Exploration of Social-economic and Environmental Impacts on Lung Cancer Mortality in 94 Countries With Artificial Neural Network and Random Decision Tree Analysis

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Research Article

Keywords: Lung Cancer Mortality, Artificial Neural Network, Random Decision Tree, Spatial-temporal Analysis

Posted Date: December 20th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-1167346/v1>

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Abstract

Background

Since lung cancer is the biggest killer in cancer families, extremely threatening to human health, an understanding of social-economic and environmental impacts on lung cancer mortality (LCM) is imperative to improve patient psychological health and potentially mitigate lung cancer incidences and multimorbidity. Figuring out key indicators in social-economic and environment impacts which are sensitive to LCM on spatial-temporal scales contributes to preclinical control and systemic treatments for lung cancer with standard chemotherapy agents are still relatively ineffective.

Methods

Based on lung cancer mortalities in 94 countries within a decade (2006-2016), this research appropriately dissects social-economic, demographic, and environmental independent variable effects using Artificial Neural Network (ANN) and CRT Random Decision Tree algorithms (CRT-CRT-RDF).

Results

With the two methods comparison, the similarity is that education and carbon emission were two etiologies. Education in low and middle countries of lung cancer was related with total ecological footprint and total population. Carbon emission in extreme countries was linked to ecological forestland footprint. Spatial-temporal analysis postulated China and the U.S were the two largest countries whereas China and India were the two fastest countries of LCM growth. Both models have a high precision of prediction (96.1% of CRT-CRT-RDF and 98.4% of ANN).

Conclusions

This research will facilitate preventive lung cancer services, prioritize the geographical allocation of lung cancer investment for WHO, and provide evidence for shrinking carbon emission and deforestation.

1. Introduction

Lung cancer is increasingly common as a second primary malignancy. It was defined using the International Classification of Diseases as malignant neoplasm of trachea, bronchus, and lung. In 2017, 1.88 million mortality was likely two-time folds of colon and stomach cancer, called the first killer in carcinomas family for patients in the globe [1]. In the United States, lung and bronchus cancer is the first leading source of cancer death. The death rate was 38.5 [38.4, 38.6] under 95% Confidence Interval (CI) per 100,000 men and women per year based on 2014–2018 deaths of adjusted-age in the U.S, reducing 5% of the death rate. There are 34.1% [33.8, 34.4] of the death rate of CI in Texas, reducing 4.6% of the death rate. Cancer statistics reported that the estimated new case of lung and bronchus cancer in 2021 in 235,760 cases, representing 12.4% of all new cancer cases, and estimated deaths are 131,880 cases, accounting for 21.7% of all cancer deaths [2-3]. Identifying related lung cancer factors will be beneficial to prevent from occurrence of lung cancer and improve patients' treatment with lung cancer.

Lung cancer incidence is directly relevant to the patient's lived ambiance. Underground miners' death from lung cancer was 2.36 times higher than the general population [4]. Smoking is widely recognized as the leading cause of lung cancer so that the effect of smoky coal exposure was higher for the risk of lung cancer [5]. Lung cancer is the result of lung infections and lesions for a long time, and lung infections are originated from fungal, viral, protozoal, and parasitic

infections [6]. For instance, the COVID-19 virus is automatically detected in lung infections [7]. Air spreading is one of the main routes of COVID-19 spreading. PM2.5 pollution led to a negative effect on human health and economic growth [8]. Thus, it is necessary to consider individual ecological footprint impacts on lung cancer research. The ecological footprint is an indicator of evaluation in environmental sustainability, including total ecological footprint, total bio-capacity, ecological carbon footprint, ecological crop-land footprint, ecological fish-land footprint, ecological built-up land footprint, ecological grazing-land footprint, and ecological forest-land footprint. The ecological footprint is relatively related to human wellbeing [9-11]. Total bio-capacity (TBC), ecological crop-land footprints (ECL), ecological grazing-land footprint (EGL), and ecological built-up land footprint (EBL) have significant positive influences on human subjective-wellbeing, but ecological fish-land (EFL) has significant negative influences on SWB. Ecological carbon footprint (ECF) is significantly negatively related to SWB in developed countries [12].

