A Data-driven Framework on Mining Relationships between Air Quality and Cancer Diseases

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Abstract: According to the report on global health risks, published by World Health Organization, environmental issues are urged to be dealt with in the world. Especially, air pollution causes great damage to human health. In this work, we build a framework for finding the correlations between air pollution and cancer diseases. This framework consists of a data access flow and a data analytics flow. The data access flow is designed to process raw data and to make the data able to be accessed by APIs. The cancer statistics is then mapped to air pollution data through temporal and spatial information. The analytics flow is used to find insights, based on the data exploration and data classification methods. The data exploration methods use statistics, clustering, and a series of mining techniques to interpret data. Then, the data mining methods are applied to find the relationships between air quality and cancer diseases by viewing air pollution indicators and cancer statistics as features and labels, respectively. The experiment results show that NO and NO_2 air pollutants have a significant influence on the breast cancer, and the lung cancer is significantly influenced by NO_2, NO, PM_{10} and O_3, which are consistent with those from traditional statistical methods. Moreover, our results also cover the research results from several other studies. The proposed framework is flexible and can be applied to other applications with spatiotemporal data.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

Rapid development of industry has caused serious environmental damage since the Industrial Revolution. Air pollution is the biggest environmental issue of the world, which we must urgently face (Pope III, 2016) (W.H.O., 2009). According to the report on global health risks, published by World Health Organization, air pollution is the 14th biggest health risk in terms of global deaths (W.H.O, 2014). In Taiwan, air quality has been getting worse. The Environmental Protection Administration (EPA) of Taiwan conducted a survey on the perceptions of the environment and found out that air pollution is perceived as the most serious environmental problem among Taiwanese people. There are many latent effects of air pollution on health, ranging from minute physiological changes to slight symptoms and to more obvious diseases. For example, the conditions of patients with chronic respiratory diseases will worsen when they breathe in air pollutants. With the release of open data (Delen, 2009), people will no longer be hindered by inadequate information and the limited right of access in conducting analysis and developing relevant applications. The open data of air pollution indicators and cancer statistics from the EPA and the Ministry of Health and Welfare (MHW) in Taiwan are analysed in this work. We build a framework for data collection and insight finding to investigate the influence of air pollution on cancers. Our framework consists of a data access flow and an analytics flow. The data access flow is used to convert raw data into Object Relational Mapping (ORM) objects and release the data using the standard Web APIs to improve data accessibility. The analytics flow is composed of the steps of data access, data exploration, and data mining. The step of date access is to get raw data by APIs. Then, the characteristics of the data are explored in the phase of data exploration, followed by the phase of data mining to discover knowledge and to find rules. The rules indicate which air pollution indicators are related to which cancers. A number of rules identified are consistent with the results generated by the

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statistical methods in the existing studies.

The remainder of the paper is organized as follows. The related works are reviewed in Section 2. Section 3 introduces the framework and the analytics flow. The analytics flow is composed of three stages including data access, data exploration, and data mining, to be detailed in Sections 4, 5, and 6, respectively. Finally, Section 7 concludes this work.

2 RELATED WORK

Air pollution influences human health and destructs environment. Many governments have established air quality monitoring stations in many areas to collect air pollution data for analysis. Sahafizadeh and Ahmadi predicted air pollution using data mining techniques with the Boushehr data (Sahafizadeh and Ahmadi, 2009). They employed decision tree to predict the trend of air pollution based on various features such as atmospheric pressure and humidity. Hsieh et al. inferred real-time air quality of various locations given environmental data and the data from very sparse monitoring locations (Hsieh et al., 2015).

Payus et al. integrated health data with an air quality database, and analysed data using a straightforward mining method (Payus et al., 2013). Dicken et al. applied clustering and classification methods to study air pollution. They employed data driven method to examine NIDCH disease data as well as local air pollution data acquired from Dhaka, Bangladesh, in an attempt to find out the correlation between air pollutants and the number of inpatients admitted into local hospitals. The reasons behind the increase/decrease of the number of inpatients were further analysed in (Dicken et al., 2015). K-means clustering algorithms were employed to analyse air pollutants in different seasons while the inpatients admitted into hospitals were classified using CART. Moreover, environmental streaming data were collected using heterogeneous sensors while events were detected using the association rule mining method as well as classification method. Dao and Zettsu predicted the occurrence of asthma based on the environmental monitoring data (Dao and Zettsu, 2016).

