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Diagnosis and Classification of Level of Kidney Function Using Associative Neural Network and Polynomial Neural Network

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ABSTRACT

Artificial neural networks are often used as a powerful discriminating classifier for tasks in medical diagnosis. They have several advantages over parametric classifiers such as discriminate analysis. Acute and Chronic Renal failures or Kidney Diseases (CKD) are being observed as a serious challenge to the field of Medical and health industry with its impact on a mass population of the world. This paper presents an efficient and effective model of forecast and classification of functional abnormalities of kidney using Associative Neural Network (ASNN) and Polynomial Neural Network (PNN). The ASNN and PNN are constructed with neurons arranged in such a way that the network consists of ten, eight and one neurons in the input, hidden and output layers respectively. Glomerular Filtration Rate (GFR) which can indicate the efficiency of functionality of kidneys is arrived using Modification of Diet in Renal Disease (MDRD) formula and the network is trained with these data sets. The trained ASNN and PNN are used for testing and used as an effective model for the forecast, categorization of renal functional abnormalities and severity level of CKD. The result of this study shows that ASNN provides satisfactory results for the diagnosis and classification of kidney dysfunction with excellent correlation co-efficient (R^2 = 0.987) for training and 0.951 for testing. In the end part the results are cross validated by Leave-One-Out (LOO) procedure. Correlation coefficient of 0.955for training and 0.958 for testing confirms the classification ability of PNN. The projected model has been proved to be the most reliable tool with high degree of accuracy of its kind in terms of forecasting and classification of renal functionality. The Network model is also useful as an effective tool for the physicians in the diagnosis or screening of CKD, communicating the patients about the risk factor involved in their renal function and deciding the course of therapy and medication.

Keywords: Kidney dysfunction, Glomerular Filtration Rate (GFR), Chronic Kidney Diseases (CKD), Associative Neural Network (ASNN), cross validation, Polynomial Neural Network (PNN).

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INTRODUCTION

Renal failures or dysfunction of kidneys are resulting from the reduced efficiency of Kidneys to perform the process of excretion by means of filtering the body wastes from the blood [1]. Renal failures may be permanent (Chronic) or temporary (Acute) or a progressive disease which may depend on the possible therapeutic procedures [2]. CKD is a widespread physiological condition on a massive population that may get coupled with influenced risks of Cardio Vascular Disease (CVD). Most of the renal failures are avoidable when detected in their earlier stages of infections by proper identification and proper therapeutic procedures [3-4]. As people's life level become more and more modernized and life span becomes longer in our society, Chronic Kidney Disease (CKD) becomes more common which may result in developing different levels of ill function and damage of patient kidneys. In case of the renal or kidney failures, the capacity of the kidneys to filter the body waste products from the blood (urine) is highly affected due to the death of renal cells (nephrons) and the body fails to maintain the normal fluidic balance. This results in the accumulation of toxic elements and products in the blood, targeting the vital organs like brain, heart etc. leading to loss of life. Renal failures fall into two categories viz., Acute and Chronic. Acute failures are recoverable and last for shorter periods of life as it is originated from dehydration or some other common infections. Chronic or permanent failures are dreadful ending up with loss of life and have their origin as abusing of certain pain killer medications like ibuprofen, acetaminophen etc. Chronic failures are very common in cases of long term clinical conditions such as Hypertension and Diabetes mellitus. The problem of chronic failures are that they were not diagnosed at an earlier stage of inflammation due to the lack of observed clinical symptoms and makes the condition to get worsen delaying the therapeutic decisions [5].

The functional ability of kidneys are influenced by the two factors estimated glomerular Filtration Rate (eGFR) and Urinary protein (Albumin). Glomeruli are small filters made of blood vessels. One million such glomeruli are there in each kidney. An estimation of the amount of blood filtered by the glomeruli per minute gives a measure of the kidney function. From the amount of waste product, Creatinine present in the blood eGFR is calculated. Creatinine content of blood is inversely proportional to eGFR. When eGFR falls less than 60 ml/L, it is an indication of kidney disease. The ratio between albumin and creatinine in the excreted urine is a direct measure of kidney function. There is a clear indication of kidney damage when the ratio is above 30 mg of albumin per one gram of Creatinine irrespective of high or low eGFR. The most common problem in the field of automatic diagnostic is the diagnostics using fast and accurate algorithm which doesn't require long time to run and give accurate and correct results [6]. Though there are many diagnostic technique with automation, the prime issues are the time consumption and accuracy. Medical diagnostic industry is a complicated fuzzy complex system. So the implementation of fuzzy and neural based network system may suit for such a complicated system of diagnosis and decision making with better accuracy. In disease diagnosis the learning and detection of partial disease can be helpful when time and information constraints are present. Thus artificial neural networks provide a good means to partial diagnosis.

