Journal of Theoretical and Applied Information Technology
15th March 2022. Vol.100. No 5
2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A NEURAL NETWORK BASED DATA MINING APPROACH FOR RECOGNITION OF CHRONIC KIDNEY DISEASE

RAVINDRA BV[1] , NARENDRA VG[2] ,SHIVAPRASAD G[3]

[1]Associate Professor, Manipal School of Information Sciences, Manipal Academy of Higher Education, Manipal, India-576104

[2]Associate Professor Senior Scale, Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India-576104

[3] Assistant Professor Selection Grade, Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India-576104

E-mail: [1]ravindra.bv@manipal.edu, [2]narendra.vg@manipal.edu, [3]shiva.prasad@manipal.edu

ABSTRACT

Chronic kidney failure occur when the regular kidney filtration functionalities fails which leads to accumulation of electrolytes, wastes and other fluids in the body. One has to go appropriate dialysis procedure for their survival. It is very critical to recognize the level of chronic kidney disease (CKD) for the nephrologist and further dialysis period cannot be predicted appropriately for individuals. Data mining approaches have shown a promising path in the last decade to develop automated decision making tool for clinical diagnosis. This specific research suggests the application of neural network as critical qualitative indicator to mine the kidney dialysis attributes for classification of CKD from non-chronic kidney disease (NCKD). Two datasets one from open source UCI machine learning repository CKD database and other local hospital were considered for this study. Initially clustering was applied to remove the inconsistency from the datasets. Numerical and nominal normalized data was employed to multilayer perceptron neural network (MLPNN) to perform the classification of CKD and NCKD.MLPNN was configured optimally by appropriate network parameters and was evaluated in terms of Specificity, Sensitivity and classification accuracy. Further other classifier performance metrics, such as, position and negative predictions, error rate, F-Score, MCC and Kappa test were also evaluated. Experimental simulation shows that the proposed pattern classifier yields a classification accuracy of 93.22% and 92.78% respectively for the two different data sets.

Keywords: *Chronic Kidney Disease, Non-Chronic Kidney Disease, Multilayer Perceptron Neural Network, Classification*

1. INTRODUCTION

Kidney health is a top priority around the world. This reflects the kidneys' critical role in maintaining fluid and electrolyte balance as well as removing waste (including medicine processing), releasing hormones to control blood pressure (BP) and stimulate red blood cell production (and thus reduce the risk of cardiovascular disease and anemia), and activating vitamin D to maintain bone health [1].

Chronic kidney disease (CKD) is a serious and widespread non-communicable disease that affects people all over the world. CKD is defined and staged according to national and international recommendations based on measures of kidney function that allow for a degree of risk stratification using generally available data in its early stages, and early detection is critical to reducing future risk. For most people with CKD, the risk of cardiovascular consequences is greater than the chance of progression to end-stage kidney disease [1].

The demand for non-invasive, early, real-time, and pain-free alternative medical diagnostics of the human kidney or renal has increased in recent years, and some reasons for this include its non-invasive, early, real-time, and pain-free mechanism. One of the major kidney issues that requires early identification is chronic renal disease [2].

Chronic kidney disease (CKD) recognition and classification is a difficult research topic for the biomedical engineering and clinical communities [8] [15] [27]. Typical blood and urine tests reveal the subject's health status, and the severity of CKD leads

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

to additional symptoms such as anemia, bone disease, high blood pressure, and so on [10] [36].

In general, kidney dialysis is conducted owing to renal failure, and depending on the severity of the clinical situation, either hemodialysis, peritoneal dialysis, or full transformation is required. The pathological test provides a clear indicator of whether CKD is present.

The rest of this paper is organized as follows: Section 2 reviews the literature related to data mining for kidney disease. In Section 3, we present the materials and methods. In Section 4, results and discussion. Finally, Section 5 presents the conclusions and future work.

2. RELATEDWORK

Peritoneal dialysis (PD) was first developed in India in 1962, followed by hemodialysis (HD), and then transplantation. Currently, over 1,30,000 people are undergoing dialysis, with the number of patients growing by approximately 232 cases per one million people in the population. Only a few patients with severe CKD were given hepatitis B immunization [3], and only a few of those who received the vaccine had protection against hepatitis B surface antibodies [4]. Those who were referred late to therapy had a higher risk of suffering from anemia, having a bad prognosis, beginning dialysis without an arteriovenous fistula, having a lower likelihood of receiving Hepatitis B vaccination, and having a higher overall death rate [5]. Protein energy waste is observed in 68%–93% of dialysis patients from low and moderate socioeconomic groups.

