ISSN 2229-5518

Comparison Ratio of NO2 and O3 in Suspended Particulate Matter Using Machine Learning Methods at DG Khan

Abstract

Total carbon monoxide, dioxide and suspended particulate matters in the town of DG Khan, Pakistan. In DG Khan it was developed computer models to prevent AQIs that enable the modelling of complex, unsupervised processes within the training framework. Machine algorithms forecast air quality indexes in the DG Khan. The models can: (1) learn from pollutants; (2) afterwards use actual data; and (3) ultimately handle uncertainties linked to monitoring both APs and meteorological factors. These models are: Random Forest and Support Vector Machine, as well as ranking methods of determining top pollutants such as the suspendedNO2, and the meteorological Dg Khan particles with diameters that are generally micrometers and less, such as Suspended Particulate Materials, NO2 and O3 inhaled inhalable parts] to PM10 inhaled parts of DG Khan Machine study algorithms for the calculation of air pollution index calculation techniques, various algorithms used: ANN, k-Nearest Neighbor' Algorithm, linear return and SVM. The experiment was carried out in the city of DG Khan using a dataset.

A. Background:

The most common health danger is suspended particulate matter. These particles may enter the lungs deeply and some may even reach the circulation. Such particles may damage the lungs and heart of a person. The objective of this study is to compute the NO2 and 03 ratio of suspended particulate matter in DG Khan using machine learning methods. It also emphasizes the fundamental concepts of machine learning techniques and their function in improving their prediction performance. Air pollution is projected to kill seven million people globally year, according to the World Health Organization. WHO data indicates that 9 out of 10 individuals respire air, with poor and medium-income nations having the greatest exposures that exceed the WHO guideline limits containing high amounts of contaminants. Air pollution is caused by various particles. My research focuses on N03 and NO2, both of which may induce pulmonary illness with suspended particles NO3 and NO2. The egregious abuse of WHO statistics indicates that 6% of fatalities are caused by public exposure to air pollution in Pakistan India and Iran. 70% of the global air traffic and carbon dioxide pollution in many metropolitan areas is fully regulated. Carbon monoxide substitutes hemoglobin oxygen for 200 and produces a shortage of oxygen. The exposure of pollutants and particles, which has raised the interest in air pollution and its impact in the scientific community, has a direct effect on human health in particular. Burning fossil fuels, agriculture, factory and industrial waste, home heating and natural catastrophes are the major factors linked with air pollution (Wu, 2003).

The Air Quality Index (AQI) is an indicator for evaluating the cleanliness and unhealthiness of air and the related health consequences particularly for groups of risk. It focuses on health consequences which may occur within a few of hours or days after exposure to contaminated air. The maximum individual AQI is determined based on the aforementioned criteria of contaminants. The creation of a provision system will allow the AQI to be more flexible and beneficial for people's health depending on the concentrations of the particular polluter, which can anticipate air quality hourly. Consequently, systems that can produce air quality alerts are necessary and essential to communities. They may also play a significant part in health warranties when atmospheric pollution levels may exceed the set limits, for example by enabling environmental authorities to reduce emissions on demand, operational plan or even to respond to emergencies (Vallero, 2011).

B. Literature Review

In some ways, the Air Quality Index (AQI) may be thought of as a communication channel between weather agencies and the general public since it defines the air quality in a certain region. Generally speaking, it may be described as a broad measure that represents the quality of the air in the immediate vicinity (Laskov, 2004). The health risks linked with air and particle pollution are represented by this symbol. Describe the air quality in a straightforward and comprehensible manner. It is an approach that is comprehensible (Albritton, 1998). These indicators allow the general public to monitor air quality at the local, regional, and national levels without having to grasp the specifics of the underlying data (Lopman, 2012). People should be informed about air pollution so that they may take appropriate precautions to protect themselves from the negative impacts of pollution. The second aim is to increase public knowledge of the consequences of existing air pollution exposure and to encourage changes in both attitudes and actions. In addition, there are government policies. Color schemes, graphs, names of air quality categories (such as excellent, medium, or poor), and other messages are utilized in conjunction with the AQI, despite the fact that the number alone represents specific elements of air quality (Albritton, 1998). Explain the anticipated effect of the index at various levels, as well as the actions that individuals may take to minimize the likelihood of being affected. When this is done, the findings will almost always indicate which particular regions are most at risk of becoming more dangerous (Semenza, 2004). As a result, it is illogical to believe that the same air quality index works on a worldwide scale. In

1976, the United States Environmental Protection Agency (USEPA) established the "Pollutant Standard Index (PSI),".

