An Approach to Diagnosis of Prostate Cancer using Fuzzy Logic

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Abstract- **Early diagnosis of cancers is a major requirement for the patients and a complicated job for the oncologist. If it is diagnosed early, it could have made the patient more likely to live. For a few decades, fuzzy logic emerged as an emphatic technique in the identification of diseases like different types of cancers. Mostly the recognition of cancers diseases operated with inexactness, inaccuracy, and vagueness. This paper aims to design the fuzzy expert system and its implementation for the detection of prostate cancer. Specifically, Prostate-Specific Antigen (PSA), Prostate Volume (PV), Age, and Percentage Free PSA (%FPSA) are used to determine prostate cancer risk, while Prostate Cancer Risk (PCR) serves as an output parameter. Mamdani Fuzzy Inference Method is used to calculate a range of PCR. The system provides a scale of risk of prostate cancer and clears the path for the oncologist to the determination whether their patients need a biopsy or not. This system is fast as it requires minimum calculation and hence comparatively lesser time which reduces mortality, morbidity and is more reliable than other systems, economical, and can be frequently used by doctors.**

Keywords- – Fuzzy Logic; Fuzzy Expert System; Prostate Cancer; Prostate Specific Antigen; Prostate Volume; % Free Prostate Specific Antigen

1. INTRODUCTION

Artificial intelligence approaches have been employed in a variety of fields over the last few decades, including robotics, insurance, education, market research, and medical applications. Expert systems have been created in a variety of fields. Fuzzy logic has a crucial role in the medical area [1-8]. For the improvement of decision making in radiation therapy [11], detection of breast cancer[12-14], lung cancer[15-18], prostate cancer[19-31], to differentiate benign skin lesions from malignant melanomas[32, 33], an MRI-based method for calculating the volume of brain tissue [9], to assist doctors in making a rapid and effective decision regarding the dose of medicine for the treatment of 200 dialysis patients [10]. The fuzzy logic controller system assists the doctor in determining the correct dose of medicine to provide to the patient based on all parameters related to the ailment. Doctors may have a hazy picture due to the large amount of medical information offered to them. Any patient's many medical diagnoses point doctors in the direction of suitable treatment. Medical investigations are quite complex, and it would be difficult to cover all of the linkages to explain the situation's rationality. When doctors begin treating a patient, they analyze all medical records and use their academic knowledge, personal experience, and intellectual power to determine the origin of the ailment. As a result, the purpose of the fuzzy intelligent system is to control the behavior of doctors by providing them with a conference. Fuzzy logic addresses several aspects of fuzzy expert systems, and its applications in the medical domain are vast [19]. Fuzzy logic is now widely used by doctors and engineers to tackle difficulties in a variety of disciplines, including agriculture, banking and economics, electronics, and other real-world issues. Previous research has shown that detecting prostate cancer using solely image processing and ultrasonography is difficult. For this, we created a knowledge-based fuzzy expert system that uses the patient's laboratory and other data and mimics the expert's advice. If it is found early, the patient can be thoroughly treated, increasing the patient's chances of survival. Biopsy for cancer detection, on the other hand, has the potential to spread to other organs. As a result, the biopsy process is unappealing and unacceptably painful. We developed a fuzzy rule-based technique that incorporates PSA [34], PV [35], AGE [36], and percent FPSA [37] as input elements and prostate Cancer Risk (PCR) as an output component to determine how much biopsy is required.

2. FUZZY EXPERT SYSTEM

This expert system is fuzzy in nature since the rules in the expert system (ES) incorporate fuzziness and the parameters can be fuzzified. In

the calculation of collective data, a fuzzy expert system employs membership functions and a few prescriptive rules.

AGE (year), PV (ml), PSA (ng/ml), FPSA (percent), and PCR (percent) are the units used for input and output parameters. In a fuzzy expert system, the trapezoidal and triangular membership functions are employed to fuzzify input and output parameters. Fuzzy sets are used to represent each input parameter.

