Development of Intelligent Breast Cancer Prediction using Extreme Learning Machine in Java

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***Abstract*—**Breast cancer is second cause of death for women which its risk can be minimized by accurate early detection and appropriate treatment. A lot of data mining techniques have been developed to support breast cancer diagnosis. However, the existing works mostly focus on prediction performance with limited attention with medical professional as end user and applicability aspect in real medical setting. In this paper, we designed and developed intelligent breast cancer prediction in Java called Breast Cancer Clinical Decision Support Systems. The systems has intuitive graphical user interface with eleven functionalities based on discussion with domain expert. Extreme learning machine was utilized as main intelligent component for predicting benign and malignant. Results showed that all functionalities were work well and done without significant delay. The accuracy performance outperformed average manual diagnosis from unaided medical professional. These showed that the proposed system is promising to be applied in the real medical setting to support breast cancer early detection.

***Keywords*—**Breast cancer, clinical decision support systems, extreme learning machine, data mining, java.

I. Introduction

WHO reported that annually over half million women died because of breast cancer which make it the second cause of death for women worldwide [1]. Accurate early detection, especially before cancerous cell spreading to other organs, followed by appropriate treatment can achieve more than 97% of survival patient' rates [2]. Clinical decision support systems with data mining and machine learning methods can help medical professional to deliver better performance compare with diagnosis (79.9%) made by unaided experienced doctor [3]. Therefore, intelligent breast cancer early decision support systems should be developed.

Extensive research had been done with backpropagation artificial neural network (BP-ANN) method and its variations in breast cancer diagnosis [4]–[7]. Nevertheless, this technique has some limitations such as no guarantee to global optima, a lot of tuning parameters, and long training time. Single Hidden Layer Neural Networks (SFLN) was proposed by Huang and Babri [8] to tackle those problems with tree steps learning process that called extreme learning machine (ELM). Standard [9] and best parameterized [10] ELM model were proposed for breast cancer early prediction. Results showed that it generally gave better accuracy, specificity, and sensitivity compared to BP ANN. However, most existing works focus on prediction performance with limited attention with medical professional as end user and applicability aspect in real medical setting.

In this paper, we proposed Breast Cancer Clinical Decision Support Systems with Extreme Learning Machine in Java based on our discussion with domain expert. The proposed system has three subsystems that are experiment, training, and diagnosis. Eleven functionalities were developed within these subsystems. The systems has intuitive graphical user interface. Standard ELM with several modifications was utilized as main intelligent component for predicting benign and malignant. Results showed that all functionalities were work well and done without significant delay. The accuracy performance outperformed average manual diagnosis from unaided medical professional.

There are three main contributions of the proposed system in this paper. First, it proved that ELM in java is applicable for breast cancer prediction. Second, the GUI can be used to communicate with domain experts in order to get more meaningful and useful feedback. Third, the system is promising to be applied in real medical setting and be customized to others disease prediction.

The rest of the paper is organized as the following. Section 2 will discuss designs and implementation of breast cancer clinical decision support systems. Experiments and results will be presented in section 3. Finally, section 4 will give conclusion and future works.

II. Design and Implementation

A. Subsystems

There are three subsystems in the proposed systems. The first subsystem is experiment. This subsystem allows user to measure benign and malignant prediction performances of ELM. User can submit their experimental data then chose method of experiments such as 10-fold cross-validation and random subsampling. This subsystem also provides options so that user can determine their ELM architecture by customizing number of hidden neurons and type of activation functions. Performance measurement such as training and

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testing accuracy, recall, precision, and f-measure are calculated.

The second subsystem is training. In this subsystem, user can initiate and increase their data in order to re-train the systems and achieve better performance. There are two ways of adding new data to existing training data. If user has multiple patients' records, the data can be submitted from file. Otherwise, it can be added by filling the variable form. There is specified template to add new training data from file. The whole existing training can be viewed in this subsystem.

The third subsystem is diagnosis. After extreme learning machine is trained using dataset given in the training subsystem, user can use this subsystem to help making better decision with this diagnosis subsystem. Simple form which is similar with single case functionality in the training subsystem is provided. The different is without target value since it will be predicted. There are nine variables to be filled that are clump thickness, uniformity of cell size, uniformity of cell shape, marginal adhesion, single epithelial cell size, bare nuclei, bland chromatin, normal nucleoli, and mitoses. After provide that data, system will give prediction, either benign or malignant, and show current system performance.