HD is used to filter water and waste from the blood in the same way that the kidneys did when they were healthy. HD helps to keep blood pressure under control and balance minerals like calcium, potassium, and sodium in the blood [6], which helps people with high blood pressure. In a lot of hospitals, there are a lot of different types of data about patients on a daily basis. This needs to be fixed right away by systems that can turn this data into useful information. So, Knowledge Discovery in Databases (KDD) was created to find the important patterns. If you want to make sense of the hospital database, you'll need good knowledge discovery methods and good visualization tools to make it easier to see and understand.

In order to learn more about kidney diseases and how they are classified, you can look at the reports by [9] [18] [19]. We looked at the age-based classification of CKD in [16]. In [23], have written about clinical practice guidelines for CKD classification rules that can help people with CKD get better. A method for predicting the survival of kidney dialysis patients has been reported [8]. Two data mining approaches were used, and the classification accuracy was reported to be 97.78 percent. The same research group suggested an improved version of the data mining approach [38]. For the proposed study, a database of 188 patients was developed based on 707 visits, with two categories: "living" and "diseased," to determine the patient's survival span. On the basis of two data mining techniques, the rough set theory and decision tree, a three-day dialysis time was explored. The complete database was separated into eight trails, each of which was classified. The rules were created using lower and upper approximations. The survival rate may be predicted using sixteen distinct classifiers based on data mining algorithms. Overall, a classifier accuracy range of 75% to 85% was achieved. The researchers came to the conclusion that the renal dialysis parameters chosen have a major influence in predicting survival. A decision tree approach was reported for Bacille Calmette-Guerin (BCG) naive and prior BCG linked subpopulations.

In [22], used an integrated intelligent fuzzy expert system to analyze the evolution of renal failure in chronic kidney disease. The experimental investigation made use of clinical data spanning ten years and involving ten vital indicators. In this study, the effect of GFR was accurately predicted, with a normalized mean absolute error of 4.88 percent. The findings of the study were promising, and they should be carried forward into clinical practice.

In [29], proposed a comparison analysis report for predicting CKD at an early stage. Three models were used: multilayer perceptron neural network, radial basis neural network, and logistic regression, with characteristics like F-score, kappa, and accuracy evaluated. For the experimental study, an open source UCI [20] machine learning repository was employed.

There have been several attempts to distinguish between chronic kidney disease (CKD) and non-CKD [21] [27] [29] [37].CKD and NCKD were predicted and classified by [13], who used a wrapper subset attribute evaluator and best first search methods to distinguish between the two conditions. They took advantage of the UCI kidney dialysis database repository, which is free source. Using

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ultrasound imaging for stage categorization in chronic renal disease, In [17], have demonstrated that it is possible. This was the first attempt to calculate the creatinine index without using the creatinine index. A random forest data mining technique for the diagnosis of chronic kidney disease (CKD) has been presented [35].

Banarjee, Noor, and colleagues (2019) [10] attempted to predict chronic kidney disease (CKD) using Random Forest, Naive Bayes, Support Vector Machine (SVM), and potassium level data, among other methods. The study used a dataset that had 16 parameters, including the name of the item, the total amount of fat, the salt level, the number of calories, and the potassium level. Accuracy and potassium levels were used to evaluate the performance of the machine. It was possible to achieve an overall accuracy of 99.75 percent by using a dietary system that provided a meal chart that assisted in maintaining the health of CKD patients even further by maintaining the salt level.

The use of a data mining tool has been chosen as the quantitative technique for the automated categorization of chronic kidney disease from non-chronic kidney disease in this study (NCKD). In the pursuit of better prediction and classification of kidney disorders, several approaches have been tried.

This paper describes the classification of CKD and NCKD using multilayer precision neural network (MPLNN). Two databases, one from open source UCI repository CKD database and another from local hospital were considered for the study.

3. MATERIALS AND METHODS

3.1 Study Dataset

Two databases are used in the proposed research. The first database (DB1) contains kidney dialysis data obtained after ethical clearance from a local general hospital. [2] [17] [19] [20]. The suggested study omitted attributes that were judged to be negligible. The exact details are shown in Table 1.

Table 1. Attributes and their properties in patient dataset

No	Attribute	Type	Units or Values
1	ID NO.	Numerical	
2	DOB	Numerical	
3	Gender	Nominal	Male/Female
4	Race	Nominal	Chinese/Indian/Malay/lban
5	Blood Type	Nominal	A-/B-/o-
6	Weight Pre	Numerical	
7	Weight Post	Numerical	
8	B/P Sitting Pre	Numerical	mm/Hg
9	B/p Sitting Post	Numerical	mm/Hg
10	B/P Standing-Pre	Numerical	mm/Hg
11	B/P Standing Post	Numerical	mm/Hg
12	pulse Rate Pre	Numerical	
13	Pulse Rate Post	Numerical	
14	Bicarbonate	Numerical	mEq/L
15	Potassium	Numerical	
16	Total Time Fr Dialysis	Numerical	
17	Blood Flow Rate	Nominal	
18	Blood Volume Processed	Numerical	mmHg
19	Dialysate Flow Rate	Nominal	
20	Blood Pressure	Numerical	
21	Pulse Rate	Numerical	
22	Dialysate	Numerical	
23	Type Of Dialysis Machine	Nominal	
24	Overall Average Arterial Pressure	Nominal	(yes, no)
25	Type Of Access	Nominal	
26	Kt/V	Numerical	
27	URR	Numerical	
28	Primary Diagnosis Code	Nominal	
29	Secondary Diagnosis Code	Nominal	ESD/HYPERTENSION

