Original Article

Implementation of an Adaptive Artificial Neural Network with Fuzzy Expert System for Diagnoses the Breast and Prostate Cancer: A Hybrid Technique

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Abstract

Expert systems for medical applications have emerged as a result of recent developments in artificial intelligence. Additionally, in the recent years, computational tools have been developed to enhance the knowledge and skills of doctors when it comes to making decisions regarding their patients. The second-leading cause of cancer-related death is breast cancer, which is the most prevalent malignancy in women. About one-third of women with breast cancer pass away from the condition, even though it is treatable when found early. One of the main causes of death in the globe is cancer. Prostate cancer is one type of cancer that claims lives among men. This study is to evaluate the model's accuracy to expert forecasts regarding prostate cancer. Based on patient prostate volume, age, and prostate specific antigen data, predictions are made. Due to the absence of a prostate-like appearance in women, this disease mainly affects men. However, it might be challenging to distinguish between benign and malignant mammographic results, therefore in this work, we designed an expert system for Diagnosis of Breast Cancer and Prostate Cancer. The findings demonstrate that the proposed fuzzy model can be used effectively to aid in the diagnosis and analysis of the possibility of prostate cancer and is one of the factors that doctors consider when determining whether or not a biopsy is necessary for these patients. The PCR value provided by the fuzzy model is within the PCR interval predicted by a specialist doctor. This technique makes it possible to avoid needless biopsy. Additionally, this technique can be useful for training medical students.

Keywords: Fuzzy Expert System, ANN, Prostate Specific Antigen, Artificial intelligence, Neuro-fuzzy

1. INTRODUCTION

The three malignancies that affect women most frequently are those of the breast, the colon, and the rectum. It is anticipated that these cancers will account for around 55% of all new cancer cases. In 2003, the number of new cases of breast cancer among women will make up 32% (211,300) of all new cancer cases [1]. Despite being treatable when found early, breast cancer kills about one-third of its victims in female patients [2]. Unfortunately, early-stage breast cancers do not show any symptoms while the tumour is still small and hence easily curable. As a result, it is challenging but crucial to identify breast cancers in their early stages.

Early diagnosis of breast cancer with mammography significantly increases the likelihood of survival, according to both randomised trials and population-based analyses of screening mammography [3, 4]. Mammography is the most effective breast cancer screening technology currently available since it can detect cancer years before physical signs appear.

However, unless additional tests, such as ultrasound imaging or breast biopsy, result in a final diagnosis of normal or benign breast tissue, roughly 5–10% of the mammography results are classified as abnormal or ambiguous. According to reports, only 10 to 30 percent of breast biopsies truly reveal a malignant disease [5]. The high rate of pointless breast biopsies results in significant physical and mental suffering for the patients as well as needless spending on exams. Several researchers have employed statistical and artificial intelligence methods to forecast the development of breast cancer [6, 7]. Classification issues related to breast cancer diagnosis are more prevalent and widely explored [8-11].

In previous decades, PSA renderings were used by Egawa et al. [12] to distinguish prostate carcinoma, PSA concentrations were utilised to detect prostate cancer [13] and created the pre-diagnosis expert system for medicine [14]. Roehrborn et al. [15] looked at serum PSA as a stronger predictor of prostate growth. While Lascio [16] created a fuzzy system study of diabetic neuropathy at the same time by some other researhcers employed fuzzy knowledge to use fuzzy systems [17-30]. Allahverdi [31] examines the application of artificial intelligence, which is widely employed in many other disciplines, such as robotics, marketing, and medical applications, to a variety of medical issues. Numerous expert systems were taken into consideration for the advancement of fuzzy logic, which has a large role in the field of medicine [32] and is used to examine blood pressure, predict the forecast to citalopram treatment in alcohol dependence [33], investigate diabetic neuropathy [16], and analyse MRI data [34]. Without presuming a time series, Lu et al. [34] created fMRI activation detection for picture segmentation. By using PSA (prostate specific antigen), PV (prostate volume), and PCR (prostate cancer risk) as input parameters and output parameters, Boadh et al. [25] study a fuzzy expert system to diagnose prostate cancer. Many authors worked on FIS and mathematical modelling [35-46].

In this study, we created an expert system with Neuro/ ANN to accurately diagnose breast cancer and prostate cancer in response to the need for a potent diagnostic tool. The created system uses fuzzy rules to make diagnoses. We created a fuzzy rule-based technique with ANN that uses PSA, PV, AGE, and %FPSA as input factors and prostate cancer risk (PCR) as an output parameter to determine whether a biopsy is necessary.

