Adaptive Neuro-Fuzzy Inferential Approach for the Diagnosis of Prostate Diseases

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Abstract: In this study, Adaptive Neuro-fuzzy Inferential System (ANFIS) is adapted for diagnosing prostate diseases. The system involves generating and tuning a fuzzy inference system to handle the imprecise terms used for describing prostate cases and severity. Several diagnostic variables were used to learn the feature statistics present in a typical data, while the trained model was validated and adapted for testing new prostate cases. A total of 335 data from patients' records were collected at the Medi Moses Prostate Centre, Kumasi Ghana. The dataset was partitioned into 70% which was used for model training, and the other 30% was utilized in the validation phase. The proposed model was implemented in the MATLAB environment. Evaluation result from the proposed system demonstrated that the system achieved an accurate diagnostic result with an RMSE value of 11%. This indicates that the system has a relatively high accuracy and could be accepted for prostate diagnosis. Furthermore, the model was able to learn well and generalize the features in the data set, making the proposed ANFIS model suitable for new cases. Performance analysis showed that the ANFIS is well suited for handling the crispy values used in prostate diagnosis; thus, it can be extensively employed in other similar areas of medical diagnosis.

Index Terms: Prostate Diseases Diagnosis, Artificial Intelligence, Soft Computing, ANFIS, RMSE.

1. Introduction

The prostate gland or simply prostate is one of the organs of the male reproductive system with a walnut-size located beneath the bladder, through which the urethra runs through during semen and urine excretion from the penis [1]. The management of prostate diseases depends on careful procedures including evaluation, diagnosis, treatment, and continuing care. The three most common diseases associated with the prostate gland are prostate cancer, Inflammation (prostatitis) and Benign Prostatic Hyperplasia, (BPH). Medical results from the host firm showed that prostate cancer is more prevalent in the age bracket 50 to 75 age group, mostly associated with males. The prostate cancer cells are confined to the prostate gland during their initial stages. However, some of the cancer cells are aggressive and thus they early enter the lymphatic and vascular systems even at their early stages; these cancer cells then spread to other parts of the body and develop secondary cancers, mostly in the bones.

Prostatitis is either a bacterial or non-bacterial infection of the prostate gland. This infection leads to an inflammation of the prostate. Bacterial prostatitis can be either chronic or acute. Acute prostatitis is not common like chronic prostatitis but it can be easily detected because of its more uniform clinical presentation, unlike chronic inflammation of the prostate gland which is poorly understood due to its uncertain etiology and absence of distinctive characteristics. Benign Prostatic Hyperplasia (BPH), is a non-cancerous enlargement of the prostate gland which is more prevalent with advancing age in men. BPH is the most common prostate disease among the three diseases.

Several psychosocial and medical characteristics of patients are mostly followed in diagnosing prostate diseases. Mostly, an intelligent or expert system that aids clinical diagnosis and prognosis is devised to recognize patient-specific

clinical situations based on vital laboratory and clinical examination variables and accordingly suggest a theoretical diagnostic plan. Depending on the data on the patient, the intelligent system models the patient's scenario based on some techniques that suggest probable treatment guidelines to the patient. These treatment guidelines are then employed in the management of the patient's condition. Artificial Intelligence is one of these techniques. Research on Artificial Intelligence (AI) has greatly improved in the area of diagnosing diseases, making the diagnosis of complex chronic diseases like prostate-related disease, easy to manage.

Marrying the effectiveness and efficiencies of neural network and fuzzy logic in an adaptive neuro-fuzzy inferential system (ANFIS) in this study would undeniably be one of the best techniques in diagnosing prostate issues in artificial intelligence. Basically, the contribution of this paper is to adapt the ANFIS approach for the diagnosis of prostate diseases (Prostate Cancer, Benign Prostatic Hyperplasia and Prostatitis) based on five inputs parameters (AGE, Prostate Specific Antigen (PSA), Prostate Volume (PV), Lower Urinary Tract Symptoms (LUTS), and Laboratory Test (Lab Test)). The model can then serve as an expert support and learning system for medical doctors and medical students who are unskilled in prostate diagnosis in managing and diagnosing prostate diseases.

