

A Soft Computing Decision Support System in the Diagnosis of Breast Cancer

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ABSTRACT

It is well known that most of Breast cancer diagnosis characterization processes are entirely based on physician's intuition and experience. Since diagnosis of breast cancer involves several layers of uncertainty and imprecision that makes traditional approaches inappropriate. In the present research paper a soft computing diagnostic support system for breast cancer is proposed which is capable enough to capture ambiguous and imprecise information prevalent in breast cancer diagnosis. It is user friendly and will sharpen diagnostic skill of medical practitioners.

Keywords

Soft Computing, Breast Cancer, Fuzzy Tools

1. INTRODUCTION

Breast cancer may be one of the oldest known forms of cancer in human. The oldest description of cancer was discovered in Egypt and dates back to approximately 1600 BC. Breast cancer is a disease of humans and other mammals while the overwhelming majority of cases in human are women [1]. Breast cancer is more than 100 times more common in women than breast cancer in men [2]. Prominent women who died of breast cancer include Empress Theodora, wife of Justinine; Anne of Austria, mother of Louis XIV of France; Mary Washington, mother of George and Rachel Carson, the environmentalist [1]. Janet Lane- Claypon conducted the first study on breast cancer epidemiology that has published in 1926 [1]. Worldwide breast cancer comprises 22.9% of all cancers in women. In 2008 breast cancer caused 458,253 deaths worldwide (13.7% of cancer deaths in women) [3]. Landis et al. [4] reported that Breast cancer is most frequently diagnosed cancer and second leading cause of cancer deaths in women after **Lung cancer**. The latest report of NCF, 2012 [5] reported that in 2010 approximately 207090 newly diagnosed case of Breast cancer and 30840 deaths due to Breast cancer in USA. Danaei et al. [6] found that 21% of all breast cancer deaths worldwide are attributable to alcohol use, overweight and obesity, and physical inactivity. This proportion was higher in high-income countries (27%). In low- and middle-income countries, the proportion of breast cancers attributable to these risk factors was 18%. IARC and Lacey et al. [7, 8] found that Breastfeeding has a protective effect. Clemons and Goss et al. [9] concluded that Estrogen through direct and indirect proliferative effects play role in development and growth of breast cancer. Prognosis and survival rates vary greatly depending on cancer type, staging and treatment and geographical location of the patient. Survival rates in the western world are very good [3]. Overall more than 8 out of 10 women in England that are diagnosed

with the disease survive it for at least 5 years [10]. In the developing countries, however, survival rates are much poorer. Rao K. V. K et al. [11] discussed that despite advances in cancer treatment over the past decade, the prognosis of patients with breast cancer has improved only to small extent. Ford and Easton et al. [12] were of the view that hormonal imbalance and genetics are considered to be main risk of breast cancer.

Most of the real world problems that we are facing in day to day life are not ideal problems. These kinds of problems cannot be solved using the conventional way of computing but rather it is preferred to be solved using soft computing techniques [13]. Balanica, V. et al. [14] proposed a fuzzy logic technique for prediction of most probable risk estimation of breast cancer based on set of fuzzy rule that help in decision making process for the most suited treatment for a suspected breast cancer patient. Sipper et al. [15] examined the performance of fuzzy rule generation methods on Wisconsin breast cancer data (WBCD). WBCD problem combined with fuzzy genetic approach to evaluate system exhibit high classification performance. For accurate recognition of breast cancer tumour Khosravi et al. [16] proposed an automated and accurate hybrid system for identification of breast cancer. They have used fuzzy feature to increase the accuracy of their proposed system and this system tested against the data of WBCD. Oprea et al. [17] and Ekeh et al. [18] discussed about new segmentation technique for breast cancer detection based on the mammography. Cheng et al. [19] proposed a Fuzzy neural network approach to detect the malignant mass on mammograms which was somewhat useful for breast cancer control. Pandey, D. et al. [20] proposed a rule based system for cardiac analysis. Further Novruz Allahverdi et al. [21] proposed a fuzzy expert system to determination of coronary heart disease risk (CHD) of patient. Djam, X.Y. and Kimbi, Y.H. [22] developed a Fuzzy Expert System for the Management of Hypertension. Recently Srivastava, Pankaj and Srivastava, Amit [23, 24] proposed a soft computing diagnostic system to evaluate risk factor for coronary heart disease (CHD) and hypertension respectively. Srivastava, Pankaj et al [25] proposed a soft computing diagnostic system for the diagnosis of Hepatitis B. Srivastava, Pankaj and Sharma, Neeraja [26] proposed a soft computing decision support Diagnostic system for diabetes. Srivastava, Pankaj and Sharma, Neeraja [27] designed a soft computing diagnostic system that classify ECG beats in different phases and enables us to identify the status of cardiac health as per available ECG graphs. The present paper introduces a new soft computing model that measures risk factor on the basis of linguistic variables for the breast cancer.