3 FRAMEWORK AND ANALYTICS FLOW

As shown in Figure 1, the framework is made up of *data access flow* and *analytics flow*. The data access flow refers to a procedure in which data are processed for the purpose of *Data-as-a-Service* (*DaaS*). Data are analysed in four steps based on the analytics flow, including the steps of *data access*, *data exploration*, *data mining*, and *data evaluation* based on the data driven strategy. We use open-source tools and libraries to implement the solutions for open data analysis.

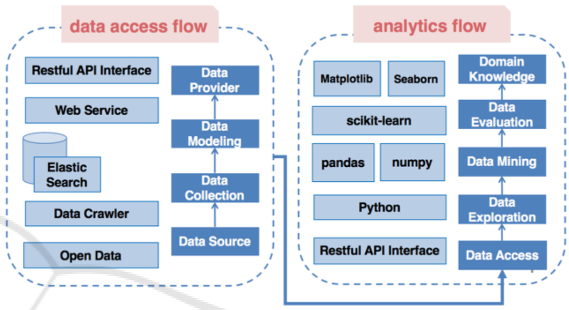


Figure 1: The flows of data access and analytics.

Since open data are published in different formats and by different agencies, much time is often needed to do the data pre-processing. The data access flow is used to describe how raw data are converted into *Object Relational Mapping* (ORM) objects and then released by using the standard *RESTFul* APIs for improving data accessibility and realizing data-as-a-service, therefore allowing data to be repeatedly and conveniently used.

The analytics flow comprises a series of steps, including data access, data exploration, data mining, and data evaluation. The step of data access is to call APIs to get the data for analysis from DaaS to be detailed in Section 4. In the step of data exploration, the characteristics of data are explored and then used to make up the absence of professional backgrounds. The data are interpreted by a data driven method which is effective for data scientists without domain knowledge. Then, the data mining methods extract rules from data. Finally, experts with domain knowledge and expertise are introduced to evaluate the results. All steps in the analytics flow are explained and discussed in Sections 4, 5, and 6.

4 DATA ACCESS

The step of date access refers to a procedure in which raw data are collected and then processed to be ready for analysis. This procedure is divided into three parts: *data-as-a-service*, *data description*, and *data pre-processing* to be discussed in the following.

4.1 Data-as-a-Service (DaaS)

Many government agencies have released enormous data for public use, so called *open data*. However, some of these open data are not easy to use due to their formats or access methods. A successful analysis relies on the quantity of usable data. The more the usable data are, the better the research quality may be. Moreover, with a reliable architecture, raw data can be processed easily and data availability can be upgraded to 5-star level or higher (Bertot et al, 2010). Therefore, the data access flow, shown in Figure 1 and divided into three parts including *data collection*, *data modeling*, and *data provider*, is proposed to ensure that the data sources are available for analysis.

The first issue of interdisciplinary data analysis is to deal with different data sources and convert the collected data into a consistent format. In this paper, we collect open data from web pages by crawlers, originally with a low level of usability. The open data are then repackaged using object-oriented methods in an attempt to convert the data into objects within a specific timeframe and space. For this purpose, Object-Relational Mapping (ORM) technique is employed. ORM is a data abstraction technique designed to map database contents into object-oriented data, thus allowing developers to manipulate the database simply by manipulating objects without using SQL syntax. In other words, developers may write access logic using the same syntax regardless of the lower-layer database systems. Apparently, ORM sets data access logic free from lower-layer database systems and thereby minimizes the coupling relationship between development and the database, allowing data access architecture to be more flexible.

With the ORM technique, object-oriented data can be packaged easily and the data can be accessed flexibly. In an effort to enhance the benefits associated with the ORM technique, the API access interface has to be implemented. The API interface is designed in compliance with RESTFul standard specifications, thus allowing users to manipulate the data using the HTTP protocol. Once the API access interface is implemented, all remote hosts are allowed to manipulate the data. Apparently, all researchers and developers benefit from the API access interface. The API access interface allows them to concentrate on the data analysis and applications without worrying about the problems related to data processing. This work releases the procedure and open data access interface to the general public, allowing all researchers to access the data effortlessly through the Web API.