Only n = 180 of the 230 patient pathology data (both nominal and numerical values) recorded over a two-year period were judged to be significant. The baseline characteristics of the research population (n = 180) are shown in Table 2. For the sake of brevity, the mean ± SD is presented for each variable.

Because of insufficient data, only four qualities were taken into consideration: creatinine, urea, sodium, and potassium. Patients/subjects were classified as having chronic kidney disease (CKD) or not having chronic kidney disease (NCKD) based on the priority region (low, medium, or high) in which each feature was found, as well as the length of time they had spent in the dialysis centre. Table 3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

displays the data that has been labelled. Training with MLPNN was carried out using male data, female data, and male-female data in accordance with the four attributes identified. The three groups of patients (male, female, and male and female) that were considered for the local database were as follows: The University of California, Irvine Machine Learning Repository (DB2) [14] [30] is used for the second study, which makes use of open source data from that repository. There were a total of n=400 subjects whose data was saved. There were a total of 25 quality options available to choose from. Table 4 lists the characteristics of DB2 at its most basic level. Table 5 displays the data that has been labelled.

Table 2. Baseline characteristics of DB1 (n=180)

Variable	***CKD***	***NCKD***
Sex(Male=1,Female=0)	0.544828± 0.499713	0.428571 ± 0.502096445
Age (Years)	42.48966 ± 8.589494	43.25714 ± 9.586580256
Creatinine (mgs/dl)	4.13931 ± 0.947606	6.354286 ± 0.245360308
Urea (mgs/dl)	25.15862 ± 10.18078	25.25714 ± 9.974505316
Sodium (mEq/L)	142.9448 ± 3.658664	140.7429 ± 1.94547525
Potassium (mEq/L)	4.66 ± 0.562534	4.162857 ± 0.842295782
Months(Numeric)	18.13793 ± 9.862683	0 ± 0

Table 3. Labelled data (DB1)

	n
CKD	145
NCKD	35

Table 4. Baseline characteristics of DB2 (n=400)

Variable	**CKD**	**NCKD**
Age	54.54132 ± 17.70215	46.51678 ± 16.0349
Blood Pressure	79.625 ± 16.04422	71.35135 ± 10.32793
Specific Gravity	1.013918 ± 0.070286	1.022414 ± 0.084652
Albumin	1.722488 ± 1.374507	0 ± 0
Sugar	0.76699 ± 1.346338	0 ± 0
Blood Glucose Random	175.4198 ± 92.64777	107.7222 ± 20.54956
Blood Urea	72.38903 ± 58.6515	32.79861 ± 11.73122
Serum Creatinine	4.414916 ± 6.941535	0.868966 ± 0.264187
Sodium	133.9018 ± 16.0937	141.731 ± 12.67433
Potassium	4.878443 ± 4.325	4.337931 ± 0.686571
Hemoglobin	10.64755 ± 2.303754	15.18819 ± 1.792113
Packed Cell Volume	32.93989 ±7.58827	46.33562 ± 5.619766
White Blood Cell Count	9069.536 ± 3643.678	7705.594 ± 1942.53

Table 5. Labelled Data of DB2

	n
CKD	250
NCKD	150

In order to make efficient training of the network model, four cases were considered for the DB2. Attributes which were closely correlated were grouped together and thereby multi parameters were employed for training the MLPNN model. Based on this, four cases were considered (Table 6)

Table 6 Selection of training attributes using DB2

CASE 1	**CASE 2**	**CASE 3**	**CASE 4**
Blood Pressure	Albumin	Packed Cell Volume	Albumin
Specific Gravity	Sugar	White Blood Cell Count	Sugar
Serum Creatinine	Blood Glucose Random	Red Blood Cell Count	Blood Glucose Random
	Hemoglobin		Blood Urea
			Serum Creatinine
			Sodium
			Potassium

3.2 Data Normalization

Inorder to ensure that the applied data suits well for training using the MLPNN, a sample normalization function was applied [11].

$$\textbf{Data Normalization} = \frac{(\textit{Actual attribute value} - \textit{Lower limit})}{(\textit{Upper limit of the attribute} - \textit{Lower limit of the attribute} + 1)}$$

3.3. MLPNN

The multilayer perception neural network (MLPNN) has found widespread use in pattern recognition [13] [32] [33] [35]. This model is used in the majority of clinical decision-making because of its self-tolerance, robustness, and generalization capabilities. Figure 1 depicts the MLPNN model that

Journal of Theoretical and Applied Information Technology
15th March 2022. Vol.100. No 5
2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

will be used in the proposed research. Three-seven inputs were selected for open-source databases, and four nodes were evaluated for local databases.

