REST Journal on Emerging trends in Modelling and Manufacturing
Vol: 3 (4), 2017
REST Publisher
ISSN: 2455-4537

Website: www.restpublisher.com/journals/jemm

Evaluation of Prediction of Cancer Using weighted Product Method

C. Kalpana N. Rameshkumar
SSt College of Arts and Commerce, Maharashtra, India.
ckalpana@sstcollege.edu.in

Abstract
Predicting the number of cancer patients in the future is of great interest to society. Classical approach Age-period-cohort modeling should be used to generate cancer incidence projections. The number of predicted cases was calculated for these 160 combinations of gender and country. Averages vary from 10.4 percent to 15.3 percent for projections 10 years ahead, and from 15.1 percent to 32.0 percent for 20-year projections. Most cancer genes are physiologically inactive background of disease development. Tumors are the source of similar non-point mutations that are immunogenic and protected by tumors. Immunity. Cancer is classified as a heterogeneous disease with various subtypes. Early research - Cancer type and prognosis has become essential in cancer research because of the subsequent.

Key Words: Prediction, cancer

1. Introduction

In the field of oncology, their use can identify different expression of genes in the outcome of different tumors. 1–9 these gene expression profiles or molecular signatures are expected to help select optimal treatment strategies by allowing treatment to be tailored to disease severity. The number of breast cancer patients receiving chemotherapy used in clinical trials. Such tests are initiated. A major challenge of massive data output in DNA microarray technology analysis is the need to account for multiple sources of variation arising from biological samples, hybridization. The nearest central projection evaluate the accuracy of a classification system. According to a multifactorial cellular disorder in which many interacting cellular pathways produce tumorigenesis and growth.

Cancer therapy: Increased vascular permeability in tumors is a rapid characteristic and impaired angiogenesis (formation of existing blood vessels). Furthermore, impaired lymphatic drainage can retain nanocarriers that accumulate in tumors, allowing drug release close to tumor cells. Experiments using liposome's of different mean sizes indicate a threshold vesicle size of ~400 nm (ref. 8) for release into tumors, but other studies have shown that particles <200 nm in diameter are more effective. It is 15-20% 1-2 annual incidence of all cases of leukemia per 100 000 persons per year. Medically, disease It progresses in three different stages. The chronic or stable phase of the disease is characterized by excessive numbers of normally differentiating myeloid cells over an average of 4–6 years. Acute leukemia where the disease goes through an 'accelerated phase', also known as blast crisis. The disease progresses with the accumulation of molecular abnormalities. In addition, 5% of all patients are Ph-positive in childhood, and 80% of them present with the p185 Bcr-Abl product. Fusion of p230 results in site cleavage of downstream c-abl sequences in bcr.

Cancer incidence: The authors used strict criteria for inclusion of data from cancer registries. These standards apply to the collection of census data relating to a defined geographical area: Good medical facilities; Includes some basic materials and appropriate coding systems for cancer reporting. The reliability of each registry is that of cancer. Assessed depending on histological verification; Proportion of cases registered only from death certificate; and the number of deaths expressed as a percentage of incident cases. This is 89% higher than in 1980. Population changes account for nearly half of that increase. The rest is mostly explained by the increase in prostate cancer and the incidence of breast cancer in men and women. The relative increase in the global age-adjusted incidence rate was 39%. The number of cancer deaths increased from 130,000 to 146,000. This 13% increase is much lower than expected based on population changes (37%). Meanwhile, the incidence of breast cancer has continued to rise, and the death rate has slowly declined since the late 1990s.

2. Cancer prognosis

The tumor microenvironment is a spatially organized landscape of T lymphocytes and macrophages. In the center and penetrating edges. Classification of malignancy by tissue origin is the first step in predicting survival and treatment choice. Anatomy of the tumor location is rarely required as it usually indicates the tissue of its molecular markers. Two electronic databases, PubMed and Scopus, were accessed. Papers that focused on using techniques for tumor classification or identification of prognostic factors, predicting cancer progression by conventional statistical methods (eg chi-square, Cox regression) were excluded. Well-known limitations of this approach are the determination of the population size classifier (training set), which should be a large binding validation in sufficient representation, and the independent dataset(s) (testing set).

