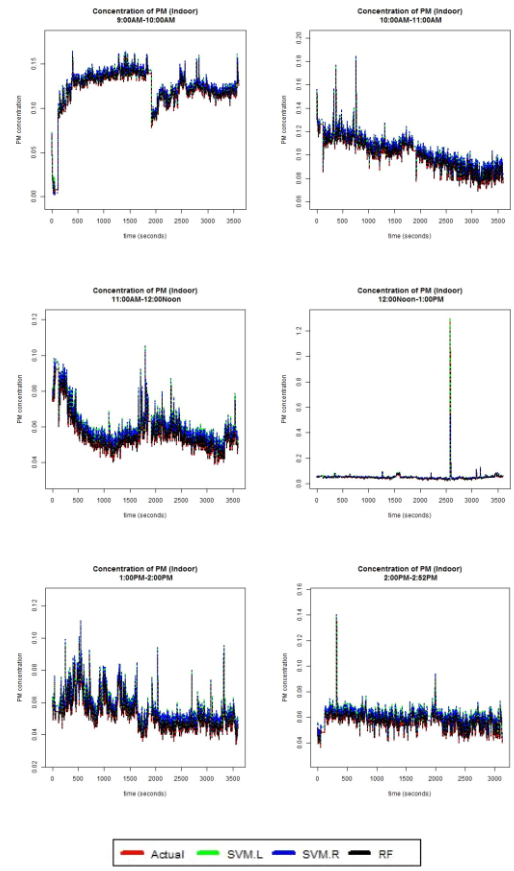

Figure 3: Mass concentrations predictions in indoor environment using SVR.L, SVR.R and RF based prediction models

6. Comparison of Predictions Models For Indoor Mass Concentrations

In this section, test set obtained from indoor data is divided into six different test sets on the basis of time (hour-wise data). In the figure 4 RSME valued computed for linear SVR (SVR.L), radial SVR (SVR.R) and RF are presented using bar charts. It is clear from the figure that prediction model based on RF is the robust model with least RMSE values for all six hours of test set. Figures 3 & 4 show that for time period from 11:00 to 12:00Noon and from 01:00 PM to 2:52PM, RMSE values of SVR.L and RVR.R are almost the same. During this period of time most of mass concentrations values lie between 0.04 and 0.08 with few exceptions. For rest of the time periods the RMSE values of SVR.L are much lower than SVR.R. Showing that SVR.L is the second robust predictor for indoor data used in this work

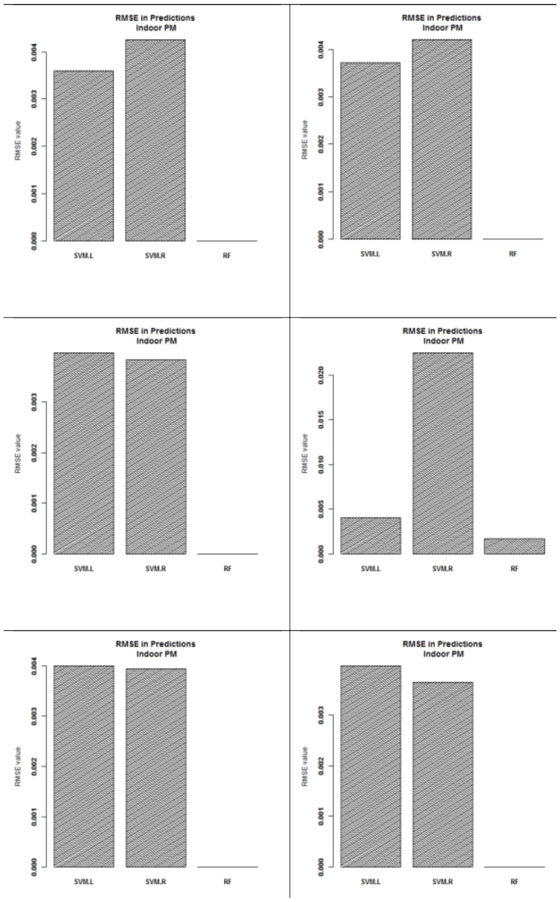

Figure 4: RMSE values of SVR.L, SVR.R and RF based prediction models in indoor environment.