The MLPNN was trained using a variety of nominal and numerical attribute combinations. Using a trial and error process, the network model was optimized in terms of hidden neurons, activation function, learning algorithm, learning rate, and learning momentum. The models are assessed using performance criteria such as sensitivity, specificity, and classification accuracy. In terms of network architecture, kernel selection, and decision rules formulated to distinguish CKD from NCKD, the efficiency of the data mining framework is based on supervised models.

The performance of the MLPNN classifier is evaluated by estimating the parameters sensitivity, specificity and overall classification accuracy. Figure 2 shows the proposed framework.

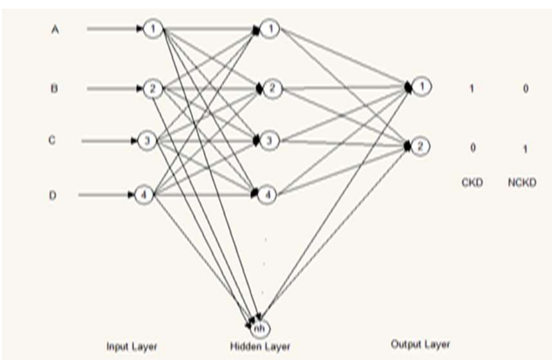
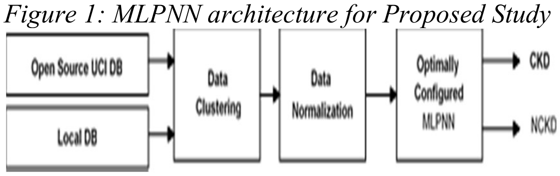


Figure 1: MLPNN architecture for Proposed Study



1.

Figure 2: Proposed NN based data mining framework

The network model was optimally configured to obtain better classification [24] [30] [31]. The performance of the proposed framework is evaluated using the following parameters:

$$\text{Sensitivity}(\%) - \text{SE} = \text{TP}/(\text{TP} + \text{TN}) \quad (1)$$

$$\text{Specificity}\ (\%) - \text{SP} = \text{TN}/(\text{FP} + \text{TN}) \quad (2)$$

$$\text{Positive Precision}\ (\%) - \text{PP} = \text{FP}/(\text{TP} + \text{FP}) \quad (3)$$

$$\text{Negative Precision}\ (\%) - \text{NP} = \text{FN}/(\text{TN} + \text{FN}) \quad (4)$$

$$\text{Accuracy}\ (\%) - \text{AC} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{TN} + \text{FN}) \quad (5)$$

$$\text{Error Rate}\ (\%) - \text{ER} = (\text{FP} + \text{FN})/(\text{TP} + \text{FP} + \text{TN} + \text{FN}) \quad (6)$$

$$\text{F} - \text{Score} = (2 * \text{TP})/(2 * \text{TP} + \text{FP} + \text{TN}) \quad (7)$$

$$\text{MCC} = \left(\frac{(\text{TP}*\text{TN})-(\text{FP}*\text{FN})}{\text{SQRT}\ (\text{TP}+\text{T}\quad)*(\text{TN}\qquad)*(\text{TP}+\text{FP})*(\text{FN}*\text{TN}))}\right) \quad (8)$$

$$\text{Kappa Test} = \frac{(\text{Observed agreement}*\text{Expected Agreement})}{100} * \text{Expected Agreement} \quad (9)$$

Where

Observed Agreement = %(Overall Accuracy)

Expected Agreement = $((\text{TP} + \text{FP}) * (\text{TP} + \text{FN}) * (\text{TN} + \text{FN}) * (\text{FP} + \text{TN}))$

TP = Correctly recognized as CKD attributes

FN= Incorrectly recognized as NCKD attributes

TN = Correctly recognized as NCKD attributes

FP = Incorrectly recognized as CKD attributes

4. RESULT AND DISCUSSION

The kidney dialysis attributes that were recorded were normalized using [27]. Then, the MLPNN model was trained with the results of this process. For this proposed study, 60% and 40% of the training and testing models were chosen, respectively. To make sure the MLPNN model was set up correctly, different work parameters were looked at, and the one shown in Table 7 was used. The MLPNN was trained in a way that was supervised.

