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Predictive Model for Likelihood of Survival among Breast Cancer Patients using Machine Learning Techniques

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ABSTRACT
Providing a prediction model that can give survival rate of breast cancer patients among women based on past records collected over the years in an underdeveloped country like Nigeria poses a challenge. This is because of their poor data collection habit and underdeveloped health care system. Machine learning (ML) offers a different approach and cheaper alternative of identifying survival rate among breast cancer patients among women. The purpose of this study is to provide survival rate or mortality rate of breast cancer patients after treatments has been administered. Naïve Bayes' Machine learning techniques was used in developing a predictive model to predict survival rate of breast cancer patients among women. Data was gathered from 30 different health center location ranging from hospitals and institute. The data included all women who have been diagnosed with breast cancer from 2000 to 2005 and all death cases encountered so far. The simulation of the model was done using R Studio software. The result of the model was good as survival rate was above 85% showing incredible in the model used. Comparisons were made between some of the factors affecting breast cancer and survival rate using box plot. The results showed there is high survival rate in breast cancer patients among women in Nigeria. Other ML techniques can also be considered using same data to further improve the model.

General Terms
Machine Learning and data mining techniques

Keywords
Breast cancer, Survival, Nigeria, Predictive model, Naïve Baye, Machine learning

1. INTRODUCTION
Cervical and breast cancers are the two most common cancers among women in Nigeria, and other developing countries contributing significantly to a high morbidity and mortality rate in the country (Forman, Ferlay, Stewart & Wild, 2014). Breast cancer is the most common cancer in women worldwide, in Nigeria, with population of about 187 million people and it represents about 12% of all new cancer cases and 25% of all cancers in women (DeSantis, Ma, Bryan & Jemal, 2013). According to Centre for disease control and prevention (2018), breast cancer is a disease in which cells in the breast grow out of control. It is a type of cancer that starts in the breast and gradually grows to and wreak havoc on its host. Cancer starts when cells begin to grow out of control. Breast cancer cells usually form a tumor that can often be seen on an x-ray or felt as a lump. Breast cancer occurs almost entirely in women, but men can get breast cancer, too. Breast cancer can begin in different parts of the breast.

A breast is made up of three main parts: lobules, ducts, and connective tissue. The lobules are the glands that produce milk. The ducts are tubes that carry milk to the nipple. The connective tissue (which consists of fibrous and fatty tissue) surrounds and holds everything together. Most breast cancers begin in the ducts or lobules. Breast cancer can spread outside the breast through blood vessels and lymph vessels. When breast cancer spreads to other parts of the body, it is said to have metastasized. Breast cancers has better prognosis if diagnosed and treated early. Ajekigbe, 1991 and Ezeome, 2010 did some studies in breast cancer that suggested large number of women who got diagnosed early could beat breast cancer. Some of the reasons that were listed in the article include low literacy levels, high rates of poverty, cultural and religious traditions, poor geographical access to cancer care, low level of awareness of breast and cervical cancers, lack of screening, and poor diagnostic procedure and treatment among health-care provider (Wang, McLafferty, Escamilla, Luo, 2008). The effects of late presentation include complicated diagnosis and treatment, poor prognosis, increased risks of side effects from the use of second- or third-line therapies, huge costs of treatment, loss of productivity, and increased mortality rates (Singletary, Allred, Ashley, Bassett, Berry, Bland, 2002).

Most breast lumps are benign and not cancer (malignant). Non-cancerous breast tumors are abnormal growths, but they do not spread outside of the breast. They are not life threatening, but some types of benign breast lumps can increase a woman's risk of getting breast cancer. Any breast lump or change needs to be checked by a health care professional to determine if it is benign or malignant (cancer) and if it might affect the patient in future.

