PREDICTION MODELS FOR CARDIOTOXICITY INDUCED BY ANTICANCER DRUG IN WOMEN WITH BREAST CANCER

MSR100

Quynh T.N. Nguyen[1], Phung-Anh Nguyen[2,3,5], Shwu-Jiuan Lin[1], Jason C. Hsu[2,3,4,5]

1. School of Pharmacy, College of Pharmacy, Taipei Medical University, Taipei City, Taiwan
2. Clinical Data Center, Office of Data Science, Taipei Medical University, Taipei City, Taiwan
3. Clinical Big Data Research Center, Taipei Medical University Hospital, Taipei Medical University, Taipei City, Taiwan
4. International Ph.D. Program in Biotech and Healthcare Management, College of Management, Taipei Medical University, Taipei City, Taiwan
5. Research Center of Health Care Industry Data Science, College of Management, Taipei Medical University, Taipei City, Taiwan

Background

Breast cancer, regardless of gender, exhibits the highest incidence rate among all cancer types, with a higher prevalence in females than males [1]. Nonetheless, 5-year survival rate for female breast cancer patients is relatively high at 90% [2]. Given the shared risk factors between cardiovascular disease and cancer, such as diabetes, obesity, smoking, and drinking [3], individuals with cancer face an elevated risk of cardiac complications. Another significant concern is the potential association between cancer treatment and cardiac disease. Cardiotoxicity of anticancer drugs has been recognized since the 1960s, for example: anthracycline-induced heart failure and antimetabolites with an increased risk of myocardial infarction [4]. Cardiotoxicity can lead to limitations on drug usage and adversely affect patients' quality of life. In this study, we developed machine-learning models to predict cardiovascular events in female breast cancer patients undergoing anticancer medications.

Methods

This is a retrospective study using data from Taipei Medical University Clinical Research Database (TMUCRD) and Taiwan Cancer Registry.

In the study, we selected female patients who were diagnosed with primary breast cancer (ICD-O-3 code: C50) and underwent chemotherapy or targeted therapy from 2004 to 2020.

Patients were monitored at the date of prescription until cardiovascular events occurred during a year. The study outcome consisted of myocardial infarction, arrhythmia, conduction disorders, heart failure, and coronary artery diseases.

Several clinical features were utilized to build the prediction model, including demographics, comorbidities, medications, and lab values.

Data from Taipei Medical University and Wan-Fang hospitals was used as the training dataset. Data from Shuang-ho hospital was used for external testing and model generalization.

Results

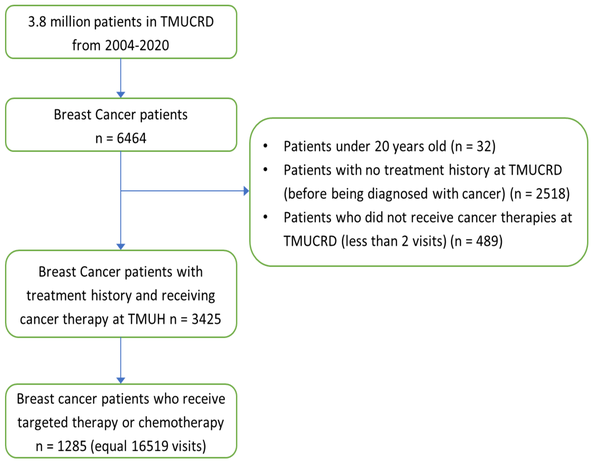

Figure 1. Cohort selection

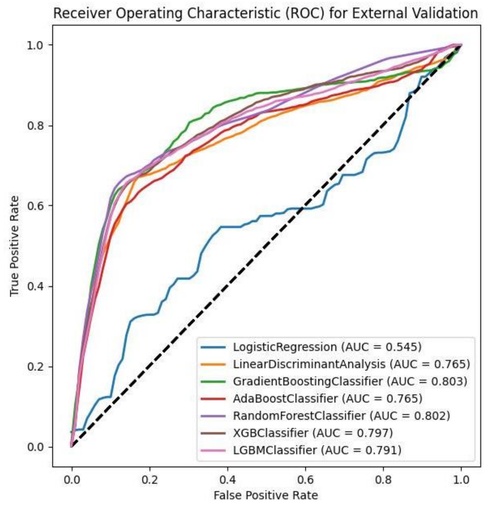

Figure 2. Performance of the models in the testing dataset

Table 1. Baseline demographic characteristics of the study population

Variables	Overall (n=1,285)	Training (n=703)	Testing (n=582)
Age, Mean (SD), years	56.1 (11.5)	56.6 (12.1)	55.5 (10.7)
BMI, Mean (SD), kg/m2	24.3 (4.0)	24.1 (4.0)	24.6 (4.1)
Smoking, N (%)	94 (7.3)	46 (6.5)	48 (8.2)
Drinking, N (%)	69 (5.4)	45 (6.4)	24 (4.1)
Tumor size, Mean (SD), mm	29.3 (20.0)	29.6 (21.1)	28.9 (18.4)
Cancer stage, N (%)			
0 - 2	1,040 (80.9)	598 (85.1)	442 (75.9)
3 - 4	174 (13.5)	96 (13.7)	78 (13.4)
HER2, N (%)	358 (27.9)	193 (27.5)	165 (28.4)
PR, N (%)	841 (65.4)	447 (63.6)	394 (67.7)
ER, N (%)	934 (72.7)	520 (74.0)	414 (71.1)
Radiation therapy, N (%)	802 (62.4)	355 (50.5)	447 (76.8)
Surgery, N (%)	1178 (91.7)	638 (90.8)	540 (92.8)
Cardiac Outcomes, N (%)	138 (10.7)	91 (12.9)	47(8.1)

Random forest and gradient boosting achieved the highest AUC (around 0.80). Regarding other metrics, random forest had an overall better performance compared to gradient boosting (i.e., precision 0.26 versus 0.16; recall: 0.68 versus 0.82; and F1-score: 0.38 versus 0.28).

Conclusions

Prediction models were built for cardiac risk assessment among breast cancer patients. These prediction models offer potential approaches for cardio-oncology clinical practice. Further research is necessary to determine the feasibility of applying the tool in the clinical setting and explore whether this tool could improve care and outcomes.

References

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Contact

Quynh Nguyen (Rachel)
School of Pharmacy, TMU, Taiwan
D301110001@tmu.edu.tw