During the simulation, it was discovered that a learning rate of 0.8 in conjunction with a momentum of 0.6 produces consistent outcomes. The maximum number of epochs was set at 1000, and the Mean Square Error (MSE) criterion was employed to determine whether the network had reached its convergence. The performance of the network throughout the training phase is depicted in Figures 3a and 3b. As shown in Table 7, the MSE plots for both datasets were created using the Levenberg-Marquardt (LM) training algorithm.

Table 7. Optimal Configuration of MLPNN

Neural Network Parameter	Values Selected
Hidden Neuron	HN = 1,5,10
Learning / Training algorithm	LM
Activation Function: Input layer hidden -output	Log sigmoid
Stopping criteria: MSE	0.01
Learning Rate	0.5-0.8
Learning momentum	0.6

It can be observed from the Figures 3a and 3b that the convergence was found to be good with single

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

hidden neurons. As the iteration increases, the network reach to yield better convergence.

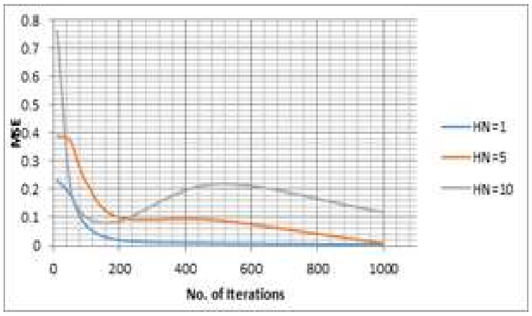


Figure 3a: Performance of the MLPNN (DB1) during training phase

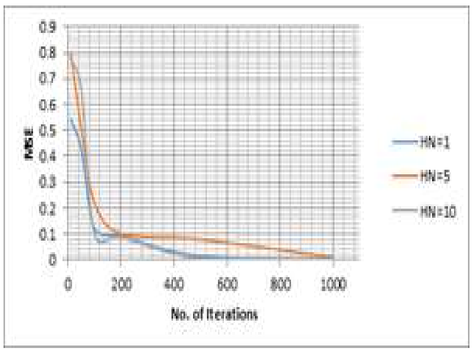


Figure 3b: Performance of the MLPNN (DB2) during training phase

Figures 4 and 5 show the MLPNN classification performance using the test samples (training mode, HN=1 was found to be obtained for all training algorithms). For better brevity, results were shown by considering all learning/training algorithm during the training phase.

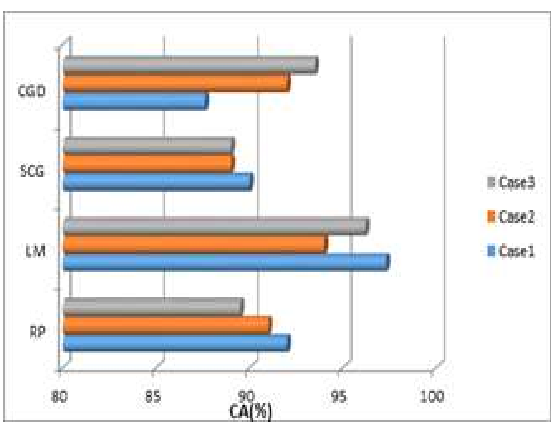


Figure 4. MLPNN classifier performance using DB1

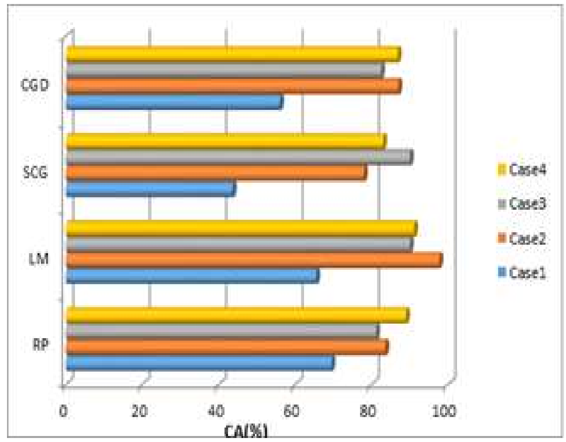


Figure 5: MLPNN classifier performance using DB2

According to the results of the proposed study, the MLPNN produces good classification accuracy when the LM training strategy is applied. This can be seen in Figures 4 and 5. When using the open source dataset, the accuracy is 92.78 percent in all situations, but the local data set has an accuracy of 93.22 percent in all cases. Tables 8, 9, 10, and 11 demonstrate the overall performance measures for the classifiers based on the LM algorithm.