As stated by the Division of Cancer Prevention and Control, Centers for Disease Control and Prevention (2018), there are different kinds of breast cancer. The kind of breast cancer depends on which cells in the breast turn into cancer. The most common kinds of breast cancer are;

- Invasive ductal carcinoma in which the cancer cells grow outside the ducts into other parts of the breast tissue. Invasive cancer cells can also spread, or metastasize, to other parts of the body.
- Invasive lobular carcinoma. Cancer cells spread from the lobules to the breast tissues that are close by. These invasive cancer cells can also spread to other parts of the body.

The American Cancer Society (2020) stated that breast cancers can start from different parts of the breast. Most breast cancers begin in the ducts that carry milk to the nipple (ductal cancers). Some start in the glands that make breast milk (lobular cancers). There are also other types of breast cancer that are less common like phyllodes tumor and angiosarcoma. A small number of cancers start in other tissues in the breast. These cancers are called sarcomas and lymphomas and are not really thought of as breast cancers. Although many types of breast cancer can cause a lump in the breast, not all do. Many breast cancers are also found on screening mammograms, which can detect cancers at an earlier stage, often before they can be felt, and before symptoms develop.

2. RELATED WORKS

Elwood, Tawfiq, TinTin, Marshall, Phung, Campbell, Harvey & Lawrenson (2018) worked on the development and validation of a new predictive model for breast cancer survival in New Zealand and comparison to the Nottingham prognostic index. The team developed a model to predict 10-year breast cancer-specific survival, using data collected prospectively in the largest population-based regional breast cancer registry in NZ (Auckland, 9182 patients), and assessed its performance in this data set (internal validation) and in an independent NZ population-based series of 2625 patients in Waikato (external validation). The data included all women with primary invasive breast cancer diagnosed from 1 June 2000 to 30 June 2014, with follow up to death or Dec 31, 2014. Multivariate Cox proportional hazards regression to assess predictors and to calculate predicted 10-year breast cancer mortality was used, and therefore survival, probability for each patient. The team also assessed observed survival by the Kaplan Meier method. Elwood and his team also assessed discrimination by the C statistic, and calibration by comparing predicted and observed survival rates for patients in 10 groups ordered by predicted 10-year survival. The team compared the NZ model with the Nottingham Prognostic Index (NPI) in this validation data set. The data collected prospectively through the two largest and longest-established population- based regional breast cancer registries in NZ, in the Auckland and Waikato regions. These two regional registries are linked to include over 40% of all patients with breast cancer in NZ, and are representative of NZ women in terms of socioeconomic, demographic and ethnic background (Lawrenson, Lao, Campbell, Harvey, Seneviratne & Edwards, 2017). The result of the team work stated that for the 9182 eligible women in the Auckland database, there were 864 breast cancer specific deaths over the 14-year time period; median follow up time was 67.6 months, and mean age of patients 56.9 years. Patients were predominantly Stage 1 (43%) and 2 (39%), ER and PR positive (79 and 68%), HER-2 negative (69%), without lymphovascular invasion (73%), and with ductal tumors (81%). Of the patients, 71% were of NZ European ethnic group, with 8% Maori, 7% Pacific, and 14% other (such as Asian countries). The risk of breast cancer mortality within 10 years of diagnosis increased significantly with age being over 70 years; higher tumor grade, larger tumor size, greater number of positive lymph nodes, presence of metastases at diagnosis, and with ER or PR negative tumors. Also discrimination was good, the C statistics were 0.84 for internal validity and 0.83 for an independent external validity. For calibration, for both internal and external validity the predicted 10-year survival probabilities in all groups of patients, ordered by predicted survival, were within the 95% confidence intervals (CI) of the observed Kaplan-Meier survival probabilities. The NZ model showed good discrimination even within the prognostic groups defined by the NPI.