Artificial Neural Network [7] is one of the best suitable techniques in practice for such a complex system of diagnosis with priorities of decision making and risk analysis. Earlier practices have proved that Neural Networks are better performing method for such a complex system than that of statistical analysis [8]. A review on the past history reveled the best implementation of Neural Network in Radiological studies [9], certain short term or temporary (Acute) illness [10], forecast analysis on ICU (Intensive care unit) patients [11], analysis or judgment on clinical conditions such as Appendicitis [12], analysis and classification of neuro-psychiatric disorders [13, 14], pulmonary embolism [15] and prostate cancer [16]. There has been several studies reported focusing on kidney disease diagnosis calculating eGFR using different Neural Network Structures [17,18,19,20,21,22] But this study is unique in its own way as no study is available using ASNN and PNN for kidney disease and using different input parameters.

The objective of this research is to frame an efficient model for decision making and classification applying Associative Neural Network and Polynomial Neural Network which attempts to provide physicians a powerful tool to clinically analyze the kidney dysfunction and get best solutions, using the various kinds of diagnostic laboratories and clinics as the primary variable.

MATERIAL AND METHODS

Database description

The dataset of diagnosis for kidney dysfunction is purely real set data. The dataset used in this work is collected from renowned hospitals in Thanjavur, Tamilnadu, India. Age, Sex, Diabetes mellitus, Hypertension, Obesity, Polymer chain reaction, Hemoglobin, Cholesterol, Serum creatinine, estimated Glomerular Filtration Rate (eGFR)for150subjects were analyzed in diagnostic laboratories. The analyzed cases were formed in to two main classes viz., one fortraining (100) the algorithm and the other for the testing (50). (Software for ASNN is used from www.vcclab.org/asnn). [23]

The MDRD formula, which is recognized as a more accurate and most accepted method by Nephrologists for the estimation of GFR from Creatinine level in the blood serum, is adopted for the renal diagnosis. GFR is calculated using equation 1[24,25] and the data provided by the hospital and diagnostic laboratories. The target values as calculated are used to train the neural network model.

$$\mathrm{GFR} = 186 \times \mathrm{Creatinine}^{-1.157} \times \mathrm{age}^{-0.203} \left(\frac{\frac{\mathrm{ml}}{\mathrm{min}}}{1}.73\mathrm{m}^2 \right). \ldots (1)$$

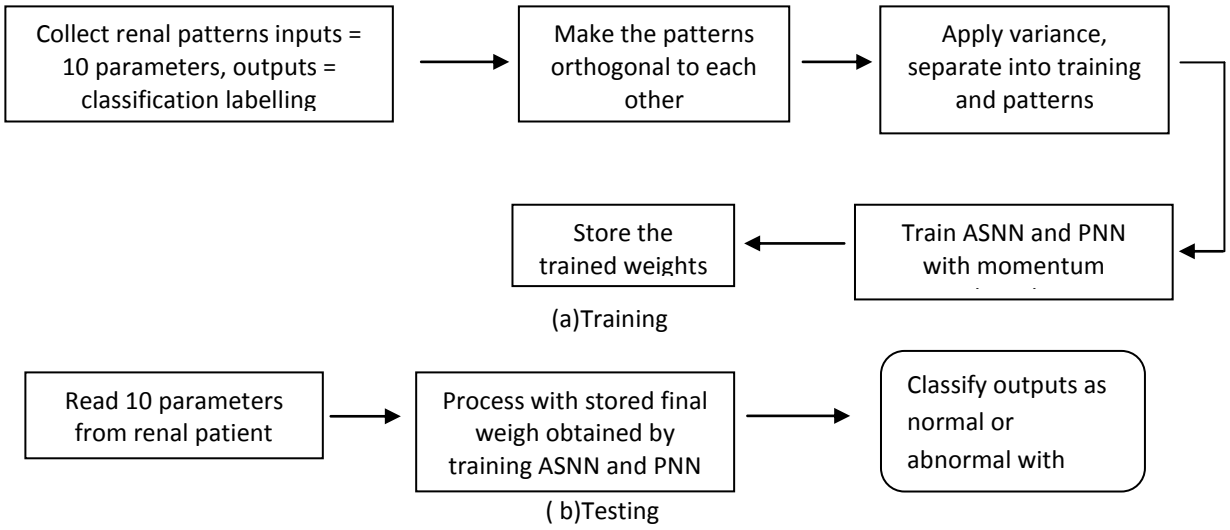
For female the result should be multiplied by a factor of 0.742