Table 8. Performance measures for DB1

Case	SE (%)	SP (%)	AC(%)	PP (%)	NP (%)	ER (%)
1	88.75	90.00	89.00	02.73	33.33	11.00
2	95.38	100.0	96.25	∞	16.66	03.75
3	95.17	91.42	94.40	02.12	17.94	05.55

Table 9. Performance measures for DB2

Case	SE (%)	SP (%)	AC (%)	PP (%)	NP (%)	ER (%)
1	95.00	92.00	93.84	05.00	08.00	06.15
2	85.60	93.33	88.50	04.46	20.45	11.50
3	92.40	93.33	92.75	04.14	11.94	07.25
4	96.40	95.33	96.00	02.82	05.92	04.00
Average	92.35	93.50	92.78	04.10	11.58	07.22

Table 10. Fidelity measures for DB1

Case	F Score	MCC	Kappa
1	0.93	0.28	1.00
2	0.98	0.56	1.00
3	0.96	0.347	1.00

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 11. Fidelity measure for DB2

Case	F Score	MCC	Kappa
1	0.967611	0.286408	1.00
2	0.98008	0.479818	1.00
3	0.90101	0.156854	1.00
4	0.976	0.39	1.00

For the DB1 it can be inferred that the proposed scheme yields high classification accuracy compared to the earlier methods reported in the literature. Fig 6 shows the ROC analysis of the MLPNN classifier. The area under the curve confirms the suitability of the proposed classifier for CKD-NCKD.

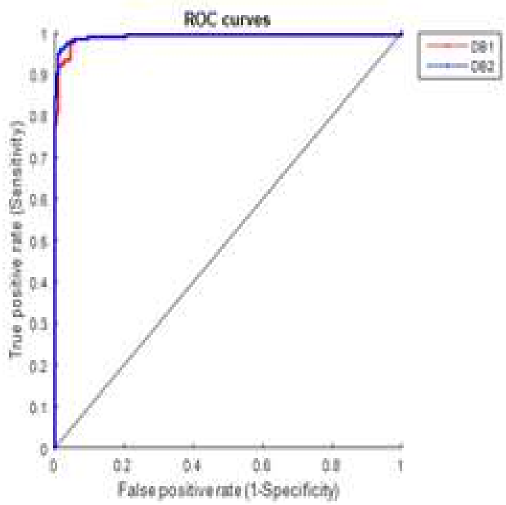


Figure 6: ROC of the proposed MLPNN for DB1 and DB2.

5. CONCLUSIONS

It is proposed that a neural network-based data mining tool be used for the classification of chronic and non-chronic kidney disease in the present study. To conduct the research, two separate databases were evaluated, and the renal dialysis properties were treated as a multi-feature for the purpose of training the neural network model. For the classification, a feed-forward multilayer sensory neural network was taken into consideration. In terms of hidden neuron activation function and learning algorithm, the network parameters were configured in the most optimal way. The classification accuracy was used to evaluate the performance of the suggested scheme in terms of learning rate. The results of the simulation demonstrate that the classification accuracy for datasets 1 and 2 was 93.22 percent and 92.78 percent, respectively. As evidenced by the area under the curve calculated using ROC analysis, the suggested neural network model for the CKD-NCKD classification problem performs admirably.

REFERENCES

[1] Simon DS Fraser, Tom Blakeman, "Chronic kidney disease: identification and management in primary care", *Pragmatic and Observational Research*, Vol. 7, 2016, pp. 21–32.

[2] Sohail Muzamil, Tassadaq Hussain, Amna Haider, Umber Waraich, Umair Ashiq and Eduard Ayguade, "An Intelligent Iris Based Chronic Kidney Identification System", *Symmetry*, Vol. 12, No. 12, 2020, 2066. https://doi.org/10.3390/sym12122066

[3] Santosh Varughese, GT John, S Alexander, MN Deborah, N Nithya, I Ahamed, V Tamilarasi, CK Jacob, et al., "Pre-tertiary hospital care of patients with chronic kidney disease in India", *Indian Journal of Medical Research*, Vol. 126, No. 1, 2007, pp. 28.

[4] J George, GT John, CK Jacob, and JCM Shastry, "Active immunization against hepatitis b infection of a hemodialysis population", *National Medical Journal Of India*, Vol. 7, 1994, pp. 115–115.

[5] Madhusudan Vijayan, Georgi Abraham, Merina E Alex, N Vijayshree, Yuvaram Reddy, Edwin Fernando, Milly Mathew, Sanjeev Nair, and Anand Yuvaraj. "Nutritional status in stage v dialyzed patient versus ckd patient on conservative therapy across different economic status", *Renal Failure*, Vol. 36, No. 3, 2014, pp. 384–389.

[6] Morteza Khavanin Zadeh, Mohammad Rezapour, and Mohammad Mehdi Sepehri, "Data mining performance in identifying the risk factors of early arteriovenous fistula failure in hemodialysis patients", *International journal of hospital research*, Vol. 2, No. 1, 2013, pp. 49–54.

[7] Jiawei Han, Jian Pei, and Micheline Kamber, "Data mining: concepts and techniques", Elsevier, 2011.