Gigi, Stark, Gregory, Hart, Bradley, Nartowt, Deng (2019) worked on predicting breast cancer risk using personal health data and machine learning models. The team developed machine learning models that used highly accessible personal health data to predict five-year breast cancer risk. They created machine learning models using only the Gail model inputs and models using both Gail model inputs and additional personal health data relevant to breast cancer risk. For both sets of inputs, six machine learning models were trained and evaluated on the Prostate, Lung, Colorectal, and Ovarian Cancer Screening Trial data set. The machine techniques used in the research work includes the logistic regressions, Naive Bayes, Decision trees, linear discriminant and Support vector machines. Models were trained and evaluated on the PLCO data set (Kramer, Gohagan, Prorok & Smart, 1993). This data set was generated as part of a randomized, controlled, prospective study that sought to determine the effectiveness of different prostate, lung, colorectal, and ovarian cancer screenings. From November 1993 to July 2001, participants enrolled in the study and filled out a baseline questionnaire detailing their previous and current health conditions. All processing of this data set was completed in Python (version 3.6.7). This data set consists of 78,215 women ages 50-78. The team chose to exclude women who met any of the following conditions: 1) were missing data regarding whether they had been diagnosed with breast cancer and / or the timing of the diagnosis, 2) were diagnosed with breast cancer before the baseline questionnaire, 3) did not self-identify as White, Black, or Hispanic, 4) identified as Hispanic but did not have information available about where they were born, or 5) were missing data for any of the thirteen selected predictors. The team excluded women who were diagnosed with breast cancer before the baseline questionnaire. The team implemented the logistic regression, naive Bayes, decision tree, support vector machine, and linear discriminant analysis models using the Python scikit-learn package (version 0.20.1). For both sets of inputs, the selected neural network hyper parameters were those that produced the highest mean minus standard deviation AUC across 10 iterations of neural networks trained using 10-fold cross-validation on the training data set. For neural networks with only BCRAT (National Cancer Institute, 2019) inputs, these hyper parameters were 6 neurons per hidden layer, 2 hidden layers, an 0.01 learning rate, and 5000 steps of back propagation. For the neural networks with a broader set of inputs, the hyper parameters were 12 neurons per hidden layer, 2 hidden layers, a 0.01 learning rate, and 2500 steps of back propagation. The logistic regression and linear discriminant analysis models tied for the highest testing data set AUC (0.613). The logistic regression was significantly stronger than the decision tree, support vector machine, and naive Bayes models, but not stronger than the linear discriminant analysis or the neural network models. Similarly, the linear discriminant analysis was significantly stronger than the decision tree, support vector machine, and naive Bayes models, but not stronger than the logistic regression or neural network models. The logistic regression, linear discriminant analysis, and neural network models had very different values for sensitivity. The logistic regression had a low sensitivity of 0.476, whereas the linear discriminant analysis had a sensitivity of 0.688. The neural network sensitivity lay

between these two values at 0.599. For specificity, the logistic regression had the highest value at 0.691, followed by the neural network (0.562), and the linear discriminant analysis (0.467). The precisions for all three of these models were low. The logistic regression had a precision of 0.0323, slightly higher than the neural network (0.0287) and linear discriminant analysis (0.0272) precisions. Again, we saw that the machine learning model sensitivities, specificities, and precisions were generally comparable to those of the BCRAT (National Cancer Institute, 2019).

