Fuzzy Decision Tree for Breast Cancer Prediction

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ABSTRACT

Medical errors are considered as the leading cause of death and injury. Breast cancer becomes one of the leading causes of death among women, not only in the Philippines but worldwide. In this paper, data mining was used to predict the stage of breast cancer using a hybrid of fuzzy logic and decision tree. This aims to help experts to make decisions rather than replacing them. The result will only give an expert a recommendation, but the final decision is still on the hands of the experts. Feature selection was used to determine the best attribute in the dataset from Surveillance Epidemiology and End Results (SEER). The data set consists of incidence from 1975 to 2016, but the study limits the analysis from 2010 to 2016. Different cleaning and preprocessing of data are conducted. After thorough preprocessing of data, six (6) attributes are selected, and one (1) target class. Performance comparison shows that the fuzzy decision tree achieved a higher accuracy of 99.96%, sensitivity of 99.26% and specificity of 99.98% than the decision tree classification technique. The simulation result shows a correctly classified instance of 165,124, which is equivalent to 99.97% and only 351 incorrect classified instances or 0.21%. Thus, a fuzzy decision tree is more robust than the traditional decision tree classifier for predicting the stage of breast cancer.

CCS CONCEPTS

Information Systems ● Information Systems Applications

KEYWORDS

Medical Errors, Breast Cancer, Stage of Breast Cancer, Prediction, Data Mining, Fuzzy Decision Tree, Decision Tree, Fuzzy Logic, Classification

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1 Introduction

Medical errors or near misses' medical errors are very common, and most of the physicians had experienced this at least once in their careers, most especially the junior doctors [1]. Medical Error in health care is one of the leading causes of death and injury [2]. In the United States, medical error is considered as the third largest cause of death [3]. Patients are the main victims of medical errors, but doctors also suffer from serious complications. Some doctors who committed medical errors also suffer from severe distress, loss of confidence, lack of concentration, poor work performance, anxiety loss, depression, decreased quality in life outside of work and even suicidality [1]. About 44,000 to 98,000 Americans die each year because of medical errors in the hospital. Avoidable medical errors in the hospitals surpass attributable deaths to such feared threats as breast cancer, AIDS and motor-vehicle wrecks, and [4].

No matter how knowledgeable or experienced a physician is, no one is exempted to diagnostic errors [5]. Diagnostic error is defined as a missed or delayed diagnosis, which accounted as an important part of medical errors [6]. A result of a nationwide survey in Danish cancer care from ages 18 years and above registered in the National Patient Registry on 6,720 adult patient with a first-time cancer diagnosis from May 1st and August 31st, 2010 shows that 10-25% experienced error during diagnosis and treatment. On the same survey, the most frequent cancer diagnoses were breast (23%), gastrointestinal (19%), prostate (17%), and lung (8%) [7]. Delayed or incorrect diagnosis rates of 10-50% have been identified in studies of patients with HIV-associated complications, tuberculosis (TB), coronary artery diseases, and a different kind of malignancies. [8]. Failure to diagnose breast cancer is considered one of the costly types of cases for malpractice insurers.

To reduce association in a suit alleging on failure to diagnose cancer, doctors need to merge certain clinical guidelines and risk management strategies in their practice [9]. The highest number of medical errors can be avoided by using classification systems; additionally, offer data from healthcare institutions to be analyzed in a more exhaustive manner and lesser time. The errors in disease diagnosis and dealing with uncertainty is essential, which can be used by healthcare professionals to control diseases [10]. Predicting breast cancer using decision support system helps the physician in making an accurate and timely decision, and lower the cost of treatment [11].

Breast Cancer is one of the leading types of cancer [12] and considered worldwide as the most prevalent cancer among women [13]. To prevent avoidable death, early diagnosis of breast cancer is very important. However, the assessment of malignancy of tissue biopsies is very complex and usually depend on the subjectivity of the observer [14].

With the emerging technology in healthcare, a vast amount of computerized data are generated about patients and their medical conditions [15]. Data collected in the Healthcare Information Systems are very diverse and interesting to be analyzed and interpreted. Different patterns can be extracted on the data collected that can be used as a tool in doing decision making, diagnosis, and eventually, can be used for the treatment of many diseases.

Clinical Diagnostic System is used to support experts rather than replacing them. This will possibly give suggestions, but it is the experts who need to filter the information, review corresponding suggestions, and decide what action to perform based on the suggestions [16].

