Diagnosis of Prostate Cancer using Soft Computing Paradigms

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Abstract

The process of diagnosing of prostate cancer using traditional methods is cumbersome because of the similarity of symptoms that are present in other diseases. Soft Computing (SC) paradigms which mimic human imprecise data manipulation and learning capabilities have been reviewed and harnessed for diagnosis and classification of prostate cancer. SC technique based on Adaptive Neuro-Fuzzy Inference System (ANFIS) facilitated symptoms analysis, diagnosis and prostate cancer classification. Age of Patient (AP), Pains in Urination (PU), Frequent Urination (FU), Blood in Semen (BS) and Pains in Pelvic (PP) served as input attributes while Prostate Risk (PR) served as output. Matrix laboratory provided the programming tools for system implementation. The practical function of the system was assessed using prostate cancer data collected from the University of Uyo Teaching Hospital. A 95

Index terms— prostate cancer, diagnosis, soft computing, ANFIS, fuzzy model.

1 Introduction

rostate cancer is a common disease in elderly men (Leonard, 2008;Ajape & Babatunde, 2009;Thomas, 2011). The rapid spread of prostate cancer disease stems from unawareness of its early symptoms. Early diagnosis and treatment of prostate cancer reduce the rate of fatality (Ifere & Ananaba, 2012;Ganesh et al., 2013;Mfon, 2017). Some symptoms of prostate cancer observed in other diseases make it difficult to obtain precise diagnosis using traditional and hard computing methods. Soft Computing (SC) methodology offers a plausible solution to this problem. SC emulates human processing capabilities. It harnesses imprecision, uncertainty, partial truth as well as learn from previous experience to provide solution in a seemingly impossible scenario. The principal techniques of SC are -fuzzy logic, neural networks, support vector machines, evolutionary computation and probabilistic reasoning (Kurhe et al., 2011).

The implementation technique of SC is complementary rather than competitive. SC has been successfully applied in medical diagnosis, prediction, pattern recognition, decision support, automotive control and infrastructure monitoring (Obot and Udoh, 2013; **??**gu et al., 2015;Udoh, 2016;Mfon 2017; Udoh et al., 2017;Arlan et al., 2018). The remainder of the paper is organized in Sections. Section 2 presents related works in soft computing techniques. Section 3 addresses the design of adaptive neuro-fuzzy inference system for prostate cancer diagnosis. Implementation and discussion on the results are carried out in Section 4 while Section 5 presents the conclusion of the work and recommendation for further research.

2 II.

3 Related Works a) Fuzzy Logic

Zadeh (1965) introduced fuzzy logic (FL) as a mathematical tool for dealing with uncertainty. The FL theory provides a mechanism for representing linguistic constructs such as "many," "low," "medium," "often," "few." It is a problem-solving methodology which provides a simple way to draw definite conclusions from vague, ambiguous or imprecise information. FL technique follows the process of fuzzification, inferencing, composition, and defuzzification (Gupta, 1995

4 c) Neuro-Fuzzy Paradigm

Neuro-fuzzy model combines the capabilities of NN and FL (Akinyokun, 2007; Udoh, 2016). Benecchi (2006) proposed a neuro-fuzzy system for predicting the presence of prostate cancer. The system made use of a co-active neuro-fuzzy inference model. The predictive ability of neuro-fuzzy system performed better than that obtained by a total prostate specific antigen. Kuo et al. (2015) proposed a fuzzy neural network (FNN) system for prognosis of prostate cancer. The use of cluster analysis helped in the determination of the initial membership function parameters. An integration of artificial immune network and a particle swarm optimization assisted the investigation of input-output relationships. FNN algorithm gave a satisfactory prediction in prostate cancer prognosis. **??**osma et al. (2016) proposed a neuro-fuzzy model for prediction of pathological state in patients with prostate cancer. The receiver operating characteristic (ROC) points obtained from neuro-fuzzy approach performed better than those obtained from fuzzy c-means, support vector machine (SVM) and Naïve Bayes classifiers. **??**ustain

5 a) Data Collection and Processing

A collection of 510 prostate cancer dataset within nine months (July 2017 to March 2018) from the University of Uyo Teaching Hospital, Uyo, (UUTH), Nigeria, assisted the assessment of the practical function of the system. The attributes: Age of Patient (AP), Pain in Urination (PU), Frequent Urination (FU), Blood in Semen (BS) and Pains in Pelvic (PV) served as input while Prostate Risk (PR) served as output. The splitting of the dataset in the ratio of 8:1:1, translated into 408, 51 and 51 datasets for system training, checking and testing respectively.

