SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Adjustment of the Height Triangular Fuzzy Regression as Early Awareness of Breast Cancer

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ARTICLE INFO

Article history:
Received 3 March 2024
Received in revised form 21 July 2024
Accepted 1 September 2024
Available online 20 September 2024

Keywords:
Breast cancer; Fuzzy linear regression; Multiple linear regression; Statistical error measurement

ABSTRACT

Breast cancer is the most popular malignancy among Malaysian women. In Malaysia, approximately one in every 19 women is at risk. Breast cancer is the most common cancer among Malaysian women (32.9%), followed by colorectal (11.9%) and ovarian cancers (7.2%). Many cases are found to be advanced, with considerable tumour development or metastasis to untreatable locations and unaware of the factors. This study aims to determine the best height triangular fuzzy regression model by adjustment between 0 – 1 and measure the value of statistical error using mean square error (MSE) and root mean square error (RMSE). Secondary data was used where 569 patients having BREAST cancer and receiving treatment in hospitals was recorded by nurses and doctors. The patient data for breast cancer were analysed using MATLAB, SPSS, and Microsoft Excel. Based on the results, $H = 0$ of fuzzy linear regression is the best model to predict the breast cancer awareness with lowest value of MSE and RMSE by 1.455 and 1.206 respectively. Malaysians must be aware of the warning factors of breast cancer to increase survival and minimise death rates.

1. Introduction

Breast cancer is the leading cause of cancer-related deaths among women. Breast cancer formation is a multi-step process involving various cell types, and prevention remains a major priority around the world. Early detection is one of the most successful strategies for preventing breast cancer [1]. The phrase “breast cancer” refers to tumours that develop in the breast tissue, typically in the lobules that supply milk to the ducts or the inner lining of the ducts. Breast cancer is the second most common non-skin cancer (after breast cancer), accounting for 10.4% of all cancer cases in women worldwide. It also ranks as the fifth biggest cause of death [2].

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https://doi.org/10.37934/araset.52.2.1891973

According to [3], breast cancer occurs because of the uncontrolled proliferation of abnormal cells in the breast tissue, which results in the production of a lump or tumour. Cells in the body develop and divide in a predictable cycle, and they multiply when new cells are required to replace damaged or ageing ones. When they are harmed, they receive signals that indicate both growth and death. However, cancer cells behave differently from normal ones. These abnormal cells not only survive, but also divide and multiply even when the body does not need them [4]. This leads more abnormal cells to grow, eventually becoming a tumour. Tumours can be classified as benign (not cancerous) or malignant (cancerous). Non-cancerous tumours have a cell structure that is comparable to normal cells. They do not spread across the body, grow slowly, and do not infect surrounding tissues. Cancerous tumours can spread throughout the body if not treated [5].

Breast cancer can develop in the lobule cells of milk-producing glands or in the channels that transport milk from the lobules to the nipple, according to [6]. Furthermore, the fatty and fibrous connective tissues (known as stromal tissues) of the breast can develop into breast cancer. malignancy cells may infect healthy breast tissue and spread to lymph nodes under the arms, depending on the stage of the malignancy. Lymph nodes are small organs in the body that eliminate outside pollutants. Cancer cells that enter lymph nodes have the potential to spread throughout the body via lymphatic fluid [7]. Breast cancer is usually caused by a genetic defect or aberration. Only 5-10% of cancers are caused by genetic abnormalities acquired from one or both parents. Age-related and daily wear and tear-induced genetic changes are considered to be responsible for around 85% of breast cancer occurrences [8]. To overcome the increasing breast cancer percentage, prediction data analysis was applied by the researchers and implement such as inferential statistics model and regression modelling.

Regression analysis's main goals are to quantify the relationship between variables, ascertain the effects of each additional independent variable, and forecast the dependent variable's value in relation to the independent variables. The most widely used statistical analysis and modelling technique, such as in commercial and medical analysis, is regression analysis [9]. This is due to the fact that regression analysis is user-friendly and applicable to a wide range of real-world scenarios. The analysis yields the statistical equation that describes the relationship between the independent and dependent variables. Its multidimensional nature contributes significantly to its explanatory power. It is simply interpretable and comes in computer packages. In the applied sciences, economics, engineering, computer science, social sciences, and other domains, it is also widely employed [10].

