Health and Technology (2020) 10:157–165
https://doi.org/10.1007/s12553-018-0279-6

ORIGINAL PAPER

Prostate cancer classification from prostate biomedical data using ant rough set algorithm with radial trained extreme learning neural network

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Received: 5 October 2018 / Accepted: 12 November 2018 / Published online: 12 December 2018

Abstract
Prostate cancer is commonly occurs in prostate that affects small walnut and generates the seminal fluid for men. This disease is happening due to urinating trouble, blood semen, bone pain, stream of urine other harmful activities such as race, obesity and genetic changes. The improper symptoms of prostate cancer disease, it is challenge to identify it in the starting stage. So, different soft computing and machine learning techniques utilized to predict the Prostate cancer due to its severe side effects. Initially prostate cancer biomedical information has been collected from DBCR dataset that manage the patient age, cancer volume, prostate weight, Gleason score, vesicle invasion, prostate specific antigen details and so on. In the wake of gathering prostate biomedical data, undesirable information has been evacuated by applying the mean mode based standardization procedures and the advanced elements are chosen with the assistance of the subterranean insect harsh set hypothesis. The chose information has been arranged utilizing the outspread prepared extraordinary learning neural systems. The classifier successfully classifies the abnormal prostate features. At that point the effectiveness of prostate cancer prediction framework is inspected using assistance of mean square error rate, hit rate, selectivity and accuracy.

Keywords Prostate cancer · Clinical attachment level · Means mode based standardization · Neural networks

1 Introduction

Prostate Cancer [1] is one of the common disease which affects men reproductive system. Most of the prostate cancer develops slowly, some other cancer gland growth faster which spreads from prostate part to other human body area especially in lymph nodes. 99% of prostate cancer [2] occurs to men at the age of 50. According to the survey conducted in 2012 around 84 countries 1.1 million men affected prostate cancer also 307,000 deaths are occurred due to the generation of seminal fluid. This serious prostate cancer is difficult to predict the earlier process because it does not have any earlier symptoms [3] but it has few symptoms such as continuous urination, hematuria, urine stream, nocturia, secretion of fluid in prostate, bone pain, femur and so on. Due to the limited symptoms of prostate cancer, it has high risk factor such as obesity, genetic changes, family history, age, medical exposure and so on., This serious prostate cancer has been predicted by applying prostate specific antigen testing [4] process that examines the prostate and trying to detect cancer but this testing process difficult to make decision with short period of time that improves overall risk and mortality factor [5]. For overcoming the conventional testing process, automatic system has been developed to minimize the risk factors [6] while predicting prostate cancer. So several automatic prostate disease identification systems are developed by utilizing the biomedical data processing and soft computing techniques with effective manner. Islam Reda et al.,2018 [7] are developing the deep learning based prostate cancer detection system from the magnetic

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resonance image. The system examines the different clinical bio-information level by level which used to determine the prostate cancer effectively. The extracted bio-information processed by deep learning approach and classified with the help of various probabilistic models that successfully predict prostate cancer with 88.9% of accuracy. Neeraj Kumar et al., [8] analyzing prostate cancer using convolution neural network approach with relevant bio-marking recurrence. Initially, the H and E input images are captured from patient which is processed by noise removal process and various features are extracted. The derived bio-features are learned by deep learning process and classified with helps of multi-layer convolution network. The method successfully analyze 30 patient input information that provides high accuracy for entire patient. The detected prostate cancer system provides the guidelines for their treatment with effective manner. Joerg D. Wichard, et al., [9] are exploring the prostate cancer detection process using one fold cross validation approach. The joerg examines the collection of data which is gathered according to the clinical examination process. The gathered data is processed by different classifiers such as regression model, multi-layer perceptron, support vector machine, decision tree approach which successfully predict the prostate related features effectively. Takumi Takeuchi et al., [10] developing prostate cancer prediction system by applying the multi-layer deep neural network. The method examines the 334 patient prostate details, in which MRI and ultrasound information is collected from patient which are processed by shrinkage and selection operator. From the obtained results, different features are extracted that are processed by artificial neural network. The developed system successfully predicts the normal and abnormal prostate features. Finally excellence of prostate cancer prediction system evaluated using 232 patient are utilized as training features and remaining 102 patient information treated as testing features and the efficiency of system is evaluated using prediction, ROC curve and accuracy metrics. Zlotta AR et al., [11] implementing artificial neural network based prostate cancer identification system is created for minimizing risk factors and death rate. During the cancer prediction process, European prostate cancer dataset is utilized in which prostate specific antigen 10 ng/ml or less is collected. The gathered information is processed in terms of examining prostate density, volume and weight parameters. From the obtained features prostate cancer is classified with 92.7% of accuracy. As indicated by the different creators sentiment, in this work, the prostate cancer has been arranged by applying the Radial Trained Extreme Learning Neural Network systems with affiliated handling steps because the earlier prostate cancer detection methods are fail to manage huge volume of cancer data. The introduced optimization methods effectively handles the high dimensional dataset by reducing the feature subset that improves overall prostate cancer identification process. Whatever remains of the segment is sorted out as takes after: segment 2 manages that the prostate cancer grouping process, segment 3 investigates the proficiency of the prostate cancer prediction framework and area 4 makes last inference.