6 b) ANFIS Design and Training

ANFIS design consists of five layers. The first and the fourth layers consist of adaptive nodes which have parameters to be learned while the second, third and fifth layers are fixed nodes and contain no learning parameters. The system employed Sugeno inference mechanism whose reasoning methodology shows the output of each rule as a sequential combination of each rule input variable plus the constant term as shown in Equation **??**.IF a is X 1 AND b is Y 1 AND? AND c is Z 1 THEN f 1 = p 1 a + q 1 b+?+r 1 c + s 1 (1)

where a, b, c are the inputs or antecedent parameters, X, Y, Z are the fuzzy sets of inputs parameters, f is the fuzzy set of output parameters and p, q, r, and s are consequent parameters.

Layer 1 is the input layer. It has AP, PU, FU, BS, and PP as inputs. Every node i in layer 1 has a node function) (1 a X O i i µ = (2)

where a is the input to node i, and i X is the linguistic label (Low, Moderate and High) associated with this node function. . Layer 2 is the rule node. Every node in layer 2 computes the firing strength of each rule as given in Equation **??**. Layer 3 is the normalization layer. Every node in layer 3 calculates the ratio of the ith rule's firing strength to the sum of all rules's firing strengths as shown in Equation **??**. Layer 4 is the defuzzification layer which consists of consequent nodes for computing the contribution of each rule to the overall output as shown in Equation **??**. Layer 5 is the output layer (a single node that computes the overall output, Prostate Risk (PR). The output as shown in Equation **??**is computed as summation of prostate cancer signals.

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) (2 a X w O i i i µ = = *) (b Y i µ) (c Z i µ (4) ? = = = n i i i i w w w O 1 1 3 (5)) ... (4 i i i i i i i i s c r b q a p w f w O + + + + = = (6) ? ? ? = = i i i i i i i i i w f w f w O 5 (7)

The training and parameters adjustments in ANFIS are facilitated either by hybrid learning algorithm or the back propagation algorithm. The hybrid learning algorithm converges faster than the traditional back propagation method. It comprises the combination of least square method in the forward pass and back propagation gradient descent procedure in the backward pass. In the forward pass, the node output goes forward until layer 4 and the consequent parameters are updated by least square method . In the backward pass, the error signal propagates backwards and the premise parameters are updated by gradient method. (Udoh et al., 2017).

IV.

8 Results and Discussion

The system as shown in Figure 2 was implemented in an environment characterized by MatLab 2015a programming tools. Prostrate cancer data samples of sizes 408, 51 and 51 records facilitated system training, checking and testing respectively. Figures 3 and 4 depict the loading of training and checking data as well as training and checking error interface respectively. The results of training and checking errors carried out in 20 iterations using hybrid learning process with Triangular, Trapezoidal, Bells or Gaussian membership functions are presented in Table **??**. As shown in Figure 5. The 51 testing data samples were loaded to ascertain the functionality of the trained and checked ANFIS. An average testing error of 0.25019 was observed between the computed and the expected output. The testing and checking errors derived from the experiment using different membership functions are depicted in Table **??**.

9 Table 1: Training and Checking Errors Based on Different Membership Functions

Triangular MF gave the best results in terms of training and checking errors, followed by Gaussian MF. The worst checking errors were observed in Bells MF. The results of prostate cancer diagnosis using the ANFIS and the fuzzy paradigms are depicted in Figure ??. The data points in the ANFIS diagnosis matched the expected output more precisely than those in the fuzzy diagnosis. Out of the 20 data points used in the experiment, 19 data points matched with the expected output in the ANFIS model, whereas the fuzzy model had 14 similar data points. In the first instance of the diagnosis, using the ANFIS model the patient with serial number 1 had a high degree of prostate cancer. This corresponds to the expected output from domain experts.