Pakistan's urban air pollution is among the worst in the world, and it has a major negative impact on human health as well as the country's economy. Islamabad is the most urbanized nation in South Asia, and the country is experiencing fast motorization as well as rising energy consumption (Afroz, 2003). Air pollution, especially in major metropolitan areas, has a negative impact on the health and quality of life of the people, as well as contributing to environmental deterioration. Several times higher than the World Health Organization's (WHO) air quality recommendations were recorded for suspended particulate matter (SPM) (NO2), and lead (Pb). It is estimated that air pollution is responsible for more premature deaths and illnesses in Pakistan than any of the other high-profile sources of public health issues that get considerably more attention in the country, such as traffic accidents (Jiang, 2015).

The mean metal concentrations in the atmosphere in DG Khan are much greater than in the surrounding environment and in European metropolitan areas, mostly as a result of human activity. Industrial metals such as iron, zinc, manganese, and potassium exhibited strong connections, while lead is linked with cadmium due to the fact that they both come from the same source (Clark, 2013). The principal component and cluster analyses showed that vehicle emissions, industrial operations, combustion processes, and mineral dust were the most significant contributors of airborne particles pollution in the atmosphere. The results of the comparative research show significant amounts of trace metals in the air (Peng, 2007). The fundamental statistical data showed that the components varied in a wide range of ways depending on the season in question (Biggio, 2011). Major pollution sources in DG Khan's atmospheric aerosols have been identified as automobile emissions, windblown soil dust, excavation operations, and biomass burning, and industrial and fugitive emissions. This area's concentrations of airborne trace elements are generally extremely high when compared to other areas, suggesting that the local people may be at risk for health problems as a result of these elevated concentrations of trace elements (Perez, 2012).

C. Methodology

When dealing with enormous amounts of data, often known as "big data," machine learning (ML) is the process of extracting valuable information from the data. This process of learning results in the development of the capacity to make intelligent choices or to anticipate forthcoming or future data sources (Sivasakthivel, 2011). As a result, machine learning has the capacity to create techniques or tools that may be utilized to find previously undiscovered patterns from provided (i.e. observed) data in order to complete a certain job or solve a problem. Following that, the model that has been developed may be utilized to forecast fresh data or information. The general method of machine learning is shown in Figure 1.