2. Literature Review

This section of the study presents literature relating to the subject matter based on definitions and discussions of some terminologies. Artificial Intelligence (AI) has been widely used in diverse fields including the medical applications to improve performances. AI systems are intelligent systems deployed to solve multifaceted tasks that would have been done by humans with intelligence. [2]. Soft computing is one notable AI technique, defined as a group of procedures that works collaboratively and offers flexible data processing ability for solving practical imprecise situations. Soft computing aims at exploiting uncertainty, imprecision, partial truth tolerance, and approximate reasoning to achieve robustness, cost-effective results, and tractability. Neural Networks, Fuzzy Logic, and Genetic Algorithms, are the most commonly used soft computing modelling techniques. [3,4]. These techniques can be hybridized to derive approaches that can exploit the benefits of all the three techniques. A typical approach is what this study proposes, adaptive-neuro-fuzzy approach, which combines neural network technique and fuzzy inferential approach to exploit the benefits of the two approaches.

Fuzzy logic by explanation is a computing method that is built on "degrees of truth" instead of the normal computer's logic, which is Boolean logic, either "true or false", or "zero (0) and one (1)". [5,10]. The theory of fuzzy logic is a form of knowledge representation which fits applications and systems that lack definite precision but depend on their contexts. Similarly, neural network on the other hand imitates the operations of the human brain. The network is made up of large interconnected nodes, inspired by the human neurons. Generally, the network is trained by feeding it with matching input data and configuring it to change its weighting functions based on predefined learning rules. When fuzzy logic and neural network are used individually, they have individual weaknesses, and these limitations have geared the approach of hybridizing the techniques.

Adaptive Neuro-Fuzzy Inferential System (ANFIS) has been used in different domains ranging from medical diagnosis to robotic systems [5, 6]. In the area of disease diagnosis, Koutsojannis et al. [7] described a fuzzy intelligent system design for prostate cancer diagnosis, analyses, and learning. The paper concluded that, a hybrid method would be better than single approach. Keles [8] also proposed a fuzzy intelligent system for prostate diagnosis. Experimental results were not impressive, the study therefore recommended hybrid techniques. Catto [9] presented a neuro-fuzzy based classification (NEFCLASS) tool for classifying prostate cancer. Though the study used few medical data of only BPH and prostate cancer, hybridizing the two techniques in their study overcame the weakness in both techniques. Hosseini [10] compared artificial neural network and neuro-fuzzy approach in their study and their result showed that both methods can precisely mark cancer behaviour but the neuro-fuzzy technique has superior diagnostic accuracy and acceptance to artificial neural network only. Çinar [11] reviewed an experiment in which the ANFIS technique was used as a classifier in the field of medical image classification. The result showed that ANFIS could be a better classifier for medical image classification. Duodu [12] also proposed a classifier based expert system using the neural network technique together with some support vector machine functions to diagnose early prostate cancer risk. The study used other irrelevant indicators such as systolic, Body Mass Index (BMI), and diastolic, as diagnostic variables, which had no effect in the diagnosis of prostate cancer. The few correct input parameters used in the study *i.e.*, *Age*, *PSA*, and *PV* proved that these variables are key markers in diagnosing prostate issues. Recently, Omisore et al. [5] developed a new convention of using multiple ANFIS simultaneously for diagnosis of diabetes and therapeutic management through diet recommendation. The system involved to deep feature analysis and training aided of the MANFIS which yielded over 90% test accuracy.

3. Methodology

A typical ANFIS model is adapted for prostates diagnosis in this study. As shown in Fig. 1, the developed ANFIS model combines the strength of two conventional soft-computing methods namely fuzzy logic and neural network,

