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Research Article

Optimal Time Intervals Between Personal Mammogram Test Decisions

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Abstract – Excluding skin cancer, breast cancer is the most common type of cancer in women in the United States, accounting for one in three diagnosed cases. A woman's chance of developing invasive breast cancer in her lifetime is approximately 1 in 8 (12%). While mammography has been effective in early detection, its use has resulted in a minor increase in the number of in situ cancers detected. However, mammography carries potential risks, such as exposure to unnecessary radiation, additional costs, psychological stress, and the possibility of false-positive results. Although the American Cancer Society recommends annual testing, it may be unnecessary for healthy women. In this paper, we aim to find the optimal interval between mammogram tests, balancing the benefits and risks of testing while reducing the false-positive rate and number of tests. To achieve this, we use decision trees, utility theory, and Bayes' theorem to calculate the quality-adjusted life years (QALYs) of patients.

Keywords – Decision Models; Mammogram Testing; Cancer; Utility Theory; Decision Trees; Bayes Theorem

I. INTRODUCTION

Breast cancer is a significant public health concern that affects millions of women worldwide. It is a malignant tumor that starts in the cells of the breast, and can grow into surrounding tissues or spread to other areas of the body if left untreated. Breast cancer is the second leading cause of cancer-related deaths among women, after lung cancer. In the United States, breast cancer is the most common type of cancer among women, and its incidence is increasing globally.

According to the American Cancer Society, approximately 281,550 new cases of invasive breast cancer will be diagnosed in women in the United States in 2021. In addition, there will be approximately 49,290 new cases of non-invasive (in situ) breast cancer. It is estimated that 43,600 women will die from breast cancer in 2021.

The risk of developing breast cancer varies depending on a number of factors, including age, gender, family history, and lifestyle factors such as diet and exercise. Women over the age of 50 are at the highest risk for developing breast cancer, and women with a family history of the disease are also at increased risk.

One of the most important tools for detecting breast cancer early is mammography. Mammography is a type of X-ray that is used to examine the breast tissue for any abnormalities or signs of cancer. It is recommended that women aged 50 to 74 years old should get mammograms every two years, and those with higher risk of breast

cancer should discuss the timing and frequency of mammograms with their doctor. Mammography has been shown to be effective in detecting breast cancer early, which can lead to better outcomes and increased chances of survival. Studies have found that mammography can reduce breast cancer mortality by up to 40% in women over the age of 50.

However, mammography is not without risks. There is a potential for overdiagnosis, which means that some women may be diagnosed with breast cancer that would not have caused them harm during their lifetime. This can lead to unnecessary treatment, including surgery, radiation therapy, and chemotherapy, which can cause physical and emotional harm. In addition, false positives are a common problem with mammography. A false positive occurs when a mammogram indicates that there is a suspicious area in the breast, but further testing reveals that there is no cancer present. False positives can lead to additional testing and procedures, which can be invasive and cause emotional distress for the patient. There is also a risk of radiation exposure with mammography, although the amount of radiation is typically very small and the benefits of early detection generally outweigh the risks.

To minimize the risks of mammography, it is important to ensure that the benefits of screening outweigh the potential harms. This may involve discussing personal risk factors with a doctor and deciding on the best timing and frequency of mammograms.

In recent years, there has been a growing interest in using artificial intelligence to improve the accuracy of mammography and reduce the risk of false positives. These algorithms can be trained to detect suspicious areas in mammograms and provide a second opinion to radiologists, potentially reducing the number of false positives and unnecessary procedures. However, there are also concerns about the potential to exacerbate existing biases in the healthcare system, such as disparities in access to care and diagnosis rates among different racial and ethnic groups.

In conclusion, breast cancer is a serious disease that affects millions of people around the world. Mammography is an important tool for detecting breast cancer early, but it is not without risks. Personal risk characteristics such as age, family history, and parity can affect the balance between health benefits and potential risks associated with mammography screening [1]. Thus, optimizing the screening interval between mammogram tests based on individual risk profiles is an important area of research. Additionally, ongoing research into new screening technologies may help to improve the accuracy of mammography and reduce the risk of false positives. In this paper, we investigate the use of decision trees, utility theory, and Bayes theorem to determine the optimal screening interval for mammography tests that balances the benefits and risks of mammogram testing and decreases the false-positive rate and number of tests.

