177

Development and Evaluation of a Predictive Ensemble Learning Framework for Breast Cancer Radiotoxicities at 2 Years.

Samana Bano
University of Leicester, Leicester, United Kingdom

Samana Bano
Please provide a brief biography for the Presenting author(s)
Samana Bano is a current MSc Medical Statistics student at University of Leicester and a HDR MSc Health Data Science UK Scholar, with a background in Medical Genetics, Bioinformatics and Data Engineering to prepare for the 2025 launch of the MTG-IRS satellite, at the National Centre of Earth Observation.

Single topic, multi-speaker session, Workshop or Single presentation submission

A single presentation/poster

Single presentation or poster submission

Breast cancer affects 1 in 8 women in the UK, with radiotherapy reducing recurrence risk by 50% at 10 years and mortality by 20% at 15 years. However, 20-40% of survivors experience clinically significant radiotherapy-induced toxicities. This study developed and evaluated an ensemble machine learning framework in R to predict nine distinct breast cancer radiotoxicity endpoints at 2 years post-treatment using the REQUITE cohort data (n=2,059) from 18 hospitals across 8 countries.

The framework integrated four supervised machine learning algorithms: Multivariate Adaptive Regression Splines (MARS), AdaBoost, Random Forest (RF), and Support Vector Machines (SVM).. Analysis of the cohort revealed significant variations in toxicity prevalence, with Atrophy G1 being most common (27%) and Arm Lymphedema G1 least frequent (3%). Through recursive feature elimination, BMI, tumor size, and total acute biologically effective dose emerged as the most significant predictors, selected by 8 out of 9 endpoints.

Random Forest emerged as the top performer for most endpoints, while MARS showed superior performance for Atrophy G2 with a 5% improvement in AUROC. Notably, Atrophy G1 and Induration Tumour G1 achieved mean AUROC values of 0.746 and 0.738, respectively. The ensemble model demonstrated varying accuracy rates (74–97%), with the highest accuracy for Arm Lymphoedema (97%) and lowest for Atrophy G1 (74%). However, a perfect negative correlation between accuracy and prevalence suggested potential class imbalance effects.

These findings establish a foundation for implementing machine learning algorithms in clinical practice for predicting radiotherapy toxicities, potentially enabling personalized treatment modifications while highlighting areas for future optimization.