In this paper, classification data mining technique was used in the SEER data set to possibly predict the stage of breast cancer using a hybrid of fuzzy logic and traditional decision tree.

2 Related Literature

Data mining is used not just used in prediction but to gain knowledge [17]. Data mining has been widely used in different domains such as healthcare, medical, education, and telecommunications, among other [18].

2.1 Decision Tree

One of the simplest and most native classifiers used in the industry is the Decision Tree [19]. A decision tree is an instance-based induction learning classification algorithm that obtains the tree classification model from a given disordered training sample [20]. J48 is a simple implementation of the C4.5 decision tree used in classification [21]. J48 is an extension of ID3. [22] J48 handles both continuous and categorical attribute. Additional features are accounting for missing values, pruning, derivation of rules, and continuous attribute value ranges [22][23]. J48 shows more classification accuracy for mortgage class in the bank data set to compare to another classification algorithm Naïve Bayes [24]. J48 is considered as the top algorithm for analyzing Diabetic Data with an accuracy rate of 67.16 % followed by CART with an accuracy of 62.29%, Support Vector Machines with an accuracy of 65.05% and k-Nearest Neighbor accuracy of 53.39% [25]. A decision tree is found to be the best predictor in the Wisconsin dataset, with 94% predicted correctly in the class-labels [26]. J48 was compared in the traditional ID3 in predicting the class in the Iris data set, which consists of 3 classes, five attributes with 250 instances. The results show that J48 gives a better performance of accuracy compare to the traditional ID3. The decision is composed of two phases. In the first phase, the training sets are taken as root, and attributes are selected based on the partition. In the second phase, the outliers are identified and remove the braches [27]. Four (4) machine learning algorithms, namely Naïve Bayes, Decision Tree (C4.5), Support Vector Machine, and k Nearest Neighbors are compared in determining the breast cancer risk prediction and diagnosis [28]. An improved J48 Classification Algorithm was used to increase the accuracy rate in the prediction of diabetes. It has an accuracy of 99.8700% compare with traditional J48 of 73.8181% [22]. Decision Tree Classification rules are IF-THEN expressions where the conditions are logically connected [29].

2.2 Fuzzy Logic

Fuzzy Logic deals with the knowledge representation problem in uncertainty [29][30]. It deals with approximate reasoning. Time consumption in Fuzzy Logic is low and interprets results easily. Fuzzy Rule-Based is the application of Rule-based in Fuzzy logic using IF-THEN rules [29]. Fuzzy logic mimics the ability of the expert to solve problems. Fuzzy logic was utilized to represent uncertainty similar to the reasoning of medical experts to the estimation of gastric cancer risk [31]. Fuzzy logic is a logic system which is capable of describing certainties with more than true or false statements and its method to compute created on the degrees of truth. It can deal with truth values between 0 and 1 which should be measured as degrees of truth [10]. Fuzzy Rule-based was used to simulate the knowledge of experts in the diagnosis of multiple sclerosis [30]. Fuzzy logic and Rule-based was used in creating a decision support system for identifying class of tuberculosis where the physicians will input the intensity of each symptom according to the description given by the experts interviewed [32]. Weighted fuzzy rule-based was used in the clinical decision support system for risk prediction of heart disease. This involves two major steps: generation of weighted fuzzy rules and developing a fuzzy rule-based decision support system [16].

2.3 Fuzzy Decision Tree

Decision tree works well in CRISP domains but cannot deal with vagueness. To deal with this vagueness, decision trees are being combined with the fuzzy set theories. A decision tree with Fuzzy Logic implementation was used to determine if the cancer is benign or malignant in a certain patient [15]. FDT can stimulate human thinking through the use of a classification technique to overcome uncertainty [10]. This allows diagnosis of the disease according to medical classification. Crisp decision tree and Fuzzy decision tree were utilized to improve the diagnosis of Chronic Vascular Disease (CVD) diagnosis. This shows that FDT is more efficient than using a crisp decision facing low error rates [33]. The role of fuzzy logic is to soften the sharp decision between attribute values in the decision tree that may result in misclassification [34]. A lot of iterations are made in the classical decision trees.

3 Methods and Materials

The data was obtained from the cases diagnosed in 1975-2016 in the Surveillance Epidemiology and End Results (SEER) [35]. This includes 142 attributes and 840665 instances. The study limits the analysis of the cases diagnosed between 2010 and 2015. The data set was converted in .csv format from a .txt file using Java Programming Language to separate attributes. WEKA, which stands for Waikato Environment for Knowledge Analysis is an open-source software issued under the GNU General Public License. This includes different tools for transforming datasets [17].