10 Figure 6: Graph of Prostate Cancer Diagnosis

However, using the same sets of input variables on the fuzzy model presented in (Mfon, 2017) Both ANFIS and fuzzy models gave high diagnosis in the second instance of the diagnosis. This is in agreement with expected output from domain experts. Nevertheless, the diagnosis value of the ANFIS model was observed to be closer to that of domain experts than the one from the fuzzy model. Investigation showed that 14 out of 20 instances (70%) gave accurate prediction in the fuzzy model while 19 out of 20 instances (95%) gave accurate predictions in the ANFIS model. The results of the experiment shown in Table 2, demonstrated the precision of ANFIS model over fuzzy model in the task of prostate cancer diagnosis.

V.

11 Conclusion and Recommendation

This paper presented a review of prostate cancer diagnosis using soft computing models. Practical function of the ANFIS paradigm was assessed in an environment characterized by matrix laboratory programming tools. The data of prostate cancer patients collected from the University of Uyo teaching hospital, Uyo, Nigeria, was used for system training and testing. A comparison of the results, showed the accuracy of the ANFIS model over the fuzzy model in the task of prostate cancer diagnosis. Future works would employ evolutionary computations and support vector machine for further investigations. [1] [2]

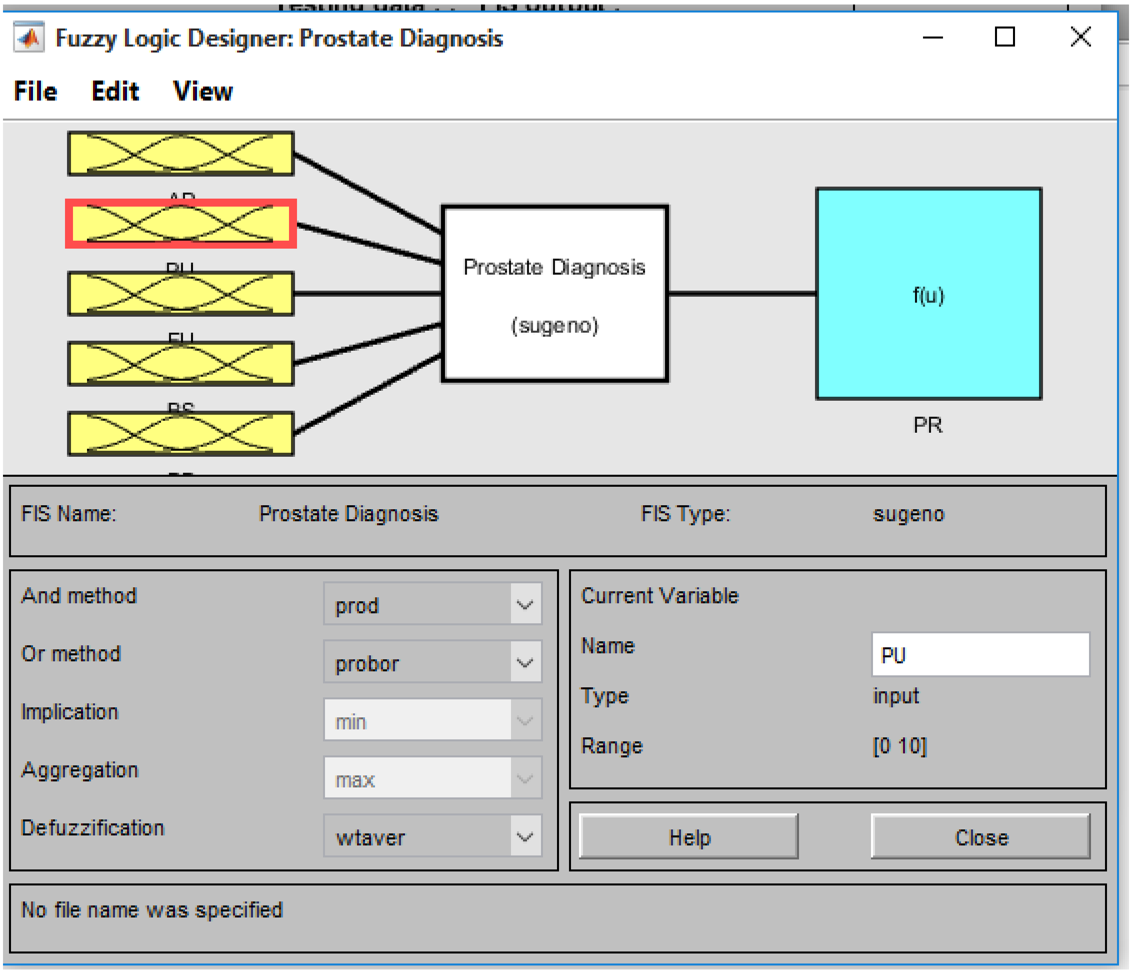
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Figure 1:

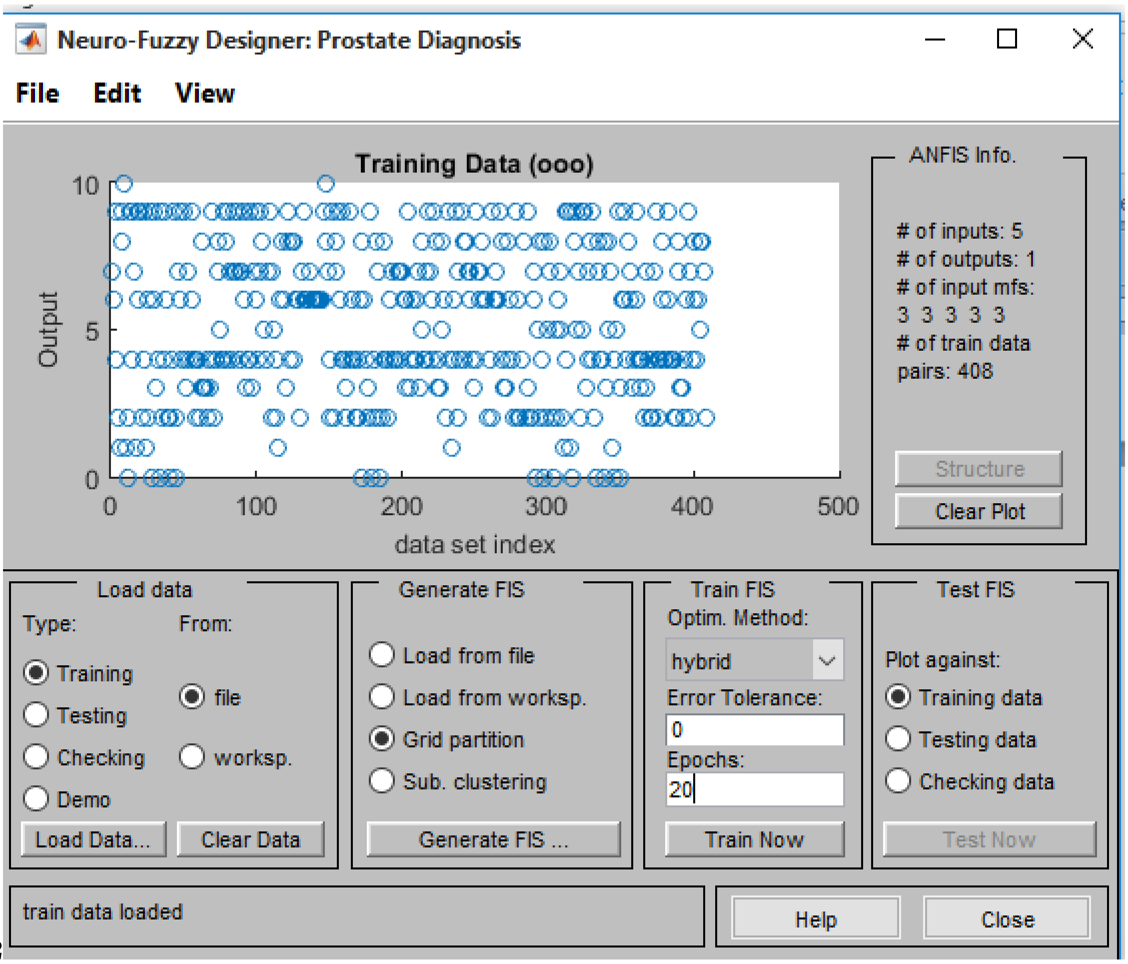

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Figure 2: Figure 2 :