2 Radial trained extreme learning neural network based prostate Cancer classification system

In this section, there is an analysis of the prostate cancer by using various researches opinions such as data mining and soft computing techniques. Amid the illness identification is handle the framework utilizes the powerful biomedical data determination and grouping methods that effectively lessens the mistake rate that prompts increment the general proficiency. At that point the general structure of the prostate cancer prediction framework is appeared in the Fig. 1.

The above figure obviously demonstrates that the prostate cancer prediction framework [12] expends a few stages, for example, biomedical preprocessing, include determination, preparing and arrangement. Each means utilizes the compelling calculation while dissecting the prostate related elements which is clarified in the accompanying segment.

2.1 Mean-mode normalization process based prostate biomedical data preprocessing

At first the prostate biomedical information has been gathered from the different patient focuses that comprise of various clamor information [13] which need to be eliminated because of the accuracy issues. So, the mean-mode process replaces the missing values by considering the mean calculation process of particular row that is estimated as follows:

$$\textbf{\textit{Mean Value}} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

In the above Eq. (1)

x_i is represented as prostate data present in the dataset row n is the number of data in the dataset

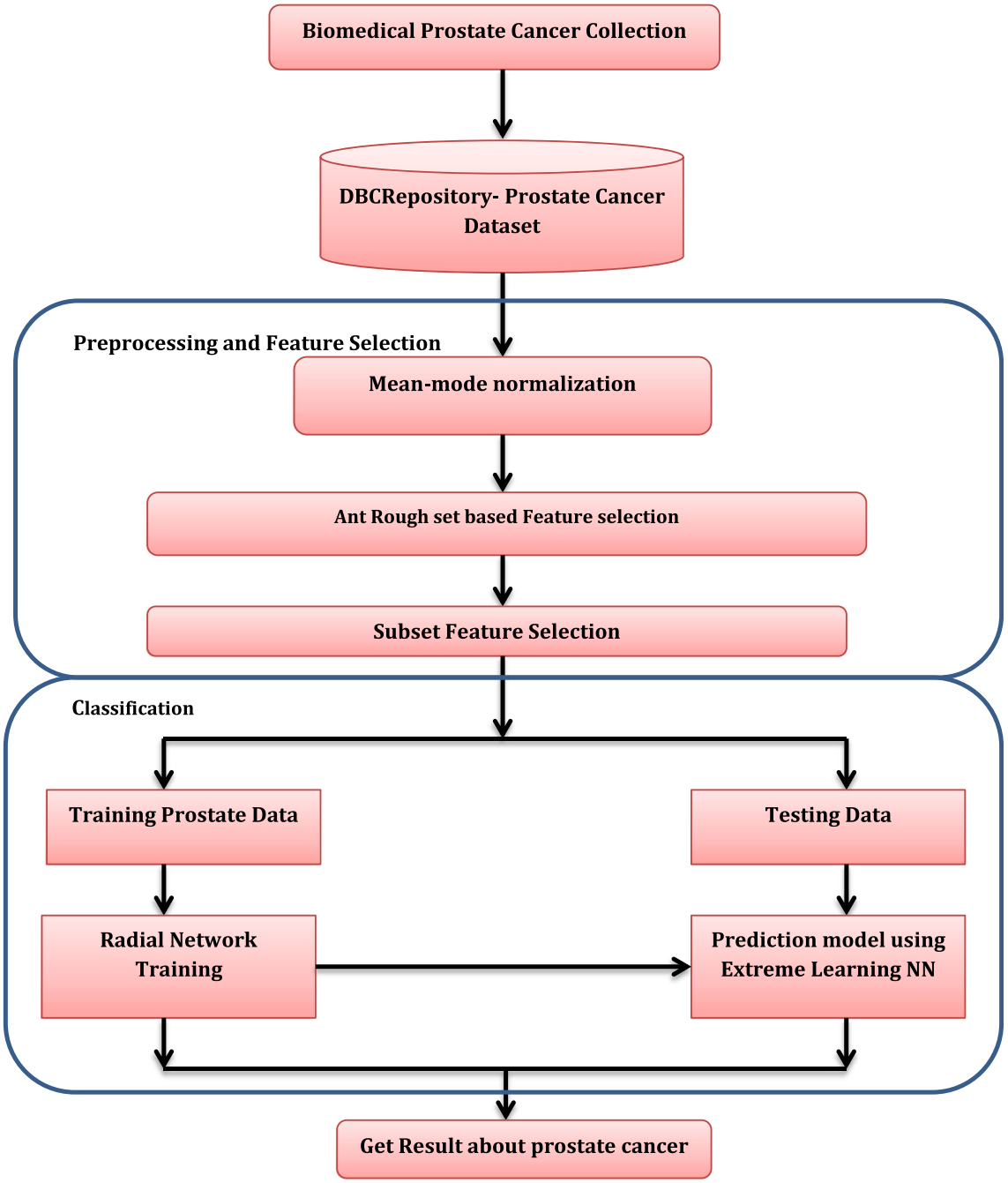


Fig. 1 Radial trained extreme learning neural networks based prostate cancer identification system architecture

After replacing the missing value present in the database, the normalization process has been performed by scaling the attributes present in the dataset. Scaling process is done by as follows:

$$V' = \frac{(V - min)}{(Max - Min)} \tag{2}$$

In the Eq. (2), V denotes that the data or attributes, min represented as minimum value of prostate cancer biomedical data and max denoted as maximum value of prostate cancer biomedical data.

***V' is the normalized data that consists of value* 0 *to* 1**

The above process is continuously performed for eliminating the inconsistent data from the prostate biomedical cancer data set. Then the dimensionality of the features is minimized for improving prostate cancer prediction process.

Table 1 Mean square error rate

S.No	Patients	Mean Square Error Value			
		SVM	NN	MLP	RTELNN
1	Patient 1	0.462	0.442	0.371	0.035
2	Patient 2	0.497	0.484	0.432	0.0312
3	Patient 3	0.521	0.502	0.458	0.0291
4	Patient 4	0.547	0.489	0.428	0.0263
5	Patient 5	0.583	0.525	0.493	0.0312
6	Patient 6	0.566	0.521	0.424	0.0329
7	Patient 7	0.532	0.495	0.361	0.026
8	Patient 8	0.535	0.472	0.346	0.028

2.2 Ant rough set based feature selection

After removing the noise in the prostate biomedical data, each feature is arranged in the graph format for selecting the optimized features with help of the transition probability value [14] that is estimated as follows,

$$P_i^k(t) = \begin{cases} \dfrac{|t_i(t)|^{\alpha}|n_j|^{\beta}}{\sum_{\mu}|t_i(t)|^{\alpha}|n_j|^{\beta}} & if\ i\ \epsilon j^k \end{cases} \tag{3}$$

Where j^k **is the set of feasible features** t and n is the pheromone values and α, βis the heuristic information. Each feature is compared with the transition probability value, if the feature satisfied the condition, then the feature heuristic value should be updated using the eq. (4)

$$\Delta t_i^k = \begin{cases} \phi.\gamma(s^k(t)) + \dfrac{\phi.(n-|S^k(t)|)}{n} & if\ i\ \epsilon\ s^k(t) \\ 0 & otherwise \end{cases} \tag{4}$$