WEKA is open-source software that can do both pre-processing of data and finding patterns in a data set. WEKA tool was used to do the preprocessing of data as well as to investigate the behavior of the algorithm. It is a machine learning software in java for data mining tasks.

Due to different irrelevant attributes in the prediction of the stage of breast cancer, data needs to undergo preprocessing phase where the data needs to be cleaned and analyzed. After reading the breast schema for collaborative stage data set, the records with missing information in the target class are removed from the data set [36].

Feature Selection is a very important phase used to recognize a pattern in a dataset. It is a process wherein the best subset of the attributes of the data set is selected based on the target attribute [37].

Data set was converted to a nominal type before selecting the attributes. To choose the most relevant information in breast cancer staging, Information Gain was used as attribute detector and Ranker as the search method. After thorough pre-processing of data, the final data set of 165,475 records, six (6) predictors and one (1) target variable was constructed. The table1 shows the selected attributes using InfoGainAttributeEval in WEKA using the target class DERIVED AJCC-7 STAGE GRP:

Table 1: Data Selected using InfoGainAttributeEval

Code	Description
CSEXTEN	CS EXTENSION Information on the extension of the Tumor.
EOD10_PN	REGIONAL NODES POSITIVE Information on positive lymph nodes with metastases greater than 0.2mm.
CS6SITE	CS SITE-SPECIFIC FACTOR 6 Size of Tumor-Invasive Component.
CSTUMSIZ	CS TUMOR SIZE Information on tumor size.
CSLYMPHN	CS LYMPH NODES Information on the involvement of lymph nodes.
CSMETSDX	CS METX AT DX Information on distant metastasis.

Fuzzy membership functions of the fuzzy logic part are created using MATLAB. MATLAB stands for matrix laboratory, which is considered as a high-performance language for doing technical computing.

Figure 1 shows the fuzzy model built in MATLAB. It has six attributes and one target class.

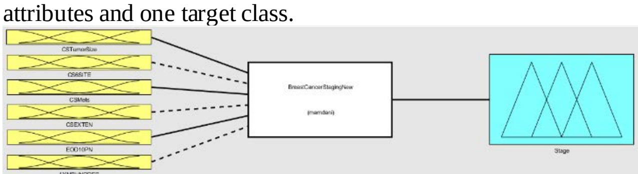

Figure 1: Fuzzy Model of the Breast Cancer Staging

Figure 2-7 shows the membership functions for the six predictors of breast cancer, and Figure 8 shows the membership functions for the output Stage.