2. METHODOLOGY

In the present study input variables consist of Age, BMI, Age of first MC, Age of last MP, Age at first pregnancy, Alcohol intake, Smoking, Tumor surface area, Duration of breast feeding. Output variable consists of percentage of risk factor for Breast cancer.

2.1 INPUT VARIABLES

- a) **Age:** Women current age is the best documented risk factor for breast cancer. The cumulative incidence of risk increase 1.8 percent at 50 year of age, 3.8 percent at 60 year age and 6.3 percent at 70 year age [28]. The incidence of breast cancer is very-very low before the age of 30 but after which it increase linearly up to the age of 80 [29]. The input variables for Age are classified in six fuzzy sets which as follows:

Age (in years)	
Young	< 30
Aged young	30- 40
Middle aged	40-55
Aged	55-70
Old	70-85
Very Old	> 85

$$\begin{aligned} \mu_{young} &= \exp((x-30)/15)^2/-2 \\ \mu_{aged\ young} &= \exp((x-40)/10)^2/-2 \\ \mu_{middle\ aged} &= \exp((x-55)/15)^2/-2 \\ \mu_{aged} &= \exp((x-70)/15)^2/-2 \\ \mu_{old} &= \exp((x-85)/15)^2/-2 \\ \mu_{very\ old} &= \exp((x-95)/10)^2/-2 \end{aligned}$$

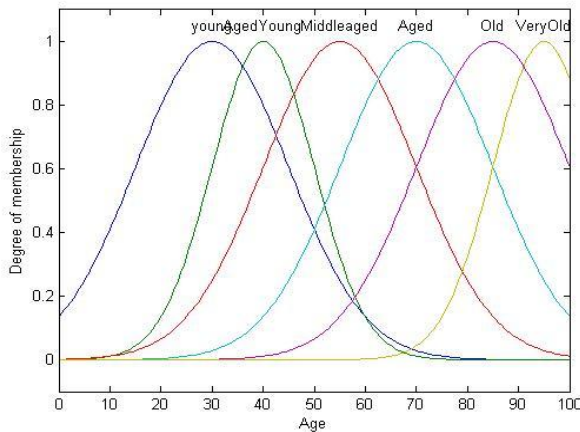


Figure1: Linguistic variables and membership function of Input variables ‘Age’

First menstrual cycle age (year)	
Early	10-12
Normal	12-14
Above normal	14-16
Extreme	≥16

$$\begin{aligned} \mu_{early} &= \exp((x-12)/2)^2/-2 \\ \mu_{normal} &= \exp((x-14)/2)^2/-2 \\ \mu_{above\ normal} &= \exp((x-16)/2)^2/-2 \\ \mu_{extreme} &= \exp((x-18)/2)^2/-2 \end{aligned}$$

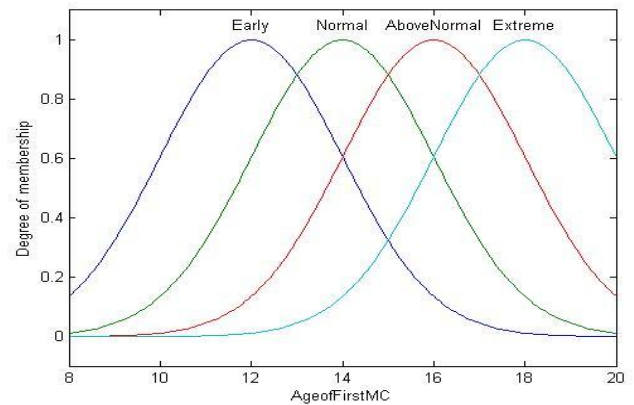


Figure2: Linguistic variables and membership function of Input variables ‘First MC Age’