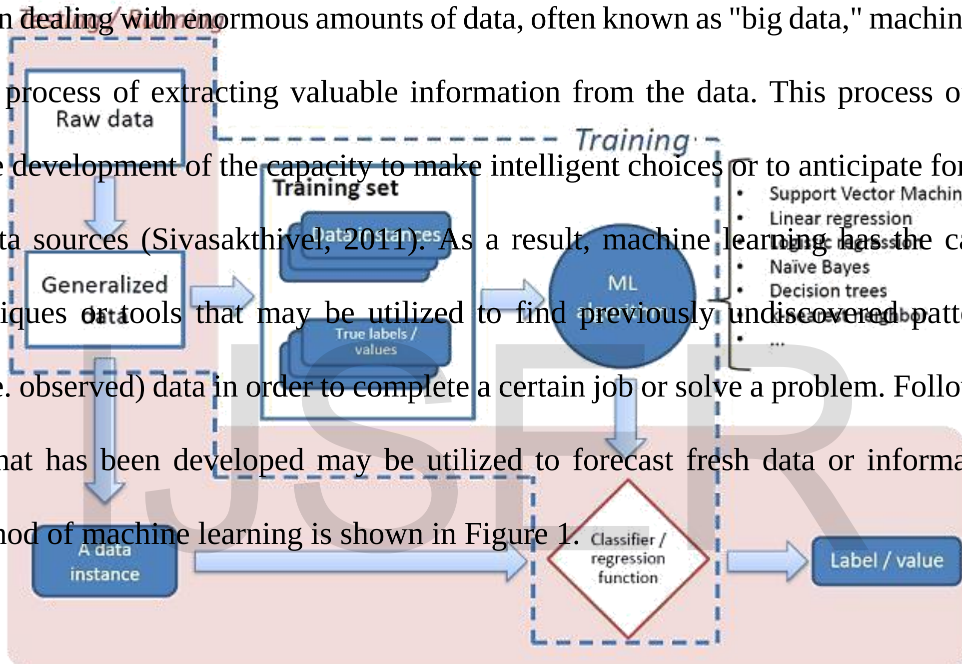

Figure 1: Processing of Machine learning (ML) techniques

When dealing with enormous amounts of data, often known as "big data," machine learning (ML) is the process of extracting valuable information from the data. This process of learning results in the development of the capacity to make intelligent choices or to anticipate forthcoming or future data sources (Sivasakthivel, 2011). As a result, machine learning has the capacity to create techniques or tools that may be utilized to find previously undiscovered patterns from provided (i.e. observed) data in order to complete a certain job or solve a problem. Following that, the model that has been developed may be utilized to forecast fresh data or information. The general method of machine learning is shown in Figure 1.

It is important to note that data mining tasks may be divided into two types: (1) classification tasks, in which the goal class to be predicted is nominal, and (2) regression tasks, in which the target class to be forecasted is numerical (the work of this thesis). Not all learning algorithms are capable of dealing with the two groups (Elbastawesy, 2020). Machine learning algorithms have been suggested in huge numbers of papers in the literature. Single learner algorithms and ensemble learner algorithms, often known as Meta learner algorithms, are two types of methods that may be split into two subcategories (Wang, 2006).

The artificial neural network is the next technique that has been chosen for this research. Because it was the first algorithm ever created, the ANN is not only regarded as the “universal approximate,” capable of accurately estimating any arbitrary function, but it is also regarded as the originator of the most recent advancement in the artificial intelligence field, known as deep learning or deep neural networks (Allen, 1990). In the process of information learning, the neural network mimics the structure and networks of the human brain by using artificial neural networks.

For a person, learning new things is accomplished via the training of biological neurons in the brain through the use of examples, from which the information acquired will subsequently be stored in memory. As part of an artificial neural network (ANN) training, a large quantity of data is fed into the artificial neurons, and the network is modified to provide a better response, or more precisely output, for example, in a prediction or recognition job (Ashmore, 1991). The network is adjusted by changing the weights (wi,1, wi,2, wi,3, ,) that each neuron has, as well as the biases that serve as the adder for each summation process, which are all updated simultaneously.

There are two components to it. NO_2 and O_3 are two characteristics that are independent of one another. The index of air quality is a dependent characteristic. Because the air quality index is computed using these two variables. Because the data is numeric and there are no missing values in the data, there is no need to do any preprocessing. Because our objective is to forecast the AQI, either classification or regression will suffice for this job. As a result, since our class label is continuous, we must use the regression method.

Predictive modelling, often known as regression, is a method for fitting data to a specified range of values. Python's regression methods are described in detail here:

- Random Forest Regressor
- Ada Boost Regressor
- Bagging Regressor
- Linear Regression etc.

Table 1: Excel file with a sample of the dataset

Dera Ghazi Khan District	**Year**	**Month**	**Date**	**O3**	**NO2**
Rajanpur	2021	September	18	14 39 μg/m³	3 5 μg/m³
Muzaffargarh	2021	September	18	19 55 μg/m³	5 7 μg/m³
Layyah	2021	September	18	40 83 μg/m³	7 14 μg/m³
DG Khan	2021	September	18	30 67 μg/m³	2 4 μg/m³

The Air Quality Index (AQI) captures the daily pollutant parameters in accordance with the DG Khan City Standard (2021). The Excel dataset has been enhanced by the addition of a new attribute column that has a binary categorization (The Area is Polluted or Not Polluted). There was an additional column added to indicate the name of the most effective pollutant and, therefore, the categorization values. In addition, one of the two contaminants or sources of contamination should be labelled. The characteristics are independent factors, and they all have an impact on the dependent variables (class label), which are also independent variables (pollution column).