Results presented in this section shat that RF based predictions (compared to other two prediction models) are closest to actual mass concentration values obtained during data collection. Moreover, RMSE values for RF based prediction models are the least. All this reflects that RF is more suitable learning algorithm for mass concentration predictions compared to SVR.L and SVR.R. Analysis of results presented in Figures 4.15 through 4.18 also shows that mass concentration predictions in indoor environment are more accurate than those of outdoor environment. This difference may be due to the reason that in indoor environment impurities/noise is less in data than outdoor environment data which may have more contaminations.

7. Comparison of Predictions Models For Indoor Mass Concentrations

As in case of indoor data, test set obtained from outdoor data is divided into six different test sets on the basis of time (hour-wise data) for clear representation of predicted results. In the figure 5 actual values of test set are plotted in red colour lines, predicted mass concentrations by linear SVRs in green color, radial SVRs in blue color and RF algorithm by black color. It is evident from this figure that predictions based on RF are closest to actual mass concentrations for all six hours data of test set representing that RF method is more efficient and accurate for outdoor mass concentration predictions compared to other two methods of predictions used in this work.

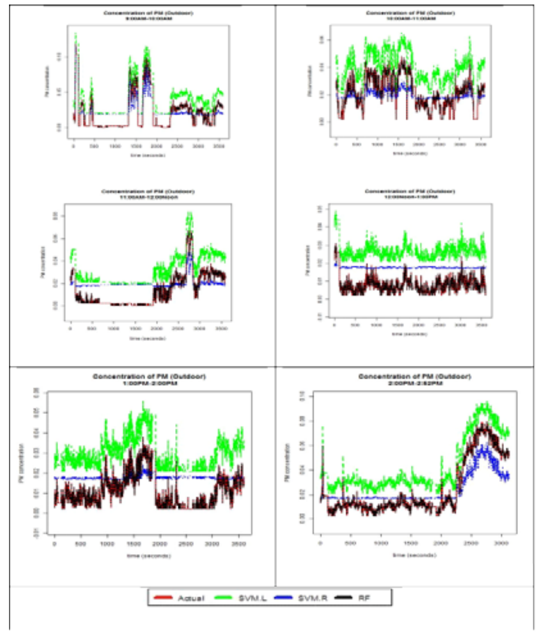

Figure 5: Mass concentrations predictions in Outdoor environment using SVR.L, SVR.R and RF based prediction models.

8. Comparison of Predictions

Prediction models built using outdoor mass concentration data are compared on the basis of RMSE values computed by using simulation plan presented in figure 2 and outdoor data (divided into six different test sets on the basis of time (hour-wise data)) discussed before. In figure 6, RSME values computed for linear SVR (SVR.L), radial SVR (SVR.R) and RF are presented using bar charts. It is clear from the figure that RF based prediction model is the robust model with least RMSE values for all six hours of test set. From 10:00AM onwards the RMSE values of SVR.R remain almost half of the RMSE values of SVR.L. Making SVR.R the second robust predictor for data used in this work.

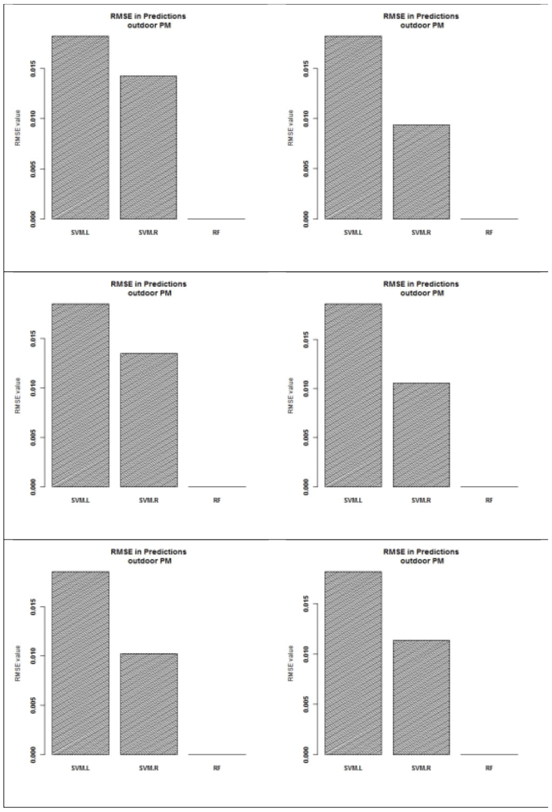

Figure 6: RMSE values of SVR.L, SVR.R and RF based prediction models in Outdoor environment