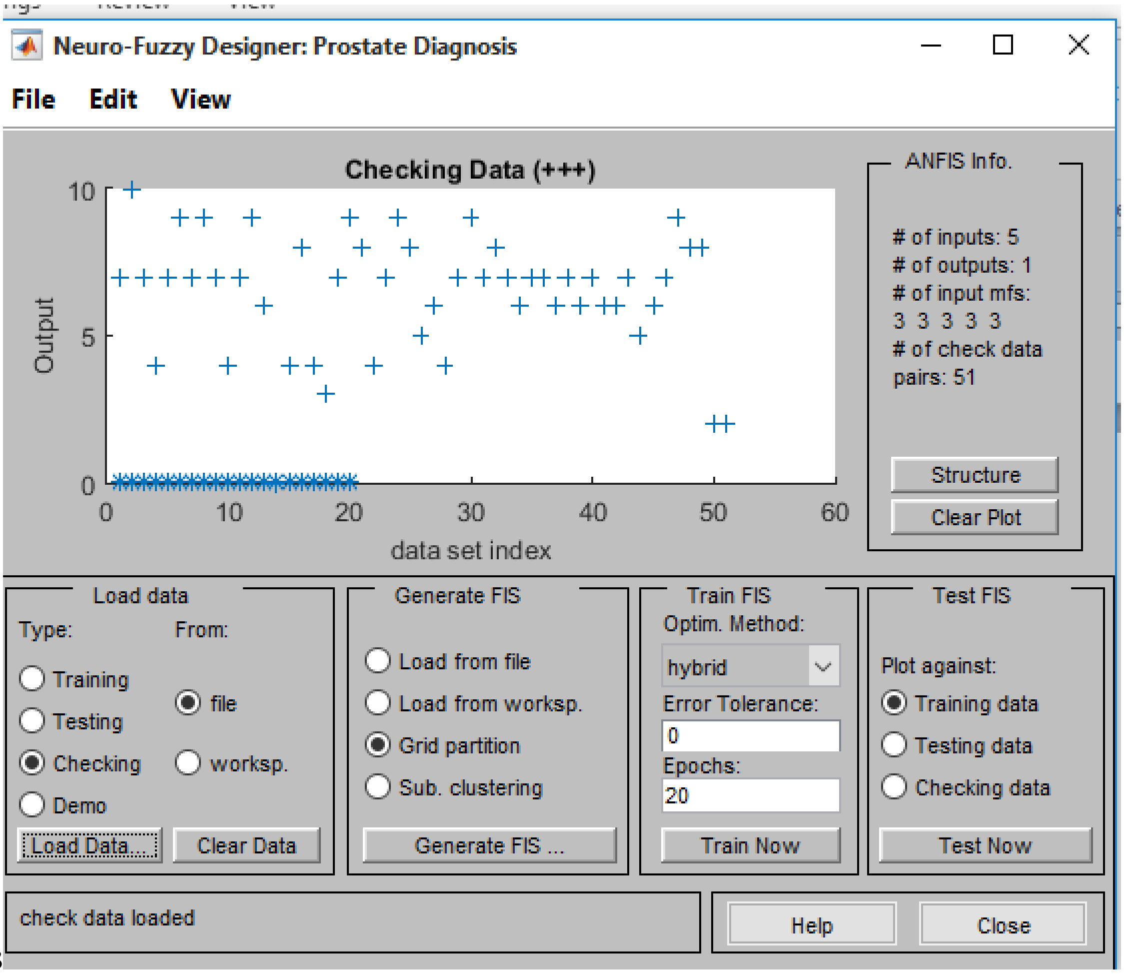

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Figure 3: Figure 3 :