2. DATA AND METHODOLOGY

The UCI Machine Learning Repository offers the mammography mass data collection for breast cancer. Using BI-RADS features and the patient's age, this data set can be utilised to estimate the severity (benign or malignant) of a mammographic mass lesion. It includes a BI-RADS assessment, the patient's age, three BI-RADS qualities, and the severity field, which serves as the ground truth, for the 516 benign and 445 malignant masses found on full field digital mammograms gathered from 2015 to 2018. In a double-review procedure, doctors award a BI-RADS score to each event, ranging from 1 (certainly benign) to 5 (strongly suggestive of cancer). Sensitivity and associated specificities can be estimated by assuming that all instances with BI-RADS assessments greater than or equal to a specified value (ranging from 1 to 5) are malignant and the remaining cases benign.

The approach described in the current section is essentially divided into determining the characteristics of PSA level in blood, age, PV, and %FPSA of ten patients and used as information boundaries into FIS, with fuzzy 230 rules being used to estimate the PCR status as a system output. 75 patients' data from the Delhi-NCR region's lab and clinical PSA, PV, and age data were used for prostate cancer.

FIS and neuro-fuzzy method

A computer programme that mimics the knowledge and skill of a human expert is known as an expert system. A huge knowledge database, the ability to query the database, and a set of rules (an inference engine) are all characteristics of an expert system. Expert systems are used, for instance, in medicine to diagnose diseases. When the system receives the patient's information and symptoms, it generates possible diagnoses, suggested therapies, or even prescribed medications. The benefits of a doctor expert system such as a vast database of information can store more knowledge than a person and can be updated and added to. The system is unable to "forget" or misremember facts. It endures forever. As when a doctor retires, there is no knowledge loss. A doctor might not have access to some specialised knowledge, but the computer does.

This technique, which is based on the mapping process, uses fuzzy logic to map an input to an output. The defined fuzzy rule to ascertain the rule outcome from the information provided as the rule input. Membership functions represent the expert interpretation of those variables, while fuzzy rules [20].

Neuro-Fuzzy System

The neuro-fuzzy system features a 3-layer feed-forward architecture that is developed from a general fuzzy perception. T-norms or T-conorms are used by the units in this network as activation functions. Fuzzy rules are represented in the hidden layer. (Fuzzy) connection weights are used to encode fuzzy sets. This illustration of a fuzzy system shows how data (including error signals) travel through the system and how parallel it is. A unique three-layered feed-forward neural network called a "neuro-fuzzy system" [39].

The pattern tuples are represented by the first layer's input variables, while the fuzzy rules are represented by the hidden layer. One unit per class is represented by the third layer's output variables, which use t-norms and t-conorms as activation functions. Fuzzy sets are stored as (fuzzy) connection weights. We investigated the most effective fuzzy model for classifying the Mammographic Mass data set. We were able to obtain the best rules for the inference engine as a result.

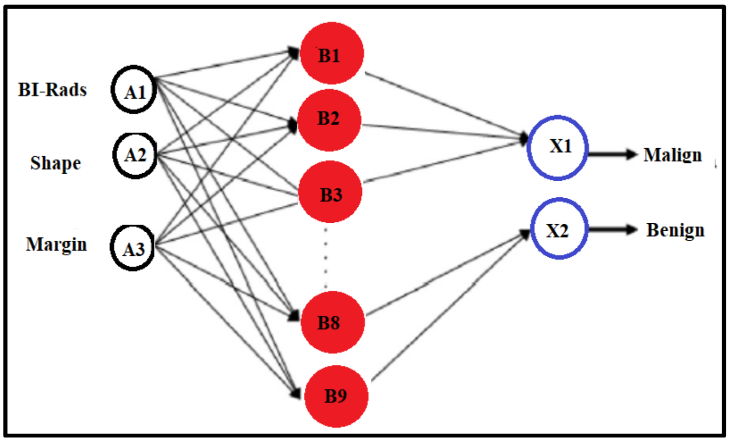

Fig. 1: Neuro-Fuzzy model for Inference System.

The hidden layer, nine fuzzy rules using BI-RADS, Shape, and Margin attributes are used in this study's based on previous study.