Although the clinical impacts of lung cancer have been explored previously [13-15], the relationships between socioeconomic and environmental variables and lung cancer on a national scale have been never touched. Up to date, only four articles examined the national driving forces of lung cancer [16-19], all of which have assessed the effects of gender, age structure, religion, and race on the national wide lung cancer, while they neglected the roles of environmental factors on lung cancer. Therefore, it was urgent to explore possible contributions of social-economic, and environmental variables to global lung cancer mortality (LCM). Moreover, most of these studies used logistical regression to determine whether the odds ratio (OR) was beyond 1 or not [20], whereas they did not consider the space-time clusters with the lung cancer concentration. The spatial effects of socioeconomic and environmental factors on lung cancer during different historical periods should not be ignored because the countries worldwide have undergone divergent development progress during different historical periods. Additionally, these studies generally classified specific groups based on their gender and age, while they paid less attention to the globe or continent. Although the relationships of socioeconomic factors and covid-19 in the world have been clarified recently [21], the association between ecological footprint and lung cancer in the world is still unknown.

To fill these knowledge gaps, we developed an Artificial Neural Network (ANN) model and CRT Random Decision Tree algorithms (CRT-RDF) model to assess the global and regional contributions of socioeconomic and environmental impacts on lung cancer, respectively. The present study made potential contributions to the inherent knowledge. In this research, to begin with, we standardized 17 explanatory variables with social-economic, and environmental matrixes and performed ANN and CRT-RDF models. Secondly, through two different approaches, the common characteristic or determinants are revealed in the end.

2. Data And Method

2.1 Data

Ecological footprint data were captured from an open dataset published by the global ecological footprint network (<https://www.footprintnetwork.org/>). The dataset included a worldwide ecological footprint during 1961-2016. Global lung cancer data were collected from an open dataset published our world in data (<https://ourworldindata.org/>). The other factors (e.g., urbanization rate, education, health, happiness, and religion) are from the open dataset of the World Bank (<https://data.worldbank.org/>). Via the combination of three datasets, 94 countries were locked in this research, including 1097 observations during 2006-2016. When conducting two approaches, lung cancer death rate is classified into three-level from low to high as a unique dependent variable. Independent variables incorporate social-economic and environment two aspects, involving 16 explanatory variables in total. Social-economic impacts had 8 factors, which refers to education, stability, economic (per GDP), health, total population, urbanization rate, happiness, and religion aspect of Christian. Environmental impacts had 7 factors that contain EF consumption per capital (EF), carbon footprint

(CBF), Cropland footprint (CLF), Forestland footprint (FLF), Bio-capacity (BC), Built-up land footprint (BLF), Fishing land footprint (FIF), Grazing-land footprint (GLF), as shown in supplement 1.

2.2 Study Framework

In this research, we firstly performed standardization of independent variables and classify dependent variables in 94 countries, then implemented spatial autocorrelation to detect lung cancer clusters. Furthermore, we repeatedly investigated the ANN model and CRT-RDF model until optimal models coming out. The study framework is in Figure.1.

2.3 Study Area

Despite ecological footprint in the world is computed in 187 countries and happiness index records 101 countries, 94 countries in Table 1 without missing data are left in this research. We used the death population in 94 countries to divide by total population as mortality rate, ranking three classes to represent 33%, 67%, and 100% of lung cancer death from low to high. 1 in Figure 2 indicates the low level of lung cancer death in 54 countries. 2 in Figure 2 points to mediate the level of lung cancer death in eight countries.3 in Figure 2 described the high level of lung cancer death in 32 countries.

Table 1 LCM Ranking

Ranking	Country
1	Afghanistan, Angola, Azerbaijan, Bahrain, Benin, Bhutan, Bolivia, Botswana, Burkina Faso, Burundi, Cameroon, Chad, Chile, Colombia, Congo, Costa Rica, Dominican Republic, El Salvador, Ethiopia, Ghana, Haiti, Jordan, Kazakhstan, Kenya, Kuwait, Lebanon, Madagascar, Malawi, Malaysia, Mali, Mexico, Myanmar, Nepal, Nicaragua, Niger, Panama, Paraguay, Peru, Rwanda, Saudi Arabia, Sierra Leone, Singapore, Somalia, Sri Lanka, Tanzania, Togo, Tunisia, Uganda, United Arab Emirates, Uzbekistan, Venezuela, Yemen, Zambia, Zimbabwe
2	Albania, Armenia, Australia, Austria, Belarus, Israel, Lithuania, Luxembourg, Norway Portugal, Sweden, Switzerland
3	Argentina, Bangladesh, Belgium, Bosnia and Herzegovina, Brazil, Canada, China, Croatia, Czech Republic, Denmark, Estonia, France, Germany, Greece, India, Indonesia, Italy, Japan, Latvia, Montenegro, Netherlands, Pakistan, Philippines, Poland, Romania, Russia, Serbia, Slovenia, Spain, Thailand, Turkey, United Kingdom, United States, Vietnam