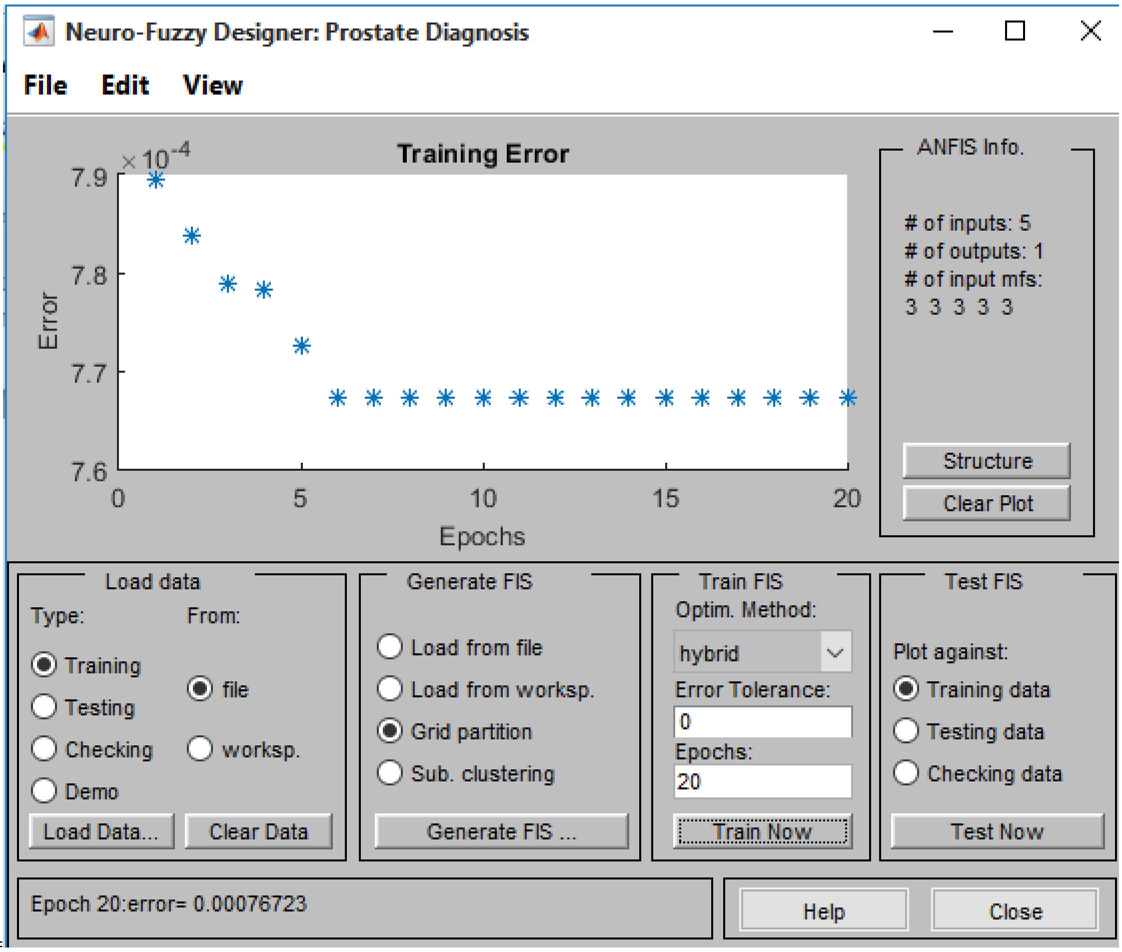

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Figure 4: Figure 4 :