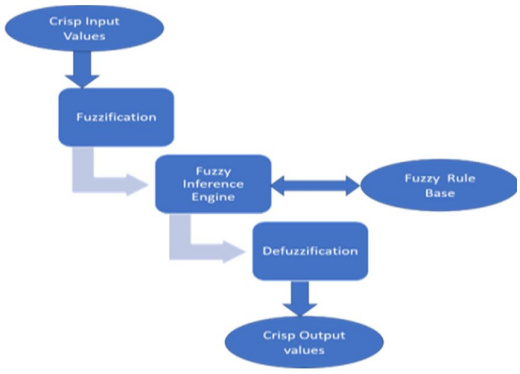

Fig. 1 General Structure of Fuzzy Expert System

3. INPUT VARIABLES ARRAY

3.1 Age

The age of a person has a big impact on how much prostate cancer costs. Prostate cancer is most commonly detected in men over the age of 65. The number differs from one person to the next. For Age, four fuzzy sets are used: "Very Young," "Young," "Middle," and "Old." After that, trapezoidal membership functions are used to interpret all four fuzzy sets.

3.2 PSA

PSA is a protein produced by the prostate gland and found primarily in the sperm, however a small quantity can also be found in the blood. When a person gets older or their prostate gland grows larger, the amount of PSA in their blood increases somewhat. A high PSA level indicates that you may have a problem with your prostate, but it does not always mean that it is cancer. A healthy prostate, according to specialists, produces less PSA in the blood than a malignant one. As a result, an increase in PSA could be a sign of prostate cancer. For PSA five fuzzy sets: “Very Low”, “Low”, “Middle”, “High” and “Very High” are used and for first and fifth fuzzy sets are interpreted by trapezoidal membership function while for the remaining we used triangular membership function.

3.3 PV

The prostate of a healthy guy is about the size of a chestnut, and its role is to create a small amount of seminal fluid, which combines with sperm to form semen. The prostate gland begins to expand at the age of 40, but the pattern varies from person to person. It's critical for the early detection of prostate cancer. Total prostate volume is calculated using the elliptical formula, TPV, which is defined as /6 W L H, where W denotes prostate width, L denotes prostate length, and H denotes prostate height. PV uses four fuzzy sets: "Small," "Medium," "Large," and "Very Large." The trapezoidal membership function is used to interpret the first and fourth fuzzy sets, whereas the triangle membership function is used to understand the second and third fuzzy sets.

3.4 %FPSA

PSA testing provides total PSA, which includes both bound and unbound PSA levels, whereas Free PSA provides the ratio of unbound to bound PSA levels by calculating (Free PSA)/(Total PSA) 100 percent [38]. On average, a free PSA test can cut the number of needless biopsies by 20%.The higher the PSA level and the lower the Free PSA level, the greater the risk of Prostate Cancer. For percent FPSA, four fuzzy sets are used: "Low," "Medium," "High," and "Very High," with the first and fourth fuzzy sets interpreted using a trapezoidal membership function, and the second and third fuzzy sets interpreted using a triangle membership function.

4. OUTPUT VARIABLES ARRAY

4.1 PCR

The fuzzy sets are classified as "Low," "Middle," "High," and "Very High," and the first and fourth fuzzy sets are interpreted using a trapezoidal membership function, while the remainder are interpreted using a triangle membership function. The created technology can diagnose and treat a variety of prostate cancers in patients.

5. FORMING OF MEMBERSHIP FUNCTION AND FUZZIFICATION OF THE INPUT VARIABLE

5.1. Membership Function for PSA

$$\mu_{\text{very low}}(A) = \begin{cases} 1\,; 0 \le a \le 2 \\ \frac{4-a}{2}\,; 2 \le a \le 4 \\ 0\,; a \ge 4 \end{cases}$$

$$\mu_{\text{low}}(A) = \begin{cases} 0\,; 0 \le a \le 2 \\ \frac{a-2}{2.5}\,; 2 \le a \le 4.5 \\ \frac{6.5-a}{2}; 4.5 \le a \le 6.5 \\ 0\,; a \ge 6.5 \end{cases}$$

$$\mu_{\text{middle}}(A) = \begin{cases} 0 \;; a \le 4.5 \\ \frac{a-4.5}{4}; 4.5 \le a \le 8.5 \\ \frac{12.5-a}{4}; 8.5 \le a \le 12.5 \\ 0\,; a \ge 12.5 \end{cases}$$