II. Literature Review

There are similar studies related to mammogram testing. But, the only study we am aware of that suggests risk-based recommendations for mammography screening is by Gail and Rimer to screen for women between age 40-49 only if the woman's risk at this age equals or exceeds that of the one at 50-year old who has no risk factors for breast cancer [2]. For women over age 50, Gail and Rimer assume that annual screening is optimal. Several other studies investigate population-based breast cancer screening policies using simulation and analytical models [3]. Among these population-based analyses, the most relevant analytical study is by Maillart et al. which provides an upper bound on lifetime breast cancer mortality risk by evaluating numerous alternative screening scenarios [4]. Another relevant study is by Ivy et al. which works on cost effective method for mammography screening. She approximately solves this problem assuming that death probabilities and test accuracies are age-independent [5].

Sanders and Samei approaches the problem in a different way. They use the proportional hazards model to measure the timing of correct and incorrect reading decisions in mammography and to exploit those dependencies to improve accuracy in mammographic interpretation [6]. Markov decision processes are also studied by several authors [7,8]. The other techniques that are used for breast cancer mammogram screening problem are Artificial Neural Networks [9,10,11], Bayesian Network [3,12].

III. Problem Definition and Contirbution

Breast cancer is the most common cancer among women in the United States, resulting in more lost years of potential life than any other cancer due to its higher occurrence in younger age groups compared to most other cancers. About one in eight women in the US will develop breast cancer in their lifetime. In 2022 alone, an estimated 254,650 women were diagnosed with breast cancer and 40,170 died from the disease, making it the second leading cause of cancer-related deaths in US women [1].

While there is no guaranteed way to prevent breast cancer, early detection of the disease increases the likelihood of a cure. For instance, the 5-year survival rate increases from 27% to 98% when breast cancer is detected at early stages compared to later stages [1]. However, mammography is not a perfect screening tool and has several potential risks, including radiation exposure, cost, unnecessary tests, and risks associated with false-positive mammograms, i.e., mammograms with a positive outcome when the disease is absent [13].

In particular, false-positive mammograms are serious and harmful since they may lead to unnecessary diagnostic follow-up procedures, such as additional imaging and invasive procedures like biopsies. These procedures may, in turn, result in associated morbidities, psychological distress (including anxiety and depression), a considerable amount of time loss, and a significant reduction in the quality of life [13]. Moreover, the rate of false positives is around 7%. Therefore, the balance between the health benefits and potential risks is critical for designing an effective mammography screening program.

If we look at Table-1, we can see that breast screening recommendations from different organizations vary between every year or every two years. Screening every year is a considerable number of tests for a healthy woman. The contribution of our study is finding the optimal interval time between mammogram tests while balancing the benefits and risks of mammography testing. This would help decrease the false-positive rate and the number of unnecessary tests.

Table 1. Breast Cancer Screening Recommendations

Organization/Nation	Start Mammograms (age)	Frequency (years)
USPSTF[1]	50	2
AAFP[2]	40	1-2
American Cancer Society	40	1
American College of Ob-Gyn[3]	40	1-2
A College of Preventive Medicine	50	1-2
A College of Radiologists	40	1
World Health Organization	50	1-2

IV. Analysis of the Problem

In analysis part, we assume a patient starts her mammogram testing by the age of 40. When she is 40, she makes a decision whether take the test or don't take the test. If she prefers not to take the test this year, then she waits for a year for next year's test. In a year, she would be healthy or she would die because of any reason including breast cancer. On the other hand, if she takes the test, the result of the mammogram test would be positive or negative. If it is positive, which means there would be a tumor in her breast, the cancer would be normal, benign, or malign. If the test is negative, which means no tumor is found, she would be either healthy or cancer or she would die because of any reason. The related decision tree for a patient is found in Figure-1. For every year she make this decision again. Decision tree in Figure-1 is the 40 years Old's decision tree. For the following age, age 41, she has a new decision situation. And when she is alive, she makes this decision every year.