Huang, Chan, Lee, Chiang, Lu & Cheng, 2019 worked on the development of a prediction model for breast cancer based on the national cancer registry in Taiwan. The study aimed to develop a prognostic model to predict the breast cancer-specific survival and overall survival for breast cancer patients in Asia and to demonstrate a significant difference in clinical outcomes between Asian and non-Asian patients. The team developed our prognostic models by applying a multivariate Cox proportional hazards model to Taiwan Cancer Registry (TCR) data. A data-splitting strategy was used for internal validation, and a multivariable fractional polynomial approach was adopted for prognostic continuous variables. Subjects who were Asian, black, or white in the US-based Surveillance, Epidemiology, and End Results (SEER) database were analyzed for external validation. Model discrimination and calibration were evaluated in both internal and external datasets. In the internal validation, both training data and testing data calibrated well and generated good area under the ROC curves (AUC; 0.865 in training data and 0.846 in testing data). In the external validation, although the AUC values were larger than 0.85 in all populations, a lack of model calibration in non-Asian groups revealed that racial differences had a significant impact on the prediction of breast cancer mortality. For the calibration of breast cancer specific mortality, P values < 0.001 at 1 year and 0.018 at 4 years in whites, and P values ≤ 0.001 at 1 and 2 years and 0.032 at 3 years in blacks, indicated that there were significant differences (P value < 0.05) between the predicted mortality and the observed mortality. Our model generally underestimated the mortality of the black population. In the white population, the model underestimated mortality at 1 year and overestimated it at 4 years. And in the Asian population, all P values > 0.05, indicating predicted mortality and actual mortality at 1 to 4 years were consistent. The team developed and validated a pioneering prognostic model that especially benefits breast cancer patients in Asia. The study could serve as an important reference for breast cancer prediction in the future.

3. METHODOLOGY

3.1 Data Source and Sample Selection

The original data for our primary analysis were retrieved from different medical centers in Nigeria who specializes in breast cancer diagnosis and treatment. The data were collected from

Lagos State University teaching hospital Ikeja, Crystal Hospital Akowonjo, Orile Agege Government Hospital Agege, Onikan Health Centre, General Hospital Lagos, General Hospital Isolo, General Hospital Ajerom, Awadiora Health Centre, Oluwaseun Medical Centre, Harvey Road Health Cent, Mike Medics Hospital, Longing Medical Centre, LagPath Consulting, General Hospital Badagry, General Hospital Surulere, Lagos State Government Alausa, General Hospital Ikorodu, Merit Hospital General Hospital Alimos, Olatunwa Clinic, Alagba General Hospital Epe, Osuntuyi Medical Centre, EKO Hospital, Island Maternity Lagos, General Hosp. Randle, General Hospital Gbagada, General Hospital Ibeju, NAF Base Ikeja and Cancer Institute of Nigeria. . The data included all women who have been diagnosed with breast cancer from 2000 to 2005 and all death cases encountered so far. It consisted of 927 records of different women who had been diagnosed with breast cancer. From the dataset, 11 attributes were used for the analysis which are represented as:

i. Status of patient (Stat)

Table 1.1 – number 1 on the data spread represent patient who are alive while 2 represent dead patient after diagnosis and treatment

1	Alive
0	Dead

ii. Position of the tumor (Top)

Table 1.2 – represent the position of the tumor in the breast where it was diagnosed

505	C50.5 Lower-outer quadrant of breast
506	C50.6 Axillary tail of breast
509	C50.9 Breast, NOS
502	C50.2 Upper-inner quadrant of breast
500	C50.0 Nipple
501	C50.1 Central portion of breast
504	C50.4 Upper-outer quadrant of breast
508	C50.8 Overly lesion of breast
503	C50.3 Lower-inner quadrant of breast

iii. Marital Status (maritstatus)

Table 1.3 – represent the marital status of the patient

1	Married
2	Single
3	Divorced

iv. Types of Malignant tumour (Mor)

Table 1.4 – Represent the types of malignant tumour in the breast

8440	Cystadenocarcinoma, NOS
8022	Pleomorphic carcinoma
8500	Infiltrating duct carcinoma, NOS
8504	Intracystic carcinoma, NOS
8521	Infiltrating ductular carcinoma
8941	Carcinoma in pleomorphic adenoma
8010	Carcinoma, NOS
8140	Adenocarcinoma, NOS
8514	Duct carcinoma, desmoplastic type