while harnessing their individual limitations. The model was fully simulated or observed in the Matrix Laboratory (MATLAB version 8.5) environment.
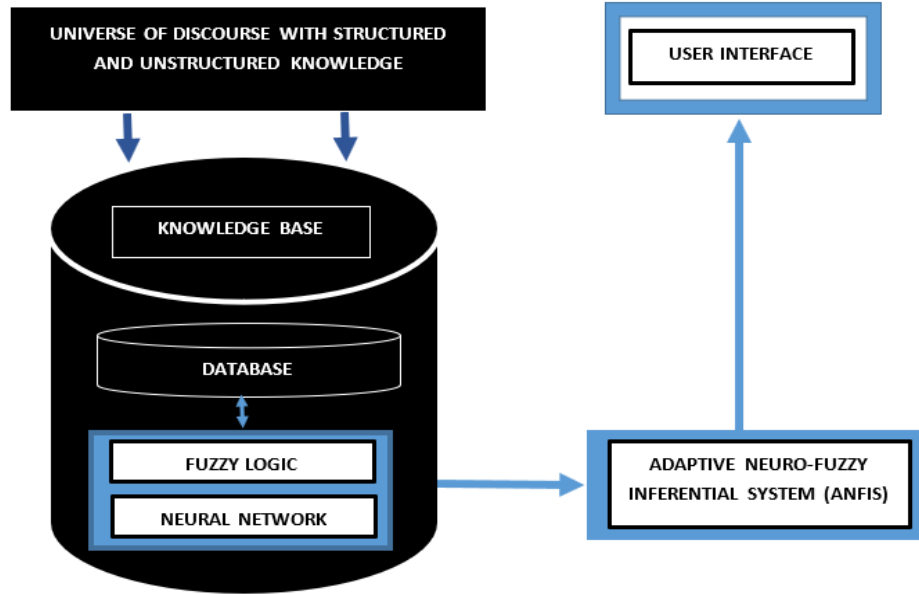

Fig.1. Framework of the proposed ANFIS model.

3.1. Framework

A. Knowledge base

In the Knowledge base are stored unstructured and structured information from the universe of discourse. This information will be the decision involved in prostate disease diagnosis which will be formulated with the help of a medical expert.

B. Database

The database contains mainly the facts and established rules which form the bases of the inference for the fuzzy component. The facts are the various symptoms and laboratory tests to be gathered with the support of a medical doctor from the Medi-Moses Prostate Centre. Variables such as Age, Prostate Specific Antigen (PSA), Prostate Volume (PV), Lower Urinary Tract Symptoms (LUTS), and Laboratory Test (Lab Test) form the fact component. The established rules are expert diagnosis variables that involve a combination of the variables from the fact component which form the fuzzy rule base.

C. Fuzzy Logic Component

The fuzzy logic component comprises of three main parts, input members, inference engine, and Output phase. An initial Fuzzy Inference System (FIS) was modelled to aid in the categorization of the inputs and output parameter of the proposed system's parameters. The initial FIS also served as a validation reference for the proposed model.

The input members are the input parameters for modelling the system. A thorough understanding of prostate diagnosis was undertaken with the help of a medical expert from the Medi-Moses Prostate Centre, Kumasi Ghana. The inputs variables, Age, PSA, PV, LUTS, and Lab Test, totalling five diagnostic variables (inputs) were fed into the fuzzy logic control and fuzzified into degrees of membership through the process of fuzzification.

The fuzzification interface of the system produces a fuzzy linguistic value from the input variables. Fuzzification of the inputs was done by applying an appropriate membership function. An initial fuzzy inference system was first developed to aid in the categorization of the dataset. For the initial fuzzy system, the triangular membership function was employed due to its simplicity advantage. The Triangular Membership Function (MF) is a type of MF governed by a triangular shape as a vector function x, dependent on *a, b, and c,* as scalar parameters, as shown in equation 1.

$$f(x;a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), o \right) \tag{1}$$

The inference engine is what controls the decision-making function (rules) of the fuzzy controller [13]. The Mamdani Inference Engine has been widely used in modelling fuzzy system. The wide use of the Mamdani system has been because it works not only with crisp data as inputs but, also with intervals and/or linguistic terms. This

necessitated its usage in the initial FIS construction. Its rule bases are easy and more intuitive and are well-suited for developing intelligent system applications where the rules are created from human expert knowledge.