2.4 Spatial autocorrelation

Spatial autocorrelation is a basic skill of spatial analysis [22]. It is defined as the dependence of a given variable's values on the values of the geographically weighted matrix at neighboring locations [23]. SAC is also called global Moran I. When it is positive, that means high values are associated with relatively high values at neighboring locations, conversely, it is negative, which means high values correspond to relatively low values at neighboring locations [24]. The presence of spatial autocorrelation is important, either because it is usually taken as indicating that there is something of interest in the distribution of map values that calls for further investigation in order to understand the reasons behind the observed spatial variation, or because the presence of spatial autocorrelation implies information redundancy and has important implications for the methodology of spatial data analysis [25]. Thus, Global Moran I reflect the association between the dependent variable and its spatial dependence.

2.5 Artificial Neural Network Algorithm

Artificial Neural Network is one of the available methods of machine learning. ANN has been shown superior to algorithmic methods in estimating environmental uncertainty due to its high generalization ability and accuracy [26]. A

neural network model is considered as a directed graph with the implied properties, including: "A state variable n_i is associated with each node i , A real-valued weight w_{ik} is associated with each connection (ik) between two nodes i and k , A real-valued bias v_i is associated with each node i , A transfer function $f_i[n_k, w_{ik}, v_i, (i \neq k)]$ is defined for each node i , which determines the state of the node as a function composed of its bias, the weights of incoming connections, and the states of nodes connected to it. " [27-28].

2.6 CRT Random Decision Tree regression

Random Decision Forests have been shown to be effective in a wide range of classification and regression problems [29]. They consist of a set of binary trees, each stochastically trained on random subsets of the data. Despite any one tree may be overfitted, the randomness in the training process encourages the trees to give independent estimates, which can be combined to achieve an accurate and robust result. It runs efficiently on large databases. The advantages of CRT-RDF are that it can handle thousands of input variables without variable deletion. Variable with high importance has a significant impact on the outcome values. In this research, the CRT-RDF model is performed in SPSS software.

3. Results

3.1 The spatial-temporal variation of LCM

In this paper, we chose inverse distance and Euclidean distance row to conduct spatial autocorrelation. The results include, global Moran of the LCM was 0.76, expected index was -0.01, the variance was 0.0027, z-score was 14.82, and p-value was 0. That means LCM exists positively significant spatial autocorrelation and is clustered. It also tells us that lung cancer outbreak is positively related to spatial neighboring lung cancer death. In Figure 3, LCM is classified into two clusters in terms of HH and LL. HH has distributed 2 countries Chad and Rwanda at the top of the map, and LL occupied 33 countries, including Angola, Azerbaijan, Bahrain, Belgium, Bosnia and Herzegovina, Brazil, Burkina Faso, Burundi, Canada, China, Colombia, Czech Republic, Denmark, El Salvador, France, Ghana, India, Jordan, Kazakhstan, Lithuania, Luxembourg, Montenegro, Myanmar, Nicaragua, Poland, Portugal, Romania, Saudi Arabia, Spain, Switzerland, Uganda, United Arab Emirates, United Kingdom the middle bottom of the map.

3.2 Spatial-temporal Comparison of LCM

During the study period of 2006-2016, concerning the number of total cases, China and the U.S are the two largest countries of LCM among ten countries in Figure 4. The mortality of lung cancer dramatically increased from 422144.6 to 685286.4 while the U.S increased from 174411.3 to 185121.1 within a decade. The lowest mortality was less than 7500 in South Africa, compared to other countries. Nevertheless, as far as increasing speed, China and India had the fastest growth rate of LCM that tended to two-time increased speed in a decade, based on Figure 5. The mortality in Italy displayed an inverse U-shape with a down-turn tendency, which is opposed to the going-up tendency in other eight countries. Interestingly, only had Russia negatively growth in ten countries, decreased 11% of mortality rate in a decade. Furthermore, Germany and Japan increased beyond 15% whereas Canada, Italy, South Africa, and the U.S increased no more than 10%. In Figure 5, U.K had the lowest increased speed of less than 5%.