8003	Malignant tumor, giant cell type
8502	Secretory carcinoma of breast
8513	Atypical medullary carcinoma
8520	Lobular carcinoma, NOS
8501	Comedocarcinoma, NOS
8200	Adenoid cystic carcinoma
8523	Infiltrating duct mixed with other types of car
8522	Infiltrating duct and lobular carcinoma
8314	Lipid-rich carcinoma
8530	Inflammatory carcinoma
8543	Paget disease and intraductal carcinoma of breast
8508	Cystic hypersecretory carcinoma
8002	Malignant tumor, small cell type
8082	Lymphoepithelial carcinoma
8810	Fibrosarcoma, NOS
8524	Infiltrating lobular mixed with other types of
8811	Fibromyxosarcoma
8050	Papillary carcinoma, NOS
8480	Mucinous adenocarcinoma
8000	Neoplasm, malignant
9020	Phyllodes tumor, malignant
8503	Intraductal papillary adenocarcinoma with invas
8510	Medullary carcinoma, NOS
8072	Squamous cell carcinoma, large cell, nonkeratin
8320	Granular cell carcinoma
8840	Myxosarcoma
8801	Spindle cell sarcoma
8073	Squamous cell carcinoma, small cell, nonkeratin
8575	Metaplastic carcinoma, NOS
8310	Clear cell adenocarcinoma, NOS
8071	Squamous cell carcinoma, keratinizing, NOS
8211	Tubular adenocarcinoma
8806	Desmoplastic small round cell tumor
8895	Myosarcoma
8190	Trabecular adenocarcinoma
8850	Liposarcoma, NOS
8201	Cribriform carcinoma, NOS
8857	Fibroblastic liposarcoma
8540	Paget disease, mammary
8031	Giant cell carcinoma
8260	Papillary adenocarcinoma, NOS
8070	Squamous cell carcinoma, NOS
8890	Leiomyosarcoma, NOS
9740	Mast cell sarcoma
9580	Granular cell tumor, malignant
8562	Epithelial-myoepithelial carcinoma
8315	Glycogen-rich carcinoma
8005	Malignant tumor, clear cell type
8033	Pseudosarcomatous carcinoma
8550	Acinar cell carcinoma
8573	Adenocarcinoma with apocrine metaplasia
8935	Stromal sarcoma, NOS
9596	Composite Hodgkin and non-Hodgkin lymphoma
8001	Tumor cells, malignant
8990	Mesenchymoma, malignant
8004	Malignant tumor, spindle cell type
9652	Hodgkin lymphoma, mixed cellularity, NOS
8541	Paget disease and infiltrating duct carcinoma o
8076	Squamous cell carcinoma, micro invasive

v. Religion

Table 1.5 – religion of the patient

1	Muslim
2	Christianity

vi. Investigative method carried out on breast (Bas)

Table 1.6 – investigative method used in diagnosing breast cancer in patient

7	Histology of primary
9	Unknown
5	Cytology
6	Histology of metastases
1	Clinical only
2	Clinical Invest/Ultra Sound

vii. Tumor difference after examination (tumourdiff)

Table 1.7 – Tumor difference status

1	Well
2	Moderate
3	Poor
4	Undifferentiated

viii. Symptoms diagnosis of the breast (tdiag)

Table 1.8 – method of symptom diagnosis of the breast

1	Symptomatic
3	Screening
4	Unknown
2	Asymptomatic

ix. Method of treatment of the patient (treatmt)

Table 1.9 – describes the method of treatment applied to treat breast cancer of patient

1	Surgery
3	Chemotherapy
0	None
2	Radiotherapy
4	Palliative Care
5	Others

x. Age (age): general age of each of the patient

xi. Address (Addr): home address of each patient

Each of the attributes were represented in numeral forms to enable pre-processing on R-studio.

4. RESULTS AND DISCUSSION

The R-studio machine learning toolkit version 1.1.456 was used for analysis on breast cancer patients. The confusion matrix is a table that presents the number of correctly and incorrectly classified instances of the actual and predicted class instances on the data set distribution. Also the dataset was partitioned into two – Training and testing. 193 observables were used for testing while 734 observables were used for training the model. The density plot is a representation of the distribution of a numeric variable which shows the probability density function of the variable.