4.2 Data Description

This subsection introduces the datasets, followed by an overview of the analysis methods.

4.2.1 Air Quality Monitoring Data

The EPA established 77 air quality monitoring stations across Taiwan in an attempt to monitor the air quality all over Taiwan, and broadcast warning notices accordingly. The Pollutant Standards Index (PSI) is calculated using the monitoring data obtained from major pollution sources to convert air densities into various pollutants' vice-values. After that, the data were transformed and released through API. The monitoring stations have been established for nearly 20 years and the monitoring data released by all monitoring stations have been collected by this study, including all major pollution sources and monitoring data across Taiwan.

Table 1: Schema for air quality monitoring data.

Attribute			**Range**
station			77 cities in Taiwan
time			1979 – 2014
Attribute	**Unit**	**Normal Scale**	**Mean**
CO	ppm	0.47 - 0.83	0.71
PM_{10}	μg/m3	46-86	67.96
NO	ppb	3.84-11.55	10.81
NO_2	ppb	15.7-28.41	22.62
NO_x	ppb	20.07-39.4	33.47
SO_2	ppb	3.3-6.7	7.06
O_3	ppb	19.6-30.5	25.44

4.2.2 Cancer Occurrence Statistical Data

According to the report of catastrophic illness published by the MHW of Taiwan, cancer is one of the major diseases in Taiwan. Cancer refers to the proliferation of abnormal cells in human body. The abnormal cells grow so fast that the normal organs are jeopardized, resulting in hemorrhages, pains, and functional incapacitation. Cancer has ranked the top of the ten major causes of death for a long time, and has imposed a far-reaching influence on health. This study has collected the statistical data released by the MHW over the past 30 years, including the occurrence rates and mortality rates of ten major cancers. In the next section, the data driven method is introduced so as to make up for the inadequate knowledge in cross domain data analysis and to discover knowledge using data mining methods.

Table 2: Schema of cancer occurrence statistical data.

Attribute		Range	
city		21 cities in Taiwan	
area		373 districts in Taiwan	
time		1979 – 2012	
Attribute	**Unit**	**Scale**	**Mean**
Lung Cancer	Standardized Incidence Rate (%)	29.30-58.50	44.48
Liver Cancer		26.35-42.80	34.85
Colorectal Cancer		26-46.46	37.48
Breast Cancer		23-35.07	29.25
Oral Cancer		19.62-27.11	19.68
Prostate Cancer		8.64-21.27	15.79
Gastric Cancer		10.25-16.34	13.45
Pancreatic Cancer		11.6-26.28	19.64
Esophagus Cancer		4.92-10.9	8.63
Cervix Cancer		4.41-10.77	8.11

4.3 Data Pre-processing

The interdisciplinary data analysis involves an effective integration of various datasets (Fotopoulou et al., 2016). Data integration refers to the connection between the datasets located in similar geographic areas and occurring in the same period of time. It is necessary to convert geographic areas into coordinates in order to integrate the data located in similar geographic areas.

In view of the implementation, the raw data do not have the coordinate field. It is necessary to import external resources such as NGIS or Google Maps to convert the address into coordinates using Geopy Additionally. How to transfer different diseases to the corresponding monitoring stations is an important work that has to be contemplated. This study uses the K-d tree structure to minimize the time complexity when searching for correspondence (Bentley, 1975). First, the points representing air quality monitoring data are built up as a K-d tree. Then, we select one point from the cancer occurrence statistical data to query the nearest point as shown in Figure 2. The different diseases can correspond to the nearest monitoring stations in the valid coverage based on the K-d tree. In general, an air monitoring station has a 25km valid coverage (Wen, 2003).

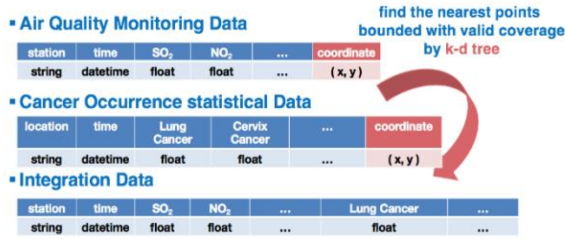


Figure 2: Data integration.

5 DATA EXPLORATION

5.1 Statistical Analysis

The first method of data exploration is learning about the data preliminarily using simple statistics and observations. Statistics includes descriptive statistics and inferential statistics. Descriptive statistics is employed in this work because it has better intuition and interpretability. In descriptive statistics, data are processed and categorized to describe and summarize the characteristics of data as well as the relationships between variables.