- c) **Age at last menstrual Period (LMP):** At the age after 45 year the risk factor increase by 3 percent per year as the menopause is delayed. The increase in risk may be due to a longer lifetime exposure to the hormones estrogen and progesterone [31]. The input variables for Age of last menstrual period are classified in four fuzzy sets which are as follows:

The last menstrual Period age (year)	
Normal	≤ 40
Above Normal	36- 48
Middle aged	45- 60
Aged	≥ 55

$$\mu_{normal} = \begin{cases} 1 & x \leq 30 \\ \left(\frac{x-30}{5}\right)^2 & 30 \leq x < 35 \\ 1 - \left(\frac{x-35}{5}\right)^2 & 35 \leq x < 40 \\ 0 & x \geq 40 \end{cases}$$

$$\mu_{above\ normal} = \begin{cases} 0 & x \leq 36 \\ \frac{x-36}{4} & 36 < x \leq 40 \\ 1 & 40 < x \leq 44 \\ \frac{48-x}{4} & 44 < x \leq 48 \\ 0 & x \geq 48 \end{cases}$$

- b) **Age of first menstrual cycle:** Risk increase significantly with the age of menarche. If the first menstruated age is 15 or above 15, risk factor decreases up to 23 percent than those having menarche prior to the age of 12[30]. The input variables for Age of first menstrual cycle are categorized in four fuzzy sets which are as follows:

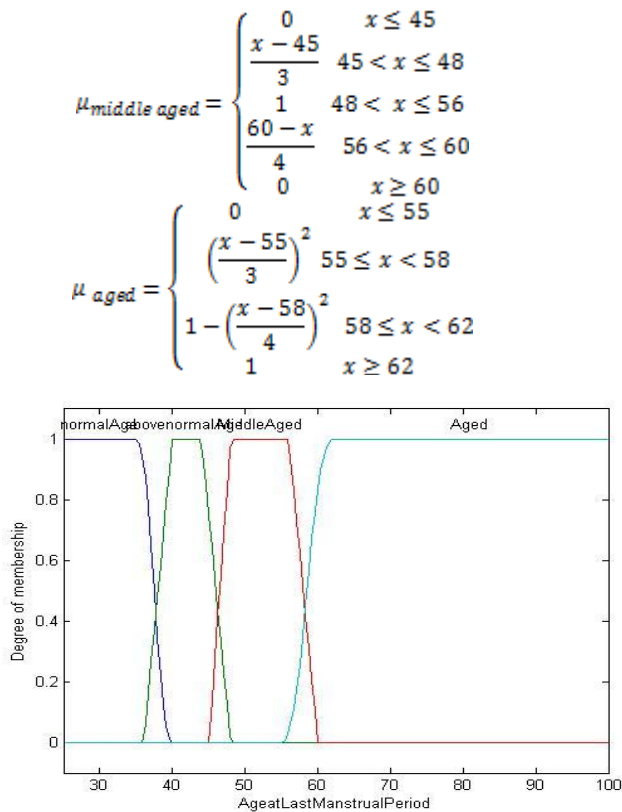


Figure3: Linguistic variables and membership function of Input variables ‘last Menstrual Period age’

- d) **Age at First pregnancy:** The women having pregnancy before 20 year of age have low risk of breast cancer in compare to the women having pregnancy after the age of 20 [32]. The input variables for Age at first pregnancy are classified in five fuzzy sets which are as follows:

First pregnancy Age (years)	
Early	≤ 21
Normal	19- 30
Above normal	28- 40
Middle aged	38- 48
Aged	≥ 45

$$\mu_{\text{early}} = \begin{cases} 1 & x \leq 17 \\ \left(\frac{x-17}{2}\right)^2 & 17 \leq x < 19 \\ 1 - \left(\frac{x-19}{2}\right)^2 & 19 \leq x < 21 \\ 0 & x \geq 21 \end{cases}$$

$$\mu_{\text{normal}} = \begin{cases} 0 & x \leq 19 \\ \frac{x-19}{3} & 19 < x \leq 22 \\ 1 & 22 < x \leq 27 \\ \frac{30-x}{3} & 27 < x \leq 30 \\ 0 & x \geq 30 \end{cases}$$