Snyder and Pendergraph [26] indicated that the MDRD is suitable to be used to the group of diabetes mellitus, adults with kidney replacement therapy (dialysis, transplantation). It also takes less number of factors than other two popular methods, which are Creatinine Clearance Rate computation and Cockcroft-Gault formula. It becomes easier

and simple but still maintains the result effectiveness for calculating GFR. Hence, this paper adopts MDRD to conduct the calculation of GFR directly from the data collection of Creatinine, age, and sex.

Schematic Architecture

The schematic architecture for training and testing is given in figure-1



ARTIFICIAL NEURAL NETWORK

ANN is a real simulation of biological system of neurons just like the brain of a computer. The group of nodes, neurons and the associated connection between them represents the artificial neural network [27, 28]. These associated connections have their own strength and weight. Hence this model of Neural Network can well be applied for any complicated system of diagnosis where we could arrive at an efficient and better algorithm. In others words the kind of problems in which inputs and outputs variables does not have a clear relationship between them, a neural networks is a efficient approach in such problems. Most neural network architecture has three layers in its structure. First layer is input layer which provides an interface with the environment, second layer is hidden layer where computation is done and last layer is output layer where output is stored. After the date is being propagated through the layers in succession, we get the output layer as the final result as illustrated in figure-2. Transfer function as may be a simple linear or a complex sigmoid function was used to arrive at the value of activation for each and every neuron. Other hyperbolic tangent, step or thresholds logic functions can also be used. The ANN is trained by means of adjusting the weights of the connections as input until the desired output is got.

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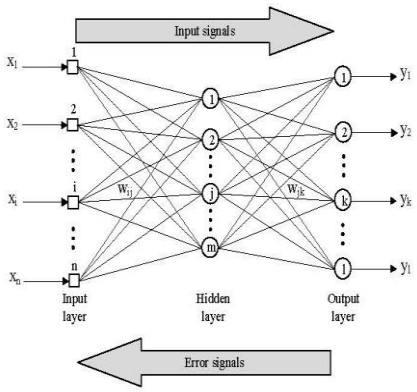

Fig 2. Artificial Neural Network

Associative Neural Network

Associative neural network plays a vital role to establish non-linear relationship between input (attributes) and output (class attributes). The conventional artificial feed forward neural network has no memory. It is to say that once the training is completed, all data about the input patterns is stored in the neural network weights and input data are not required. i.e., there is no definite storage of any example presented in the system. Quite opposed to it, Associative Neural Network (ASNN) is a group of memory-based and memory-less methods [29, 30]. The Associative neural network (ASNN) offers an innovative approach to integrate "on the fly" the user's data. ASNN uses the correspondence in between ensemble responses as a determination of distance among the cases analyzed for the closest neighbor method. By this correction or adjustment of the ensemble of neural network we arrive at a definite forecast and prediction. It is very much clear that ASNN holds a memory as synchronized with its training set of neurons. Whenever there is an available new data the network is provided with a chance of increasing its capacity towards prediction. This feature of the network is very much significant as compared to conventional neural networks. ASNN has a special capacity to interrupt the results of the network by means of analysis on correspondence between the case data [31].