3. Weight Product Method

Weighted Product Model (WPM) is a well known Multi-Criteria Decision Making (MCDM)/ Multi-Criteria Decision Analysis (MCDA) method. AHP is combined with the Weight Product Method (WPM). The complexity of these methods does not increase with the AHP rate as the number of alternative websites increases. The weight Product Method (WPM) uses linguistic terms that are easy for users to understand and therefore, methods are considered easy to implement. Also, in the case of an evaluation involving several evaluators with no experience in implementation, the Weight Product Method (WPM) seems to be more appropriate. However, the Weight Product Method (WPM) as AHP does To calculate the weights of criteria Does not provide a specific route. Taking all this information into account, AHP can be successfully incorporated with the Weight Product Method (WPM). Weighted Product Method (WPM). WPM is similar to WSM. The main difference is that the Model instead of addition Includes multiplication. Each substitution is by multiplying multiple ratios Compared to others, one for each criterion. to the relative weight of each ration, the corresponding quantity is raised to an equivalent power. Therefore, one-dimensional and In both multidimensional MCDM WPM can be used. These studies discuss UtUV under the Structure of age-specific WPMs. No research has been conducted on UtUV. Considering the UtUV factor Age- and state-specific WPMs Based on the general structure WPM Designed to describe UtUV, Describe the variation in this in degradation rates between different units. The WPM method is most widely used in MCDM One of the methods. then other methods of problem-solving This method is more efficient because it takes less computation time. WPM is simple and easy to use in highly subjective cases. optimal route selection, Web activities like evaluation, production, and selection of project manager WPM is used in many areas. Between WSM and WPM the maximum mean correlation is observed, Also between WPM and TOPSIS Very little correlation is observed. The average of all these coefficients WSM, WPM, ELECTRE, and TOPSIS respectively indicates that there is a strong mean correlation.

TABLE 1. Prediction of cancer

	Male	Female
Lip, oral cavity, and pharynx	2363.00	873.00
Esophagus	2137.00	198.00
Stomach	23355.00	10976.00
Colon and rectum	23406.00	14562.00
Liver	11558.00	4456.00
Gallbladder	3,029	2,802
Pancreas	3,428	3,003
Larynx	1,000	33
Lung	16,903	8,149
Breast	73	20,356
Cervix uteri	1	3,013
Corpus uteri	1	2,565
Ovary	1	2,450
Prostate	11,062	1
Testis	269	1
Kidney	3,456	1,505
Bladder	3,051	773
Brain and CNS	1,026	903
Thyroid	11,219	34,255
Hodgkin lymphoma	199	109
Non-Hodgkin lymphoma	3,027	2,511
Multiple myeloma	833	722
Leukemia	1,822	1,401
Other and ill defined	8,008	8,123

Table 1 show that prediction of cancer in Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia are affect from the body, for male and female.

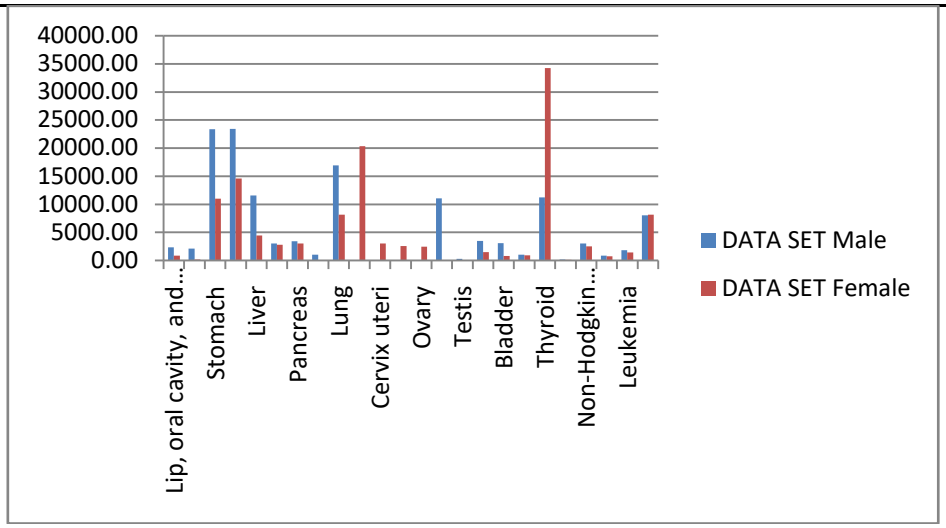

FIGURE 1. Prediction of cancer

FIGURE 1 show that prediction of cancer in Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis, Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia are affect from the body, for male and female.