The defuzzification phase is the final phase of the fuzzy controller and it produces crisp output actions. The Centroid defuzzification method was employed in the initial FIS, due to its computational simplicity. The Centroid method of defuzzification returns the centre of gravity of the fuzzy set along the x-axis [14] and is calculated with equation 2:

$$xCentroid = \frac{\sum_i \mu(x_i)x_i}{\sum_i \mu(x_i)} \tag{2}$$

Where $\mu(x_i)$ is the membership value for variable x_i. The output phase is the consequent effect of the five input variables. Three variables were modelled as the system's output. The output variables were the three prostate diseases, which are Prostate Cancer, Prostatitis, and Benign Prostatic Hyperplasia (BPH).

D. Neural Network Component

The neural network takes the raw diagnostic variables from the formulated data set as inputs and output, which then trains and learns the various features in the data set by automatically applying the appropriate Membership Function (MF) parameters that best controls the FIS.

3.2. ANFIS Architecture (Layers)

The architecture of the proposed model is a five-layer network as detailed as follows:

First Layer: Is the fuzzification layer, where real values (crisp inputs) are assigned to every imprecise value. For simplicity, taken only two inputs, the output of each node is given as equation 3:

$$O_{1,i} = \mu_A(X_1), for\ i = 1, 2\ or\ O_{1,i} = \mu_{B-2}(X_2), for\ i = 3, 4 \tag{3}$$
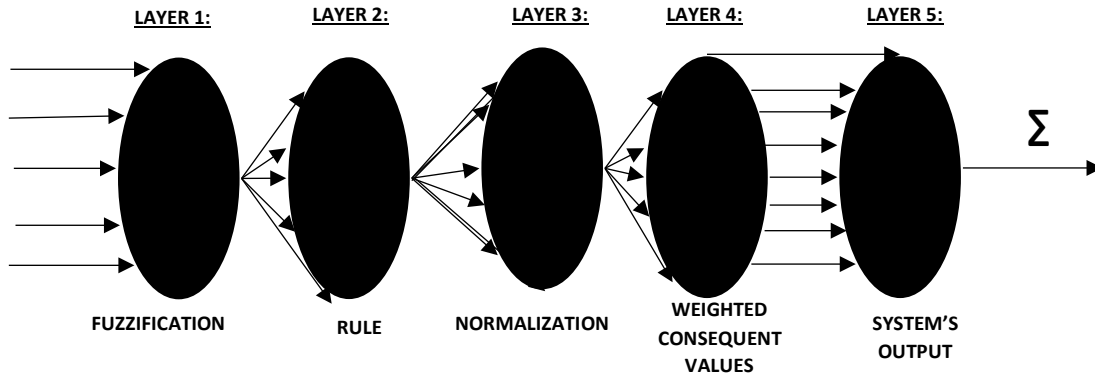

Fig.2. A five-layer (ANFIS) architecture with 5 inputs

$$where\ X_1\ and\ X_2 = \ the\ inputs;\ B_i\ and\ A_i = \ the\ linguistic\ labels\ for\ the\ node, and\ O_{1,i}$$
$$= \ the\ membership\ grade\ of\ a\ fuzzy\ set\ A(= B_1, B_2, A_1\ or\ A_2)$$

Second Layer: Each node in the layer 2 multiplies the incoming signals and store the results as each rule's firing strength. The layer 2 calculates the firing strength of each rule (Product of incoming/present signals) in equation 4:

$$O_{2,1} = w_i = \mu_A(X_1).\mu_B(X_2),\ i = 1, 2 \tag{4}$$

Third Layer: This layer is the normalization layer. The firing strength of each rule from layer 2 are then normalized. (Taking the average/ratio of every fired rule). The normalized firing strengths becomes the output of the layer three. The normalization function is given as equation 5:

$$O_{3,i} = \overline{w} = \frac{w_i}{w_i + w_2} \quad i = 1, 2 \tag{5}$$

Fourth Layer: The value of each rule's output is then multiplied by their corresponding normalized firing strength, representing the output of each node. The output function is given as equation 6:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x_i + q_i x_2 + r) \tag{6}$$

where, $\overline{w}_i$ = normalized firing strength received from the third layer; $\{p_i, x_1, q_i, x_2, r_i\}$ = adjusted parameter set.