The network is trained with ESE (Early Stopping Ensemble) method. In ESE equal sets of training and evaluation ensembles were constructed. The network's weight is adjusted through the training or learning sets. When there is a minimum error the training or learning process is stopped (Early stopping point) and the set of evaluation or validation is calculated [32-33]

Polynomial Neural Network

Polynomial Neural Network (PNN) represents a promising method for applications in medical field. It provides the model in parametric form as an equation that can be easily interpreted by the users. Group method of Data Handling (GMDH)also known as PNN was framed in 1960's by Prof. A.G.Ivakhnenko for identifying non-linear relation between input and output variables. Inductive algorithms as a group for computer aided modeling with multiple datasets represent GMDH and reduce the possibility of errors. This feature enables to have a fully automatic parametric and structural optimization of the model.PNN finds

many of its application in data mining, forecasting, knowledge finding, optimization and modeling of a system. A neuron of feed forward network is replaced by a neuron of PNN [34]. The basic structure of PNN is given in figure-3.The software for PNN is available online at [35] and it is used for training and testing...

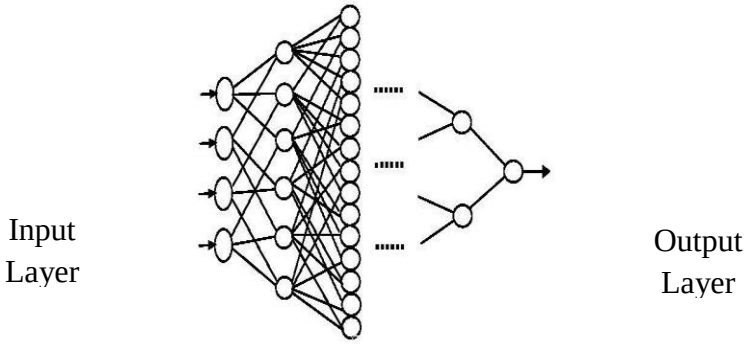

Fig3. Basic structure of PNN

RESULT AND DISCUSSION

Medical diagnosis by neural network is the black – box approach. Associative Neural Network and Polynomial Neural Network represent an efficient tool for the diagnosis of kidney health function and its classification. The ASNN is trained with 10 inputs. After successful training, the system is able to diagnosis the unknown cases and make prediction. The selected attributes involved for training (10 input parameters) are given in table -1.

Table 1.The selected attributes involved for training (10 input parameters)

Attribute	Description
1. Age	1. Age
2. Sex	2. 0 = female, 1=male
3. DM	3. Diabetes Mellitus
4. Hyp	4. Hypertension
5. Obs	5. Obesity
6. PCR	6. Polymer Chain Reaction
7. Hem	7. Hemoglobin
8. Chol	8. Cholesterol
9. Cre	9. Serum Creatinine
10. eGFR	10. eGFR (mg/dl)

The output attribute is considered as Class 1 (increasing and high GFR), Class 2 (Normal with increasing GFR), Class 3 (Mild kidney damage), Class 4 (Mild – moderate kidney damage), Class 5 (Moderate- severe kidney damage), Class 6 (Severe or rigorous kidney damage), Class 7 (Kidney failure or Chronic). The input attribute eGFR is considered with the other attributes. Class- 1 (High eGFR) (GFR ≥ 105), Class- 2 Normal (GFR 90 - 104), Class- 3 Mild (GFR 60 - 89), Class- 4 Mild moderate (GFR 45 - 59), Class- 5 Moderate severe (GFR 15 - 29), Class 7 Chronic (GFR ≤ 15). The Categorization of Kidney Disease by severity is shown in table 2.

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Table 2.Categorization of Kidney Disease

Class	Description	Categorization by Severity byGFR(ml/min/1.73m^2)
1	Increased and high GFR	GFR ≥ 105
2	Normal with increasing GFR	GFR of (90 – 104)
3	Mild kidney damage	GFR of (60 - 89)
4	Mild- moderate kidney damage	GFR of (45 – 59)
5	Moderate-severe kidney damage	GFR of (30 – 44)
6	Severe or Rigorous	GFR of (15 – 29)
7	Chronic or kidney failure	GFR of ≤ 15

The dataset has 150 samples. 100 samples are availed in learning neural network as shown in table 3 while 50 samples are availed in the network testing process (Table4). The selected attributes listed in table 3 are applied to the ASNN and PNN for training. During the training process 10, 8 and one attributes (neurons) are involved in the input, hidden and output layers respectively for 100 data sets. The numbers of hidden layers are varied accordingly in order to choose the network that is better in performance. Out of different configurations tested it is observed that best results for the diagnosis and classification of kidney diseases is arrived with eight neurons in its hidden layer. Seed number is used in to start sequence of random numbers for initialization of neural network weights and partition of initial training set data on training/test sets. The architecture of neural network is shown in Table 5.