$$\mu_{\text{high}}(A) = \begin{cases} 0\,; a \le 8.5 \\ \frac{a-8.5}{5}; 8.5 \le a \le 13.5 \\ \frac{18.5-a}{5}; 13.5 < a \le 18.5 \\ 0\,; a \ge 18.5 \end{cases}$$

$$\mu_{\text{very high}}(A) = \begin{cases} 0\ ;\ 0 \le a \le 13.5 \\ \frac{a-13.5}{8};\ 13.5 \le a \le 21.5 \\ 1\ ;\ a \ge 21.5 \end{cases}$$

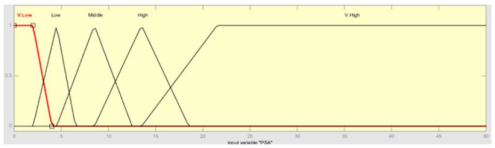

Fig. 2: Graph of membership Function for "PSA"

5.2. Membership Function for PV

$$\mu_{\text{small}}(B) = \begin{cases} 1\ ;\ 0 \le b \le 20 \\ \frac{40-b}{20};\ 20 \le c \le 40 \\ 0\ ;\ b \ge 40 \end{cases}$$

$$\mu_{\text{midium}}(B) = \begin{cases} 0\ ;0 \le b \le 30 \\ \frac{b-30}{30}\ ;\ 30 \le b \le 60 \\ \frac{90-b}{30};\ 60 \le b \le 90 \\ 0\ ;\ b \ge 90 \end{cases}$$

$$\mu_{\text{large}}(B) = \begin{cases} 0\ ;0 \le b \le 70 \\ \frac{b-70}{40};\ 70 \le b \le 110 \\ \frac{150-b}{40}\ ;110 \le b \le 150 \\ 0\ ;\quad b \ge 150 \end{cases}$$

$$\mu_{\text{very big}}(B) = \begin{cases} 0\ ;0 \le b \le 130 \\ \frac{a-130}{40};\ 130 \le b \le 170 \\ 1\ ;\ b \ge 170 \end{cases}$$

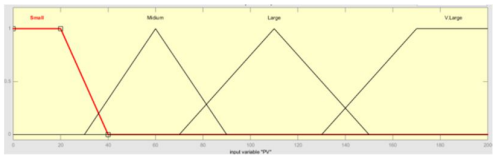

Fig 3: Graph of membership Function for "PV"

5.3. Membership Function for Age

$$\mu_{\text{very young}}(C) = \begin{cases} 1;\ 0 \le c \le 20 \\ \frac{25-c}{5}\ ;20 \le c \le 25 \\ 0\ ;\ c \ge 25 \end{cases}$$

$$\mu_{\text{young}}(C) = \begin{cases} 0\ \ ;0 \le c \le 20 \\ \frac{c-20}{5}\ ;\ 20 \le c \le 25 \\ 1;25 \le c \le 45 \\ \frac{50-c}{5}\ ;\ 45 \le c \le 50 \\ 0\ ;\quad c \ge 45 \end{cases}$$

$$\mu_{\text{middle age}}(C) = \begin{cases} 0\ ;c \le 45 \\ \frac{c-45}{10};\ 45 \le c \le 55 \\ 1\quad ;55 \le c \le 65 \\ \frac{75-c}{10}\ ;65 \le c \le 75 \\ 0\ ;\ c \ge 75 \end{cases}$$

$$\mu_{\text{old}}(C) = \begin{cases} 0\ ;\ c \le 65 \\ \frac{c-65}{10};\ 65 \le c \le 75 \\ 1\ ;\ c \ge 75 \end{cases}$$

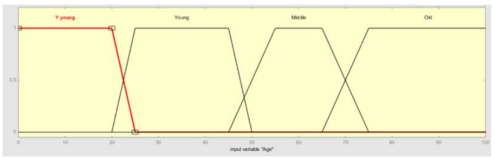

Figure 4: Graph of membership Function for "Age"