Figure 1.0 present the output of the numeric variable distribution of age attribute in the dataset showing peak at 40 year olds. This indicate most patient were in their late 30s and the rest been distributed in the plot.

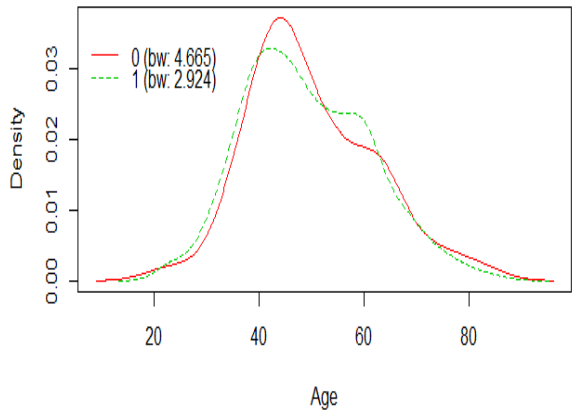

Figure 1.0: Density plot of age attribute in the dataset

Figure 1.1 present the output plot showing the chances of a patient having the tumor of the cancer at the left outer quadrant of the breast (505) has a 100% chance of survival or been alive after treatment. Also, those with the tumor positioned at the central of the breast (501) and at the nipple (500) had a lower chance of survival after treatment.

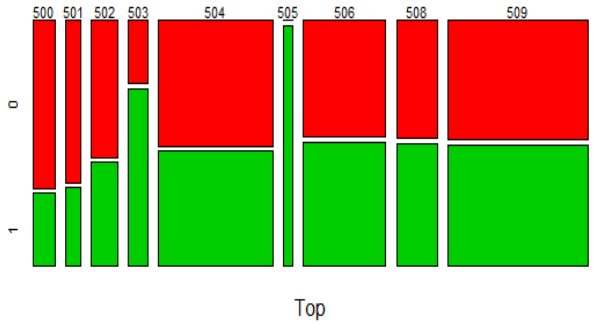

Figure 1.1: Output Plot distribution showing chances of survival based on the position of tumour in the breast

Figure 1.2 shows the output plot of the investigative method carried out on the breast (Bas). Women who were investigated using the histology of primary mode had a better chance of survival while Histology of metastases mode had the highest chance of death in patients.

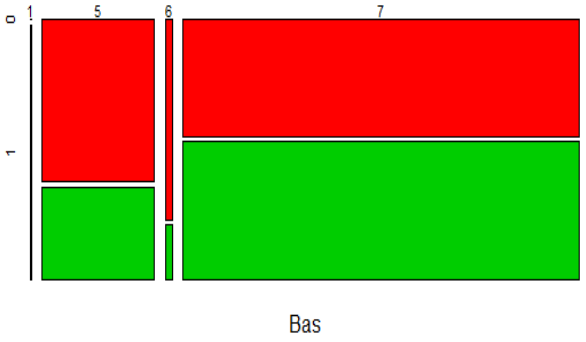

Figure 1.2: Output Plot distribution showing chances of survival based on the investigative method carried out on the breast

Figure 1.3 shows the output plot for marital status of the patients with singles having better chance of survival than married women.

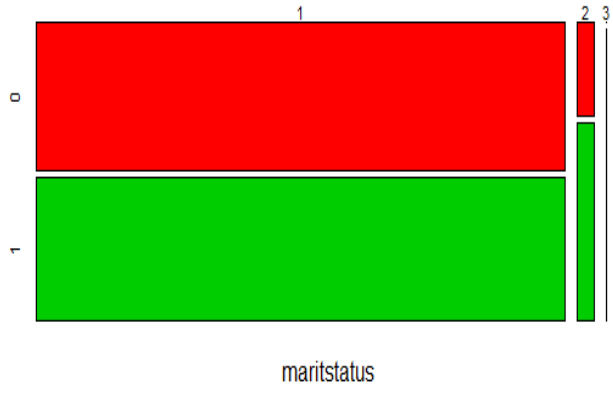

Figure 1.3: Output Plot of marriage status of the dataset

Figure 1.4 shows the output distribution of Tumor difference after examination (tumourdiff). There is high chance of a patient surviving if the tumor difference is poor and low chance if it cannot be categorized.