Fig. 1: Experiment subsystems in Breast Cancer Clinical Decision Support Systems. Given patient records, using 10-fold cross validation, 20 hidden neuron, and sigmoid activation function, the systems achieve 90.29% testing accuracy.

Fig. 2: Training subsystems in Breast Cancer Clinical Decision Support Systems. Besides adding more data from file as in the experiment subsystem, single case patient record can also be accommodated with simple form.

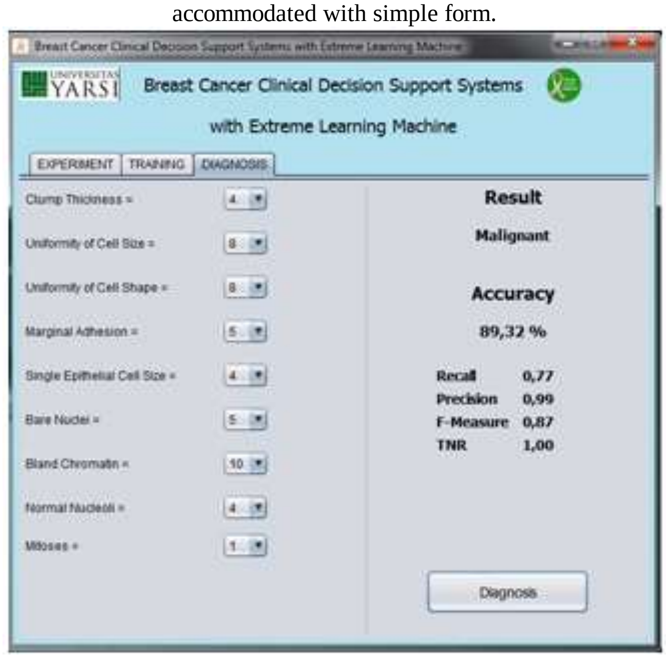

Fig. 3: Diagnosis subsystems in Breast Cancer Clinical Decision Support Systems. User submit nine variables and hit diagnosis button then system will give prediction (malignant) and current system performance (89%).

B. Implementation

The intelligent part of this Breast Cancer Clinical Decision Support Systems utilized extreme learning machine. Its architecture is similar with feedforward artificial neural network (FF-ANN) with one hidden layer which is called single layer feedforward neural network (SLFN). The main different is in the learning procedure. Common FF-ANN use backpropagation method that suffer some limitations such as long training time, several parameters tuning, and possibility to stuck in local minima. Extreme learning machine tackled that drawbacks with three steps as the following:

1. Randomly set input-hidden layer weights $\mathbf{w}_i$ and bias b_i, $i = 1,\ldots,M$.
2. Compute matrix of hidden layer output $\mathbf{H}$
3. Compute hidden-output layer weights $\hat{\boldsymbol{\beta}}$ for $\hat{\boldsymbol{\beta}} = \mathbf{H}^{\dagger}\mathbf{T}$ where $\mathbf{T} = [\mathbf{t}^{(1)},\ldots,\mathbf{t}^{(m)}]$.

ELM has three main properties which are minimum training error, smallest norm of weights, and unique solution. From those properties, it is mathematically proved to give the best generalization model. This fast and robust model is applicable in the real world prediction systems.

The initial implementation step was used extreme learning machine java module provided in the author website [11]. From this basic module, some functionalities were added. First, algorithm to produce confusion matrix, that compute true positive, true negative, false positive, and false negative, was developed. From this matrix, several performance measurements can be such as accuracy, recall, precision, and f-measure were extracted.

The second modification was addition several java classes for experiment and training subsystem. RandomSubSampling and 10-foldcrossvalidation were built as options in experimental methods. Another developed class was ViewData to show data given in the training process. The next step was building Graphical User Interface (GUI) using Netbeans IDE based on discussion with domain experts. The final step is testing and experiment to handle some issues and make sure all the functionalities were working well as given requirements.

III. Experiments and Results

A. Experimental Design

The proposed breast cancer clinical decision support systems were tested in two perspectives that were functionalities of subsystems and accuracy performance of prediction systems. TABLE 1 listed eleven tested functionalities of the systems.

TABLE I
SUBSYSTEMS AND ITS ASSOCIATED FUNCTIONALITIES

No	*Subsystems*	*Functionalities*
1	Experiment	Browse data
2		Use 10-fold cross validation
3		Use random subsampling
4		Specify number of hidden neuron
5		Use sigmoid activation function
6		Use sin activation function
7		Use hardlim activation function
8	Training	Insert data form file
9		Insert single case
10		View updated data
11	Diagnosis	Predict benign or malignant

In term of prediction performance, several experiments were conducted with different parameters. Sigmoid, sin, and hardlim were compared to see the influence of activation functions. Different numbers of hidden neurons were tested to measure the sensitivity of extreme learning machine in this parameter.