Where $s^k(t)$ **is the selected feature subset**

As indicated by the chose highlights the limit has been made with the assistance of the harsh set [15] hypothesis utilizing the eqs. (5 and 6)

$$IND(P) = \{\{(x,y)U^2 | a\ P, a(x) = a(y)\}\} \tag{5}$$

Where x,y is the incongruity estimation of P, P is the connection between the lower and upper guess. From the ascertained esteem the level of the credit estimation is utilized to distinguish the ideal elements which are characterized as takes after,

$$k = \gamma_P(Q) = \frac{|POS_P(Q)|}{|U|} \tag{6}$$

Where POS_P **is** the positive limit area |U| signifies the cardinality of set U highlights, in light of the degree esteem, the ideal elements are chosen in the positive locale which is sustained into the following element preparing and arrangement handle for recognizing the prostate cancer. Based on the above discussion, the algorithm for prostate cancer related biomedical feature selection algorithm is discussed as follows.

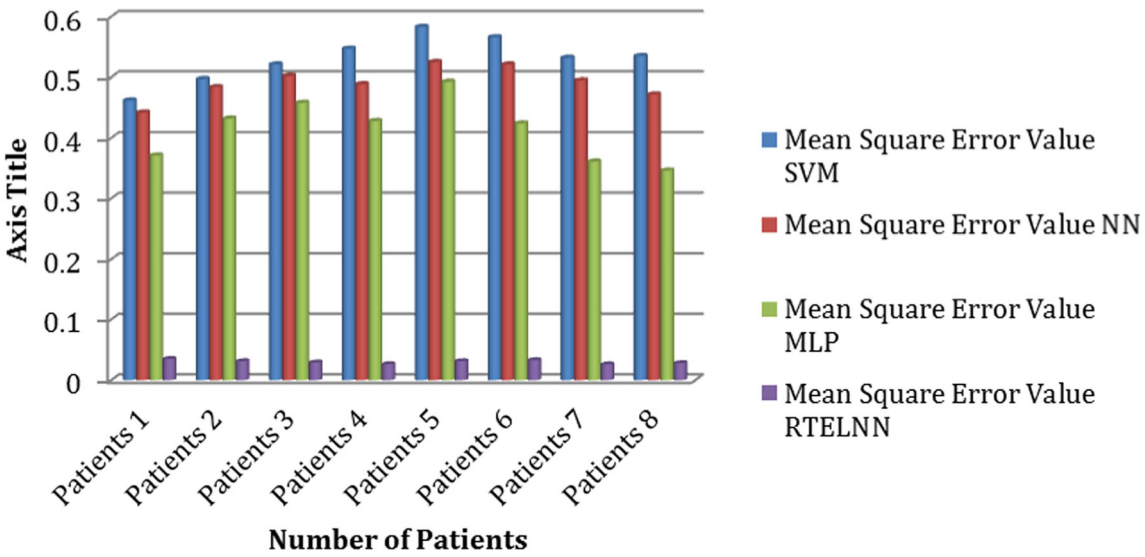


Fig. 2 Mean square error rate

Algorithm for prostate Cancer Feature Selection Process

Initialize n (number of features)
fitness function f(x):max (selected features)
transition probability value $\boldsymbol{P_i^k(t)}$ of feature, selected feature subset=$\boldsymbol{s^k(t)}$
perform until to reach max iteration
for i= 1 to n
Arrange features in graph format
compute transition probability value $\boldsymbol{P_i^k(t)}$
if (i = $\boldsymbol{P_i^k(t)}$)
then
update feature heuristic value$\boldsymbol{\Delta t_i^k}$
set the boundary value of features

$$\boldsymbol{IND(P) = \left\{\{(x,y)U^2 \middle| a\ P, a(x) = a(y)\}\right\}}$$

Compute the degree of features and select max degree feature as optimal features.
else
Check the feature until to reach max criteria.

2.3 Radial trained extreme learning neural networks based prostate Cancer classification

The last stride of the framework is prostate cancer recognizable proof which is finished by applying the Radial Trained Extreme Learning Neural Networks. Before playing out the characterization procedure, the chose components are prepared with the assistance of the spiral premise work [16] because the trained biomedical data reduce the error rate during the diseases recognition process. At the time of feature training process, the features are analyzed in terms of non-linear inputs and they produce the liner in terms of output. The radial basis (radbas) function is used as the activation function during training the input neurons. During training process, 52 tumor information and 50 normal samples are utilized for network training process. Alongside the actuation work, the system utilizes the focuses and spread elements as parameter for deciding the element prepared levels. The focuses dictated by applying the k-implies grouping process which is characterized as takes after,