Fifth Layer: layer five has a single node that is fixed and it summarises all the inputs or signals as the network's final output. Each rule's fuzzy output is then converted into crisp value through defuzzification process using the weighted average method, as stated in equation 7.

3.3. ANFIS Simulation

The initial FIS was tuned to generate a new Sugeno type with additional features in the ANFIS model. The Gaussian membership function and the appropriate number of membership functions were finally chosen after several trials.

The ANFIS model was configured to automatically create its rules and it generated over 1000 rules more than the author defined rules in the initial FIS using the Neuro-Fuzzy Designer app in MATLAB. The model started with data loading where both the training and validation data were loaded into the app. The range and parameters were assigned automatically by the ANFIS model. After several iterations, the system was finally trained with 40 epochs. The training process for the proposed system is shown in figure 3.
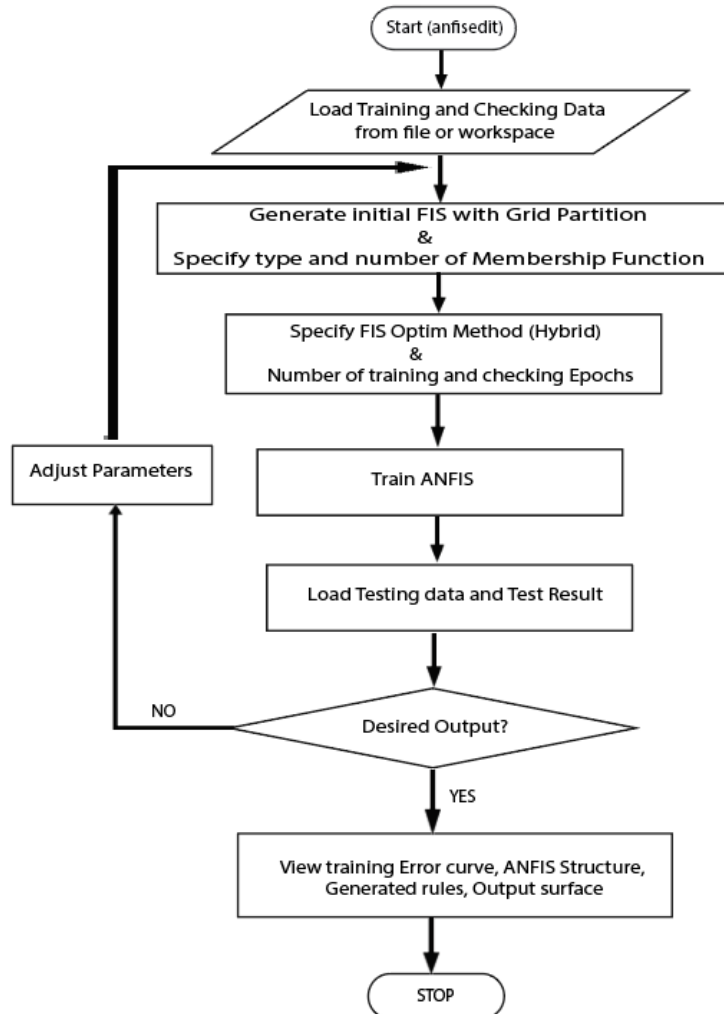

Fig.3. Summarized training process of the proposed system (ANFIS)

A. Input parameters

The ANFIS model is configured to take five input parameters namely, AGE, Prostate Specific Antigen (PSA), Prostate Volume (PV), Lower Urinary Tract Symptoms (LUTS), and Laboratory Test (Lab Test) with Prostate diagnosis as the output variable. The Sugeno controller with the weighted average defuzzification method is employed in this study. The weighted average method is given in equation 7. With the help of a medical expert in prostate diagnosis at the Medi-Moses Prostate Centre, Kumasi Ghana, the input variables were categorized, as shown in table 1.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

where Σ takes the algebraic summation of all the network's final output.

B. Data sources

A total of 335 data (as presented in table 2 and 3) from patients' records were collected at the Medi-Moses Prostate Centre, Kumasi Ghana with the guidance of a medical expert in prostate diagnosis. Seventy percent (70%) of the dataset were used for training the model and thirty percent (30%) were used for validation.

