INTRODUCTION

More than 20,000 women are being treated annually in the U.S. for breast cancer. The only proven way to detect breast cancer early and improve survival is screening. The sensitivity of most screens is relatively low. Radiologists estimate breast cancer risk based on imaging observations and medical history to provide additional staging options. We are developing Computer Aided Diagnostic (CADx) tools to help physicians with interpretation, risk predictions, and decision making.

We have developed two breast cancer risk prediction models—the Mammography Bayesian Network (MBN) and the Mammography Artificial Neural Network (MANN)—based on mammographic, demographics, and diagnostic factors. We have also created a model to differentiate invasive and non-invasive breast cancer.

MAMMOGRAPHY BAYESIAN NETWORK

A Bayesian network is a probabilistic graphical model that uses nodes to represent probability variables, and arcs to represent dependencies among these variables. In our application, we are interested in predicting the probability of breast cancer from demographic risk factors and mammographic findings. The predictions generated by the MBN have the potential to both refine radiologists’ input into mammographic interpretations, as well as aid patients and referring physicians in clinical decision-making. In a recent study, we demonstrated that the MBN can exceed the performance of radiologists in predicting the risk of breast cancer to a high population baseline. We enrolled radiologists in routine screening examinations on 130,078 patients from 4/1995 to 3/2004. We created 2,273 mammographic findings with our state cancer registry which served as our reference standard. Using an algorithm called Harvest, we have generated 5,000 and 1,000 cross-validation sets. Using this data, we built a Mammography Bayesian Network (Figure 1) that can simulate the performance of mammography findings compared with the BI-RADS system. We validated our network using 130,078 patients from 4/1995 to 3/2004. We created 2,273 mammographic findings with our state cancer registry which served as our reference standard. Using an algorithm called Harvest, we have generated 5,000 and 1,000 cross-validation sets. Using this data, we built a Mammography Bayesian Network (Figure 1) that can simulate the performance of mammography findings compared with the BI-RADS system. We validated our network using 130,078 patients from 4/1995 to 3/2004.

Figure 1 Mammography Bayesian Network

MAMMOGRAPHY ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks are machine learning tools that are used to aid in mammographic interpretations, as well as aid patients and referring physicians in clinical decision-making.

We built a three-layer feed-forward neural network to estimate the likelihood of malignancy using the same dataset detailed above. The layers of the Mammography Artificial Neural Network (MANN) included an input layer for mammographic findings, a hidden layer of nodes, and an output layer with a single node generating the probability of malignancy (figure 3).

Figure 3 Mammography Artificial Neural Network

We then demonstrate that the Bayesian Network performed better in older women compared to younger women. We show that the ROC curves for the older women dominate the ROC curve for the Bayesian Network (Figure 4).

Figure 4 ROC curve of TAN Trained Model with Age Stratification

DISSEMINATION

When facing the breast cancer diagnostic process, women and their families need information and support to help them through this difficult period. Increasingly, we are seeing the use of Interactive Cancer Communication Systems to help women during the diagnostic process. Interactive education during the diagnostic process provides an opportunity for patients to explore decisions they are overwhelmed by the information given at the time of diagnosis.

DISSeMINATION

We developed a Bayesian Network to predict the risk of ductal carcinomas in situ (DCIS) versus invasive breast cancer using mammographic features and patient demographic features. The Bayesian Network helped quantify the probability of invasive cancer given mammographic features and mammographic findings. Of 211 malignant cases, there were 1796 correct classifications with 355 of them being invasive cancer, 253 false negatives and 102 false positives where 50% is deemed as the level above which the predictions be invasive (Figure 5). Clearly, analyzing the misclassified cases, we found that for DCIS cases as being misclassified tend to go down for older ages (Table 1).

Figure 5 Stratified Error Rate Trade–Off

Table 1 Error Rates in Age Groups

Secondly, we showed that the improved performance of the Bayesian Network in older women is attributable to a decrease in false negatives which is important clinically. Figure 6 shows the improved performance in TAN as we move from the trade–off between FNE and FPR over different threshold values.

Understanding the risk of invasive cancer aids in the clinical management of the disease such as the need for metastatic imaging at biopsy and the appropriate selection of surgical intervention. The ability to accurately predict the probability of DCIS versus invasive cancer is extremely important and can make a significant impact on improving women’s quality of life. We believe that the use of Interactive Cancer Communication Systems will make more informed decisions about managing the breast health of the current and future expected lifespan and cost–effectiveness.

Figure 7 Opportunity for Decision–making

Mammography Artificial Neural Network Performance Calibration curve of the network under the LL (dotted line) and the LL+ (solid line) and the top likelihood of malignancy (left panel). The top likelihood of malignancy is equal to the posterior probability of malignancy (1 - (1 - P (malignant)) + (1 - P (benign)) / 2) where P (malignant) and P (benign) are the posterior probabilities of malignancy and benignity given a mammographic finding. We also calculated the empirical calibration (dashed line). This is a plot of the actual prevalence of malignancy vs. the predicted prevalence of malignancy in the data.

Figure 2 Mammography Bayesian Network Performance

Mammography Artificial Neural Network Performance

Calculation curve of the network under the LL (dotted line) and the LL+ (solid line) and the top likelihood of malignancy (left panel). The top likelihood of malignancy is equal to the posterior probability of malignancy (1 - (1 - P (malignant)) + (1 - P (benign)) / 2) where P (malignant) and P (benign) are the posterior probabilities of malignancy and benignity given a mammographic finding. We also calculated the empirical calibration (dashed line). This is a plot of the actual prevalence of malignancy vs. the predicted prevalence of malignancy in the data.

Figure 6 Calibration Curve of the MANN and the MAMMOGRAPHY BAYeSIAN NETWORK

DISCUSSION

When facing the breast cancer diagnostic process, women and their families need information and support to help them through this difficult period. Increasingly, we are seeing the use of Interactive Cancer Communication Systems to help women during the diagnostic process. Interactive education during the diagnostic process provides an opportunity for patients to explore decisions they are overwhelmed by the information given at the time of diagnosis.