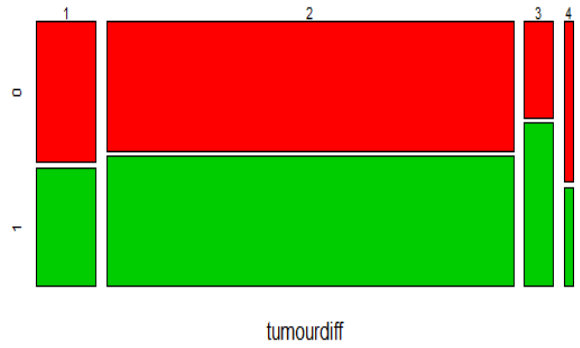

Figure 1.4: Output distribution of tumor difference among patients

Figure 1.5 shows the distribution output of Symptoms diagnosis of the breast (tdiag) whether it was symptomatic, screening, and asymptomatic or an unknown symptoms diagnosis. Patient who showed symptomatic symptoms had a worst chance of survival most.

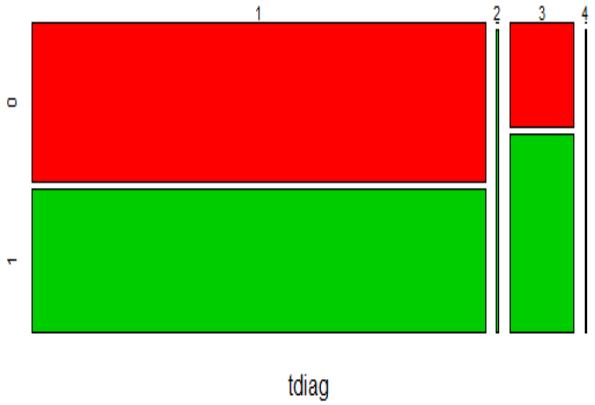

Figure 1.5: Output distribution of Symptoms diagnosis of the breast (tdiag)

Figure 1.6 shows the method of treatment of the patient (treatmt). Patient who were treated using radiotherapy had a better chance of surviving.

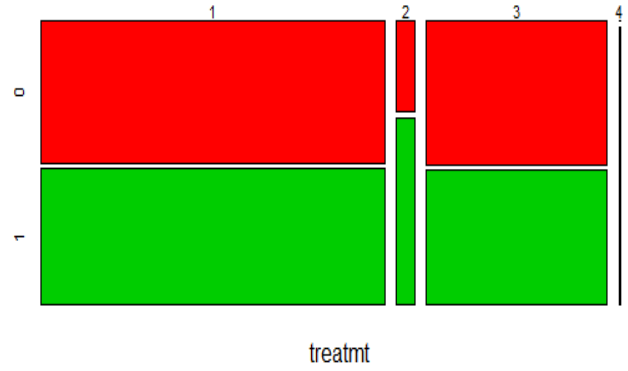

Table 2.0 shows the confusion matrix for both the trained and test data and the accuracy of the algorithm when implemented on both dataset.

Table 2.0: Confusion matrix of the trained and test data

Trained Data			
	0	1	Accuracy
0	2	0	99.9386921
1	45	687	
Test Data			
	0	1	Accuracy
0	1	5	99.9171
1	11	176	

It was observed from this study that the Naïve Bayes have good performance accuracy on the data sets. The result will help to identify patients that are susceptible or chances of survival of breast cancer patients so that appropriate measures can be taken early enough to improve survival rate.

5. CONCLUSION

This research was able to study trends in breast cancer patients among women and further build models that can be used for prediction of survival rate of breast cancer patients using Naïve Bayes machine learning techniques. The result gave a high accuracy after modelling and suitable for mining data.

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