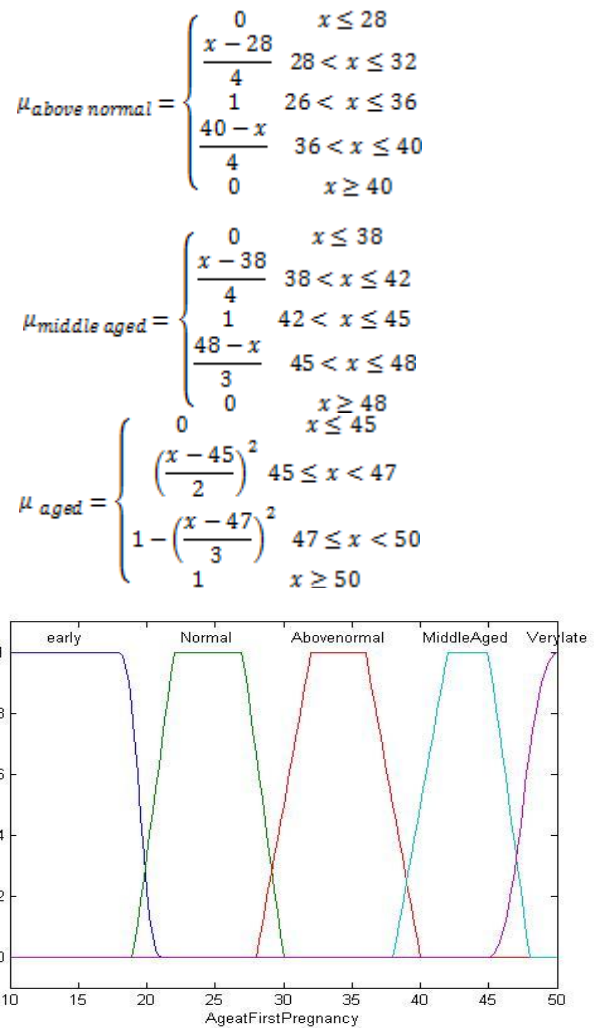


Figure4: Linguistic variables and membership function of Input variables ‘First Pregnancy age’

- e) **Duration of breast feeding:** Breast feeding protects women against developing breast cancer. Some studies have shown that breast-feeding slightly lowers breast cancer risk in women, especially in those women who had breast-feeding for 1½ to 2 years. As longer the women had breast feed to their child the risk of developing breast cancer decrease significantly [33]. The input variables for duration of breast feeding are categorized in six fuzzy sets which are as follows.

Duration of breast feeding (months)	
Very less	≤ 4
less	2-8
Normal	6-14
Above normal	12-18
High	17-20
Very high	≥ 18

$$\mu_{very\ less} = \begin{cases} 1 & x \leq 0 \\ \left(\frac{x-0}{2}\right)^2 & 0 \leq x < 2 \\ 1 - \left(\frac{x-2}{2}\right)^2 & 2 \leq x < 4 \\ 0 & x \geq 4 \end{cases}$$

$$\mu_{less} = \begin{cases} 0 & x \leq 2 \\ \frac{x-2}{2} & 2 < x \leq 4 \\ 1 & 4 < x \leq 6 \\ \frac{8-x}{2} & 6 < x \leq 8 \\ 0 & x \geq 8 \end{cases}$$

$$\mu_{normal} = \begin{cases} 0 & x \leq 6 \\ \frac{x-6}{2} & 6 < x \leq 8 \\ 1 & 8 < x \leq 12 \\ \frac{14-x}{2} & 12 < x \leq 14 \\ 0 & x \geq 14 \end{cases}$$

$$\mu_{above\ normal} = \begin{cases} 0 & x \leq 12 \\ \frac{x-12}{2} & 12 < x \leq 14 \\ 1 & 14 < x \leq 16 \\ \frac{18-x}{2} & 16 < x \leq 18 \\ 0 & x \geq 18 \end{cases}$$

$$\mu_{high} = \begin{cases} 0 & x \leq 17 \\ \frac{x-17}{2} & 17 < x \leq 19 \\ 1 & 19 < x \leq 21 \\ \frac{23-x}{2} & 21 < x \leq 23 \\ 0 & x \geq 23 \end{cases}$$

$$\mu_{very\ high} = \begin{cases} 0 & x \leq 21 \\ \left(\frac{x-21}{1}\right)^2 & 21 \leq x < 22 \\ 1 - \left(\frac{x-22}{1}\right)^2 & 22 \leq x < 23 \\ 1 & x \geq 23 \end{cases}$$