[8] Al-Aly, Ziyad, "Prediction of renal end points in chronic kidney disease", *Kidney International*, Vol. 83, No. 2, 2013, pp. 189 – 191. http://doi.org/10.1038/ki.2012.418

[9] Andrew S. Levey, Adeera Levin, John A. Kellum, (2013). Definition and Classification of Kidney Diseases, American Journal of Kidney Diseases Vol. 61, No. 5, 2013, pp. 686-688. https://doi.org/10.1053/j.ajkd.2013.03.003

[10] Anonnya Banerjee, Alaa Noor, Nasrin Siddiqua, Mohammed Nazim Uddin, "Food Recommendation using Machine Learning for Chronic Kidney Disease Patients" Proceedings of 2019 International Conference on Computer Communication and Informatics (ICCCI - 2019), Coimbatore (India), Jan. 23 – 25, 2019, pp. 1-5. https://doi.org/10.1109/ICCCI.2019.8821871.

[11] AO Osofisan, OO Adeyemo, BA Sawyerr, O Eweje," Prediction of kidney failure using artificial neural networks, *European, Journal of Scientific Research*, Vol. 6, No. 4, 2011, pp. 487-492.

[12] Babitt, J. L., & Lin, H. Y., "Mechanisms of anemia in CKD", *Journal of the American Society of Nephrology*, Vol. 23, No. 10, 2012, pp. 1631–1634. http://doi.org/10.1681/ASN.2011111078

[13] N. Chetty, K. S. Vaisla and S. D. Sudarsan, "Role of attributes selection in classification of Chronic Kidney Disease patients," Proceedings of International Conference on Computing, Communication and Security (ICCCS), Pointe aux Piments (Mauritius), Dec. 4-5 2015, pp. 1-6, http://doi.org/10.1109/CCCS.2015.7374193

[14] Dokur, Z., & Ölmez, T., "Classification of respiratory sounds by using an Artificial Neural Network", *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 17, No. 04, 2003, pp. 567–580. http://doi.org/10.1142/s0218001403002526

[15] Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

[16] Echouffo-Tcheugui, Justin B, and Andre P Kengne. "Risk models to predict chronic kidney disease and its progression: a systematic review." *PLoS medicine,* Vol. 9, No. 11, 2012, e1001344. http://doi.org/10.1371/journal.pmed.1001344

[17] Glassock R, Delanaye P, El Nahas M, "An Age-Calibrated Classification of Chronic Kidney Disease". *JAMA,* Vol. 314, No. 6, 2015, pp. 559-560. http://doi.org/10.1001/jama.2015.6731

[18] Hsieh, J.-W., Lee, C.-H., Chen, Y.-C., Lee, W.-S., & Chiang, H.-F., "Stage Classification in Chronic Kidney Disease by Ultrasound Image", Proceedings of 29th International Conference on Image and Vision Computing New Zealand (IVCNZ '14), Nov. 2014, pp. 271-276. http://doi.org/10.1145/2683405.2683457

[19] Levey AS, Eckardt KU, Tsukamoto Y, Levin A, Coresh J, Rossert J, De Zeeuw D, Hostetter TH, Lameire N, Eknoyan G, "Definition and classification of chronic kidney disease: a position statement from Kidney Disease: Improving Global Outcomes (KDIGO)", *Kidney Int.,* Vol. 67, No. 6, pp. 2089-2100. http://doi.org/10.1111/j.1523-1755.2005.00365.x

[20] Lichman, M. (2013). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

[21] M. S. Wibawa, I. M. D. Maysanjaya and I. M. A. W. Putra, "Boosted classifier and features selection for enhancing chronic kidney disease diagnose", Proceedings of 5th International Conference on Cyber and IT Service Management (CITSM) Denpasar (Indonesia), Aug. 8-10, 2017, pp. 1-6. http://doi.org/10.1109/CITSM.2017.8089245

[22] Norouzi, Jamshid et al. "Predicting Renal Failure Progression in Chronic Kidney Disease Using Integrated Intelligent Fuzzy Expert System." *Computational and mathematical methods in medicine*, Vol. 2016, 6080814. https://doi.org/10.1155/2016/6080814

[23] Ognibene A, Grandi G, Lorubbio M, Rapi S, Salvadori B, Terreni A, Veroni F., "KDIGO 2012 Clinical Practice Guideline CKD classification rules out creatinine clearance 24 hour urine collection?." *Clinical biochemistry,* Vol. 49, No. 1-2, 2016, pp. 85-9. http://doi.org/10.1016/j.clinbiochem.2015.07.030

[24] Raghu, S., & Sriraam, N., "Optimal configuration of multilayer perceptron neu- ral network classifier for recognition of intracranial epileptic seizures". *Expert Systems with Applications*, Vol. 89, 2017, pp. 205–221.