1. if BI-RADS is medium then Benign;
2. if BI-RADS is very large and Shape is very large and Margin is medium then Malign;
3. if BI-RADS is very large and Shape is large and Margin is small then Malign;
4. if BI-RADS is very large and Shape is large and Margin is medium then Malign;
5. if BI-RADS is very large and Shape is large and Margin is very large then Malign;
6. if BI-RADS is very large and Shape is small then Malign;
7. if BI-RADS is very large and Shape is very large and Margin is very large then Malign;
8. if BI-RADS is small then Benign;
9. if BI-RADS is large then Benign.

3. RESULTS AND DISCUSSION

The present section used age, PV, PSA, and %FPSA as four input variables for explore the risk factor for prostate cancer. For breast cancer used mammographic mass data such as age, BI-RIDS, Shape, margin, density, and class.

3.1 Prostate Cancer

For identifying the prostate cancer, we generate the 200 fuzzy rules by using fuzzy rule generator in MATLAB 14b version. Age, PV, PSA, and %FPSA are the four input factors used to analyse prostate cancer risk. These guidelines are of utmost importance when testing the behaviour of prostate cancer. In Fig. 2, the rules generator is displayed. These are the few guidelines:

Rule 1: If a patient's age is deemed to be Middle, their PV is Small, their PSA is Very Low, and their %FPSA is Low, then their risk of developing prostate cancer is Low.

Rule 16: Prostate cancer risk is low if the patient's age is middle, their PV is small, their PSA is low, and their %FPSA is very high.

Rule 159: Prostate cancer risk is moderate if the patient is old, the PV is small, the PSA is low, and the %FPSA is low.

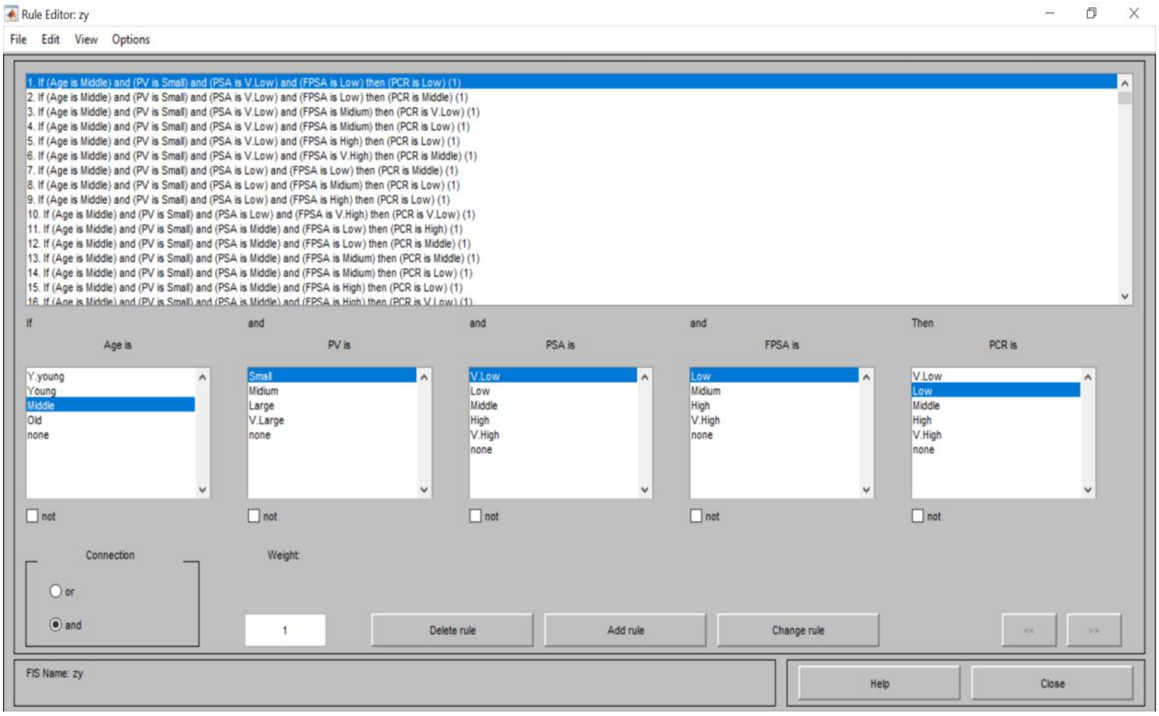

Fig.2: Generate the 200 fuzzy rules in MATLAB 14b using fuzzy rule generator

Rule 188: states that a patient's age, PV size, PSA level, and %FPSA level all indicate a high probability of prostate cancer.