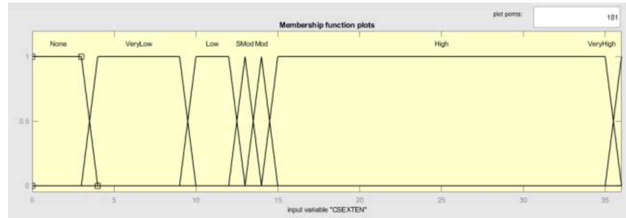

Figure 2: Fuzzy Membership Functions of CSEXTEN

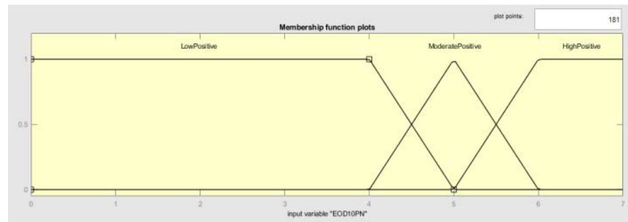

Figure 3: Fuzzy Membership Functions of EOD10PN

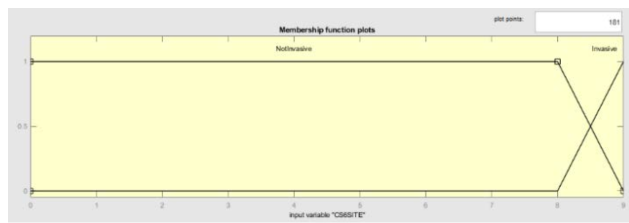

Figure 4: Fuzzy Membership Functions of CS6SITE

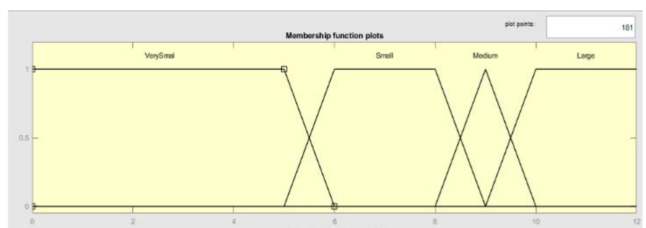

Figure 5: Fuzzy Membership Functions of CSTUMORSIZE

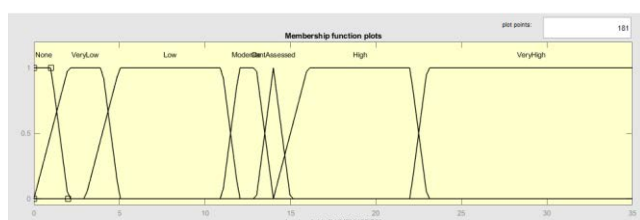

Figure 6: Fuzzy Membership Functions of LYMPH NODES

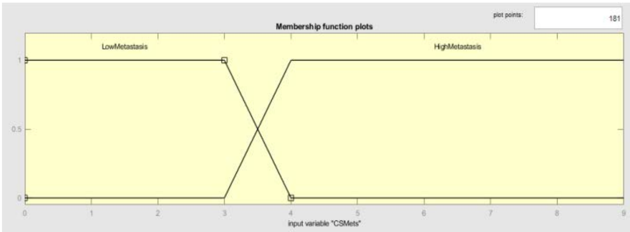

Figure 7: Fuzzy Membership Functions of CSMETS

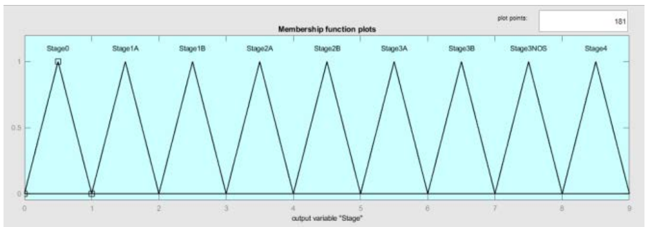

Figure 8: Fuzzy Membership Functions of STAGE

The following are the steps used in the fuzzy decision tree implementation:

- Conversion of data sets into fuzzy input.
- Decision tree implementation in the fuzzified data.
- Converting the decision tree into a set of rules
- Apply the set of rules for classification to be used in the prediction

4 Findings

After the conversion of CRISP input into fuzzy input, experiments are performed using WEKA. Decision Tree was used in the data set to classify the stage of breast cancer of a patient. Three (3) performance measures are used in this research work: Accuracy, Sensitivity, and Specificity with formula as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

where TP, TN, FP, and FN denotes the following:

TP - true positive

TN - true negative

FP - false positive

FN - false negative

Table 2 shows the summary performance of Decision Tree and Fuzzy Decision Tree. The decision tree has an accuracy of 99.75% while Fuzzy Decision Tree has 99.96%. In terms of Sensitivity, Decision Tree got 94.31% while Fuzzy Decision Tree is 99.26%. In the Specificity, Decision tree has 99.86%, and Fuzzy Decision tree has 99.98% results.

Table 2: Summary Performance of Decision Tree and Fuzzy Decision Tree

	Accuracy	Sensitivity	Specificity
Decision Tree	99.75%	94.31%	99.86%
Fuzzy Decision Tree	99.96%	99.26%	99.98%

Figure 9 shows the graphical representation of Performance Comparison of Decision Tree and Fuzzy Decision Tree to visualize the direct effect of conversion of the input from CRISP to linguistic form. The graph shows the big effect of conversion of sharp input into fuzzy input.

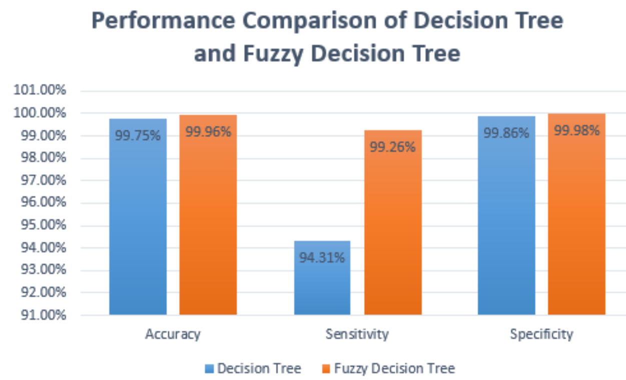

Figure 9: Performance Comparison of the two algorithms

Table 3 shows the detailed performance by class of the J48 Decision Tree using the original data using CRISP as its input.