5.4 Membership Function for % FPSA

$$\mu_{\text{v. low}}(D) = \begin{cases} 1\ ;\ 0 \le d \le 10 \\ \frac{15-d}{5};\ 10 \le d \le 15 \\ 0\ ;\ d \ge 15 \end{cases}$$

$$\mu_{\text{medium}}(D) = \begin{cases} 0\ ;0 \le d \le 10 \\ \frac{d-10}{7.5}\ ;\ 10 \le d \le 17.5 \\ \frac{25-d}{7.5};\ 17.5 \le d \le 25 \\ 0\ ;\ d \ge 25 \end{cases}$$

$$\mu_{\text{high}}(D) = \begin{cases} 0\ ;0 \le d \le 20 \\ \frac{d-20}{7.5}\ ;\ 20 \le d \le 27.5 \\ \frac{35-d}{7.5};\ 27.5 \le d \le 35 \\ 0\ ;\ d \ge 35 \end{cases}$$

$$\mu_{\text{v.high}}(D) = \begin{cases} 0\ ;\ d \le 30 \\ \frac{d-30}{10};\ 30 \le d \le 40 \\ 1\ ;\ d \ge 40 \end{cases}$$

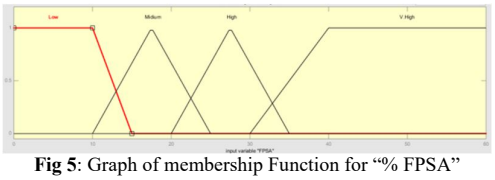

Fig 5: Graph of membership Function for "% FPSA"

5.6 Membership Function for PCR

$$\mu_{\text{very low}}(X) = \begin{cases} 1\ ;\ 0 \le x \le 10 \\ \frac{15-x}{5};\ 10 \le x \le 15 \\ 0\ ;\ x \ge 15 \end{cases}$$

$$\mu_{\text{low}}(X) = \begin{cases} 0\ ;\ 0 \le x \le 10 \\ \frac{x-10}{15}\ ;10 \le x \le 25 \\ \frac{20-x}{15};\ 25 \le x \le 40 \\ 0\ ;\ x \ge 40 \end{cases}$$

$$\mu_{\text{middle}}(X) = \begin{cases} 0\ ;0 \le x \le 25 \\ \frac{x-25}{15};\ 25 \le x \le 40 \\ \frac{55-x}{15}\ ;40 \le x \le 55 \\ 0\ ;\ x \ge 55 \end{cases}$$

$$\mu_{high}(X) = \begin{cases} 0; x \le 40 \\ \frac{x-40}{15}; 40 \le x \le 55 \\ \frac{70-x}{15}; 55 \le x \le 70 \\ 0; x \ge 70 \end{cases}$$

$$\mu_{very\ high}(X) = \begin{cases} 0; x \le 50 \\ \frac{x-50}{20}; 50 \le x \le 70 \\ 1; 70 \le x \end{cases}$$

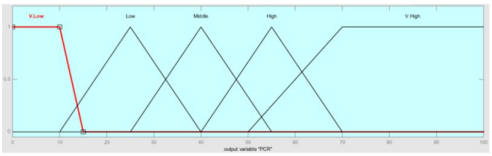

Fig 6: Graph of membership Function for "PCR"

5. FORMATION OF FUZZY KNOWLEDGE RULE BASE AND DEFUZZIFICATION

We utilize four input variables, Age, PV, PSA, and %FPSA, as inputs, and interpret these variables using four, four, five, and four membership functions, accordingly. Total 255 rules are setup to calculate PCR which is expressed by five membership functions. Listed below are a few fuzzy rules we developed:

Table 1 ……

Rule No.	Age	PV	PSA	%FPSA	PCR
1	Middle	Small	V. Low	Low	Low
53	Middle	Medium	High	Low	High
92	Middle	V. Large	Low	High	Middle
150	Old	Small	V.High	High	High
191	Old	Large	Middle	Medium	Middle
200	Old	Large	High	V. High	V.High
230	Young	Small	Low	V. High	V. Low