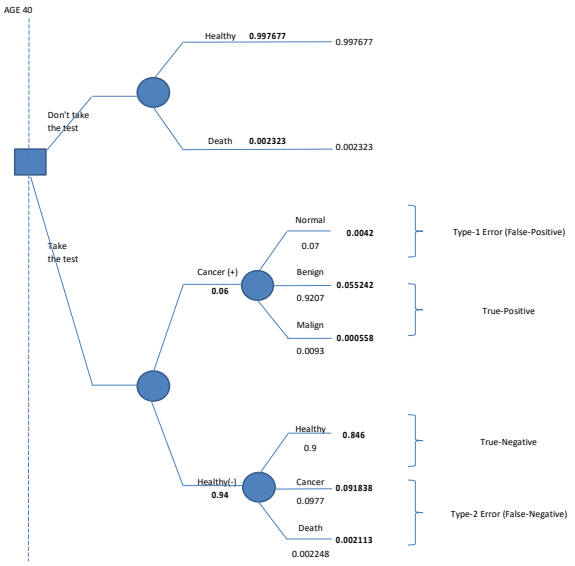

Fig. 1 Decision tree for the age of 40

In my analysis, our first aim is to find the utility functions of the individual patient. We use lottery method to find the patient's utility function. We ask current life for use versus probability of p living till 90 years old without cancer and probability (1-p) die at the current age immediately. The illustrated lottery tree is shown in figure-2. After we find the utility function of the patient, we calculate the utilities of each year and we find the remaining life for each patient.

$$U(x) = 1 - e^{-\gamma x} \quad where\ \gamma = risk\ aversion\ coefficient$$
$$x = remaining\ life\ time$$

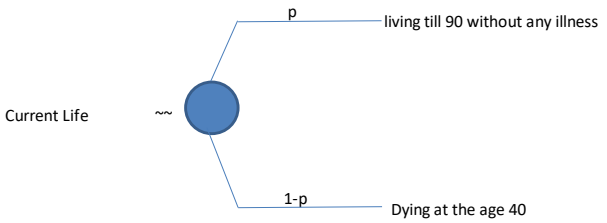

Fig. 2 Lottery method for finding patient's lottery

If there is a difference in the calculated remaining life and actual remaining life which can be found in Table-2. Then, we recommend the patient not to take the test next year and calculate the next test's time by the difference between calculated remaining life from her utility function and average remaining life from the table-2. (for the whole table look at Appendix)

Table 2. Life Expectancy at the given age

	MALE		FEMALE	
Exact Age	Death Probability	Life Expectancy	Death Probability	Life Expectancy
38	0.001979	39.68	0.001153	43.81
39	0.00214	38.76	0.00126	42.86
40	0.002323	37.84	0.001377	41.91
41	0.002526	36.93	0.001506	40.97
42	0.00275	36.02	0.00165	40.03
43	0.002993	35.12	0.00181	39.1
44	0.003257	34.22	0.001985	38.17
45	0.003543	33.33	0.002174	37.24
46	0.003856	32.45	0.002375	36.32
47	0.004208	31.57	0.002582	35.41

The final part of the analysis is the solving the big decision tree which is shown at table-3. For each age we calculate the decision trees and for each branch of the tree, we attach a new tree with the conditional probabilities and the utilities for each branch. By solving the expected utilities, we finish our analysis. So, for each individual patient, we can find the optimal interval times between two mammogram tests. So, for our analysis we only need the utility function of the patient. Once we find the utility function, risk aversion coefficient, we just need to calculate the expected remaining life for the year which a patient took the test. So, we recommend the patient the following mammogram testing time.

V. Conclusion and Future Work

Individualizing mammography screening decisions based on each patient's utility function is crucial for improving breast cancer diagnosis, as recognized by numerous researchers and several health organizations. However, there are no exact studies that exist to individualize this process. Most studies recommend population-based mammography screening. In this study, we develop a decision tree model to personalize mammography screening decisions based on a patient's individual utility function.