5.2 Row-wise Analysis

Row-wise analysis is designed to observe the transverse relationships between data using clustering techniques. Clustering methods are used to gather similar data into a cluster as shown in Figure 3.

The Clustering Method. As soon as data access procedure is completed, data could be easily accessed through Web API. The data formats are shown in the following table in which each row of data represents the data in an area, including the monitoring station's location, time, and various values related to air pollutions. Firstly, the transverse data, or the data in different areas, are clustered so that all row data with similar properties are grouped into a cluster. In other words, the locations with similar indices of air pollutions are grouped into the same cluster.

The Clustering Representation. Upon the completion of the clustering procedure, the compositions of a cluster are analysed, followed by the discussion of the clustering representation. However, it is not easy to observe the data characteristics contained in the cluster.

stations	time	SO_2	NO_2	...	Lung Cancer
Shalu, Taichung	200101	1	2	...	120
Shalu, Taichung	200102	1	2		126
Shalu, Taichung	200103	2	2		128
Shalu, Taichung	200104	1	2		...
Fengyuan, Taichung	200101	6	3		
Fengyuan, Taichung	200102	7	3		

Figure 3: Row-wise analysis.

5.3 Column-wise Analysis

Column-wise analysis is designed to observe the longitudinal relationships or the relationships among attributes. The correlation coefficient is employed to calculate the correlation between attributes. In short, the relationship between different attributes is observed by comparing the correlation between attributes as shown in Figure 4.

Cancer Occurrence Statistical Data. As shown in Figure 4, all attributes in all locations are serialized to acquire the data related to every attribute in every location within a certain timeframe. Each series indicates the changes of every attribute in the same location for the period.

Correlation. The correlation coefficient is employed to calculate the correlation between different attributes. Next, the correlation between any two time-series is calculated using the correlation coefficient.

stations	time	SO_2	NO_2	...	Lung Cancer
Shalu, Taichung	200101	1	2	...	120
Shalu, Taichung	200102	1	2		126
Shalu, Taichung	200103	2	2		128
Shalu, Taichung	200104	1	2		...
Fengyuan, Taichung	200101	6	3		
Fengyuan, Taichung	200102	7	3		

{ Shalu, Taichung, SO_2 : 1, 1, 2, ... }
{ Shalu, Taichung, NO_2 : 2, 2, 2, ... } Correlation
{ Shalu, Taichung, Lung Cancer : 120, 126, 128 ... }

Figure 4: Column-wise analysis.

5.4 Results and Observations

5.4.1 Statistical Analysis

Figure 5 shows different pollutant statuses in individual cities and Figure 6 shows different pollutant statuses with different cancers.

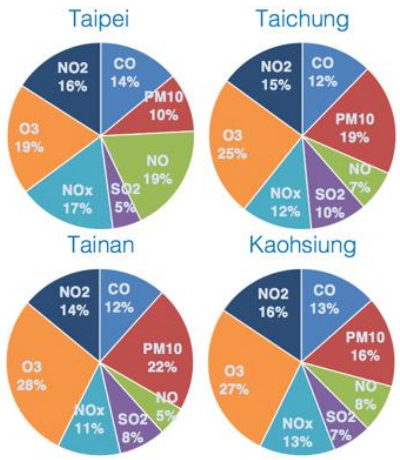
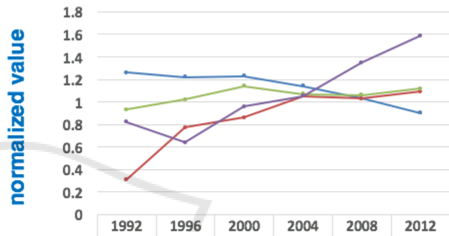


Figure 5: Statistical analysis: the status of air pollution in 2012.



	1992	1996	2000	2004	2008	2012
NO2	1.26	1.22	1.23	1.14	1.03	0.9
O3	0.31	0.77	0.86	1.05	1.03	1.09
Lung cancer	0.93	1.02	1.14	1.07	1.06	1.12
Cervical cancer	0.82	0.64	0.96	1.05	1.35	1.59

Figure 6: Statistical analysis: the status of air pollution and cancer in Taipei from 1992 to 2012.