3.3 ANN results

We took advantage of Multilayer Perceptron Network to choose the standardized option for the Rescaling Method for Covariates. Figure 6 exhibited the ANN chart. We see one hidden layer in Figure 6. The input layer on the left of Figure 6 consisted of 14 standardized independent variables. Output layer on the right comprised three classes of LCM. In table 2, observed cases are divided into training cases of 70% and testing cases of 30%. The predicted accuracy reached 97% regardless of training cases and test cases. Figure 7 further demonstrated predicted cluster distribution in the three

levels. The dots of class 1 concentrated on 100% with blue color, rather than the dots of class 2 and class 3. The dots on the second class in the middle of figure 5 were located at proximately 100% with red color, instead of the dots of the first class and the last lass. The dots in the third class were distributed at a high percent with green color.

Table 2 Predicted Accuracy

Sample	Observed	Predicted with ANN				Observed	Predicted with CRT			
		1	2	3	Percent Correct		1	2	3	Percent Correct
Training	1	215	4	0	98.20%	1	343	16	2	95.0%
	2	1	221	9	95.70%	2	6	354	15	94.4%
	3	0	5	218	97.80%	3	2	1	358	99.2%
	Overall Percent	32.10%	34.20%	33.70%	97.20%	Overall Percent	32.0%	33.8%	34.2%	96.2%
Testing	1	138	3	1	97.20%					
	2	0	141	3	97.90%					
	3	1	1	136	98.60%					
	Overall Percent	32.80%	34.20%	33.00%	97.90%					

Table 4 described the importance of independent variables in this research. The most important variable was the education index, taking up 100%, indicating education degrees were closely related to lung cancer. That means people with high education have a low occurrence of lung cancer, otherwise, those who had low education exposure on high risk of lung cancer. The second significant variable was ecological carbon footprint with 74.4%, meaning carbon emission directly impacts lung cancer rise. At the same time, carbon consumption is crucial in improving environmental quality. Health and GDP after carbon footprint account for 67% of important effects, which point out economic development and health positive impacts on LCM. Notably, the health index is defined by life expectancy, which is easy to think that high aging has a high risk of lung cancer. Lastly, ecological grazing-land footprint, total population, and ecological crop-land footprint also contributed to LCM. Unsurprisingly, the population increased more resulted in a high risk of lung cancer such as China. This explained why China took stringent quarantine policy in the pandemic.

Table 3 The Comparison of Independent Variable Importance

Independent Variable	No.	ANN Method		CRT-RDF Method	
		Importance	Normalized Importance	Importance	Normalized Importance
Zscore(CBF)	1	0.098	74.4%	0.383	100.0%
Zscore(education)	2	0.131	100.0%	0.343	89.4%
Zscore(pergdp)	3	0.089	67.8%	0.326	85.0%
Zscore(health)	4	0.089	67.5%	0.323	84.1%
Zscore(EF)	5	0.041	18.9%	0.319	83.1%
Zscore(CLF)	6	0.078	59.3%	0.265	69.2%
Zscore(SWB)	7	0.029	22.3%	0.198	51.7%
Zscore(FLF)	8	0.064	48.6%	0.194	50.6%
Zscore(stability)	9	0.054	41.3%	0.174	45.3%
Zscore(BC)	10	0.044	20.1%	0.148	38.6%
Zscore(TP)	11	0.083	63.0%	0.137	35.6%
Zscore(BLF)	12	0.060	45.7%	0.124	32.3%
Zscore(FIF)	13	0.071	54.2%	0.122	31.9%
Zscore(URB)	14	0.028	12.8%	0.108	28.1%
Zscore(GLF)	15	0.086	65.7%	0.103	26.9%
Zscore(Christian)	16	0.067	51.3%	0.100	26.1%

3.4 CRT-CRT-RDF results

In this research, classification and Regression Trees (CRT) is used to perform CRT-RDF methods. CRT mainly present associations between variables via hierarchical and graphical tree structures [30]. In figure 8, the maximum tree depth was 5, minimum cases in parent node were 10, minimum cases in child node were 5. We got 35 nodes, 18 terminal nodes, 5 depths of the tree, 0.038 estimated risk, and 0.006 Std. error. The predicted percentage of three levels of LCM was 95%, 94.4%, 99.2%, respectively. The overall percentage was 96.2%. The tree structure of LCM in figure 8 broke down education in two parts of 662 cases and 435 cases. Class 3 of LCM is the most severe part of the three classes. It derives from the ecological carbon footprint that depends on the urbanization of each country. Urbanization ascribes from ecological forestland shrinking on a large scale. Class 1 of LCM relied on total bio-capacity, which was from less than 0.51 ecological built-up land footprints that were generated by more than -0.37 total ecological footprints. Class 2 of LCM originated from less than 0.07 GDP, which was contributed by beyond -1.2 ecological crop-land footprints that were produced by no more than 6.94 total population. Thus, the root of LCM is deforestation that impacts ecological imbalance.