Regression analysis is extensively utilized in forecasting and prediction, where its application significantly overlaps with machine learning [11]. In order to investigate the types of relationships between independent variables and dependent variables, regression analysis is also utilized to determine which of the independent variables is associated to the latter. Accordingly, causal links between the independent and dependent variables can be deduced using regression analysis [12]. But since this can result in erroneous relationships or illusions, it's best to exercise caution when using data.

However, Regression models are quite susceptible to outliers, though. A data point that deviates noticeably from other observations is called an outlier. Measurement variability may be a sign of experimental error, and regression analysis may have major issues due to an outlier [13]. Another linear model, the fuzzy regression, was discovered by the researcher that does not focus on outliers.

Fuzzy models have many advantages in analysis and can be applied without making any assumptions. The data is still usable even if its error is not regularly distributed. It differs from a different regression analysis in terms of statistics. A fundamental mathematical framework for handling vagueness is offered by fuzzy logic [14].

In a vagueness environment, fuzzy regression analysis provides a fuzzy functional relationship between the independent and dependent variables. To make better decisions using fuzzy data, linear regression is advised as the first analysis to be conducted before moving on to fuzzy regression analysis. Either crisp or fuzzy data may be entered. Fuzzy least-squares and Tanaka's linear programming technique are two examples of fuzzy regression models [15]. A few techniques for estimating fuzzy regression models have been proposed. Tanaka *et al.,* proposed fuzzy regression as the first model in 1982 for the linear case, concentrating on the extension concept [16].

Fuzzy regression is more imprecise when applied to complex systems like those found in the economics, industry, finance, marketing, and ecology. These systems incorporate human–machine interactions and demand judgmental decisions based on human thought processes [17]. Humans are frequently unable to gather precise numerical data about the system in such environments. Oftentimes, the knowledge regarding complex systems is of a hazy nature. Fuzzy regression appears to be more naturally suited for solving problems in real life overall. As a result, fuzzy regression analysis works better when modelling intricate systems. The groundbreaking research in this area said that the authors developed a fuzzy linear regression analysis using interval arithmetic, linear programming techniques, A-level approach, and Zadeh's extension principle. Systems of equations can be solved by minimising these distances in the fuzzy number space with regard to the regression models' unknown parameters [18].

2. Methodology

2.1 Materials

Adjusted fuzzy regression model with simulated data will be used where the data are generated using Monte Carlo simulation [19]. For the real data of breast cancer as secondary data, the data were obtained from the general hospital in Malaysia. It involves around 569 patients as respondents for breast cancer and the data were collected and recorded by doctor and nurses using cluster sampling. As a continuous data, dependent variable is tumour size and six factors of breast cancer as independent variable. Several potential software soft computing will use to get the accurate results such as Statistical Package for Social Sciences (SPSS), MATLAB and Microsoft Excel.

2.2 Fuzzy Linear Regression Model

Particularly when it comes to the linear regression method, statistical analysis is adaptable and may be applied in any field. Some model elements are represented by fuzzy numbers in fuzzy linear regression, a fuzzy sort of regression analysis. In 1982, Hideo Tanaka investigated the FLRM technique. His main goal in the research was to use approximated values to create fuzzy sets that express the fuzziness of the system structure; in contrast, the traditional confidential interval is associated with observation errors. In a fuzzy model, there are no required assumptions.

Fuzzy parameters are the source of the vagueness of the data input and output [20]. The model explains data deviations as the ambiguity of the system structure expressed by fuzzy parameters. The following presumptions were made in order to create a fuzzy linear regression model and the data can be represented by a fuzzy linear model [21].

$$Y_e * = A_1 * x_{e1} + \ldots + A_g * x_{eg} \triangleq A^* x_e, \tag{1}$$

where,
Fuzzy parameter A_g

The variable of fuzzy parameter X_e
Equation of the fuzzy parameter Y^*_e

The degree of the fitting of the estimated fuzzy linear model $Y_e^* = A^* x_e$ to the given data $Ye = (y_e, \varepsilon_e)$ was measured by the following index h_e, which maximizes h subject to $Y_e^h \subset Y_e^{*h}$, where:

$$Y_e^h = \{y \mid \mu_{Ye}(y) \geq h\}$$
$$Y_e^* = \{y \mid \mu_{Y_e^*}(y) \geq h\} \tag{2}$$