5.4.2 Row-wise Analysis

We conduct the experiment of the row-wise analysis as follows. To start with, the data are divided into two parts, air pollution and cancer occurrence, and then grouping these data by a cluster algorithm. If the ground truth labels are not known, the evaluation must be performed using the model itself such as the Silhouette Coefficient, where a higher Silhouette Coefficient score relates to a model with better defined clusters (Rousseeuw, 1987).

Silhouette Coefficient score is bounded between -1 for incorrect clustering and +1 for highly dense clustering. Scores around zero indicate overlapping clusters. The score is higher when clusters are dense and well separated, which relates to a standard concept of a cluster. The results in Table 3 indicate that: 1) when all of the air quality indicators were used as a feature, the value of Silhouette Coefficients reached a certain level and could be grouped in clusters, 2) when all of the statistical values of cancerous cases were used as a feature, the value of Silhouette

Coefficients did not reach a certain level and the data could not be effectively grouped and clustered, and 3) when individual statistical values of cancerous cases were used as a feature, we obtained many remarkable results and concluded that individual data could produce data clustering effect. Different cancers were divided into clusters using different methods. Thus, putting them all together would cause confusion and a failure of grouping. For instance, one cancer was mainly affected by demographical factors, while another cancer was decided by economic structural problems. When taking these two into consideration simultaneously, cross-influence effects might happen and cause grouping errors.

Table 3: Silhouette Coefficient.

Silhouette Coefficient with N clusters for Air pollution						
N	20	60	120	360	600	1200
Score	0.33	0.35	0.37	0.49	0.62	0.68
Silhouette Coefficient with N clusters for All Cancers						
N	3	6	9	12	18	20
Score	0.21	0.10	0.07	0.10	0.09	0.07
Silhouette Coefficient with N clusters for Lung Cancer						
N	20	60	120	360	600	1200
Score	0.51	0.51	0.50	0.49	0.52	0.54
Silhouette Coefficient with N clusters for Cervix Cancer						
N	20	60	120	360	600	1200
Score	0.51	0.51	0.50	0.50	0.552	0.55

Figure 7 shows how certain cancers were distributed in certain geographical areas in Taiwan (left figure) and how air pollution played a part in it (right figure). The same signs are meant for clustering of the same type. The results indicate that clustering effects in the geographic and temporal dimensions can be spotted in the data. However, these observations are not necessarily the cause of the overall condition. In other words, data exploration can only help us better comprehend the data without rushing to conclusions.

Figure 7: Visualization on Google Map: clusters for all air pollutant indicators (left) and lung cancer statistics data (right).

5.4.3 Column-Wise Analysis

Through the exploration into the column-wise analysis, we discussed the correlations among attributes via an observation of sequential correlation coefficients. A sequence should be viewed as the changing process of an attribute in time. In this work. Pearson product-moment correlation coefficient is used for the measure of the linear correlation between two variables, giving a value between +1 and −1 inclusive, where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation. However, correlation is not sufficient to demonstrate the presence of such a causal relationship (i.e., correlation does not imply causation).

Table 4 reveals how Lung Cancer or Cervix Cancer was associated with air pollution in certain areas. Disparate results were discovered in the Lung Cancer case, suggesting Lung Cancer was associated with different air pollutants in a different way. In addition, obvious differences can be found in the results from Lung Cancer and Cervix Cancer, implying not all cancers are highly relevant to air pollution. For the sake of observation, we purposely chose the same area. Cross-area observations, however, are also worth discussing.

Table 4: Correlation on cancer series.

Correlation on All series as Lung Cancer		
Series1	***Series2***	***Correlation***
South District, Tainan - Lung Cancer	South District, Tainan - NO	0.7878
South District, Tainan - Lung Cancer	South District, Tainan - NO	0.7793
South District, Tainan - Lung Cancer	South District, Tainan - PM_{10}	0.7573
Correlation on All series as Cervix Cancer		
Series1	***Series2***	***Correlation***
South District, Tainan - Cervix Cancer	South District, Tainan – O_3	0.4652
South District, Tainan - Cervix Cancer	South District, Tainan - NO_x	0.4470
South District, Tainan - Cervix Cancer	South District, Tainan - PM_{10}	0.4327

6 DATA MINING

Data mining techniques are used to figure out the implications hidden behind the data. The models are constructed to interpret the data. We employ classification in data mining for the following two purposes: 1) describing why the model is constructed and explaining data characteristics as well as its applications, and 2) predicting the trend of data based on the data models. As stated in Section 5, various air pollutants resulted in diseases. In this section, classification techniques are employed to analyse the influence on the disease imposed by air pollutants. After that, the influences on all diseases related to air pollutions are summed up. Lastly, the results are presented.