DG Khan Division	**Year**	**Month**	**Date**	**O3**	**PM_{10}**	**$PM_{2.5}$**	**SO2**	**CO**	**NO2**
Rajanpur	2021	September	18	15 39 $\mu g/m^3$	11 11 $\mu g/m^3$	10 5 $\mu g/m^3$	9 9 $\mu g/m^3$	1 203 $\mu g/m^3$	2 5 $\mu g/m^3$
Muzaffargarh	2021	September	18	23 55 $\mu g/m^3$	37 37 $\mu g/m^3$	32 16 $\mu g/m^3$	11 11 $\mu g/m^3$	1 177 $\mu g/m^3$	3 7 $\mu g/m^3$
Layyah	2021	September	18	40 83 $\mu g/m^3$	43 43 $\mu g/m^3$	29 14 $\mu g/m^3$	7 7 $\mu g/m^3$	1 192 $\mu g/m^3$	7 14 $\mu g/m^3$
DG Khan	2021	September	18	30 67 $\mu g/m^3$	33 33 $\mu g/m^3$	30 15 $\mu g/m^3$	10 10 $\mu g/m^3$	1 178 $\mu g/m^3$	2 4 $\mu g/m^3$

Table 2: DG Khan Divison Levels.

D. Air Quality Scale

Excellent
0–19
The air quality is acceptable for most people; enjoy your regular outside activities.

Fair

20–49

The air quality is usually considered to be satisfactory by the majority of people. Long-term exposure, on the other hand, may cause mild to significant symptoms in those who are sensitive to it.

Poor

50–99

The air has reached a dangerously high level of pollution, making it unsafe for sensitive populations to breathe. If you are experiencing symptoms like as difficulty breathing or throat discomfort, you should limit your time spent outdoors.

Unhealthy

100 – 149

Sensitive populations may experience health consequences very quickly. Individuals in good health may have difficulties breathing and throat discomfort after being exposed for an extended period of time. Limit your time spent outside.

Very Unhealthy

150 – 249

Sensitive groups will have immediate health consequences and should refrain from engaging in outdoor activities. If you're in good health, you may have difficulties breathing and throat discomfort. Consider remaining inside and postponing outside activities.

Dangerous

250+

Any exposure to the air, even for a little period of time, has the potential to have severe health consequences for everyone. Avoid engaging with outdoor activities.

E. Discussion

To develop a predictive model for atmospheric air quality, almost all recent research in the field of atmospheric air quality prediction and modelling have used an artificial neural network (ANN). The explanation for this may be traced back to the established characteristics of typical atmospheric ozone concentration datasets. As a result, the majority of researchers in this field have restricted their investigations to the use of ANN and SVM. ANN and SVM have been utilized in a number of researches, which are summarized in the following section of the literature. It should be emphasized that just a few researchers tried to use various machine learning methods and conducted comparisons using artificial neural networks. As well as utilizing machine learning to improve air quality predictions, other research projects have shown the model's ability to do a sensitivity analysis, among other things (Hasan, 2021).

F.

A Neural Network was one of the methods that was investigated and compared to the other statistical tools available. However, the majority of the attention was paid to statistical tools alone. The study came to the conclusion that only techniques capable of dealing with non-linear data were able to provide an acceptable outcome. As a result, it has been shown that the Neural Network performs the best. The findings of this study showed that Neural Networks may be used to analyses non-linear datasets. Thus, the researchers who wrote the articles in this section acknowledged the findings of this study as the inspiration for their use of neural networks in their research (Hamdi, 2019).

G. Conclusion

Due to increasing urbanization, industry, and modernization, together with regular dust storms, the ambient air quality in DG Khan has deteriorated. According to the computed AQI (air quality index) values, the goal of this research is to identify the most important atmospheric air pollutants, with a focus on their potential harm to human health and environmental quality. Between January 2012 and September 2021, five mobile air quality monitoring stations were deployed throughout the country to collect data on particulate matter (PM10), fine particulate matter (PM2.5), ozone (O_3), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and carbon monoxide

(CO). According to the findings of this research, PM10 and PM2.5 are the most harmful air pollutants in DG Khan, with PM2.5 being the most prevalent during September 2021 and PM10 being the most prevalent during August 2012, respectively. Evaluation of spatial variability of particle matter in five governorates was carried out using the AQI categories corresponding to each governorate. The influence of climatic variables such as ambient air temperature, wind speed, relative humidity, and total precipitation on ambient air quality was examined. Research presented in this thesis aims to investigate the most effective and accurate modelling, prediction, and forecasting approaches for the determination of ground level ozone concentration, employing the most recent generation of machine learning algorithms, in particular ensemble learning algorithms, for the determination of ground level ozone concentration (Beygelzimer, 2006).