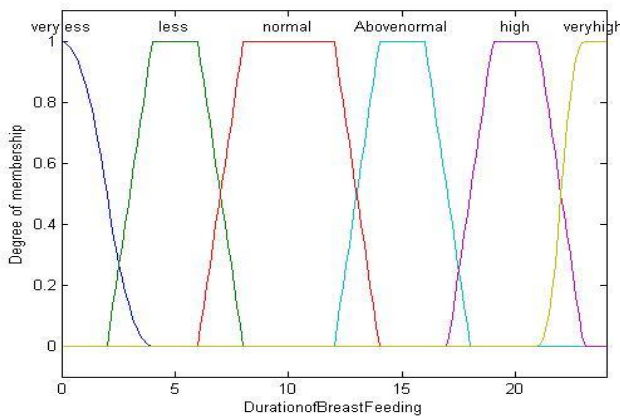


Figure5: Linguistic variables and membership function of Input variables ‘Duration of Breast Feeding’

Alcoholic Intake (per drink)	
Very low	0-1
Low	1-3
Moderate	2-4
High	3-5
Very high	≥ 4

$$\mu_{very\ low} = \begin{cases} 1 & x \leq 0 \\ \left(\frac{x-0.5}{0.5}\right)^2 & 0 \leq x < 0.5 \\ 1 - \left(\frac{x-0.5}{0.5}\right)^2 & 0.5 \leq x < 1 \\ 0 & x \geq 1 \end{cases}$$

$$\mu_{low} = \begin{cases} 0 & x \leq 1 \\ \frac{x-1}{1} & 1 < x \leq 2 \\ 2-x & 2 < x \leq 3 \\ 0 & x \geq 3 \end{cases}$$

$$\mu_{moderate} = \begin{cases} 0 & x \leq 2 \\ \frac{x-2}{1} & 2 < x \leq 3 \\ 4-x & 3 < x \leq 4 \\ 0 & x \geq 4 \end{cases}$$

$$\mu_{high} = \begin{cases} 0 & x \leq 3 \\ \frac{x-3}{1} & 3 < x \leq 4 \\ 5-x & 4 < x \leq 5 \\ 0 & x \geq 5 \end{cases}$$

$$\mu_{very\ high} = \begin{cases} 0 & x \leq 4 \\ \left(\frac{x-4}{1}\right)^2 & 4 \leq x < 5 \\ 1 - \left(\frac{x-5}{1}\right)^2 & 5 \leq x < 6 \\ 1 & x \geq 6 \end{cases}$$

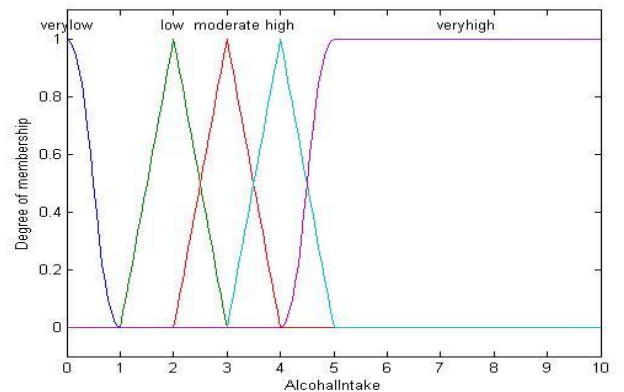


Figure6: Linguistic variables and membership function of Input variables ‘Alcohol Intake’

f) **Alcohol Intake:** Consumption of alcohol might increase the risk of breast cancer as it stimulates the metabolism of carcinogens such as acetaldehyde [34]. The input variables for alcoholic intake are classified in five fuzzy sets which are as follows:

g) **Body Mass Index (BMI) of women:** BMI of women after post menopause age increase the risk of breast cancer. Weight gain during the age of 18 to between the ages of 50 and 60, has been consistently associated with risk of breast cancer after menopause [35]. The relative risk of breast cancer increase as we increase the intake of per drink (approximately