Table 3: Detailed Performance by Class – Decision Tree

	Accuracy	Sensitivity	Specificity
Stage0	100.00	100.00	100.00
StageIA	99.91	99.98	99.87
StageIB	99.93	98.79	99.95
StageIIA	99.67	99.12	99.78
StageIIB	99.30	97.86	99.43
StageIIINOS	99.95	72.77	99.98%
StageIIIA	99.46	92.36	99.80
StageIIIB	99.87	99.07	99.88
StageIIIC	99.75	89.72	99.93
StageIV	99.69	93.43	99.99
Average	99.75	94.31	99.86

Table 4 shows the detailed performance by a class of the Fuzzy Decision Tree the converted CRISP input into the linguistic form.

Table 4: Detailed Performance by Class – Fuzzy Decision Tree

	Accuracy	Sensitivity	Specificity
Stage0	100.00	100.00	100.00
StageIA	100.00	100.00	100.00
StageIB	100.00	99.97	100.00

StageIIA	99.95	99.72	100.00
StageIIB	99.88	98.63	100.00
StageIIINOS	99.99	96.34	99.99
StageIIIA	99.85	99.34	99.87
StageIIIB	99.99	99.33	100.00
StageIIIC	99.90	99.27	99.91
StageIV	100.00	100.00	100.00
Average	99.96	99.26	99.98

The Decision Tree was converted into sets of rules for classification. Figure 10 shows the sample simulation result of the fuzzy decision tree model. The actual class is compared to the predicted class, as shown in Figure 10. The simulation result shows a correctly classified instances of 165123 or 99.79% as compared to 351 incorrectly classified instances or 0.21%.

EOD10_PN	CSTUMSIZ	CSEXTEN	CSLYMPHN	CSMETSDX	CS6SITE	ACTUAL	PREDICTED
0	1	0	0	0	10	Stage0	Stage0
98	14	0	0	0	10	Stage0	Stage0
98	1	100	0	0	20	Stage1A	Stage1A
0	990	100	0	0	50	Stage1A	Stage1A
1	10	100	150	0	50	Stage1B	Stage1B
1	992	140	150	0	30	Stage1B	Stage1B
2	0	950	250	0	987	Stage2A	Stage2A
98	38	100	0	0	20	Stage2A	Stage2A
95	21	100	255	0	987	Stage2B	Stage2B
1	25	100	150	0	20	Stage2B	Stage2B
4	3	999	250	0	20	Stage3NOS	Stage3NOS
98	10	512	999	0	20	Stage3NOS	Stage3NOS
8	2	100	250	0	30	Stage3A	Stage3A
95	2	100	510	0	0	Stage3A	Stage3A
98	32	790	0	0	20	Stage3B	Stage3B
98	33	400	255	0	0	Stage3B	Stage3B
22	20	750	250	0	50	Stage3C	Stage3C
11	21	100	250	0	20	Stage3C	Stage3C
97	11	100	257	60	0	Stage4	Stage4
95	11	100	800	44	987	Stage4	Stage4

Figure 10: Simulation Result of the Fuzzy Decision Tree Model

5 Conclusion and Future Work

In this study, the researchers analyzed the potential of using a hybrid of the fuzzy decision tree in classifying a stage of breast cancer that can be used by experts in the SEER dataset. Three (3) performance indicators are used to compare the two (2) algorithms: accuracy, sensitivity, and specificity. The result shows that the performance of Fuzzy Decision Tree is significantly higher than the traditional J8 Decision Tree. Performance comparison shows that the fuzzy decision tree achieved a higher accuracy of 99.96%, the sensitivity of 99.26% and specificity of 99.98% than the decision tree classification technique with 99.75%, 94.31%, and 99.86% respectively. The simulation results show fuzzy decision tree classifier classifies the data with 165,124 instances which is equivalent to 99.97% and only 351 incorrect classified instances or 0.21%. Thus, a fuzzy decision tree is more robust than the traditional decision tree classifier for predicting breast cancer. This can be of great help to experts to determine the particular stage that the patient has.

Future researchers can create a clinical diagnosis system so that experts can easily input values and easily view the results of a particular stage.

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