The problem was elucidated by acquiring fuzzy parameters A* which minimized JJ subject to $\bar{h}_e \geq H$ for all e , where *H* was selected by the decision maker as the degree of fit of the fuzzy linear model. The $\bar{h}_e$ can be acquired by utilizing:

$$\bar{h}_e = 1 - \frac{|y_e - x_e^T \alpha|}{\sum_f \varsigma_f |x_{ef}| - \varepsilon_e} \tag{3}$$

Fuzzy regression model estimated the fuzzy parameter $A_e^* = (\alpha_e, \varsigma_e)$, which are the solutions of the following linear programming problem:

Subject to $\varsigma \geq 0$ and

$$\min_{\alpha,\varsigma} = \varsigma_1 + \ldots + \varsigma_g$$
$$\alpha^T x_e + (1-H)\sum_f \varsigma_f |x_{ef}| \geq y_e + (1-H)\varepsilon_e$$
$$-\alpha^T x_e + (1-H)\sum_f \varsigma_f |x_{ef}| \geq -y_e + (1-H)\varepsilon_e \tag{4}$$

The standard linear programming problem can be solved to find the model that fits the data the best. Generally, there were much more limitations than variables. Therefore, resolving the dual issue is less complicated than resolving the main issue [22].

The definition of the fuzzy linear regression model (FLRM) is as follows:

$$Y = A_0(\alpha_0, \varsigma_0) + A(\alpha, \varsigma)\, x + \ldots + A(\alpha, \varsigma)\, x_g \tag{5}$$

2.3 Statistical Measurement Error

Statistical measurement error is another name for cross validation. This method is applied to an independent data set in order to evaluate the outcomes of a statistical study. It is usually utilised in scenarios where the objective is anticipated, as well as for determining the approximate accuracy of a predictive model's performance in real-world scenarios. Mean square error and root mean square error are the methods that are most frequently used.

$$\frac{\sum^N (y_i - \hat{y}_i)^2}{N}$$
$$\sqrt{\frac{\sum^N (y_i - \hat{y}_i)^2}{N}} \tag{6}$$

3. Results

3.1 Adjusted Fuzzy Linear Regression

In 1982, Hideo Tanaka proposed a fuzzy model for investigating linear regression. In one fuzzy model, dealing with fuzzy structures relies heavily on human judgement and specialized technology. The study used fuzzy linear regression to estimate the size of breast cancer patients' tumours. Overall, 569 patients participated. The study used fuzzy parameters like age, concavity, radius, area, smoothness, compactness, and malignant versus benign characteristics. The centre and width of each fuzzy parameter were calculated with an *H*-value of 0.0. Tables 1 and 2 show the results of adjusted the height triangular fuzzy regression from 0 – 1 in this model.

Table 1
Fuzzy Parameter of *H*=0.0

Variables	Fuzzy Parameter	
	Centre ai	*Width* e_i
(Constant)	0.3623	1.251
Age	2.890	0
1. Malignant 2. Benign	3.566	0
Radius	4.402	0
Area	2.309	0
Smoothness	-3.259	0
Compactness	7.8590	0
Concavity	-1.322	0

The computed fuzzy linear regression model for patients with breast cancer approximates this:

$\hat{Y}$ = 0.3623 + (2.890, 0) age + (3.566, 0) malignant and benign + (4.402, 0) radius + (2.309, 0) area - (3.259, 0) smoothness – (7.8590, 0) compactness - (1.322, 0) concavity

Table 2
Mean Square Error Value

MSE Values	
H-Values	Mean Square Error
0.0	1.455
0.1	1.467
0.2	1.481
0.3	1.497
0.4	1.517
0.5	1.781
0.6	1.592
0.7	1.657
0.8	1.774
0.9	2.101
1.0	2.138

The mean square error (MSE) values for the *H*-values are displayed in Table 2. The observed *Y* is determined from the reactions of 569 patients with breast cancer. *H*-value = 0.0 with the lowest value of MSE. The model with the lowest mean square error (MSE) of the H-value of 0.0 among the other values was found to be the most appropriate and successful model for anticipating high-risk breast cancer factors.