12 g alcohol) [36]. The input variables for body mass index are classified in to four fuzzy sets which are as follows:

Body mass index(kg/m ²)	
Low	10-20
Medium	20- 30
High	30- 40
Very high	40- 50

$$\begin{aligned} \mu_{low} &= \exp\left(\frac{(x-20)}{10}\right)^2 / -2 \\ \mu_{medium} &= \exp\left(\frac{(x-30)}{10}\right)^2 / -2 \\ \mu_{high} &= \exp\left(\frac{(x-40)}{10}\right)^2 / -2 \\ \mu_{very\ high} &= \exp\left(\frac{(x-50)}{10}\right)^2 / -2 \end{aligned}$$

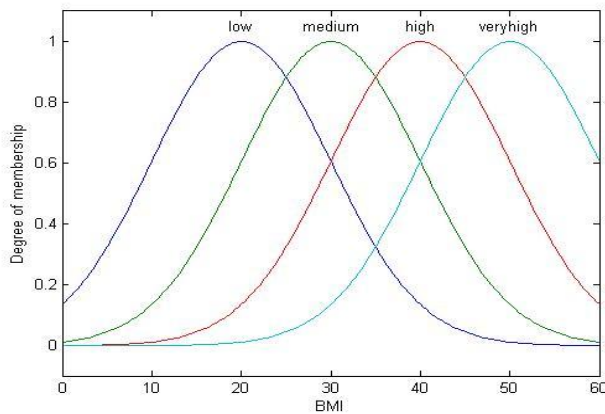


Figure7: Linguistic variables and membership function of Input variables ‘BMI’

h) **Tumor surface:** The input variables for tumor surface are categorized in six fuzzy sets. which are as follows:

Tumor surface Area (pixels)	
Very small	≤ 1000
Small	1000- 2000
Medium	2000- 3500
Above medium	3500- 5000
Large	5000- 6500
Very large	≥ 6500

$$\begin{aligned} \mu_{very\ small} &= \exp\left(\frac{(x-1000)}{500}\right)^2 / -2 \\ \mu_{small} &= \exp\left(\frac{(x-2000)}{1000}\right)^2 / -2 \\ \mu_{medium} &= \exp\left(\frac{(x-3500)}{1500}\right)^2 / -2 \\ \mu_{above\ medium} &= \exp\left(\frac{(x-5000)}{1500}\right)^2 / -2 \\ \mu_{large} &= \exp\left(\frac{(x-6500)}{1500}\right)^2 / -2 \\ \mu_{very\ large} &= \exp\left(\frac{(x-8000)}{1500}\right)^2 / -2 \end{aligned}$$

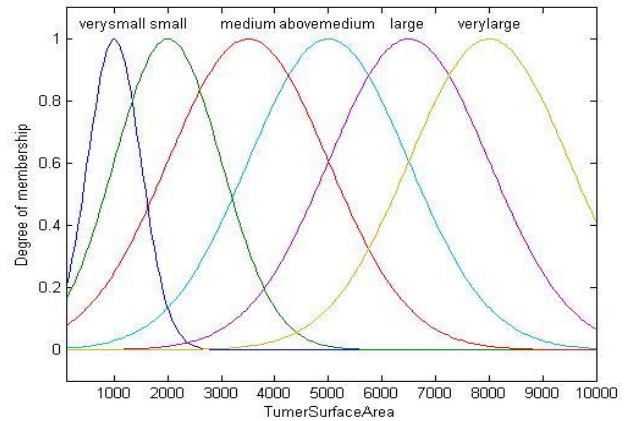


Figure8: Linguistic variables and membership function of Input variables ‘Tumor Surface Area ’

i) **Smoking:** The input variables for smoking are classified in five fuzzy sets which are as follows:

Smoking	
Very Low	2-6
Low	4-12
Moderate	10-16
High	14-22
Very high	≥ 20

$$\mu_{very\ low} = \begin{cases} 1 & x \leq 2 \\ \left(\frac{x-2}{2}\right)^2 & 2 \leq x < 4 \\ 1 - \left(\frac{x-4}{2}\right)^2 & 4 \leq x < 6 \\ 0 & x \geq 6 \end{cases}$$

$$\mu_{low} = \begin{cases} 0 & x \leq 4 \\ \frac{x-4}{2} & 4 < x \leq 6 \\ 1 & 6 < x \leq 10 \\ \frac{12-x}{2} & 10 < x \leq 12 \\ 0 & x \geq 12 \end{cases}$$

$$\mu_{high} = \begin{cases} 0 & x \leq 10 \\ \frac{x-10}{2} & 10 < x \leq 12 \\ 1 & 12 < x \leq 14 \\ \frac{14-x}{2} & 14 < x \leq 16 \\ 0 & x \geq 16 \end{cases}$$

$$\mu_{high} = \begin{cases} 0 & x \leq 14 \\ \frac{x-14}{2} & 14 < x \leq 16 \\ 1 & 16 < x \leq 20 \\ \frac{22-x}{2} & 20 < x \leq 22 \\ 0 & x \geq 22 \end{cases}$$

$$\mu_{very\ high} = \begin{cases} 0 & x \leq 20 \\ \left(\frac{x-20}{2}\right)^2 & 20 \leq x < 22 \\ 1 - \left(\frac{x-22}{2}\right)^2 & 22 \leq x < 24 \\ 1 & x \geq 24 \end{cases}$$

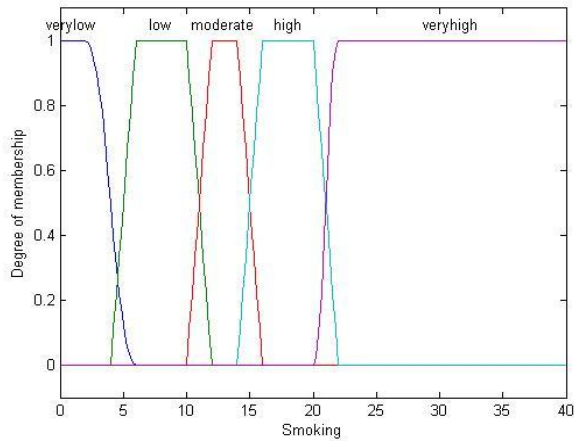


Figure9: Linguistic variables and membership function of Input variables 'Smoking'

2.2 OUTPUT VARIABLE:

The output zone reflects the percentage of risk factor for breast cancer in the patient under observation. It is classified in five layers such as; very less, less, medium, high and very high. Increasing order of percentage indicates increasing order of risk factor for breast cancer.

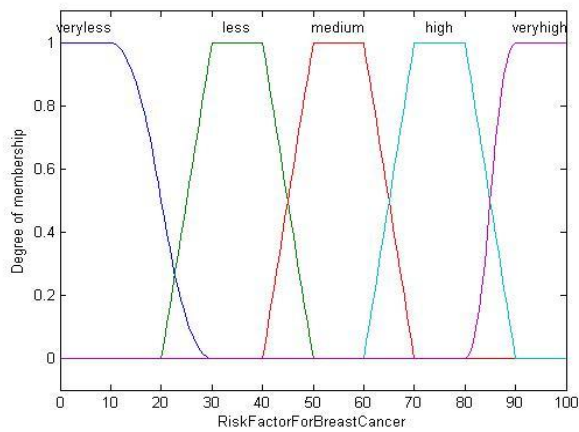


Figure10: Linguistic variables and membership function of Output variables 'Risk Factor for Breast Cancer'

3. FUZZY RULES

The proposed rule Base consists of a set of Fuzzy compositions and is derived from the Knowledge Base of Medical Experts. A fuzzy statement establishes a relationship between different input fuzzy sets and output sets. Some of the rules are given below in table.