Table 1. Categorization of input (diagnosis) variables

Category	Linguistic Term	Category	Linguistic Term
AGE		**PSA**	
<50	Normal	-1 – 0 ng/ml	Nil
50-59	High	0.1–2.5 ng/ml	Normal
>60	Abnormal	2.6–4.0 ng/ml	Middle
		4.1–10.0 ng/ml	High
		>10 ng/ml	Abnormal
PV		**Other Lab Test**	
-1 – 0mL	Nil	Pyuria Haematuria	
0.1-39.9 mL	Normal		
40-60mL	High		
>60mL	Abnormal		
LUTS			
0-1	Painful Ejaculation	6-7	Incomplete Urination
1-2	Perineal Pain	7-8	Frequent Urination
2-3	Fever	8-9	Delayed Urination
3-4	Bone Pain	9-10	Straining
4-5	Headache	10-11	Discharge
5-6	Painful Urination	11-12	Abdominal Pain

(*Source: Medi-Moses Prostate Centre, Kumasi Ghana*)

Table 2. Training Data

No.	AGE	PSA	PV	LUTS	LAB TEST	OUTPUT
1.	70	6.7	120	1.4	1.8	**1**
2.	66	7	122	6.6	1.9	**2**
3.	74	70	104	6.1	1	**3**
4.	68	8.2	46	9.6	0	**83**
5.	68	0	45	3.2	0	**84**
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233.	55	2.5	82	7.1	1.5	**20**
235.	46	0.4	32	7.5	1.5	**21**

Table 3. Validation

No.	AGE	PSA	PV	LUTS	LAB TEST	OUTPUT
1.	49	1	35	6.8	1.9	5
2.	66	6.9	126	6.3	1.5	6
3.	80	2.7	60	1.5	1.5	7
4.	32	0	22	7.7	0	92
5.	28	0	61	7.8	0	60
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99.	30	3.7	55	6.6	6	51
100.	37	0	30	1.4	0	56

4. Result and Discussion

The model was trained and validated with the data presented in table 2 and table 3. The proposed system's performance accuracy was evaluated using the Root Means Squared Error (RMSE). RMSE is a standard way of measuring performance errors in such expert models. It evaluates the sensitive and accuracy of the trained model. The RMSE function is given in equation 8 as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_J)} \tag{8}$$

where $\frac{1}{N}\sum_{j=1}^{N}|y_j - \hat{y}_J| = Mean\ Average\ Error\ (MAE), N = $ the total number of predictions, y_j being the predicted series and $\hat{y}_J$ being the original series.