6.1 Classification

Classification. Firstly, the influence on the disease imposed by air pollutants has to be identified. For this purpose, health information is classified using classification models in accordance with the pollutions in all geographic areas. A classifier is trained for each disease and all classifiers are compared through experiments in order to find out the rationality of the classifiers.

Applications. Most importantly, the results will be able to develop more applications, such as summary of influences or geographic visualization. For example, the results can sum up the influences on each disease and find out the influence on health imposed by air pollutions. The health risks can be fitted into maps using geographic information, allowing users to easily find out the difference in health risks between different geographic areas.

6.2 Results and Evaluation

Table 5: Accuracy score.

Accuracy Score of RandomForestClassifier as two types					
N	**1200**	**6000**	**12000**	**18000**	**64000**
Breast Cancer	0.75	0.72	0.70	0.65	0.63
Lung Cancer	0.74	0.76	0.65	0.68	0.64
Cervix Cancer	0.52	0.57	0.60	0.56	0.61
Accuracy Score of RandomForestClassifier as three types					
N	**1200**	**6000**	**12000**	**18000**	**64000**
Breast Cancer	0.70	0.54	0.61	0.62	0.6
Lung Cancer	0.81	0.67	0.56	0.65	0.56
Cervix Cancer	0.50	0.46	0.44	0.50	0.47

Result. Table 5 shows two types of labels: 1) dividing the cancer occurrence into two types of high and low based on the mean; 2) dividing the cancer occurrence into three types of high, medium and low based on quartile. The results indicate that different diseases incur different results in both tables, regardless of the algorithms used. A stronger separability can be found in breast cancer and lung cancer than uterine cancer, which might be evidence for a closer correlation between the former two diseases and the properties of the air pollutants. The result is improved by dividing the value of cancer occurrence into more types.

We discovered the level of impact of various attributes using classification algorithms. Take the tree-based classification algorithms as an example. The importance of a feature is computed as the total reduction of the criterion brought by that feature. In the table below, similar results are produced by a different classification method. We consider that these common results for the specific cancer are significant.

Table 6: Importance of features for breast cancer and lung cancer.

	Importance	
Classifier	**Breast Cancer**	**Lung Cancer**
LogisticRegression	NO, O_3, NO_2	O_3, PM_{10}, NO_2, NO
SVC	NO_2, NO	NO_2, NO, O_3, PM_{10}
Ensemble method	NO_2, NO	NO_2, NO, PM_{10}, O_3

Evaluation. In our work, the occurrence of breast cancer is affected by NO_2 and NO. In the past research, the relationship was also found. A link between post-menopausal breast cancer and exposure to nitrogen dioxide was found in (Crouse et al., 2010; Hystad et al., 2013). It found out that women living in the areas with the highest levels of pollution were almost twice as likely to develop breast cancer as those living in the least polluted areas. These results can be used to strengthen the monitoring of air pollutant emissions. It also provides medical institutions for breast cancer awareness advocacy to enhance people's knowledge on risk factors for breast cancer.

The occurrence of lung cancer is effected by NO_2, NO, PM_{10} and O_3, found in our results. The results are also consistent with the past studies. In a study, lung cancer incidence was increased most strongly with NO_2 exposure (Hystad et al., 2015). Further investigation is needed into possible effects of O_3 on the development of lung cancer. Another study aimed to assess the association between long-term exposure to ambient air pollution and lung cancer incidence (Raaschou-Nielsen et al., 2013).

Summing up the above literature, the results in the cases of lung cancer or breast cancer are consistent with ours. We also compare the results for lung cancer and breast cancer to see that lung cancer has a more extensive relationship to air pollution than breast cancer. From the comparison of the results from different classifiers, we can see that some features are considered more important in the different classifiers.