The root means square error, which has the lowest error value, is derived by taking the square root of the total mean square error, as shown in Table 3. The mean square error was used to evaluate the models. *H*-values = 0.0 equate to an RMSE of 1.206. Given that it has the lowest RMSE of the models, the fuzzy linear regression model with an *H*-value of 0.0 is the most accurate model for predicting the high-risk factors reported by breast cancer patients at general hospitals.

Table 3
Root Mean Square Error Value

RMSE Values	
H-Values	Root Mean Square Error
0.0	1.206
0.1	1.211
0.2	1.217
0.3	1.224
0.4	1.232
0.5	1.335
0.6	1.262
0.7	1.287
0.8	1.332
0.9	1.450
1.0	1.462

The most successful model for predicting high-risk breast cancer factors in general hospital patients is fuzzy linear regression with an *H*-value of 0.0. When compared to other *H*-values, fuzzy linear regression with an *H*-value of 0.0 produces the lowest mean square error (MSE) and root mean square error (RMSE) values were 1.455 and 1.206, respectively. Given the lowest measurement error, the fuzzy linear regression of *H*-value with 0.0 has been demonstrated to be the best model. Table 4 shows the MSE and RMSE summary values.

Table 4
MSE And RMSE Values of the Models

Summary of MSE and RMSE Values		
H-Values	MSE	RMSE
0.0	1.455	1.206
0.1	1.467	1.211
0.2	1.481	1.217
0.3	1.497	1.224
0.4	1.517	1.232
0.5	1.781	1.335
0.6	1.592	1.262
0.7	1.657	1.287
0.8	1.774	1.332
0.9	2.101	1.450
1.0	2.138	1.462

The best parameter for fuzzy linear regression was determined using the values of mean square error and root mean square error. As shown in Table 1, compactness has the highest fuzzy mean parameter in the model, with an *H*-value of 0.0 and a value of 7.859, making it the most influential symptom in diagnosing high-risk breast cancer factors. Similar to the findings in [23], those who had been diagnosed with breast cancer had a significantly greater prevalence of persistent compactness. [24,25] emphasized that compactness is the leading cause of breast cancer in all age groups. Radius is the second most risky breast cancer symptom, with a fuzzy mean parameter value of 4.402.

Furthermore, due to negative fuzzy mean parameter values, high-risk breast cancer factors are inversely connected to Chinese ethnicity and female gender.

The purpose of this study was to find early markers of high-risk breast cancer factors so that patients may begin receiving preventative therapy. Compactness and radius of breast cancer were discovered to be high-risk markers of breast cancer in patients at the general hospital. Nonetheless, persons with advanced breast cancer (stages 3 and 4) accounted for the vast majority of patient data collected from general hospitals. Smaller tumours in stages I and II express less texture and shape information than larger tumours in later stages, making it difficult to recognize factors in the early stages of breast cancer [26]. It is believed that the more advanced the stage of breast cancer, the larger the tumour's diameter, and that the disease's factors, such as compactness and radius, will appear one after another. Regardless of when the factors are noticed, physicians and patients can still take proactive or preventative steps early on for more specific factors, as indicated by the results, rather than factors that appear at random.

4. Conclusions

The goal of this study was to identify high-risk factors of breast cancer so that preventative interventions could be implemented. Compactness and radius were identified as high-risk factors among breast cancer patients in general hospitals. Medical experts and nurses in ordinary hospitals can be alerted about both high-risk factors, allowing them to treat patients earlier. Additional breast cancer factors include swelling, nipple discharge, and pain in the breast or armpit. Fuzzy linear regression with adjusted height triangular H=0.0, which has the lowest measurement error (MSE) and root mean square error (RMSE) values of 1.455 and 1.206, respectively, is the best model for predicting high-risk breast cancer factors in patients in general hospitals.

Additional researchers should address the difficulty of detecting breast cancer stages among patients in general hospitals in future investigations. Every state in Malaysia should have more public hospitals included in the study. In that circumstance, Malaysia and other countries may perform in-depth investigations into breast cancer.

Acknowledgement

This research was supported by Universiti Tun Hussein Onn Malaysia (UTHM) through Multidisciplinary Research Grant (MDR) vot (Q701).

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