One of the key features of the personalized optimal mammography screening strategy proposed in this study is that it considers not only individual utility functions but also the personal history of screening when making recommendations for mammography decisions. Specifically, we illustrate how this extra piece of information might change the optimal decisions and help make better screening decisions. We can calculate the optimal interval time between two tests by using the previous test results, which update our information on following tests.

We show that our personalized screening strategies significantly decrease the expected number of mammograms compared with population-based screening guidelines. Our model might help reduce the number of unnecessary mammograms, the cost of mammogram testing, and the negative impact of false positive results on patients' psychology.

There are several future research directions. One is to explore the utility functions of each individual patient by adding more attributes instead of two attributes. Additionally, we may incorporate the economic costs associated with mammography and follow-up tests into the decision problem to gain insight about the optimal strategy from society's perspective. Lastly, we may consider the utilities and risk behaviours of decision makers and investigate how different attributes change the

mammography decision process. We assume there is only one type of breast cancer, but in reality, there are many more. We may consider different types of breast cancers in our analysis. All these analyses require different model formulations and are left for future work.

REFERENCES

[1] ACS. 2009. Breast cancer facts and figures: 2009-2010. American Cancer Society, Atlanta.

[2] Gail, M., & Rimer, B. (1998). Risk-based recommendations for mammographic screening for women in their forties. Journal of clinical oncology, 16(9), 3105-3114.

[3] Olson, D. L., & Araz, Ö. M. (2023). Multiple Criteria Decision Models in Healthcare. Data Mining and Analytics in Healthcare Management: Applications and Tools, 151-160.

[4] Maillart, L. M., Ivy, J. S., Ransom, S., & Diehl, K. (2008). Assessing dynamic breast cancer screening policies. Operations Research, 56(6), 1411-1427.

[5] Ivy, J. L., Goforth Jr, H. W., Damon, B. M., McCauley, T. R., Parsons, E. C., & Price, T. B. (2002). Early postexercise muscle glycogen recovery is enhanced with a carbohydrate-protein supplement. Journal of applied physiology, 93(4), 1337-1344.

[6] Saunders, RS, Samei, E, 2006, Improving mammographic decision accuracy by incorporating observer ratings with interpretation time, The British Journal of Radiology, 79, S117–S122

[7] Peterman, RM, Anderson JL,1999, Decision Analysis: A Method for Taking Uncertainties into Account in Risk-Based Decision Making, Human and Ecological Risk Assessment: An International Journal, Volume 5, Issue-2

[8] Schaefer, A.J., M.D. Bailey, S.M. Shechter, M.S. Roberts. 2004. Modeling medical treatment using Markov decision processes. Operations Research and Health Care: A Handbook of Methods and Applications 597-616.

[9] Baker JA, Kornguth PJ, Lo JY, Williford ME, Floyd CE Jr. 1995, Breast cancer: prediction with artificial neural network based on BI-RADS standardized lexicon. Radiology.;196(3):817-22.

[10] Baker JA, Kornguth PJ, Lo JY, Floyd CE Jr., 1996, Artificial neural network: improving the quality of breast biopsy recommendations. Radiology. 198(1):131-5.

[11] Floyd CE, JY Lo, AJ Yun, DC Sullivan, PJ, 1994, Kornguth, Prediction of breast cancer malignancy using an artificial neural network., Cancer, United States, , 2944-8.

[12] Sütçü, M., Güner, P., & Ersöz, N. Ş. (2022). Analysis of under-five mortality by diseases in countries with different levels of development: a comparative analysis. The European Research Journal, 1-13.

[13] Brewer, N.T., T. Salz, S.E. Lillie. 2007. Systematic review: the long-term effects of false-positive mammograms. Annals of Internal Medicine 146(7) 502-510.