[25] B. V. Ravindra, N. Sriraam and M. Geetha, "Discovery of significant parameters in kidney dialysis data sets by K-means algorithm", Proceedings of International Conference on Circuits, Communication, Control and Computing, Bangalore (India), Nov. 21-22, 2014, pp. 452-454. http://doi.org/10.1109/CIMCA.2014.7057843

[26] B. V. Ravindra. & N Sriraam, & , M. Geetha (2017), "Classification of non-chronic and chronic kidney disease using SVM neural networks", *International Journal of Engineering & Technology*, Vol. 7, No. 1.3, 2017, pp. 191-194. http://doi.org/10.14419/ijet.v7i1.3.10669

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[27] B. V. Ravindra, N. Sriraam and M. Geetha, "Chronic Kidney Disease Detection Using Back Propagation Neural Network Classifier," Proceedings of International Conference on Communication, Computing and Internet of Things (IC3IoT) Chennai (India), Feb. 15-17, 2018, pp. 65-68, http://doi.org/10.1109/IC3IoT.2018.8668110

[28] Rothberg, M. B., Kehoe, E. D., Courtemanche, A. L., Kenosi, T., Pekow, P. S., Brennan, M. J., Braden, G. L., "Recognition and management of chronic kidney disease in an elderly ambulatory population", *Journal of general internal medicine*, Vol. 23, No. 8, 2008, pp. 1125–1130. http://doi.org/10.1007/s11606-008-0607-z

[29] Rubini, L.J., & Eswaran, P., "Generating comparative analysis of early stage prediction of Chronic Kidney Disease", *International Journal of Modern Engineering Research (IJMER)*, Vol. 5, 2015, pp. 50-55.

[30] D. S. Sisodia and A. Verma, "Prediction performance of individual and ensemble learners for chronic kidney disease," Proceedings of International Conference on Inventive Computing and Informatics (ICICI), Coimbatore (India), Nov. 23-24, 2017, pp. 1027-1031. http://doi.org/10.1109/ICICI.2017.8365295

[31] Sriraam, N., "EEG Based Thought Translator: A BCI Model for Paraplegic Patients", *International Journal of Biomedical and Clinical Engineering (IJBCE)*, Vol. 2, No. 1, 2013, pp. 50-62. http://doi.org/10.4018/ijbce.2013010105

[32] Sriraam, N., Natasha, V., & Kaur, H., "Data Mining Techniques and Medical Decision Making for Urological Dysfunction", In A. Lazakidou (Ed.), *Handbook of Research on Informatics in Healthcare and Biomedicine*, 2006, pp. 154-165. IGI Global. http://doi:10.4018/978-1-59140-982-3.ch020

[33] Sriraam, N., Raghu, S., Tamanna, K. Narayan, L., Khanum, M., Hegde, A. S., & Kumar, A. B., "Automated epileptic seizures detection using multi-features and multilayer perceptron neural network". *Brain Inf.* Vol. 5, No. 10, 2018. https://doi.org/10.1186/s40708-018-0088-8

[34] Subasi A., Alickovic E., Kevric J., "Diagnosis of Chronic Kidney Disease by Using Random Forest", In: Badnjevic A. (eds) CMBEBIH 2017, IFMBE Proceedings, 62, Springer, Singapore. https://doi.org/10.1007/978-981-10-4166-2_89

[35] Sumsion, G Rex, Bradshaw, M. S., Hill, K. T., Pinto, L., & Piccolo, S. R., "Remote sensing tree classification with a multilayer perceptron." *PeerJ* Vol. 7, 2019, e6101. https://doi.org/10.7717/peerj.6101

[36] Thomas, R., Kanso, A., & Sedor, J. R., "Chronic kidney disease and its complications", *Primary care*, Vol. 35, No. 2, pp. 329–vii. https://doi.org/10.1016/j.pop.2008.01.008

[37] W. H. S. D. Gunarathne, K. D. M. Perera and K. A. D. C. P. Kahandawaarachchi, "Performance Evaluation on Machine Learning Classification Techniques for Disease Classification and Forecasting through Data Analytics for Chronic Kidney Disease (CKD)," Proceedings of 17th International Conference on Bioinformatics and Bioengineering (BIBE), Washington, DC (USA), Oct. 23-25, 2017, pp. 291-296, http://doi.org/10.1109/BIBE.2017.00-39

[38] Kusiak A., Caldarone C.A., Kelleher M.D., Lamb F.S., Persoon T.J., Burns A., "Hypoplastic left heart syndrome: Knowledge discovery with a data mining approach", *Comput. Biol. Med.,* Vol. 36, 2006, pp. 21–40. http://doi.org/10.1016/j.compbiomed.2004.07.007