The prediction of the accuracy of LCM in the CRT-CRT-RDF model is beyond 96% in table 2. Table 3 described the importance of independent variables in the CRT-RDF method. The most important variable was carbon footprint, taking up 100%, articulating carbon release is the primary factor in the detection of LCM. The second significant variable was the education index, accounting for 89.4%, expressing education levels were relatively link to LCM, just like the scenario of the ANN method. Health and GDP after education index account for 84.1% and 85% of important effects, which is the

same as the ANN method. Remarkably, the total ecological footprint occupied 83.1%, instead of 18.9% in the ANN method in Table 3, portraying total ecological footprint played a vital role in the generation of LCM. What is more, ecological crop-land footprint and ecological forest footprint had the same contribution as the ANN approach. Finally, ecological grazing-land footprint, total population, and Christian impacts were decreased in the CRT-RDF method. The distinction in the CRT-RDF was that population dedicated health and GDP while ecological grazing-land is the reason for carbon footprint increasing in figure 8.

4. Discussion

Everything is health and health is everything in the theory of social determinants of health (SDOH) [31]. Health is a product of vulnerability, being subjected to multi-dimensional change, such as the environment, food security, race, gender, economy, education, geography [32].

4.1 Social factor Impacts

In this research, we focused on social factor impacts on LCM, involving education, health, happiness, and urbanization four aspects. First, education is overweight by 90% impact factor regardless of the ANN model or the CRT-CRT-RDF model. This is a breakthrough. Although previous studies reported that income and education are likely to contribute to disparities in non-small cell lung cancer, education interventions mainly pay attention to training health workers, community health service organizations that provide valued information or services to increase lung cancer screening benefits and shrinking lung cancer stigma [33]. Second, health and happiness are linked to mitigate lung cancer suffering and improve patients' life quality physically and mentally. Sunwha et al. (2021) took a view that lung cancer stigma had a negative impact on resilience and happiness so that encouraging patients with non-judgmental methods is beneficial to increase the happiness of individuals with advanced cancer [34]. Health is linked to lung cancer due to a high-quality diet. Myneni et al. proposed (2021) a high-quality diet was inversely associated with lung cancer of the squamous cell subtype [35]. Lastly, urbanization is the least factor in conducting lung cancer investigations. Lower urbanization produced either decreasing mortality or increased mortality. In the U.S, lung cancer incidence rate during 2007-2016 was detected in both urban and rural areas [36-37].

4.2 Demographical and Political Factor Impacts

Total population contribution fluctuates as a result of 63% importance in the ANN model but 35.6% importance in the CRT-RDC model. In other words, a demographical factor is not directly correlated with LCM, instead, it indirectly is associated with economic development that contributes to LCM via ecological crop-land footprint and health in figure 8. Qian et al. (2020) advanced Age 50–79 years, black race, and history of radiotherapy were more exposed high risk for second primary lung cancer than another disease in patients [38]. Demographical Disparity, therefore, is not an ignorable factor that determines the appearance of other reasons in lung cancer research. Stability took up about 45% importance in the two methods, which means it is stable, but not important. In our research, political stability has not affected LCM and its related factors in figure 8. As matter of fact, the politics of pollution such as media interest, provoke public disquiet and unease, aggravating social contradiction, indirectly dedicating public health [39].

4.3 Economic and religious factor Impacts

GDP is an indicator of economic development. In our research, GDP presented a compelling performance in both methods. In the ANN method, GDP attained 67.8% importance. At the same time, GDP is suitable as the third contributor in the CRT-CRT-RDF approach. GDP, as node 4 in figure 8, directly influenced LCM. GDP contribution on lung cancer also was documented well in many journals. For example, higher health spending was significantly associated with higher cancer survival value, which leads to the state-level health disparities in the United States [40]. Christian is worthy of

skepticism due to slothful performance in the two regressions. It triggered 51.3% significance in the ANN model and 26.1% importance in the CRT-CRT-RDF model for LCM. We chose Christianity as an explanatory variable to probe whether religion objectively helps patients with lung cancer improve happiness at the end of their lifetime. There are no roles in religion on the decision tree. Religion, as the actor of spirituality in emotion regulation, was studied imperfectly up to now. Thus, it is possible to debate if it helps cancer patients to adjust to their disease and achieve higher well-being [41].