7. DEFUZZIFICATION BY USING MAMDANI FUZZY INFERENCE SYSTEM

Defuzzification is a technique for extracting a single quantity from a set of fuzzy numbers. It converts the output of fuzzy inference into a crisp output. The crisp value of PCR in this FES is derived using the centroid method of defuzzification, which may be calculated using

$$D^* = \frac{\int \mu_c(z).z\, dz}{\int \mu_{c(z)} dz} \quad \text{(i)}$$

If we are given a set of input data for prostate cancer detection, such as Age = 67, PSA = 9.32, PV= 36, percent FPSA= 20.37, we must first choose the appropriate fuzzy sets for each input variable and calculate the necessary degree of membership function. Assume that this set of inputs adheres to some (k) set of rules. The truth degree I of the ith applicable rule is determined after determining the minimum of related membership values for each input variable. By taking the maximum of all I we can determine the PCR membership value. In this case, the Mamdani Fuzzy Inference Technique is applied. The PCR crisp value is calculated using the centroid method. The following are the phases for the above-mentioned data:

1. Age = 67, $\mu_{middle\ age}(67) = 0.8$ and $\mu_{old}(67) = 0.2$
2. PSA = 9.32, $\mu_{middle}(9.32) = 0.795$ and $\mu_{high}(9.32) = 0$ .164
3. PV = 36, $\mu_{small}(36) = 0.2$ and $\mu_{medium}(36) = 0.2$
4. %FPSA = 20.37, $\mu_{medium}(20.37) = 0.61$ and $\mu_{high}(20.37) = 0.0491$.

According to the given input data, sixteen rules will be fired as following:

1. α_{13} = min(0.8,0.2,0.795,0.61) = 0.2,
2. α_{15} = min{0.8,0.2,0.795,0.0491} = 0.0491,
3. α_{21} = min{0.8,0.2,0.164,0.61} =0.164,
4. α_{23} = min{0.8,0.2,0.164,0.0491} = 0.0491,
5. α_{44} = min{0.8,0.2,0.795,0.61} = 0.2,
6. α_{46} = min{0.8,0.2,0.795,0.0491} = 0.0491,
7. α_{52} = min{0.8,0.2,0.164,0.61} = 0.164 ,
8. α_{54} = min{0.8,0.2,0.164,0.0491} = 0.0491,
9. α_{131} = min{0.2,0.2,0.795,0.61} = 0.2,
10. α_{134} = min{0.2,0.2,0.795,0.0491} = 0.0491,
11. α_{139} = min{0.2,0.2,0.164,0.61} = 0.164,
12. α_{141} = min{0.2,0.2,0.164,0.0491} = 0.0491,
13. α_{163} = min{0.2,0.2,0.795,0.61} = 0.2,
14. α_{165} = min{0.2,0.2,0.795,0.0491} = 0.0491,
15. α_{171} = min{0.2,0.2,0.164,0.61} = 0.164,
16. α_{172} = min{0.2,0.2,0.164,0.0491} = 0.0491,

Now, we obtain membership function from Mamdani max-min inference as

α = max {α_{13}, α_{15}, α_{21}, α_{23}, α_{44}, α_{46}, α_{52}, α_{54}, α_{131}, α_{139}, α_{141}, α_{163}, α_{165}, α_{171}, α_{172}}

= max {0.2, 0.0491, 0.164, 0.0491, 0.2, 0.0491, 0.164, 0.0491, 0.2, 0.0491, 0.164, 0.0491, 0.2, 0.0491, 0.164, 0.0491}

= 0.2

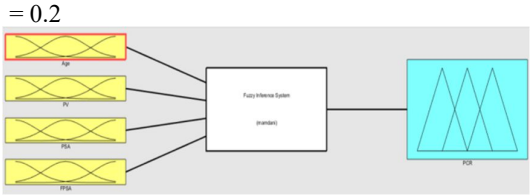

Fig. 7 The structure of FES for the detection of prostate cancer

After applying centroid method we obtain PCR = 56%which is slightly greater than our cut-off 50%. In this situation we will advise the patient to go for a biopsy.