$$\boldsymbol{argmin}\sum_{i=1}^{k}\sum_{x\in s_i}\|x-\mu_i\|^2 \tag{7}$$

Where $\boldsymbol{\mu_i}$ the mean at the middle point i. In view of the focuses the approaching components are prepared by the radbas actuation work which is put away as the layout in the database. When the new incoming features arrived into the network that has been processed with the help of the extreme learning neural networks [17]. The network consumes the incoming testing features as input and processing those features according to the single layer feed forward neural networks that consume weights and bias value. In light of the parameters, the enactment capacity is connected to perceive the component level. At that point the enactment capacity is characterized as takes after,

$$\boldsymbol{G(a_i, x_j, b_i) = \frac{1}{1 + e^{-(-a_i.x_j+b_i)}}} \tag{8}$$

Contingent upon the actuation work, the yield is contrasted with the format show in the database which perceives the periodontitis malady with compelling way. At the time of testing process, 8 normal and 13 abnormal patient information is used for initial testing process. From the testing process, radial trained extreme learning network successfully predicts the prostate cancer with effective manner. At that point the proficiency of prostate cancer prediction framework is evaluated using test results which is clarified in the upcoming area.

3 Efficiency analysis of radial trained extreme learning neural networks

The brilliance of the prostate cancer prediction framework is explored utilizing the prostate cancer DBC

Table 2 Selectivity

S.No	Patients	Selectivity			
		SVM	NN	MLP	RTELNN
1	Patient 1	95.63	97.32	98.83	99.17
2	Patient 2	95.87	97.78	98.56	99.23
3	Patient 3	96.01	97.98	98.79	99.28
4	Patient 4	95.94	97.03	97.98	99.32
5	Patient 5	96.79	97.74	98.32	99.24
6	Patient 6	95.93	97.34	98.56	99.35
7	Patient 7	96.32	98.24	98.32	99.46
8	Patient 8	95.76	97.93	98.83	99.52

Table 3 Hit rate

S.No	Patients	Hit Rate			
		SVM	NN	MLP	RTELNN
1	Patient 1	95.16	96.36	97.51	99.25
2	Patient 2	95.79	96.67	97.627	99.23
3	Patient 3	95.62	96.34	97.23	99.35
4	Patient 4	95.98	96.89	97.68	99.29
5	Patient 5	95.34	96.32	97.32	99.28
6	Patient 6	95.35	96.78	98.25	99.32
7	Patient 7	95.52	96.83	98.4	99.34
8	Patient 8	95.76	96.42	98.23	99.45

Repository dataset utilizing the radial trained extreme learning neural systems [18]. The dataset consists of collection of information in both testing (52-tumor sample, 50 non-tumor sample and training data-8 normal and 13-abnormal) [19] that used to classifies the prostate cancer with accurate manner. Gathered information comprises of more number of conflicting information that are disposed of with the assistance of mean-mode standardization prepare and the advanced components are chosen by the move likelihood esteem. At that point the outspread prepared capacity is connected to prepare the elements and the grouping is finished by utilizing the extraordinary learning neural systems. At that point the proficiency of the framework is inspected utilizing the accompanying execution measurements. During the efficiency examination process, true positive rate [20] is computed from number of features detected that is relevant to the prostate cancer and total number of features present in prostate biomedical dataset. Along with this, false positive rate is computed that is determined from number of false prostate feature detection and number of features present in dataset. Finally, number of missed to select the prostate features and total number of features present in the prostate biomedical dataset. From the calculated true positive, false negative and false positive value, following performance metrics are computed to determine the prostate cancer prediction system efficiency.