Input Variables									Output variable
Age (Y)	BMI (kg/m ²)	First menstrual cycle Age(Y)	Last menstrual Period Age(Y)	First pregnancy Age (Y)	Duration of breast feeding(mo nth)	Alcoholic Intake(per drink)	Smoking (cig.)	Tumour surface (pixel)	Risk Factor
Young	low	normal	normal	normal	Very high	no	no	Very small	Very less
Young	low	normal	normal	normal	High	Very low	2	Very small	Very less
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
young	medium	normal	normal	Ab. nor	High	Very low	4	Small	less
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
young	high	normal	Ab. nor	normal	High	low	3	medium	medium
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Aged young	medium	Ab. normal	Normal	Ab. nor	Normal	low	5	medium	medium
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Mid aged	High	Ab. normal	Ab. normal	normal	Normal	low	4	Above medium	medium
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Mid aged	medium	Ab. normal	Middle aged	Ab. normal	Normal	moderate	6	Above medium	medium
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Mid aged	High	Extreme	Middle aged	Middle aged	Low	high	12	large	High
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
Mid aged	Very high	Extreme	Aged	Aged	Very low	v. high	15	Very large	Very high
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Aged young	low	normal	normal	normal	High	Very low	4	small	Very less
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
Aged	low	Normal	normal	Normal	High	Very low	6	small	less
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
Aged	medium	Normal	Normal	Ab. normal	normal	high	12	medium	medium
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
Aged	medium	Ab. normal	Ab. normal	Normal	high	high	1	medium	medium
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
Aged	high	Ab. normal	Aged	Aged	Low	high	10	large	Very high
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
old	medium	normal	Ab. nor	normal	Very high	Very low	3	small	less
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
old	medium	Normal	Ab. normal	Ab. normal	Normal	high	5	medium	medium
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
old	medium	Ab. normal	Aged	Mid aged	Ab. normal	moderate	8	Medium	medium
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
Very old	high	Extreme	Mid aged	Mid aged	Low	high	8	large	High
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Very old	Very high	Extreme	Aged	Aged	Very low	Very high	12	Very large	Very high

4. DEFUZZIFICATION:

Under the defuzzification process, rule base description of input variables following mamdani’s approach was evaluated.

5. RESULT:

The 3D surface diagram designed on the basis of the rule base. It is clear from the following figure that high duration of breast feeding Vs. normal BMI indicates low risk factor of breast cancer whereas decreasing period of breast Feeding Vs. high BMI gives indication of high risk factor for breast cancer. Similarly number of observations can be made from various other 3D diagrams under different combinations of other input variables.

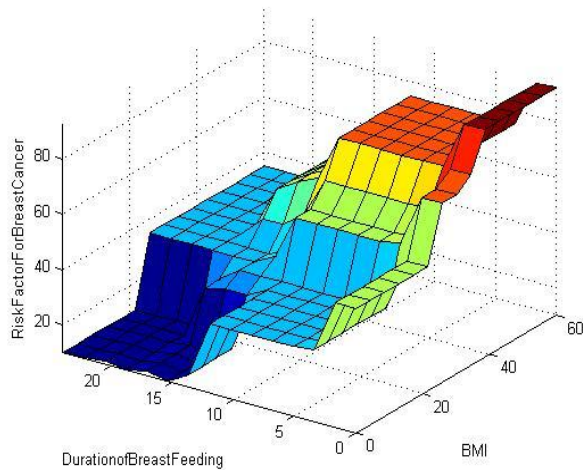


Fig 11- 3D surface view

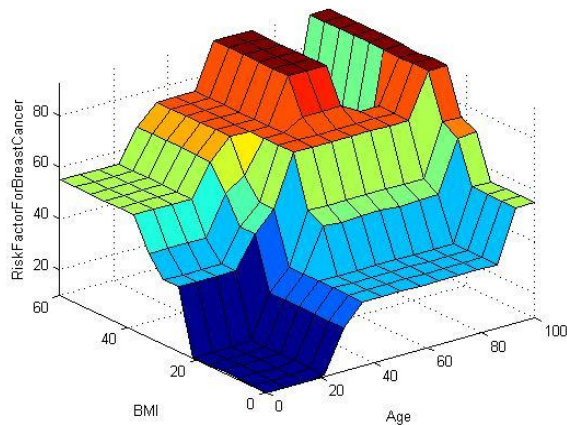


Fig 12- 3D surface view

6. CONCLUSION:

The present research article confirms that the soft computing models are competent enough to capture expert's knowledge and theoretical observations in a scientific way and handle real life problems in satisfactory manner. The proposed soft computing diagnostic system will be helpful for medical experts and it is user friendly that one can use itself.

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