4.4 Environmental factor Impacts

Undoubtedly, environmental factors impact LCM increasing based on our search. Ecological carbon footprint performed key positions in both methods. It took up 74.4% importance, located the number two ranking in the ANN model, yet it has 100% importance, standing out the top one ranking in the CRT-CRT-RDF model, directly affecting LCM. It is also verified in health issues. For example, black carbon, act as a carrier for highly toxic and carcinogenic polycyclic aromatic hydrocarbons in air, water, and soil, bringing about severe health impairment [42]. Total ecological footprint, ecological forest-land footprint, and ecological grazing-land footprint are the reasons for carbon discharge in figure 8. Especially, persistent organic pollutants (POPs) directly increased the risk of lung cancer using pre-diagnostic serum samples in a case-cohort study based on a population-based prospective cohort [43]. Furthermore, land Transportation generated the greatest impact on ozone respiratory mortality, including lung cancer [44]. That is why ozone and fine particulate matter (PM_{2.5}) exposure was well concerned by environmentalists. Albeit Environmental exposure is intangible, adverse health effects are irretrievable. Thus, environmental sustainability should be the top priority in human sustainable development. In addition, ecological crop-land footprint, ecological built-up land footprint, ecological fish-land footprint, and ecological grazing-land footprint have different great impacts on LCM. Those factors are supported each other, ultimately, the [chain reaction](#) between factors will be irreversible, causing permanent damage for humans.

Using pooled panel data of LCM, ecological footprint observations, and social-economic statistics at the cross-national level in the world from 2006 to 2016, we applied spatial autocorrelation and spatial-temporal models to examine social-economic and environmental effects of three classes of LCM from low to a high level. The results made a point that China had a high risk of LCM regardless of total amounts or dynamic growth speed, therein China implemented stringent People's Republic of China law on the prevention and treatment of infectious disease [45]. This research provided strong evidence why China put in place various strict measures to suppress the resurgence of the epidemic [46]. COVID-19 cases in China also verified the effectiveness of controlling the spread of the deadly virus. At the same time, LCM in other countries increasing, even outbreak of COVID-19 and Delta mutation, is sufficient to demonstrate that controlling virus expansion and reducing LCM should be taken uncompromising quarantine measures before eradicating the virus.

The ANN model elucidated education and ecological carbon footprint were two overarching factors of LCM. At the same time, the outcomes in the CRT-CRT-RDF model described that hierarchical LCM stems from three various factors. The ecological forestland footprint played a significant and positive role in curbing carbon emission, which directly stimulates an increase in LCM in the most severe countries of lung cancer. The total ecological footprint contributed to education impacts, which caused lung cancer in low-level countries. The total population affected on education factors that leads to lung cancer in middle countries of LCM. Thus, the conservation of forestland is imperative. Certain spatial spillover mechanisms may function to prevent deforestation [47].

5. Conclusion

The spatial-temporal analysis of LCM is powerful skill to capture sensitive clusters. Instead, the application in the global area is rare. ANN model and CRT-CRT-RDF model in the application of LCM are novel for pinpointing etiology and pathogenesis on LCM. Overfitting in the CRT-CRT-RDF model might be existed so as to generate different outcomes. Models are lack of stability and validation in context of changing different spectrums.

Declarations

Author Contributions: Conceptualization and methodology, X.W. and J.Z.; investigation, resources, and data curation, X.W.; writing—original draft preparation, X.W.; writing, reviewing, and editing, J.Z., and B.B.D.; supervision and project administration, B.B.D.: reviewing, writing, and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data, models, and code generated or used during the study appear in the submitted article.

Conflicts of Interest: The authors declare no conflict of interest.

Consent for publication: Not applicable.

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Figures

Figure 1

Study Framework

Figure 2

LCM Distribution in 94 countries

Lung Cancer Death spatial autocorrelation Map in 94 countries

Figure 3

Spatial autocorrelation of LCM

Figure 4

Cross-sectional Comparison of LCM

Figure 5

Longitudinal Comparison of LCM

Figure 6

ANN chart

Figure 7

Predicted Pseudo-probability Chart

Figure 8

CRT-CRT-RDF Tree

Figure 9

The Bar Chart of Variable importance

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