$$\textit{Selectivity} = \frac{TP}{TP + FP} \tag{9}$$

$$\textit{Hit rate} = \frac{TP}{TP + FN} \tag{10}$$

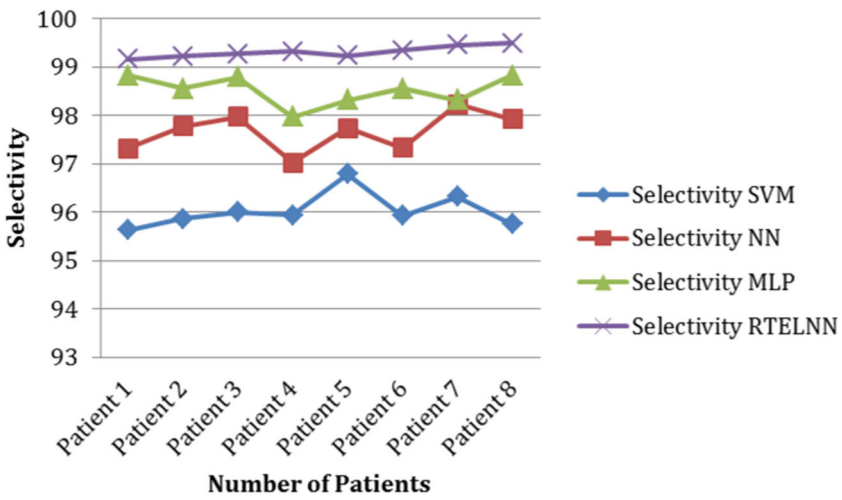
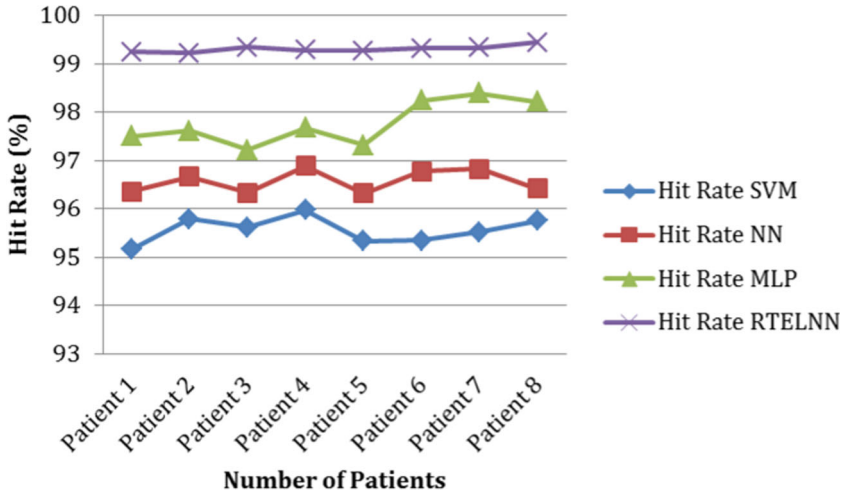


Fig. 3 Selectivity

Fig. 4 Hit rate



$$accuracy = \frac{number\ of\ true\ positive + number\ of\ true\ negative}{number\ of\ true\ positive + false\ positive + false\ negative + true\ negative} \quad (11)$$

As indicated by the above measurements, the productivity of the outspread prepared outrageous learning neural system (RTELNN) is researched by contrasting the resultant esteem and the bolster vector machine (SVM) [21], Neural Networks (NN) [22], Multi-layer Perceptron (MLP) [23]. The prostate cancer framework uses the viable preparing strategies which lessens the mistake rate while characterizing the dental elements. Then the obtained mean square mistake rate is demonstrated in Table 1.

The Table 1 demonstrates that RTELNN method successfully analyze the 8 different patient prostate biomedical details in which RTELNN method recognize the cancer with minimum error rate collate to other methods. Then the obtained result is shown in Fig. 2.

The above Fig. 2 unmistakably demonstrates that the prostate cancer RTELNN classifiers devours least mistake rate when contrasted with the customary techniques, for example, support vector machine (SVM), Neural Networks(NN), Multi-layer Perceptron (MLP) by utilizing the successful weight and predisposition refreshing qualities additionally the improved preparing approaches. The diminished mistake rate builds the precision of the periodontitis malady acknowledgment rate. The acquired selectivity is shown in Table 2 and Fig. 3.

The Table 2 demonstrates that RTELNN method successfully examines 8 different patient prostate biomedical details in which RTELNN method recognize the cancer related data with high selectivity collate to other methods. Then the obtained result is shown in Fig. 3.

The decreased mistake rate builds the RTELNN technique Selectivity which implies that the strategy effectively perceives the typical and unusual dental components while coordinating with the preparation information. From the successful selection of prostate biomedical data from collection of data in training dataset, it is ability to predict the prostate related data with high hit rate then the obtained result is shown in Table 3 and Fig. 4.