TABLE 2. Performance Value

Performance value		
Lip, oral cavity, and pharynx	0.10096	0.05995
Esophagus	0.09130	0.01360
Stomach	0.99782	0.75374
Colon and rectum	1.00000	1.00000
Liver	0.49381	0.30600
Gallbladder	0.12941	0.19242
Pancreas	0.14646	0.20622
Larynx	0.04272	0.00227
Lung	0.72217	0.55961
Breast	0.00312	1.39788
Cervix uteri	0.00004	0.20691
Corpus uteri	0.00004	0.17614
Ovary	0.00004	0.16825
Prostate	0.47261	0.00007
Testis	0.01149	0.00007
Kidney	0.14765	0.10335
Bladder	0.13035	0.05308
Brain and CNS	0.04383	0.06201
Thyroid	0.47932	2.35236
Hodgkin lymphoma	0.00850	0.00749
Non-Hodgkin lymphoma	0.12933	0.17244
Multiple myeloma	0.03559	0.04958
Leukemia	0.07784	0.09621
Other and ill defined	0.34213	0.55782

TABLE 2 Performance value in Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis, Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia obtained to gave a values. These values are calculated using by formula

TABLE 3. Weight

Weight		
Lip, oral cavity, and pharynx	0.25	0.25
Esophagus	0.25	0.25
Stomach	0.25	0.25
Colon and rectum	0.25	0.25
Liver	0.25	0.25
Gallbladder	0.25	0.25
Pancreas	0.25	0.25

Larynx	0.25	0.25
Lung	0.25	0.25
Breast	0.25	0.25
Cervix uteri	0.25	0.25
Corpus uteri	0.25	0.25
Ovary	0.25	0.25
Prostate	0.25	0.25
Testis	0.25	0.25
Kidney	0.25	0.25
Bladder	0.25	0.25
Brain and CNS	0.25	0.25
Thyroid	0.25	0.25
Hodgkin lymphoma	0.25	0.25
Non-Hodgkin lymphoma	0.25	0.25
Multiple myeloma	0.25	0.25
Leukemia	0.25	0.25
Other and ill defined	0.25	0.25

TABLE 3 Weight in Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis, Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia are same weight.

TABLE.4 Weighted normalized decision matrix

Weighted normalized decision matrix		
Lip, oral cavity, and pharynx	0.563682	0.494821
Esophagus	0.5496919	0.341477
Stomach	0.9994548	0.931764
Colon and rectum	1	1
Liver	0.8382796	0.743757
Gallbladder	0.5997814	0.662311
Pancreas	0.6186263	0.673882
Larynx	0.4546406	0.218184
Lung	0.9218476	0.86491
Breast	0.2363191	1.087346
Cervix uteri	0.0808478	0.674442
Corpus uteri	0.0808478	0.647838
Ovary	0.0808478	0.640452
Prostate	0.8291376	0.091032
Testis	0.3274208	0.091032
Kidney	0.6198857	0.566995
Bladder	0.6008676	0.479998
Brain and CNS	0.4575674	0.499019
Thyroid	0.832064	1.238442
Hodgkin lymphoma	0.3036557	0.294138
Non-Hodgkin lymphoma	0.5996824	0.644401
Multiple myeloma	0.4343396	0.471877
Leukemia	0.5282084	0.556935
Other and ill defined	0.7648024	0.864219

TABLE 4 shown that the value about the Weighted normalized decision matrix for given data set, these values are calculated using by the various methods of formulas, and then the values are shown in the tabulation.

TABLE 5. Preference Score

Preference Score	
Lip, oral cavity, and pharynx	0.27892
Esophagus	0.18771
Stomach	0.93126
Colon and rectum	1.00000
Liver	0.62348
Gallbladder	0.39724
Pancreas	0.41688

Larynx	0.09920
Lung	0.79732
Breast	0.25696
Cervix uteri	0.05453
Corpus uteri	0.05238
Ovary	0.05178
Prostate	0.07548
Testis	0.02981
Kidney	0.35147
Bladder	0.28842
Brain and CNS	0.22833
Thyroid	1.03046
Hodgkin lymphoma	0.08932
Non-Hodgkin lymphoma	0.38644
Multiple myeloma	0.20495
Leukemia	0.29418
Other and ill defined	0.66096

TABLE 5 Preference score in Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis, Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia.