Current age	Probability of Breast Cancer in the next 10 years is 1 in:	%
20	1760	0.06
30	229	0.44
40	69	1.44
50	42	2.39
60	29	3.40
70	27	3.73
Lifetime Risk	8	12.08

* American Cancer Society, Surveillance Research (www.cancer.org)

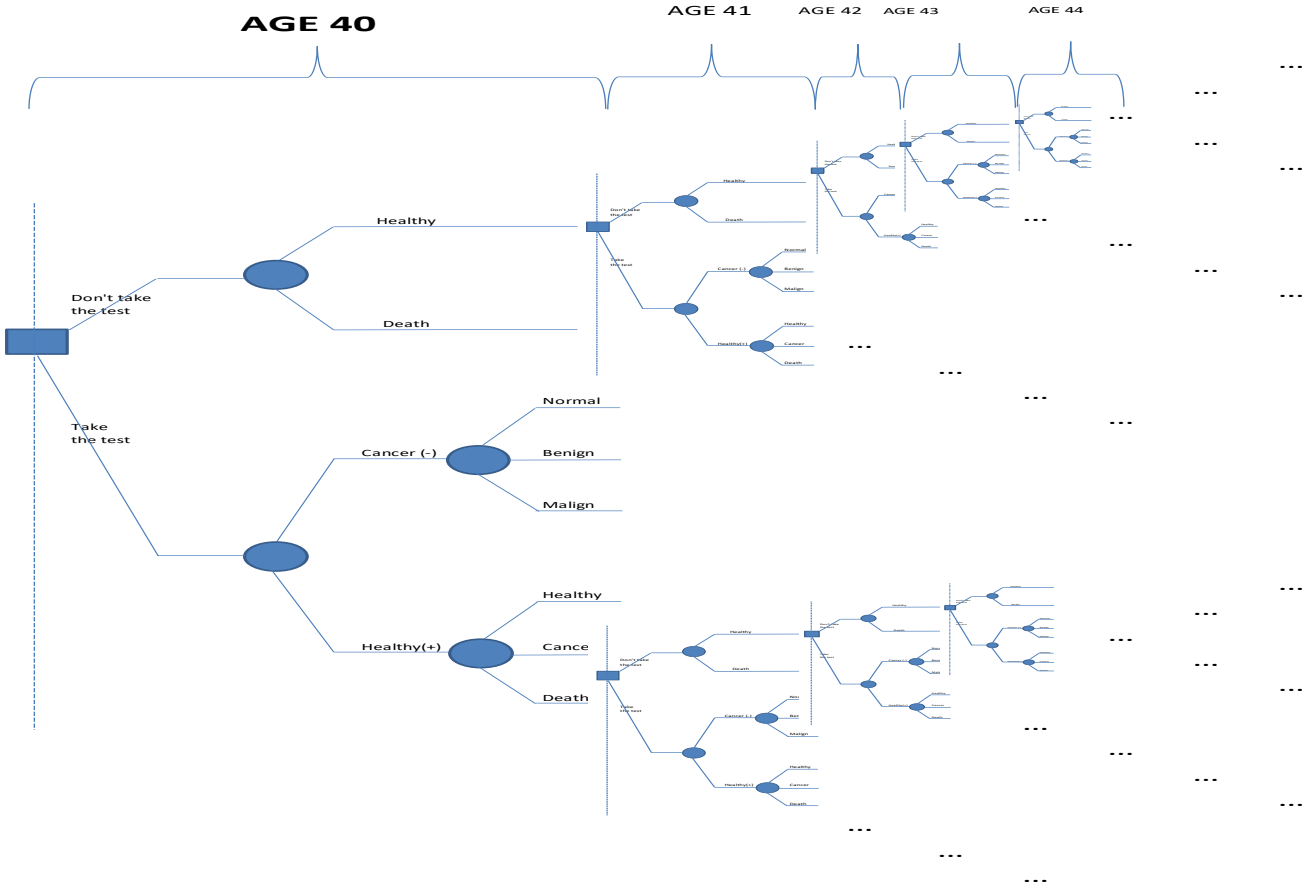

Fig. 3 Decision Tree for the long run for each age

APPENDIX

A1: Age Specific Probabilities of Developing Breast Cancer

A2: Average Life Expectancy at different ages

	MALE		FEMALE	
Exact Age	Death Probability	Life Expectancy	Death Probability	Life Expectancy
38	0.001979	39.68	0.001153	43.81
39	0.00214	38.76	0.00126	42.86
40	0.002323	37.84	0.001377	41.91
41	0.002526	36.93	0.001506	40.97
42	0.00275	36.02	0.00165	40.03
43	0.002993	35.12	0.00181	39.1
44	0.003257	34.22	0.001985	38.17
45	0.003543	33.33	0.002174	37.24
46	0.003856	32.45	0.002375	36.32
47	0.004208	31.57	0.002582	35.41
48	0.004603	30.71	0.002794	34.5
49	0.005037	29.84	0.003012	33.59
50	0.005512	28.99	0.003255	32.69
51	0.006008	28.15	0.003517	31.8
52	0.0065	27.32	0.003782	30.91
53	0.006977	26.49	0.004045	30.02
54	0.007456	25.68	0.004318	29.14
55	0.007975	24.87	0.004619	28.27
56	0.008551	24.06	0.004965	27.4
57	0.009174	23.26	0.005366	26.53
58	0.009848	22.48	0.00583	25.67
59	0.010584	21.69	0.006358	24.82
60	0.011407	20.92	0.006961	23.97
61	0.012315	20.16	0.007624	23.14
62	0.013289	19.4	0.008322	22.31
63	0.014326	18.66	0.009046	21.49
64	0.015453	17.92	0.009822	20.69
65	0.016723	17.19	0.010698	19.89
66	0.018154	16.48	0.011702	19.1
67	0.019732	15.77	0.012832	18.32
68	0.021468	15.08	0.014103	17.55
69	0.023387	14.4	0.015526	16.79