7 CONCLUSION

This study uses environmental pollution factors and health statistic reports to establish a set of health risk analysis processes in order to investigate the influence of air pollution on diseases. More specifically, we focus on the air pollution indicators in conjunction with the cancer statistics data. The proposed framework consists of the data access and analytics flows. The data access flow is to improve the availability of open data, while the analytics flow is to find insights. A number of existing studies are reviewed and the results generated by our analysis framework are compared with those from traditional statistical methods. Moreover, our results also cover the research results from several other studies. The proposed framework shows a more general approach than the traditional statistical methods, and can be applied to the other applications with spatiotemporal data.

REFERENCES

Bentley, J.L., 1975. Multidimensional binary search trees used for associative searching. Communications of the ACM, 18(9), pp.509-517.

Bertot, J.C., Jaeger, P.T. and Grimes, J.M., 2010. Using ICTs to create a culture of transparency: E-government and social media as openness and anti-corruption tools for societies. Government information quarterly, 27(3), pp.264-271.

Crouse, D.L., Goldberg, M.S., Ross, N.A., Chen, H. and Labrèche, F., 2010. Postmenopausal breast cancer is associated with exposure to traffic-related air pollution in Montreal, Canada: a case-control study. Environmental health perspectives, 118(11), p.1578.

Dao, M.S. and Zettsu, K., 2015. Discovering Environmental Impacts on Public Health Using Heterogeneous Big Sensory Data. In Proceedings of IEEE International Congress on Big Data, pp. 741-744.

Delen, D., Fuller, C., McCann, C. and Ray, D., 2009. Analysis of healthcare coverage: A data mining approach. Expert systems with applications, 36(2), pp.995-1003.

Dicken, R.A., Rubby, S.M.F., Naz, S., Khaled, A.A., Rahman, S.A., Rahman, S. and Rahman, R.M., 2015. Analysis and classification of respiratory health risks with respect to air pollution levels. In Proceedings of IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing, pp. 1-6.

Fotopoulou, E., Zafeiropoulos, A., Papaspyros, D., Hasapis, P., Tsiolis, G., Bouras, T., Mouzakitis, S. and Zanetti, N., 2016. Linked data analytics in interdisciplinary studies: The health impact of air pollution in urban areas. IEEE Access, 4, pp.149-164.

Hsieh, H.P., Lin, S.D. and Zheng, Y., 2015, August. Inferring air quality for station location recommendation based on urban big data. In Proceedings of ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 437-446. ACM.

Hystad, P., Demers, P.A., Johnson, K.C., Carpiano, R.M. and Brauer, M., 2013. Long-term residential exposure to air pollution and lung cancer risk. Epidemiology, 24(5), pp.762-772.

Hystad, P., Villeneuve, P.J., Goldberg, M.S., Crouse, D.L., Johnson, K. and Canadian Cancer Registries Epidemiology Research Group, 2015. Exposure to traffic-related air pollution and the risk of developing breast cancer among women in eight Canadian provinces: a case–control study. Environment International, 74, pp.240-248.

Payus, C., Sulaiman, N., Shahani, M. and Bakar, A.A., 2013. Association rules of data mining application for respiratory illness by air pollution database. Int J Basic Appl Sci, 13(3), pp.11-16.

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

Raaschou-Nielsen, O., Andersen, Z.J., Beelen, R., Samoli, E., Stafoggia, M., Weinmayr, G., Hoffmann, B., Fischer, P., Nieuwenhuijsen, M.J., Brunekreef, B. and Xun, W.W., 2013. Air pollution and lung cancer incidence in 17 European cohorts: prospective analyses from the European Study of Cohorts for Air Pollution Effects. The Lancet Oncology, 14(9), pp.813-822.

Rousseeuw, P.J., 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. Journal of Computational and Applied Mathematics, 20, pp.53-65.

Sahafizadeh, E. and Ahmadi, E., 2009. Prediction of air pollution of Boushehr city using data mining. In Proceedings of International Conference on Environmental and Computer Science, pp. 33-36.

World Health Organization, 2009. Global health risks: mortality and burden of disease attributable to selected major risks.

World Health Organization, 2014. Burden of disease from household air pollution for 2012.

Wen, Y. W., 2003, Two-Phase Spatiotemporal Models for Air Pollution and Health. PHD dissertation in Department of Information Management at National Chengchi University, Taiwan.