Table 3. Training set with input parameters and output classification

S.No	Age	Sex	Dia	Hyp	Obs	PCR	Hem	Chol	Cre	eGFR	Actual Class	Class ASNN	Class PNN
1	67	1	0	0	0	1.20	12.00	191	380	14.70	7	6.588	6.61
2	64	1	0	1	0	2.40	9.80	198	622	84.30	3	3.347	2.54
3	48	1	0	1	0	2.00	9.80	166	166	41.20	5	4.919	4.74
4	55	1	0	1	0	0.98	8.80	188	290	20.90	6	6.031	6.11
5	67	1	3	0	0	1.00	13.20	182	157	41.00	5	5.118	4.84
6	43	1	0	0	0	0.65	13.00	190	88	87.80	3	3.017	2.3
7	40	1	0	0	0	0.22	9.80	190	340	18.60	6	6.189	6.21
8	60	0	0	1	0	1.42	12.80	175	180	26.50	6	5.773	5.75
9	48	1	3	1	0	1.70	13.70	180	280	22.40	6	6	5.98
10	30	1	0	1	0	2.70	11.40	196	270	25.70	6	5.814	5.68
11	25	0	0	1	0	0.65	8.00	210	290	18.20	6	6.055	6.18
12	42	1	0	1	0	2.19	8.80	380	185	37.20	5	5.198	4.97
13	40	1	3	1	0	2.70	4.80	179	166	42.70	5	5.031	4.62
14	60	0	0	1	0	3.18	11.00	176	550	7.30	7	6.811	7.13
15	70	1	0	1	0	1.15	11.50	185	140	46.30	4	4.474	4.53
16	56	1	0	0	0	2.78	12.60	185	105	67.90	3	3.426	3.28
17	22	0	0	0	0	1.71	8.80	236	85	77.30	3	3.143	2.68
18	27	1	0	1	0	1.10	11.00	196	105	78.80	3	3.143	2.63
19	30	1	0	0	0	2.40	3.80	166	369	17.90	6	6.141	6.22
20	20	1	0	1	1	1.30	8.20	180	80	113.6	1	1.691	1.26
21	58	0	2	3	0	0.25	9.00	188	210	25.3	6	5.894	5.82
22	58	1	0	1	0	0.58	6.00	165	501	39.7	5	5.195	4.88
23	63	1	2	1	0	2.50	16.80	172	651	37.2	5	5.295	5.06
24	18	0	0	0	0	1.67	7.10	180	501	10.4	7	6.793	6.72