ISSN 2229-5518

References and Recommended Readings

Afroz R, Hassan M N, and Ibrahim N A Review of air pollution and health impacts in Malaysia Environ. 2003 Res. 92 71–77

Agrawal R. K. R. A, "An Introductory Study on Time Series Modeling and Forecasting," arXiv preprint arXiv: 2013 1302.6613., pp. 1–68.

Albayrak, A. S. veYılmazKoltan, Ş. VeriMadenciliği: KararAğacıAlgoritmalarıve İMKB VerileriÜzerineBirUygulama.SüleymanDemirelÜniversitesiİktisadiveİdariBilimlerFakültesiDergisi, (2009). 14(1), 31-52.

Albritton, Daniel, "What Should Be Done in a Science Assessment In Protecting the Ozone Layer: Lessons, Models, and Prospects," 1998.

Albritton, Daniel, "What Should Be Done in a Science Assessment In Protecting the Ozone Layer: Lessons, Models, and Prospects," 1998.

Alexandre Belloni, Introduction to bundle methods, Tech. report, Operation Research Center, M.I.T., 2005.

Allen Jr LH. Plant responses to rising carbon dioxide and potential interactions with air pollutants. 1990 Journal of Environmental Quality. 19, 15-34.

Ashmore MR, Bell JNB. The role of ozone in global change. Annals of Botany 1991 (Supplement 1) 67, 39-48.

Awad, M.; Khanna, R. Support Vector Regression. In Efficient Learning Machines; Apress: Berkeley, CA, USA, 2015.

Awad, M.; Khanna, R. Support Vector Regression. In Efficient Learning Machines; Apress: Berkeley, CA, USA, 2015

B. Maity, Y. Polapragada, A. Ghosh, S. Bhattacharjee, and S. Nandi, “Identifying Outdoor Context by Correlating Air and Noise Pollution Sensor Log,” 2020 Int. Conf. Commun. Syst. NETworkS, COMSNETS 2020, pp. 891–893, 2020, doi: 10.1109/COMSNETS48256.2020.9027364.

Bak, J., Kim, J. H., Liu, X., Chance, K., and Kim, J.: Evaluation of ozone profile and tropospheric ozone retrievals from GEMS and OMI spectra, Atmos. Meas. Tech., 6, 239–249, 2013 https://doi.org/10.5194/amt-6-239-2013,.

Bennett and O. L. Mangasarian, Robust linear programming discrimination of two linearly inseparable sets, Optim. Methods Softw. 1 (1992), 23–34.

Bertsekas and J.N. Tsitsiklis, Introduction to probability, Athena Scientific, 2003.

Beygelzimer, S. Kakade, and J. Langford, Cover trees for nearest neighbor, International Conference on Machine Learning, 2006.

Biggio B, Nelson B, Laskov P Support vector machines under adversarial label noise. In: JMLR:

Workshop and Conference Proceed- ings 20, MIT Press (2011), p 97112

Blei, A. Ng, and M. Jordan, Latent Dirichlet allocation, Journal of Machine Learning Research 3 (2003), 993–1022.

Boyd and L. Vandenberghe, Convex optimization, Cambridge University Press, Cambridge, England, 2004.

Brunelle JK, Chandel NS Oxygen deprivation induced cell death: an update. Apoptosis2002

7:475–482

C. Berg, J. P. R. Christensen, and P. Ressel, Harmonic analysis on semigroups, Springer, New York, 1984.

C. Cortes and V. Vapnik, “Support-vector networks,” Machine Learning, 1995. vol. 20, no. 3, pp. 273–297,

C. Cressie, Statistics for spatial data, John Wiley and Sons, New York, 1993.

C. Leslie and R. Kuang, Fast kernels for inexact string matching, Proc. Annual Conf. Computational Learning Theory, 2003.