The Table 3 demonstrates that RTELNN method successfully analyze 8 different patient prostate biomedical details in which RTELNN method effectively choose the cancer related data with high hit rate collate to other methods. Then the obtained result is shown in Fig. 4.

According to the successful selection of prostate features selection and chosen process leads to improves the overall prostate cancer prediction accuracy that is shown in Table 4.

The Table 4 depicted that RTELNN accuracy of prostate cancer biomedical data analysis process. At that point the general effectiveness of the framework is appeared in Fig. 5.

Figure 3 obviously demonstrates that the introduced strategy devours high exactness rate RTELL (99.3%) when contrasted with the customary Support Vector Machine (95.90%), Neural Networks (97.12%), and Multi-layer Perceptron (98.15%) as a result of utilizing the successful preparing and enhancement strategies. In this way, general the introduced technique effectively perceives the unusual prostate cancer related features from the accumulation of prostate cancer biomedical dataset with a compelling way.

Table 4 Accuracy

S.No	Patients	Accuracy			
		SVM	NN	MLP	RTELNN
1	Patient 1	95.395	96.84	98.17	99.21
2	Patient 2	95.83	97.22	98.09	99.23
3	Patient 3	95.81	97.16	98.01	99.31
4	Patient 4	95.96	96.96	97.83	99.3
5	Patient 5	96.96	97.03	97.82	99.26
6	Patient 6	95.64	97.06	98.4	99.33
7	Patient 7	95.92	97.53	98.36	99.4
8	Patient 8	95.76	97.17	98.53	99.47

4 Conclusion

This paper effectively analyzes the prostate cancer by applying the radial trained extreme learning neural networks. Initially the prostate biomedical data has been collected from the various patients and the mean-mode normalization process based noise has been removed. After that optimized features are selected with the help of ant rough set transition probability value. The chose elements are prepared by utilizing the radbas initiation work which is put away in the database. The prepared elements are utilized to contrast and the testing highlight utilizing the outrageous learning neural systems. Finally the effectiveness of prostate cancer prediction framework is evaluated using test results in terms of the mean square mistake rate, exactness. In this manner the introduced framework devours the higher exactness (99.3%) because of the base mistake rate. This result were examined in terms of using both training and testing prostate biomedical data examination process.

Compliance with ethical standards

Conflicts of interest The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical approval This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Conflict of interest The authors declare that they have no conflict of interest.

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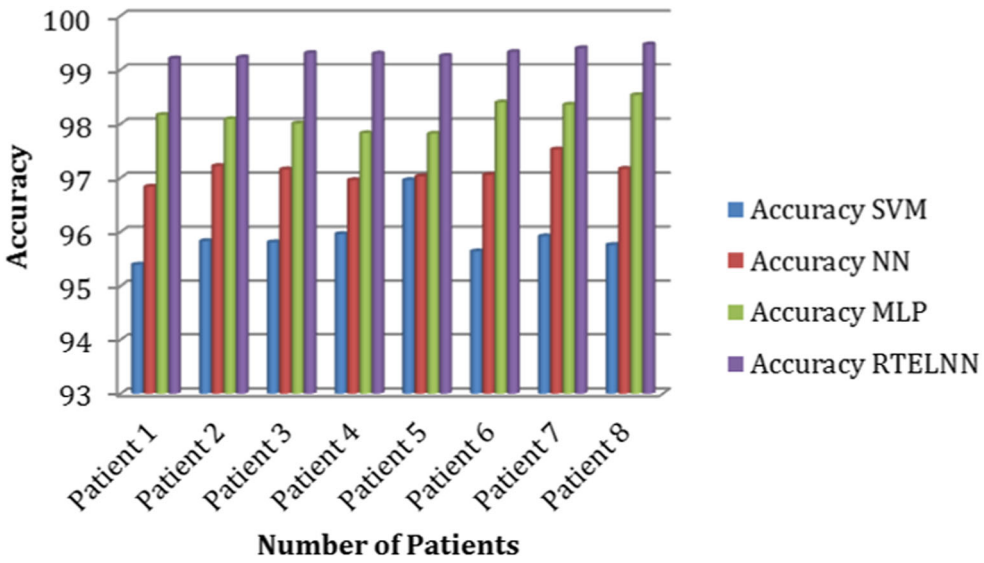

Fig. 5 Accuracy

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