25	28	1	0	1	0	1.53	9.40	168	1478	45.1	4	4.367	4.42
26	20	0	0	0	0	2.28	4.80	176	430	33.9	5	5.066	5.09
27	46	0	0	1	0	1.76	9.80	190	260	18.30	6	6.06	6.26
28	22	1	0	0	0	0.16	10.20	168	88	100.00	1	1.701	1.73
29	65	1	1	1	0	0.36	11.00	200	250	24.10	6	5.929	5.93
30	65	0	3	0	0	1.93	9.20	172	88	59.90	4	4.074	3.74
31	25	0	0	1	0	4.20	5.20	188	330	15.70	6	6.151	6.36
32	62	0	0	1	0	1.50	10.80	170	280	15.20	6	6.191	6.55
33	40	1	0	0	0	1.80	12.00	182	160	44.70	4	4.401	4.5
34	63	1	0	1	0	0.30	10.80	196	120	56.82	4	4.113	3.9
35	60	1	0	1	0	0.30	11.00	177	170	38.20	5	5.03	4.98
36	51	1	1	0	0	1.10	13.00	182	530	10.60	7	6.727	6.84
37	51	0	2	1	0	0.95	10.20	150	316	33.8	5	5.11	5.23
38	50	1	0	0	0	2.74	8.40	171	320	39.3	5	5.07	4.87
39	40	1	0	1	0	0.62	13.20	182	360	38.2	5	5.081	4.9
40	62	1	0	1	0	1.60	12.60	196	200	31.40	5	5.371	5.43
41	27	0	0	1	0	1.69	12.60	195	330	15.40	6	6.129	6.39
42	57	0	1	1	0	1.51	9.10	189	190	25.20	6	5.844	5.82
43	42	1	0	1	0	0.85	11.50	168	490	12.09	7	6.635	6.7
44	40	1	0	0	0	0.98	13.20	190	430	14.20	7	6.632	6.53
45	32	1	0	1	0	2.20	11.00	195	330	20.10	6	6.056	6.07
46	32	0	0	1	0	3.92	8.80	166	330	14.90	7	6.518	6.45
47	25	1	0	1	0	0.70	8.20	166	380	18.00	6	6.07	6.19
48	60	1	0	0	0	0.30	11.00	180	200	31.60	5	5.283	5.41
49	39	1	0	0	0	0.55	13.00	168	732	7.70	7	6.805	7.01
50	49	1	3	0	0	2.20	13.20	175	330	18.51	6	6.133	6.26
51	40	0	0	0	0	2.65	10.80	178	88	66.13	3	3.329	3.3
52	35	1	0	0	0	2.00	7.20	176	180	39.90	5	4.936	4.77
53	28	1	0	1	0	1.31	12.00	206	299	23.30	6	5.943	5.83
54	36	0	0	0	0	4.04	12.10	206	115	49.30	4	4.209	4.21
55	30	1	0	1	0	0.40	13.80	172	875	6.63	7	6.858	7.05
56	57	1	0	0	1	2.40	12.80	165	88	82.90	3	3.336	2.58
57	61	1	0	1	0	0.18	12.10	192	250	24.60	6	5.894	5.88
58	30	1	0	0	0	3.56	11.00	182	220	32.70	5	5.214	5.21
59	37	1	0	1	1	0.30	10.80	179	350	18.30	6	6.035	6.22
60	60	1	0	1	0	2.15	9.70	206	410	13.80	7	6.577	6.65
61	56	1	3	2	0	3.83	7.20	170	410	14.00	7	6.721	6.61
62	44	1	0	1	0	0.74	12.60	180	190	35.90	5	5.14	5.06
63	45	1	0	1	0	0.18	11.50	208	260	24.70	6	5.885	5.81
64	30	0	1	1	0	1.95	13.80	188	200	27.00	6	5.795	5.59
65	30	0	0	1	0	2.80	7.80	191	360	13.70	7	6.549	6.53
66	30	1	0	0	0	2.40	3.80	166	269	25.80	6	5.843	5.67
67	52	1	1	1	0	1.18	11.00	183	95	77.20	3	3.296	2.81
68	57	1	0	0	0	1.78	10.20	196	430	13.20	7	6.663	6.68
69	37	0	3	0	0	3.78	8.80	260	95	61.40	3	3.581	3.54
70	40	1	0	0	0	0.31	9.80	165	510	11.68	7	6.716	6.72
71	59	0	0	0	0	2.70	7.80	162	1500	8.19	7	6.862	7.06
72	53	1	1	1	0	2.10	8.20	186	320	18.91	6	6.122	6.25
73	48	1	0	0	0	0.76	10.80	180	470	12.36	7	6.683	6.7
74	40	0	3	1	0	2.44	11.80	165	130	41.91	5	5.043	4.67
75	35	1	0	0	0	1.47	9.20	195	710	8.17	7	6.84	6.96
76	48	1	0	2	0	1.17	9.80	177	809	6.59	7	6.85	7.13
77	13	0	0	1	0	1.34	9.40	196	600	9.02	7	6.734	6.8
78	25	1	0	1	0	1.14	12.60	196	270	26.70	6	5.754	5.59