The error result obtained is shown in table 4. A small RMSE value indicates a system's high accuracy and acceptance level. Therefore, the minimal error (0.11) indicates a high-performance accuracy and strong acceptance of the proposed model.
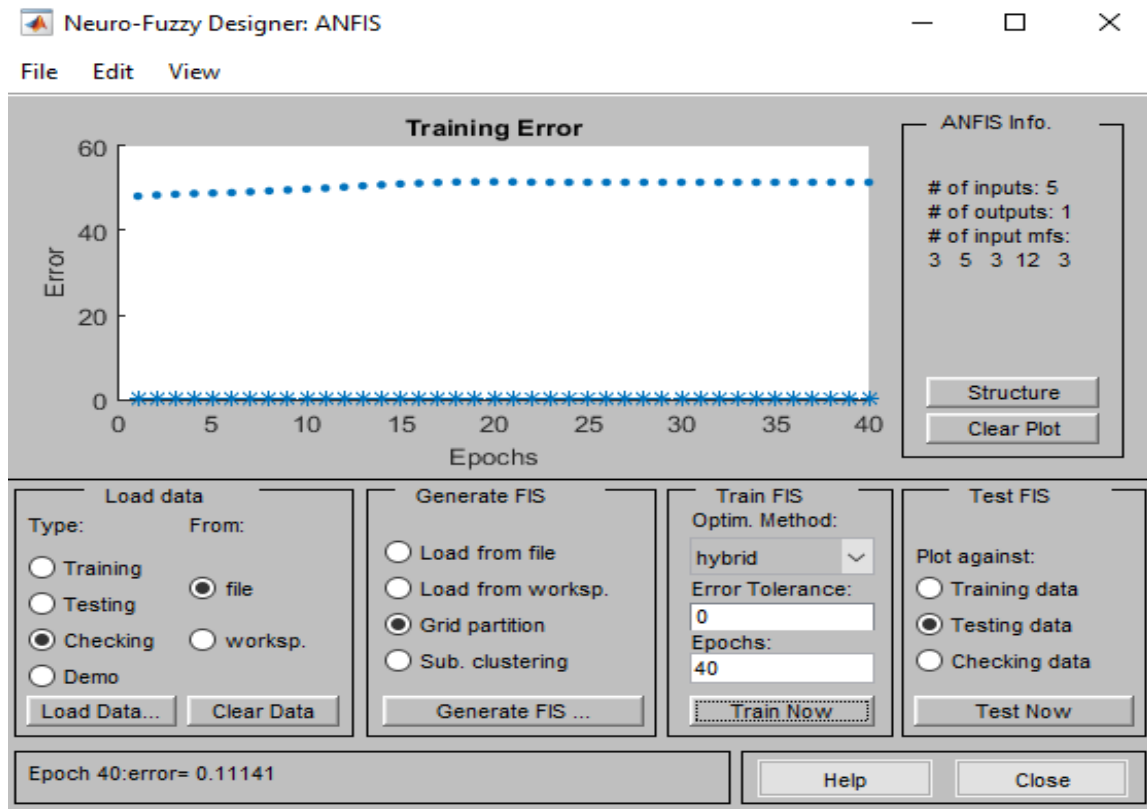

Fig.4. Training and checking error graph

The training and testing result showed a good relationship between the output values of the ANFIS model and the values of the expected output. The training and testing error levels at epoch 40 were approximately 0.11 and 0.16 respectively which is approximately an accuracy level of over 90%. The proposed model was able to learn well and generalize the features in the data set. This makes it suitable to be used for new cases. The neural network component of the ANFIS model was able to learn and generalize the features of the fuzzy component through several trainings. The model's result revealed a strong acceptance and effectiveness of the use of ANFIS in prostate disease diagnosis.

Table 4. RMSE result of proposed model

PROPOSED MODEL	R.M.S.E
ANFIS MODEL	0.11

Table 5. Computational result of proposed model

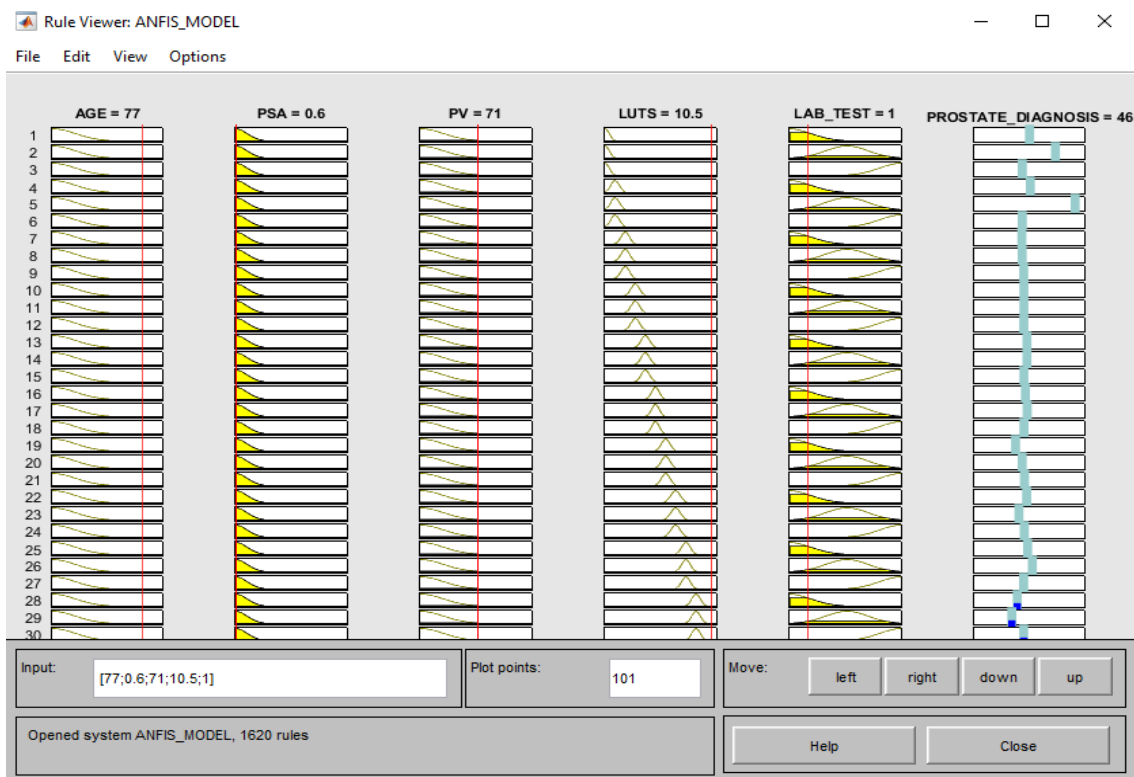| AGE	PSA	PV	LUTS	LAB TEST	EXPECTED OUTPUT	ANFIS OUTPUT
65	2	110	6.4	1.9	26	26
68	0	45	9.5	0	85	85
82	15	105	10.8	0.3	4	3.98
80	2.7	60	1.5	1.5	7	7
49	2.5	43	10.4	0.6	53	52.2
32	0	22	7.7	0	92	92
49	1	35	6.8	1.9	5	5.01
71	0.53	71	9.4	0.5	44	44
73	0.79	77	7.7	0.7	45	45
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77	0.6	71	10.5	1	46	46