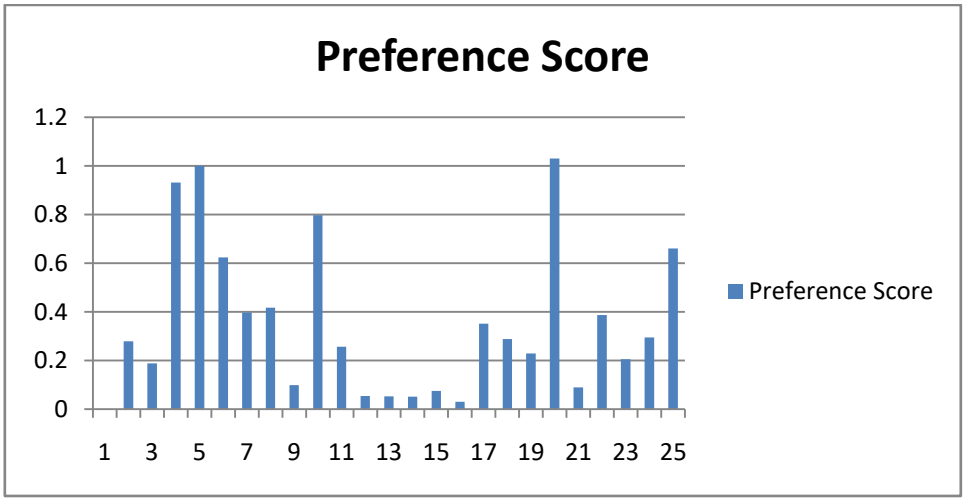

FIGURE 2. Preference Score

FIGURE 2 show that preference score in Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis, Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia.

TABLE 6. Rank

Rank	
Lip, oral cavity, and pharynx	13
Esophagus	17
Stomach	3
Colon and rectum	2
Liver	6
Gallbladder	8
Pancreas	7
Larynx	18
Lung	4
Breast	14
Cervix uteri	21
Corpus uteri	22
Ovary	23
Prostate	20

Testis	24
Kidney	10
Bladder	12
Brain and CNS	15
Thyroid	1
Hodgkin lymphoma	19
Non-Hodgkin lymphoma	9
Multiple myeloma	16
Leukemia	11
Other and ill defined	5

TABLE 6 Lip, oral cavity and pharynx, Stomach, Liver, Pancreas, Lung, Cervix uteri, Ovary, Testis, Bladder, Thyroid, Non-Hodgkin lymphoma, Leukemia shows that ranks

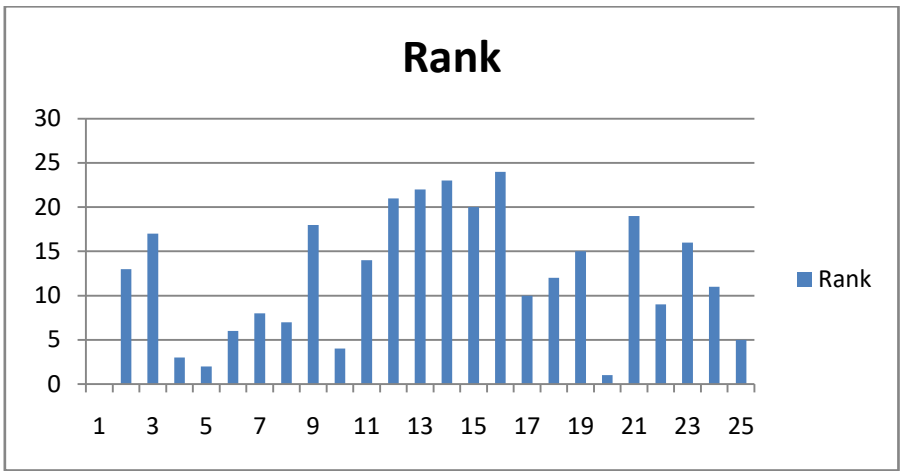

FIGURE 3. Rank

FIGURE 3 graphs is shows in ranking

4. Conclusions

Some of the early literature defines neoepitopes through the idea of assisted genetic technology. Most of the studies proposed in the past years have focused on the development of prognostic models aimed at predicting exact disease outcomes. We have tried to explain, compare and evaluate different performance machine learning is applied to cancer prediction and prognosis. In particular, the machine learning methods we use, aggregated training data types, Endpoint predictions of categories, identified several relevant trends in how these methods predict cancer risk or outcomes.