9. Discussion and Conclusion

The mass concentrations of indoor and ambient particulates were predicted using linear and radial SVRs and RF approaches. The ten days data was used for training purposes and the mass concentration for six hours of the eleventh day were predicted. The Root Mean Squared Error (RMSE) was computed to find the difference between values of the predicted model and the actual values of mass concentrations. Test data was divided into six different sets on the basis of time (hour-wise data) to represent the predicted results in more visible manner. The results demonstrated that predictions based on RF are closest to actual mass concentrations for the both ambient and indoor mass concentrations of particulates with least RMSE.

The particulate matters comprised of highly complex and nonlinear dynamics due variety of factors polluting the environment. To predict and detect the behavior of highly complex nature of data, it requires most robust machine learning classification and regression methods based on set of selected features. Hussain et al. recently [26-29] used complexity measures to investigate the dynamics of different physiological systems with various pathologies and observed the complex dynamics degrade due to loss of structural functions. The coupling dynamics and interactions among different brain regions during resting state are investigated by [30-32]. Rathore et al. [33-35] extracted combination of geometric and hybrid features to detect the colon cancer. Likewise, the nonlinear dynamics have been investigated using [36-37] to investigate the heart rate variability, emotion recognition [38] and load forecasting [39] using machine learning and neural network approaches.

The results reveal that mass concentration predictions in indoor environment are more accurate than those of outdoor environment. This difference may be due to the fact that in indoor data was collected in the absence of external influencing factors, whereas the mass concentration time series was prone to external perturbations such as, wind direction, wind speed, humidity, temperature, traffic congestion and road dust [40] show that air quality becomes depreciated due to noise which limits the accuracy of predictions particularly in the case of ambient environment. The prediction error increases in such situations because the noise part of the future measurement cannot be predicted. Moreover, the data on the basis of which the predictions are made is itself noisy and hence the estimates are affected by noise. Thus, the presence of noise has effects on the prediction results. Hence, our results are in accordance with the results of previous studies [40]. These results can be considered as the example of successful predictions for the concentrations of atmospheric particulate matters.

References

[1] Lin, L.Y., et al., The effects of indoor particles on blood pressure and heart rate among young adults in Taipei, Taiwan. Indoor Air, 2009. 19(6): p. 482-488.

[2] Srimuruganandam, B. and S.M.S. Nagendra, Analysis and interpretation of particulate matter–PM 10, PM 2.5 and PM 1 emissions from the heterogeneous traffic near an urban roadway. Atmospheric Pollution Research, 2010. 1(3): p. 184-194.

[3] Wark, K. and C.F. Warner, Air pollution: its origin and control. 1981.

[4] Thatcher, T.L. and D.W. Layton, Deposition, resuspension, and penetration of particles within a residence. Atmospheric Environment, 1995. 29(13): p. 1487-1497.

[5] Cao, J., et al., Whole-genome sequencing of multiple Arabidopsis thaliana populations. Nature genetics, 2011. 43(10): p. 956-963.

[6] Brunekreef, B. and S.T. Holgate, Air pollution and health. The lancet, 2002. 360(9341): p. 1233-1242.

[7] Pope III, C.A. and D.W. Dockery, Health effects of fine particulate air pollution: lines that connect. Journal of the air & waste management association, 2006. 56(6): p. 709-742.

[8] Brook, R.D., et al., Particulate matter air pollution and cardiovascular disease an update to the scientific statement from the American Heart Association. Circulation, 2010. 121(21): p. 2331-2378.

[9] Sun, Y., et al., The air-borne particulate pollution in Beijing—concentration, composition, distribution and sources. Atmospheric Environment, 2004. 38(35): p. 5991-6004.

[10] Kantz, H. and T. Schreiber, Nonlinear time series analysis. Vol. 7. 2004: Cambridge university press.