70	0.025579	13.73	0.017163	16.05
71	0.028032	13.08	0.018987	15.32
72	0.030665	12.44	0.020922	14.61
73	0.033467	11.82	0.022951	13.91
74	0.036519	11.21	0.025147	13.22
75	0.04001	10.62	0.027709	12.55
76	0.043987	10.04	0.030659	11.9
77	0.048359	9.48	0.033861	11.26
78	0.05314	8.94	0.037311	10.63
79	0.058434	8.41	0.041132	10.03
80	0.064457	7.9	0.045561	9.43
81	0.071259	7.41	0.050698	8.86
82	0.078741	6.94	0.056486	8.31
83	0.086923	6.49	0.062971	7.77
84	0.095935	6.06	0.070259	7.26
85	0.105937	5.65	0.078471	6.77
86	0.117063	5.26	0.087713	6.31
87	0.129407	4.89	0.098064	5.87
88	0.143015	4.55	0.109578	5.45
89	0.157889	4.22	0.122283	5.06
90	0.174013	3.92	0.13619	4.69
91	0.191354	3.64	0.1513	4.36
92	0.209867	3.38	0.167602	4.04
93	0.229502	3.15	0.185078	3.76
94	0.250198	2.93	0.2037	3.5
95	0.27075	2.75	0.222541	3.26
96	0.290814	2.58	0.241317	3.05
97	0.310029	2.44	0.259716	2.87
98	0.328021	2.3	0.277409	2.7
99	0.344422	2.19	0.294054	2.54
100	0.361644	2.07	0.311697	2.39
101	0.379726	1.96	0.330399	2.25
102	0.398712	1.85	0.350223	2.11
103	0.418648	1.75	0.371236	1.98
104	0.43958	1.66	0.39351	1.86
105	0.461559	1.56	0.417121	1.74
106	0.484637	1.47	0.442148	1.62
107	0.508869	1.39	0.468677	1.52
108	0.534312	1.3	0.496798	1.41
109	0.561028	1.22	0.526605	1.31
110	0.589079	1.15	0.558202	1.22
111	0.618533	1.07	0.591694	1.13
112	0.64946	1	0.627196	1.05
113	0.681933	0.94	0.664827	0.97
114	0.716029	0.87	0.704717	0.89
115	0.751831	0.81	0.747	0.82
116	0.789422	0.75	0.789422	0.75
117	0.828894	0.7	0.828894	0.7
118	0.870338	0.64	0.870338	0.64
119	0.913855	0.59	0.913855	0.59