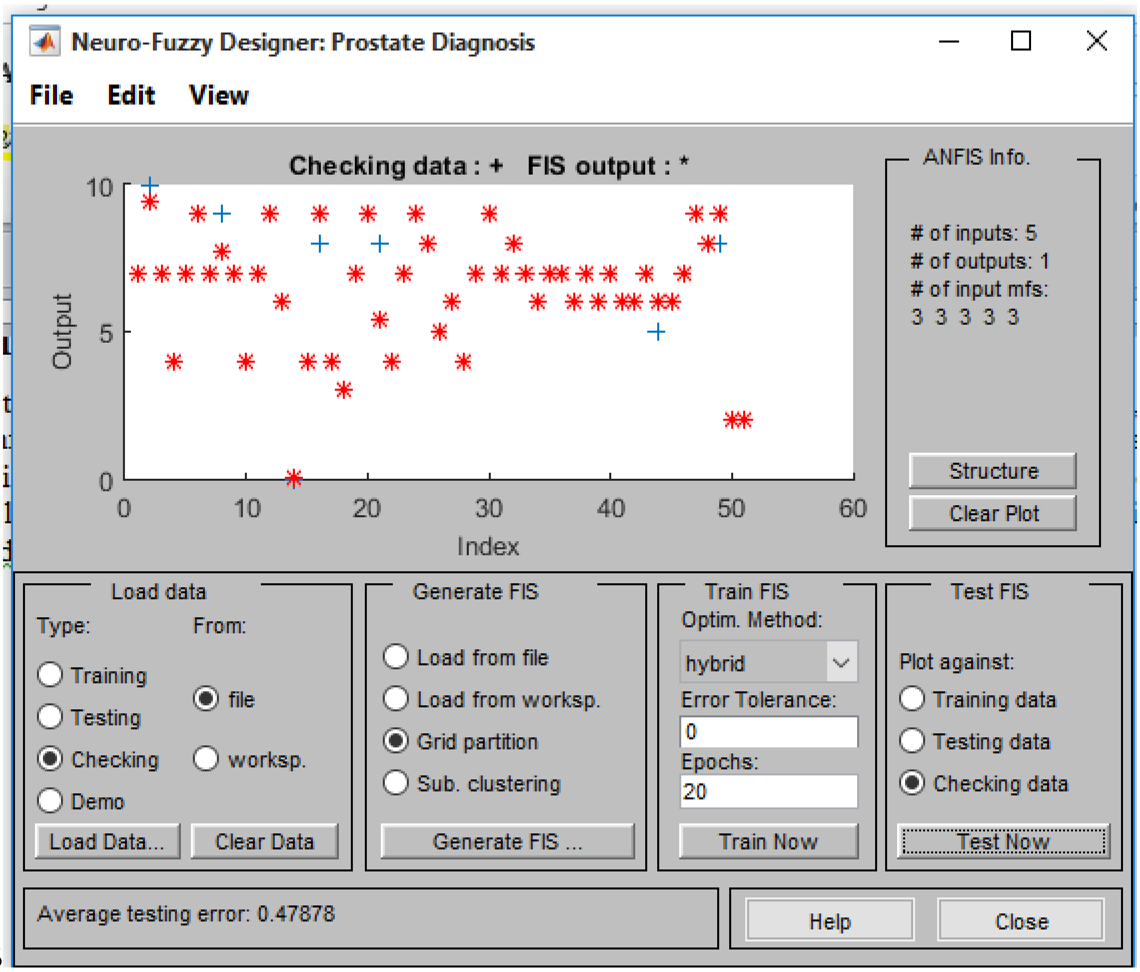

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Figure 5: Figure 5 :

III. Methodology

The method followed for prostate cancer diagnosis in this work is depicted in Figure 1. It comprises four major stages namely: 1. Data collection and preprocessing; 2. ANFIS design and training 3; ANFIS parameters checking and 4. Prostate Cancer Diagnosis.

Figure 6:

2

Iteration	Triangular MF		Trapezoidal MF		Bells MF		Gaussian MF	
No.	Training Error	Checking Error	Training Error	Checking Error	Training Error	Checking Error	Training Error	Checking Error
1	0.000148	0.531080	0.197052	1.020400	0.002829	0.619600	0.001827	0.606912
2	0.000145	0.530330	0.197007	1.014800	0.002764	0.679068	0.001760	0.612429
3	0.000141	0.529580	0.196963	1.009600	0.002699	0.745846	0.001696	0.617943
4	0.000138	0.528840	0.196919	1.004500	0.002635	0.819051	0.001633	0.623423
5	0.000135	0.528110	0.196815	0.999700	0.002571	0.897450	0.001572	0.628843
6	0.000132	0.527370	0.196831	0.995100	0.002508	0.979547	0.001514	0.634181
7	0.000129	0.526650	0.196786	0.990700	0.002445	1.063660	0.001458	0.639416
8	0.000127	0.525920	0.196742	0.986400	0.002382	1.148020	0.001403	0.644531
9	0.000124	0.525200	0.196697	0.982300	0.002320	1.230880	0.001352	0.649510
10	0.000121	0.524490	0.196653	0.978400	0.002260	1.310590	0.001302	0.654341
11	0.000119	0.523770	0.196608	0.974600	0.002200	1.385740	0.001255	0.659013
12	0.000116	0.523070	0.196564	0.970900	0.002143	1.455150	0.001209	0.663518
13	0.000114	0.522360	0.196519	0.967400	0.002087	1.517930	0.001166	0.667850
14	0.000112	0.521660	0.196475	0.964000	0.002034	1.573510	0.001125	0.672004
15	0.000110	0.520960	0.196430	0.960685	0.001983	1.621590	0.001086	0.675976
16	0.000108	0.520270	0.196385	0.957500	0.001935	1.662100	0.001048	0.679766
17	0.000105	0.519580	0.196341	0.954400	0.001889	1.695200	0.001012	0.683374
18	0.000104	0.518895	0.196296	0.951390	0.001846	1.721220	0.000978	0.686801
19	0.000102	0.518220	0.196251	0.948500	0.001805	1.740570	0.000945	0.690049
20	0.000098	0.517540	0.196207	0.945600	0.001767	1.753790	0.000914	0.693122

Figure 7: Table 2 :

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