[11] Lu, W.-Z. and W.-J. Wang, Potential assessment of the "support vector machine" method in forecasting ambient air pollutant trends. Chemosphere, 2005. 59(5): p. 693-701.

[12] Sánchez, A.S., et al., Application of an SVM-based regression model to the air quality study at local scale in the Avilés urban area (Spain). Mathematical and Computer Modelling, 2011. 54(5): p. 1453-1466.

[13] Vong, C.-M., et al., Predicting minority class for suspended particulate matters level by extreme learning machine. Neurocomputing, 2014. 128: p. 136-144.

[14] Singh, K.P., S. Gupta, and P. Rai, Identifying pollution sources and predicting urban air quality using ensemble learning methods. Atmospheric Environment, 2013. 80: p. 426-437.

[15] Deleawe, S., et al., Predicting air quality in smart environments. Journal of ambient intelligence and smart environments, 2010. 2(2): p. 145-154.

[16] Box, G.E., Time series analysis: forescasting and control. HOLDEN-DAY SERIES IN TIME SERIES ANALYSIS AND DIGITAL PROCESSING, 1976.

[17] Díaz-Robles, L.A., et al., A hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas: the case of Temuco, Chile. Atmospheric Environment, 2008. 42(35): p. 8331-8340.

[18] Zhang, G.P., Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 2003. 50: p. 159-175.

[19] Goyal, P., A.T. Chan, and N. Jaiswal, Statistical models for the prediction of respirable suspended particulate matter in urban cities. Atmospheric Environment, 2006. 40(11): p. 2068-2077.

[20] Vapnik, V. and C. Cortes, Support Vector Networks, machine learning 20, 273-297. 1995, Kunwer Acedemic Publisher.

[21] Bruzzone, L. and F. Melgani, Robust multiple estimator systems for the analysis of biophysical parameters from remotely sensed data. IEEE Transactions on Geoscience and Remote Sensing, 2005. 43(1): p. 159-174.

[22] Raimondo, G., et al. A machine learning tool to forecast PM10 level. in Proc. of the AMS 87th Annual Meeting, San Antonio, TX, USA. 2007.

[23] Slini, T., et al., PM 10 forecasting for Thessaloniki, Greece. Environmental Modelling & Software, 2006. 21(4): p. 559-565.

[24] Khan, M., Pashto phonology: The relationship between Syllable structure and word order. University of Azad Jammu and Kashmir, Muzaffarabad, 2012.

[25] Khan, M. and O. Siddique, The 2005 South Asian Earthquake: Natural Calamity or Failure of State?: State Liability and Remedies for Victims of Defective Construction in Pakistan. Australian Journal of Asian Law, 2007. 9(2): p. 187.

[26] Hussain, L., Aziz, W., Alowibdi, J. S., Habib, N., Rafique, M., Saeed, S., & Kazmi, S. Z. H. (2017). Symbolic time series analysis of electroencephalographic (EEG) epileptic seizure and brain dynamics with eye-open and eye-closed subjects during resting states. Journal of physiological anthropology, 36(1), 21.

[27] Hussain, L., Aziz, W., Saeed, S., Shah, S. A., Nadeem, M. S. A., Awan, I. A., ... & Kazmi, S. Z. H. (2017). Quantifying the dynamics of electroencephalographic (EEG) signals to distinguish alcoholic and non-alcoholic subjects using an MSE based Kd tree algorithm. Biomedical Engineering/Biomedizinische Technik.

[28] Hussain, L., Aziz, W., Khan, AS., Abbasi, AQ., Kazmi, ZH., Abbasi, MM. (2015). Classification of Electroencephalography (EEG) Alcoholic and Control Subjects using Machine Learning Ensemble Methods. Journal of Multidisciplinary Engineering Science and Technology, 2(1): 126-131

[29] Hussain, L., Aziz, W., Saeed, S., Shah, S. A., Nadeem, M. S. A., Awan, I. A., ... & Kazmi, S. Z. H. (2017). Complexity analysis of EEG motor movement with eye open and close subjects using multiscale permutation entropy (MPE) technique. Biomedical Research, 28(16).

[30] Hussain, L., & Aziz, W. (2016). Time-Frequency Spatial Wavelet Phase Coherence Analysis of EEG in EC and EO During Resting State. Procedia Computer Science, 95, 297-302.