Prostate cancer risk

The Mamdani approach is employed by the FIS to evaluate the rule that was produced utilising all four input parameters. The output variables' linguistic values are in the same format as the input variables' linguistic values, which range from very low to low, low to middle, middle to high and high to very high. According to Fig. 3, the probability of developing prostate cancer is 47.8% when the patient is 51 years old, the PV is 200, the PSA is 20, and the FPSA is 35%. The risk factor if 50% when the age of the patient is 30, PV is 130, PSA is 5 and FPSA is 20% (Fig. 4).

Due to the high frequency of each case, the rate and tendency reach a dangerous level, necessitating the need for a biopsy by the specialist. Fig. 4 illustrates the three-dimensional representation of the probabilities for risk of prostate cancer with various combinations. Fig. 5 shows that the prostate has a 50% chance of developing when the patient is older than 60 and the prostate volume is greater than 100. The risk of a positive PCR is greater than 50% if the patient's age is between 50 and 60 and their PSA is between 30 and 45.

Fig. 3: Calculated PCR = 47.8 at the age = 51, PV = 200, PSA = 20 and %FPSA = 35.

Fig. 4: Calculated PCR = 50 at the age = 30, PV = 130, PSA = 5 and %FPSA = 20.

PSA, age, and PV were utilised by for categorising prostate cancer by FIS and %FPSA is also employed in this work, along with 230 fuzzy knowledge-based criteria [47]. This trial result has shown that the FIS-based example acknowledgment framework is performing well when compared to Kar and Majumder's [47] work.

For predicting the pathological stage of prostate cancer, Castanho et al. [48] used the receiver operating characteristic (ROC) curve and 190 patient data; however, in this study, 100 patient data (PSA, %FPSA, age of the patient, and PV) from various labs throughout the Delhi-NCR region were used in the FIS. The FIS can be used as a supplementary tool to investigate the causes of cancer, according to the authors' thorough analysis.

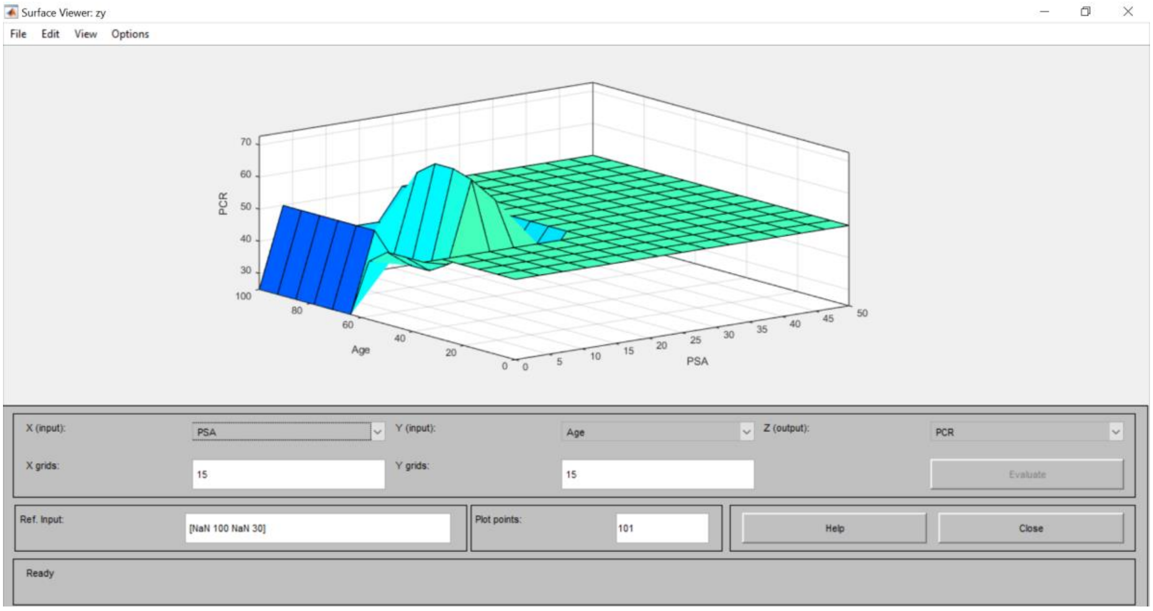

Fig. 5: Analysis of Likelihoods for PCR between Age vs PSA

3.2 Breast Cancer

In order to identify breast cancer, we just changed one NN input parameter. By means of this method. since one of the regulations is:
Input: 1-3-8-9 tends 2
Value: 1-1-1-1tends 1 confidence is 100%.