The dataset used in this experiment were collected from University of Wisconsin Hospital [12] which was called Breast Cancer Wisconsin Dataset. The data has 699 samples with 10 variables and a target variable. The class target distribution are 458 samples (65.5%) for benign and 241 samples (34.5%) for malignant. Variables' names can be seen in TABLE 2.

TABLE II
DATASET VARIABLES IN EACH PATIENT RECORDS

No	*Variables*	*Domain*
1	Sample Code Number	id
2	Clump Thickness	1 – 10
3	Uniformity of Cell Size	1 – 10
4	Uniformity of Cell Shape	1 – 10
5	Marginal Adhesion	1 – 10
6	Single Epithelial Cell Size	1 – 10
7	Bare Nuclei	1 – 10
8	Bland Chromatin	1 – 10
9	Normal Nucleoli	1 – 10
10	Mitoses	1 – 10
11	Class	2: benign; 4: malignant

B. Results and Analysis

Subsystems and its associated functionalities were tested. All the eleven functionalities mention in TABLE1 worked well and done without any significant delay. This is very important because applicable real breast cancer diagnosis setting need fast prediction to help making better decision.

In term of calculation performance prediction, confusion matrix was used to measure True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) of predicted values compared to actual values.

TP: True Positive FP: False Positive FN: False Negative TN: True Negative		Predicted Values	
		Malignant (Positive)	Benign (Negative)
Actual Values	Malignant (Positive)	TP	FN
	Benign (Negative)	FP	TN

Fig. 4: Confusion Matrix

Accuracy was used to measure the performance of the methods. This simply means how much correctly classified samples (benign predicted as benign or TP plus malignant predicted as malignant or TN) over all number of predictions. Since the class distribution was not equal (65.5% : 34.5%), it was necessary to use other performance measurements such as precision, and recall. Formula of all performance measurements can be seen in equation (1), (2), and (3).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

$$\text{Precision (p)} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall (r)} = \frac{TP}{TP + FN} \quad (3)$$

When comparing different activation functions, all other parameters were keep same. The method of experiment was 10-fold crossvalidation and number of hidden neuron was 20. TABEL 3 provided performance of prediction system with sigmoid, sin, and hardlim functions. Sigmoid produced the best results which 90.58% accuracy, 78% precision, and 99% recall. This outperformed sin (65% accuracy) and hardlim (30.43%). The best way to explain this is because sigmoid has smooth form which was suitable as extreme learning machine activation function.

TABLE III
PERFORMANCE OF DIFFERENT ACTIVATION FUNCTIONS.

Activation Functions	*Accuracy*	*Precision*	*Recall*
Sigmoid	90.58%	78%	99%
Sin	65.74%	67%	44%
Hardlim	30.43%	NaN	NaN

TABLE IV
PERFORMANCE OF DIFFERENT HIDDEN NEURONS

Hidden Neurons	*Accuracy*	*Precision*	*Recall*
5	86.87%	71%	99%
10	88.58%	75%	99%
15	90.01%	77%	99%
20	90.58%	78%	99%

Different numbers of hidden neuron from 5, 10, 15, and 20 were tested to see the sensitivity of extreme learning machine with these parameters. TABLE 4 showed the performance of those hidden neurons. It can be seen that the more hidden neurons the better prediction results achieved. This confirmed that extreme learning machine was quite sensitive with this parameter. It means that more hidden neurons produce more possible complicated calculation form which lead to more robust performance.

IV. CONCLUSION

AIn this paper, we proposed Breast Cancer Clinical Decision Support Systems using extreme learning machine in Java. The systems has interactive graphical user interface that was intuitive and easy to use, eleven functionalities that were work well without significant delays, and better performance accuracy (90.58%) than average unaided medical professional (79.9%). From those results, the proposed systems can be starting point to fill the gap of intelligent breast cancer prediction applicability issues in real medical setting.

There are some important and interesting works to be done in the future. First, improvement of extreme learning machine is essential to deliver better performance. The improvement can be done by modifying current basic techniques and re-implementing the code in Java. Second, adding more real patient records as training data. Our near future plan is to collect and utilize breast cancer patient medical records in local hospital. Third, modify the interface and functionality to fit the requirements. Iterative discussion with domain experts in several health providers will be essentials to confirm the applicability of future systems.

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