References

[1] Michiels, Stefan, Serge Koscielny, and Catherine Hill. "Prediction of cancer outcome with microarrays: a multiple random validation strategy." *The Lancet* 365, no. 9458 (2005): 488-492.

[2] Hu, Pingzhao, Gary Bader, Dennis A. Wigle, and Andrew Emili. "Computational prediction of cancer-gene function." *Nature Reviews Cancer* 7, no. 1 (2007): 23-34.

[3] Møller, Bjørn, Harald Fekjær, Timo Hakulinen, Helgi Sigvaldason, Hans H. Storm, Mats Talbäck, and Tor Haldorsen. "Prediction of cancer incidence in the Nordic countries: empirical comparison of different approaches." *Statistics in medicine* 22, no. 17 (2003): 2751-2766.

[4] Kourou, Konstantina, Themis P. Exarchos, Konstantinos P. Exarchos, Michalis V. Karamouzis, and Dimitrios I. Fotiadis. "Machine learning applications in cancer prognosis and prediction." *Computational and structural biotechnology journal* 13 (2015): 8-17.

[5] Winter, Christof, Glen Kristiansen, Stephan Kersting, Janine Roy, Daniela Aust, Thomas Knösel, Petra Rümmele et al. "Google goes cancer: improving outcome prediction for cancer patients by network-based ranking of marker genes." *PLoS computational biology* 8, no. 5 (2012): e1002511.

[6] Winter, Christof, Glen Kristiansen, Stephan Kersting, Janine Roy, Daniela Aust, Thomas Knösel, Petra Rümmele et al. "Google goes cancer: improving outcome prediction for cancer patients by network-based ranking of marker genes." *PLoS computational biology* 8, no. 5 (2012): e1002511.

[7] Jung, Kyu-Won, Young-Joo Won, Chang-Mo Oh, Hyun-Joo Kong, Hyunsoon Cho, Duk Hyoung Lee, and Kang Hyun Lee. "Prediction of cancer incidence and mortality in Korea, 2015." *Cancer research and treatment: official journal of Korean Cancer Association* 47, no. 2 (2015): 142-148.

[8] Jung, Kyu-Won, Young-Joo Won, Hyun-Joo Kong, Chang-Mo Oh, Duk Hyoung Lee, and Jin Soo Lee. "Prediction of cancer incidence and mortality in Korea, 2014." *Cancer research and treatment: official journal of Korean Cancer Association* 46, no. 2 (2014): 124-130.

[9] Kamran, Sophia C., Ellen Marqusee, Mathew I. Kim, Mary C. Frates, Julie Ritner, Hope Peters, Carol B. Benson et al. "Thyroid nodule size and prediction of cancer." *The Journal of Clinical Endocrinology & Metabolism* 98, no. 2 (2013): 564-570.

[10] Jung, Kyu-Won, Young-Joo Won, Chang-Mo Oh, Hyun-Joo Kong, Hyunsoon Cho, Jong-Keun Lee, Duk Hyoung Lee, and Kang Hyun Lee. "Prediction of cancer incidence and mortality in Korea, 2016." *Cancer research and treatment: official journal of Korean Cancer Association* 48, no. 2 (2016): 451-457.

[11] Jung, Kyu-Won, Sohee Park, Young-Joo Won, Hyun-Joo Kong, Joo Young Lee, Hong Gwan Seo, and Jin-Soo Lee. "Prediction of cancer incidence and mortality in Korea, 2012." *Cancer Research and Treatment: Official Journal of Korean Cancer Association* 44, no. 1 (2012): 25-31.

[12] Volm, Manfred, and Thomas Efferth. "Prediction of cancer drug resistance and implications for personalized medicine." *Frontiers in oncology* 5 (2015): 282.

[13] Cruz, Joseph A., and David S. Wishart. "Applications of machine learning in cancer prediction and prognosis." *Cancer informatics* 2 (2006): 117693510600200030.