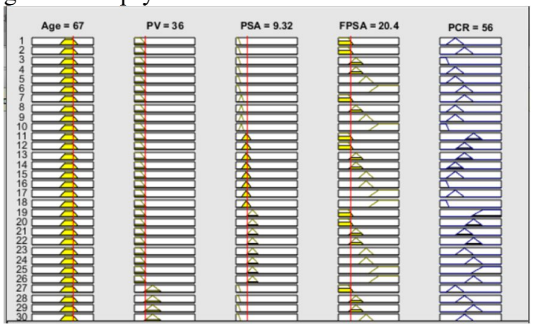

Figure 8 Calculation of PCR for Age = 67 years, PSA = 9.32ng/ml, PV= 36ml and %Free PSA = 20.4

Here we apply our developed FES and calculate risk of PCR on the data of 119 patients which contain their PSA level, PV, Age and Free PSA and result of biopsies given in paper[29].

Table 1: ……..

SINo	Age year	PV (ml)	PSA(ng /ml)	% FPSA	Biopsy Result	PCR (%)
29.	60	35	15.51	21.02	Negative	63.7
30.	61	37	4.60	10.87	Negative	29.3
31.	61	62	10.33	25.36	Negative	61.3
32.	61	35	10.36	19.79	Negative	56.2
33.	61	56	10.59	17.00	Positive	71.4
34.	61	62	18.30	6.99	Positive	72.4
35.	62	52	6.12	24.18	Negative	46.9
36.	62	25	6.20	4.35	Positive	47.5
37.	62	43	8.37	11.23	Negative	71.9
38.	62	45	8.79	10.92	Positive	72.1
39.	62	53	20	5.20	Positive	73.2
40.	62	29	51.74	6.80	Positive	50
41.	63	31	8.80	22.50	Positive	41.9
42.	64	36	5.70	29.82	Negative	40
43.	64	45	6.96	9.20	Negative	72.1
44.	64	40	8.00	7.50	Positive	71.5
45.	64	26	11.08	10.11	Negative	66.4
46.	64	21	16.28	6.94	Positive	71.9
47.	65	30	4.39	21.64	Negative	32.5
48.	65	47	5.15	15.73	Negative	35.4
49.	65	23	7.61	5.78	Positive	47.5
50.	65	75	7.82	22.76	Negative	59.8
51.	65	32	8.33	14.53	Positive	51.9
52.	66	33	4.38	23.52	Negative	27.7
53.	66	61	6.72	13.84	Positive	72.3
54.	66	89	7.65	23.66	Negative	46.8
55.	66	74	9	18.89	Positive	69.1
56.	66	49	9.86	23.83	Negative	58.5
57.	67	28	4.39	0.91	Negative	40
58.	67	24	5.65	10.27	Positive	58
59.	67	65	6.24	21.96	Negative	57.6
60.	67	36	8.2	20.37	Positive	56
61.	67	41	9.68	7.44	Positive	66.9
62.	67	69	15.93	6.09	Positive	68.6
63.	67	47	28	15.00	Positive	72.3
64.	68	47	5.09	2.36	Negative	35
65.	68	45	5.51	11.25	Negative	42.3
66.	68	33	7.2	3.61	Positive	62.7
67.	68	91	9.25	3.57	Positive	47.5
68.	68	61	12.1	16.12	Negative	68.9
69.	68	109	23.7	10.04	Positive	50
70.	68	117	140	14.29	Positive	50
71.	68	54	140	3.29	Positive	72.9
SINo	Age year	PV (ml)	PSA(ng /ml)	% FPSA	Biopsy Result	PCR (%)
72.	69	34	8.8	8.98	Positive	63.9
73.	69	38	11.06	29.84	Negative	60.5
74.	69	74	15.31	30.57	Positive	66.1
75.	69	46	61	9.93	Negative	72.2
76.	69	45	70.56	6.02	Positive	72.1
77.	69	29	146	7.33	Positive	71.7
78.	70	120	5.39	19.11	Negative	50.2
79.	70	42	5.39	12.80	Negative	43
80.	70	40	13	15.46	Negative	64
81.	70	119	13.95	13.76	Negative	47.5
82.	70	44	19.2	10.10	Positive	72
83.	70	29	21.94	7.11	Positive	72.1
84.	70	63	27.7	8.99	Negative	72.1
85.	71	48	6.08	21.38	Positive	55.9
86.	71	50	12.64	7.99	Positive	61.4
87.	71	57	22	12.00	Positive	69.8
88.	72	32	6.64	27.41	Negative	41.3
89.	72	33	13.31	3.83	Positive	68.9
90.	72	33	13.31	3.76	Positive	68.9
91.	72	48	20	7.90	Positive	67.7
92.	72	36	46	10.70	Positive	71
93.	72	48	77	8.31	Positive	67.7
94.	73	41	4.65	14.94	Negative	48.3
95.	73	19	7.25	5.52	Negative	70
96.	73	74	7.6	31.32	Positive	47.5
97.	73	90	19	6.84	Positive	50
98.	73	91	29.52	9.82	Negative	50
99.	73	87	47.4	15.89	Positive	70.7
100.	74	27	12.52	11.82	Negative	72.7
101.	74	54	150	16.67	Positive	60
102.	75	16	4.61	17.53	Positive	43
103.	75	34	10	7.60	Positive	67.5
104.	76	56	9.81	37.41	Negative	47.5
105.	76	61	13.61	19.91	Positive	47.5
106	76	54	13.83	19.96	Positive	47.5
107	76	86	21	5.43	Positive	55
108	77	60	10	6.00	Positive	68.2
109	77	28	12.05	27.05	Positive	47.5
110	77	51	56	7.34	Positive	55
111	78	180	4.5	20.44	Negative	32.5