[31] Stankovski, T., Ticcinelli, V., McClintock, P. V., & Stefanovska, A. (2017). Neural cross-frequency coupling functions. Frontiers in systems neuroscience, 11, 33.

[32] Hussain L, Aziz W, Saeed S (2017) Coupling functions between brain waves : Significance of opened / closed eyes. The Journal on Systemics, Cybernetics and Informatics, 275–280.

[33] Rathore, S., Hussain, M., Iftikhar, M. A., & Jalil, A. (2014). Ensemble classification of colon biopsy images based on information rich hybrid features. Computers in Biology and Medicine, 47, 76-92.

[34] Rathore, S., Iftikhar, A., Ali, A., Hussain, M., & Jalil, A. (2012). Capture largest included circles: An approach for counting red blood cells. Emerging Trends and Applications in Information Communication Technologies, 373-384.

[35] Rathore, S., Hussain, M., & Khan, A. (2015). Automated colon cancer detection using hybrid of novel geometric features and some traditional features. Computers in biology and medicine, 65, 279-296.

[36] Hussain, L., Aziz, W., Kazmi, Z. H., & Awan, I. A. (2014). Classification of Human Faces and Non Faces Using Machine Learning Techniques. International Journal of Electronics and Electrical Engineering, 2 (2), 116-123

[37] Hussain, L., Aziz, W., Nadeem, S. A., & Abbasi, A. Q. (2014). Classification of Normal and Pathological Heart Signal Variability Using Machine Learning Techniques. International Journal of Darshan Institute on Engineering Research and Emerging Technologies, 3(2), 13-18.

[38] Hussain, L., Shafi, I., Saeed, S., Abbas, A., Awan, I. A., Nadeem, S. A., ... & Rahman, B. (2017). A radial base neural network approach for emotion recognition in human speech. IJCSNS, 17(8), 52.

[39] Hussain, L., Aziz, W., Khan, AS., Abbasi, AQ., Kazmi, ZH., Abbasi, MM. (2015). Classification of Electroencephalography (EEG) Alcoholic and Control Subjects using Machine Learning Ensemble Methods.

Journal of Multidisciplinary Engineering Science and Technology, 2(1): 126-131
[40] Khokhlov, V. N., Glushkov, A. V., Loboda, N. S., & Bunyakova, Y. Y. (2008). Short-range forecast of atmospheric pollutants using non-linear prediction method. Atmospheric Environment, 42(31), 7284-7292.
[41] Wong, P. K., Wong, H. C., Vong, C. M., Xie, Z., & Huang, S. (2016). Model predictive engine air-ratio control using online sequential extreme learning machine. Neural Computing and Applications, 27(1), 79-92.
[42] Illoldi-Rangel, P., Sánchez-Cordero, V., & Townsend Peterson, A. (2004). Predicting distributions of Mexican mammals using ecological niche modeling. Journal of Mammalogy, 85(4), 658-662.

Biography of Correspondence Author

Dr. Lal Hussain is a Programmer at Quality Enhancement Cell, University of Azad Jammu and Kashmir, Muzaffarabad Pakistan. He obtained his MS in Communication and Networks from Iqra University, Islamabad, Pakistan in 2012 with Gold medal. He received Ph.D. from Department of Computer Science & Information Technology, University of Azad Jammu and Kashmir, Muzaffarabad, Pakistan in February 2016. He worked as visiting PhD researcher at Lancaster University UK for six months under HEC International Research Initiative Program and worked under the supervision of Dr. Aneta Stefanovska, Professor of Biomedical Physics, Physics Department, Lancaster University, UK. He is author of more than 10 publications of highly reputed peer reviewed and Impact Fact Journals. He presented various talks at Pakistan, UK and USA. His research interest includes Biomedical Signal Processing with concentration in complexity measures, Time-Frequency representation methods, Cross Frequency Coupling to analyze the dynamics of neurophysiological and physiological signals. His research interest also includes Neural Networks and Machine Learning classification, regression and prediction techniques for detection of cancer, epilepsy, Brain Dynamics and Diseases (i.e. autism spectrum disorder (ASD) and attention-deficit/hyperactivity disorder (ADHD), Alzheimer's Disease, Brain Tumor), image processing and segmentation etc.