[14] Kalaiselvi, C., and G. M. Nasira. "A new approach for diagnosis of diabetes and prediction of cancer using ANFIS." In *2014 World Congress on Computing and Communication Technologies*, pp. 188-190. IEEE, 2014.

[15] Moffat, Bradford A., Thomas L. Chenevert, Charles R. Meyer, Paul E. Mckeever, Daniel E. Hall, Benjamin A. Hoff, Timothy D. Johnson, Alnawaz Rehemtulla, and Brian D. Ross. "The functional diffusion map: an imaging biomarker for the early prediction of cancer treatment outcome." *Neoplasia* 8, no. 4 (2006): 259-267.

[16] Jang, In Sock, Elias Chaibub Neto, Justin Guinney, Stephen H. Friend, and Adam A. Margolin. "Systematic assessment of analytical methods for drug sensitivity prediction from cancer cell line data." In *Biocomputing 2014*, pp. 63-74. 2014.

[17] Shi, Mingguang, and Bing Zhang. "Semi-supervised learning improves gene expression-based prediction of cancer recurrence." *Bioinformatics* 27, no. 21 (2011): 3017-3023.

[18] Gupta, Sunil, Truyen Tran, Wei Luo, Dinh Phung, Richard Lee Kennedy, Adam Broad, David Campbell et al. "Machine-learning prediction of cancer survival: a retrospective study using electronic administrative records and a cancer registry." *BMJ open* 4, no. 3 (2014): e004007.

[19] Capriotti, Emidio, and Russ B. Altman. "A new disease-specific machine learning approach for the prediction of cancer-causing missense variants." *Genomics* 98, no. 4 (2011): 310-317.

[20] Au, William W. "Usefulness of biomarkers in population studies: from exposure to susceptibility and to prediction of cancer." *International journal of hygiene and environmental health* 210, no. 3-4 (2007): 239-246.

[21] Roxburgh, Campbell SD, Donald C. McMillan, John H. Anderson, Ruth F. McKee, Paul G. Horgan, and Alan K. Foulis. "Elastica staining for venous invasion results in superior prediction of cancer-specific survival in colorectal cancer." *Annals of surgery* 252, no. 6 (2010): 989-997.

[22] Druker, Brian J. "STI571 (Gleevec™) as a paradigm for cancer therapy." *Trends in molecular medicine* 8, no. 4 (2002): S14-S18.

[23] Kerr, John FR, Clay M. Winterford, and Brian V. Harmon. "Apoptosis. Its significance in cancer and cancer therapy." *Cancer* 73, no. 8 (1994): 2013-2026.

[24] Urruticoechea, Ander, Ramon Alemany, J. Balart, Alberto Villanueva, Francesc Vinals, and Gabriel Capella. "Recent advances in cancer therapy: an overview." *Current pharmaceutical design* 16, no. 1 (2010): 3-10.

[25] Coleman, Michel P., Jacques Esteve, Philippe Damiecki, Annie Arslan, and Helene Renard. "Trends in cancer incidence and mortality." *IARC scientific publications* 121 (1993): 1-806.

[26] Curado, Maria-Paula, Brenda Edwards, Hai Rim Shin, Hans Storm, Jacques Ferlay, Mary Heanue, and Peter Boyle. *Cancer incidence in five continents, Volume IX*. IARC Press, International Agency for Research on Cancer, 2007.

[27] Remontet, Laurent, Jacques Estève, Anne Marie Bouvier, Pascale Grosclaude, Guy Launoy, François Menegoz, Catherine Exbrayat et al. "Cancer incidence and mortality in France over the period 1978-2000." *Revue d'épidémiologie et de santé publique* 51, no. 1 Pt 1 (2003): 3-30.

[28] Dunn, Gavin P., Lloyd J. Old, and Robert D. Schreiber. "The immunobiology of cancer immunosurveillance and immunoediting." *Immunity* 21, no. 2 (2004): 137-148.

[29] Zha, Shan, Vasan Yegnasubramanian, William G. Nelson, William B. Isaacs, and Angelo M. De Marzo. "Cyclooxygenases in cancer: progress and perspective." *Cancer letters* 215, no. 1 (2004): 1-20.

[30] Deshpande, Amit, Peter Sicinski, and Philip W. Hinds. "Cyclins and cdks in development and cancer: a perspective." *Oncogene* 24, no. 17 (2005): 2909-2915.