C. M. Bishop, Neural networks for pattern recognition, Clarendon Press, Oxford, 1995.

C. McDiarmid, on the method of bounded differences, Survey in Combinatorics, Cambridge University Press, 1989, pp. 148–188.

C. Napagoda, “Web Site Visit Forecasting Using Data Mining Techniques,” International Journal of Scientific & Technology Research, vol. 2, no. 12, pp. 170– 174, 2013

Caladcad, S. Cabahug, M. R. Catamco, P. E. Villaceran, L. Cosgafa, K. N. Cabizares, M. Hermosilla, and E. J. Piedad, ‘‘Determining Philippine coconut maturity level using machine learning algorithms based on acoustic signal,’’ Comput. Electron. Agricult. vol. 172, May 2020, Art. No. 105327.

Chang, C.-C.; Lin, C.-J. Training ν-Support Vector Regression: Theory and Algorithms. Neural Comput. 2002, 14, 1959–1977.

Cheng WL, Chen YS, Zhang J, Lyons TJ, Pai JL, Chang SH (2007) Comparison of the revised air quality index with the PSI and AQI indices. Sci Total Environ 382(2):191–198

Clark M, "An introduction to machine learning: with applications in R", University of Notre Dame, USA, 2013.

Claude Lemar´echal, ArkadiiNemirovskii, and YuriiNesterov, New variants of bundle methods, Mathematical Programming 69 (1995), 111–147.

Collins, R. E. Schapire, and Y. Singer, Logistic regression, AdaBoost and Bregman distances, Proc. 13th Annu. Conference on Comput. Learning Theory, Morgan Kaufmann, San Francisco, 2000, pp. 158–169.

Conticini, E.; Frediani, B.; Caro, D. Can Atmospheric Pollution Be Considered a Co-factor in Extremely High Level of SARS-CoV-2 Lethality in Northern Italy? Environ. Pollution. 2020, 261, 114465.

Corinna Cortes and V. Vapnik, Support vector networks, Machine Learning 20 (1995), no. 3, 273–297.

Cowell, A. Dawid, S. Lauritzen, and D. Spiegelhalter, Probabilistic networks and expert sytems, Springer, New York, 1999.

Crammer and Y. Singer, Ultraconservative online algorithms for multiclass problems, Journal of Machine Learning Research 3 (2003), 951–991.

D. D. Lewis, Naive (Bayes) at forty: The independence assumption in information retrieval, Proceedings of ECML-98, 10th European Conference on Machine Learning (Chemnitz, DE) (C. N´edellec and C. Rouveirol, eds.), no. 1398, Springer Verlag, Heidelberg, DE, 1998, pp. 4–15.

D. G. Kleinbaum, K. Dietz, M. Gail, M. Klein, and M. Klein, Logistic regression. Springer, 2002.

D. Gerbing, “Time Series Components,” School of Business Administration, Portland State University, 2016

D. Meyer, “Support Vector Machines – The Interface to libsvm in package e1071”, August 2015.

D. O. Hebb, The organization of behavior, John Wiley and Sons, New York, 1949.

David McAllester, Generalization bounds and consistency for structured labeling, predicting Structured Data (Cambridge, Massachusetts), MIT Press, 2007.

Dean and S. Ghemawat, MapReduce: simplified data processing on large clusters, CACM 51 (2008), no. 1, 107–113.

Devroye, L. Gy¨orfi, and G. Lugosi, A probabilistic theory of pattern recognition, Applications of mathematics, vol. 31, Springer, New York, 1996.

Douglass AR, Newman PA, Solomon S the Antarctic ozone hole: An update. 2014

Dufour, J.M. Coefficients of Determination; McGill University: Québec, QC, Canada, 2011.

E. A. Nadaraya, on nonparametric estimates of density functions and regression curves, Theory of Probability and its Applications 10 (1965), 186–190.

F. Pianosi, K. Beven, J. Freer, J. W. Hall, J. Rougier, D. B. Stephenson, and T. Wagener, “Sensitivity analysis of environmental models: A systematic review with practical workflow,” Environmental Modelling & Software, vol. 79, pp. 214–232, 2016

Fisher, D. H. Knowledge acquisition via incremental conceptual clustering. Machine Learning, (1987). 2, 139-172.