112	78	46	26.1	8.62	Negative	55
113	78	235	26.13	8.27	Negative	47.5
SINo	Age year	PV (ml)	PSA(ng/ml)	% FPSA	Biopsy Result	PCR (%)
114	78	57	31.6	8.86	Negative	55
115	79	41	17.1	7.60	Negative	48.5
116	80	28	69.51	28.77	Positive	47.5
117	81	28	4.5	21.56	Positive	40
118	81	52	68.36	35.27	Positive	43.6
119	88	32	10.4	7.50	Positive	70.1

6. RESULTS AND DISCUSSIONS

We examine the results of biopsies taken from 119 patients who have acquired FES. The majority of FES for PCR literature focuses on three inputs (PSA, age, PV). However, the percent FPSA with PSA plays a critical role in the identification of PC, reducing unnecessary biopsy and yielding significant outcomes. That is why we created our Fuzzy-rule knowledge-based expert system, which uses four input factors and one output parameter to predict the risk of prostate cancer. If our Fuzzy expert system indicates that the PCR range is equal to or more than 50%, the patient should be encouraged to get a biopsy. The findings of our fuzzy expert system are shown in the confusion matrix below.

Table 3 : …

	Actual Positive	Actual Negative
Predicted Positive	47	28
Predicted Negative	14	30
Accuracy	64.71%	
True Positive	77.05%	
True Negative	51.72	

Out of 119 patients, 61 had biopsy results that were positive, while the remaining 58 had biopsy results that were negative. Our FES has a True Positive detection rate of 77.05 percent. Out of 61 positive patients, our Fuzzy expert system properly identified 47 positive biopsy results and accurately identified 30 negative biopsy results out of 58 patients. The proportion of proper detection after utilising our developed FES is significantly higher than that of other existing methods in the literature. Using fuzzy rules on the same data, Saritas [29] got 64.71 percent correct detection, 62.18 percent with an online calculator, and 60.50 percent with the ratio (FPSA/PSA) for PCR. So, while the addition of FPSA percent increased the number of rules, it also improved the accuracy of the findings.

7. CONCLUSION

The true detection percentage for positive biopsy is great, although it varies slightly for negative biopsy cases. Our FES is not conclusive in determining whether a patient has cancer or not. However, it provides a percentage of the likelihood of prostate cancer and aids the doctor in determining whether or not a patient should get a biopsy. Because diverse immunomodulation behaviours range from person to person, demographic variations from area to area, family history, height, eating habits, style of life, and many more hidden activities are all factors. As a result, moderation in determining cut-off values must be developed in accordance with the FES's terms and conditions. We can improve our FES by incorporating other artificial techniques.

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