This rule states that the value of the second input parameter is 1 if the values of the first, third, eighth, and ninth input parameters are all 1. The second input already depends on others, it continues. As a result, we skipped the second input parameter in the NN input.

Two classes make up the Wisconsin breast cancer database. These categories are benign and malignant. We discovered extensive item sets of benign and malignant classes using AR2, which are listed as follows:
Input: 2-8-9
Value: 1-1-1 (large item sets for benign class)
Input: 6
Value: 10 (large item for malignant class)
This extensive itemset indicates that the second, eighth, and ninth input parameters can already establish the benign class, while the sixth input parameter can define the malignant class.

Neural Network Layer

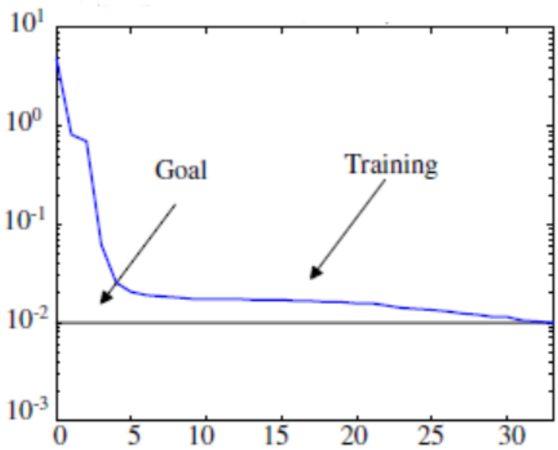

Fig. 6: Training performance of Neural Network

The most crucial parameters for issues with breast cancer detection are those listed above. Therefore, we only used these inputs in the NN Multi-layer Perceptron (MLP), which uses features from these inputs to implement intelligent categorization. Layer AR Table 1 displays the training settings and the MLP's structure employed in this investigation. After multiple tests, these were chosen for their superior performance. The training results for AR2 & NN are displayed in Fig. 6.

Table 1: The training parameters & architecture of multi-layer perceptron

The number of layers	3
The number of neurons on the layers	Input: 4, 8, 9 Hidden: 11 Output: 1
The initial weights and biases	Random
Activation functions	Tangent-sigmoid Linear
Sum-squared error	0.01
Training parameters	Levenberg–Marquardt
Learning rule	Back-propagation

A Wisconsin breast cancer database with 9 characteristics and 699 records was used for this study. The 3-fold cross validation approach was used throughout the test phase, and average results were computed. Table 2 provides the performance comparison and accurate categorization rates. According to Table 2, the AR1 + NN with eight inputs produced the best classification performance, with an accurate classification percentage of 97.4%. A 95.6% right classification rate for AR2+NN and a 95.2% correct classification rate for NN with 9 inputs were attained. Therefore, AR1 & NN offers the best classification performance, while AR2 & NN uses the fewest input parameters.

Table 2: Comparing the effectiveness of NN, AR1 + NN, and AR2 + NN for the diagnosis of breast cancer

The classifier	The epochs	Correct classified	Correct classification rate (%)	Miss classified
NN (9, 11, 1)	62	215	96.1	12
AR1 + NN (8, 11, 1)	42	222	97.9	7
AR2 + NN (4, 11, 1)	32	218	96.1	9

4. CONCLUSION

For prostate cancer, the suggested PC growth analysis method is a useful model for assisting medical professionals in the transmission therapy for prostate illness. By calculating the patient's age, prostate volume, blood PSA level, and %FPSA in the current investigation, the FIS was able to distinguish the presence of prostate cancer growth. In this study, analysis training for the diagnosis of prostate cancer is based on the FIS for the identification of prostate cells as having a regular or irregular form. The current study included additional parameters for detection and analysis of the prostate cancer risk in comparison to earlier studies like [47-48]. For breast cancer, performance of the suggested AR with NN system is compared to that of the NN model. By employing AR, the input feature space's dimension is reduced from nine to four. To assess the proposed system's performance during the testing phase, the Wisconsin breast cancer database was used with the 3-fold cross validation approach. The suggested system's correct classification rate is 96.1% for four inputs and 97.9% for eight inputs. The results presented for prostate cancer, demonstrate that the FIS approach produces the highest level of prophetic accuracy. This study also suggests that the FIS is trustworthy to provide typical evidence for correspondence of the early prostate cancer risk when individual patients are involved. This study showed how the AR with NN diagnosis the breast cancer well and it can be utilised to decrease the feature vector's dimension and how the proposed AR with NN model can be used to create effective automatic diagnosis systems for additional diseases.

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