Freund and R. E. Schapire, Large margin classification using the perceptron algorithm, Machine Learning 37 (1999), no. 3, 277–296.

Frieze and M. Jerrum, An analysis of a montecarlo algorithm for estimating the permanent, Combinatorica 15 (1995), no. 1, 67–83.

G. Bakir, T. Hofmann, B. Sch¨olkopf, A. Smola, B. Taskar, and S. V. N. Vishwanathan, Predicting structured data, MIT Press, Cambridge, Massachusetts, 2007.

G. Valentini, M. Muselli, and F. Ruffino, “Cancer recognition with bagged ensembles of support vector machines,” Neurocomputing, vol. 56, pp. 461–466, 2004.

Garcia, J.M.; Teodoro, F.; Cerdeira, R.; Coelho, R.M.; Kumar, P.; Carvalho, M.G. Developing a Methodology to Predict PM_{10} Concentrations in Urban Areas Using Generalized Linear Models. Environ. Technol. 2016, 37, 2316–2325.

Ghorani-Azam, A.; Riahi-Zanjani, B.; Balali-Mood, M. Effects of Air Pollution on Human Health and Practical Measures for Prevention in Iran. J. Res. Med. Sci. 2016, 21, 1–12.

Ghosh P., “The Impact of Data Quality in the Machine Learning Era,” Data Varsity, 2018.

Gionis, P. Indyk, and R. Motwani, Similarity search in high dimensions via hashing, Proceedings of the 25th VLDB Conference (Edinburgh, Scotland) (M. P. Atkinson, M. E. Orlowska, P. Valduriez, S. B. Zdonik, and M. L. Brodie, eds.), Morgan Kaufmann, 1999, pp. 518– 529.

H. Cram´er, Mathematical methods of statistics, Princeton University Press, 1946.

H. Hsu, P. A. Lachenbruch, H. Hsu, and P. A. Lachenbruch, “Paired T Test,” in Wiley Encyclopedia of Clinical Trials, Hoboken, NJ, USA: John Wiley & Sons, Inc., 2008.

H.W. Kuhn, the Hungarian method for the assignment problem, Naval Research Logistics Quarterly 2 (1955), 83–97.

Haidar, Dong Abdulhamid, MavridisHaiwei, and Nikolaos. Image-based date fruit classification. In 2012 IV International Congress on Ultra-Modern Telecommunications and Control Systems 2012 pages 357–363. IEEE.

Hajek P. and V. Olej, “Predicting common air quality index--The case of Czech Microregions,” Aerosol and Air Quality Research2015, vol. 15, no. 2, pp. 544–555.

HamdiAltaheri, Mansour Alsulaiman, and Ghulam Muhammad. Date fruit classification for robotic harvesting in a natural environment using deep learning 2019.

Hammadi Hamza, Mokhtar Rejili, Elbekkay Mokhtar, and Ali Ferchichi. New approach for the morphological identification of date palm (Phoenix Dactylifera L.) cultivars in tunisia.

Hasan, SattarSakibul, and Abdus. Arabian date classification using cnn algorithm with various pre-trained models. In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) 2021 pages 1431– 1436. IEEE.

Yang M. And J. A. de Loera, “A Machine Learning Approach to Evaluate Beijing Air Quality,” 2018.

Yi, X.; Zhang, J.; Wang, Z.; Li, T.; Zheng, Y. Deep Distributed Fusion Network for Air Quality Prediction. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, London, UK, 19–23 August 2018; pp. 965–973.

Yu, L.; Wang, S.; Lai, K.K. Basic Learning Principles of Artificial Neural Networks. In Foreign-Exchange-Rate Forecasting With Artificial Neural Networks; Yu, L., Wang, S., Lai, K.K., Eds.; Springer: Boston, MA, USA, 2007; pp. 27–37.

Yu, R.; Yang, Y.; Yang, L.; Han, G.; Move, O.A. RAQ A Random Forest Approach for Predicting Air Quality in Urban Sensing Systems. Sensors 2016, 16, 86.

Z. Q. Luo and P. Tseng, On the convergence of coordinate descent method 224 3 Bibliography for convex differentiable minimization, Journal of Optimization Theory and Applications 72 (1992), no. 1, 7–35.