Fig.5. Rule viewer

Table 5 is a computational result of some parameters of the ANFIS model and the expected output. The model was tested using the rule viewer function in the MATLAB software presented in figure 5, by entering only the input parameters in the input field. The error level of 0.11 is reflected in the data presented in table 5, as it shows the proposed ANFIS model output against the expected output. The difference between the desired output and the system's

output is very small, indicating how best the patterns and features in the prostate diseases data was well learned and generalised.

MATLAB software proved a very powerful and effective simulation tool in modelling expert intelligent systems like the proposed system. The entire implementation was observed using the Neuro-Fuzzy Designer App in MATLAB, which works similar to the anfisedit command in the command line. However, observing the model at the MATLAB command line gives more flexibility. The study showed that limiting the choice of membership functions in MATLAB when modelling ANFIS system, to at most four is desirable, in order not to generate a large rule base for the FIS. This will speed up the testing rate of the model. When there is no user pre-knowledge on the choice of membership function grades, ANFIS can be a reliable model in automatically determining the appropriate membership parameters. Sometimes it is possible to have poor results though the right training data is used, in such instances the model must be retrained severally using only the training data set. But when inappropriate data is used to train the model, the model will honestly perform poorly. This shows that categorization of the training data, checking data and testing data must have the same features, for the model to sufficiently recognize the patterns in the data sets.

The objectives of this study have therefore been achieved, as any data that has the features of prostate diseases diagnosis, with the right parameters, can be trained with the proposed model, for a desired output. The study aimed at adapting the ANFIS model to diagnose prostate diseases, from any prostate given data set and also providing a working model for medical students who are unskilled in prostate diagnosis.

5. Conclusion

The effectiveness of ANFIS has been demonstrated in this study as a reliable technique with impressive learning and generalization accuracy. This study has demonstrated and showed that a hybrid of fuzzy logic and neural network can offer a more efficient and effective model for prostate diseases diagnosis with improved system accuracy.

Medical practitioners or students who are unskilled in prostate diagnosis can use the model for prostate diagnosis and learning. Also, patients who can read and write can use the model if they have the input parameters.

The neural network component of the ANFIS model lacks a definite technique in determining the connection weights for the hidden layers during computation, which contribute to its high computational cost. To help minimize the computational cost, future work will include an optimization search technique like genetic algorithm to serve as an effective search technique for choosing the best input values from the diagnostic parameters.

Acknowledgement

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