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79	26	1	0	1	0	3.38	8.80	180	350	19.70	6	6.06	6.08
80	45	0	1	1	0	3.18	11.00	185	90	63.10	3	3.379	3.48
81	42	0	1	1	0	0.27	12.60	190	85	67.80	3	3.241	3.23
82	24	0	0	1	1	1.42	12.80	180	260	20.80	6	5.98	5.99
83	36	0	0	1	0	1.50	13.90	208	320	15.18	6	6.146	6.44
84	60	1	1	1	0	0.28	13.60	178	88	36.1	5	5.107	5.12
85	45	1	3	1	0	2.10	5.20	175	563	10.1	7	6.751	6.86
86	46	0	0	3	0	1.35	10.80	173	387	11.5	7	6.721	6.76
87	52	1	0	1	0	2.50	9.80	170	350	17	6	6.208	6.38
88	74	1	3	1	0	2.00	9.20	166	825	2.90	7	6.913	7.53
89	34	1	0	1	0	1.20	11.50	165	380	16.90	6	6.206	6.31
90	53	1	1	1	0	2.10	8.20	186	320	18.90	6	6.105	6.25
91	70	1	0	1	1	0.23	9.80	188	270	21.70	6	5.922	6.12
92	56	1	0	1	0	0.38	15.00	201	300	20.10	6	6.107	6.18
93	66	1	2	1	0	0.50	14.20	188	88	80.50	3	3.288	2.72
94	40	1	0	2	0	0.30	11.00	170	536	11.01	7	6.687	6.77
95	60	0	0	0	0	1.94	9.20	190	350	12.30	7	6.621	6.76
96	55	1	2	2	0	1.00	7.80	186	710	7.40	7	6.85	7.1
97	20	0	0	1	0	1.00	7.80	192	190	31.20	5	5.085	5.26
98	53	0	0	1	0	0.12	11.50	196	565	7.20	7	6.811	7.11
99	58	1	0	1	0	0.20	12.00	186	170	38.40	5	5.031	4.96
100	55	1	0	1	0	2.20	9.80	182	360	16.30	6	6.237	6.44

Table 4.Testing set with input parameters and output classification

S.No	Age	Sex	Dia	Hyp	Obs	PCR	Hem	Chol	Cre	eGFR	Actual Class	Class ASNN	Class PNN
1	53	1	2	1	0	2.80	7.80	166	704	7.59	7	6.757	7.08
2	60	1	1	1	0	1.22	13.90	162	450	12.41	7	6.527	6.75
3	72	1	0	1	0	0.25	12.80	195	200	30.4	5	5.542	5.54
4	33	1	0	1	0	1.28	14.00	199	380	17	6	6.314	6.3
5	60	0	0	1	0	0.30	11.00	178	110	46.7	4	4.373	4.46
6	59	1	2	1	0	1.46	9.40	185	450	34.7	5	5.376	5.2
7	65	1	0	1	0	1.51	11.00	200	340	16.80	6	6.334	6.45
8	54	1	3	1	0	0.97	13.20	180	88	83.80	3	3.106	2.52
9	49	1	3	3	0	1.30	5.50	186	888	5.90	7	6.93	7.19
10	65	1	0	0	0	1.80	10.20	181	580	9.10	7	6.86	7.02
11	52	0	0	0	0	0.72	10.20	185	470	9.02	7	6.743	6.97
12	28	0	0	1	0	3.00	7.20	182	350	14.40	7	6.386	6.47
13	35	1	0	0	0	1.40	12.00	210	95	83.70	3	2.925	2.45
14	65	1	0	0	0	0.75	8.20	179	350	3.95	7	6.946	7.41
15	65	1	2	1	0	2.02	8.20	170	550	9.68	7	6.68	6.97
16	54	1	2	1	0	1.67	8.80	192	120	58.60	4	4.043	3.76
17	28	1	0	1	0	0.37	10.20	188	732	8.20	7	6.788	6.93
18	51	1	0	1	0	1.10	12.06	166	200	32.72	5	5.286	5.3
19	22	0	0	1	0	2.00	12.80	185	334	15.90	6	6.248	6.33
20	57	1	3	0	0	1.08	13.00	200	88	82.94	3	3.049	2.57
21	19	0	0	0	0	1.82	8.20	195	180	33.58	5	5.025	5.1
22	75	1	0	1	0	2.40	10.20	176	190	64.00	3	3.851	3.56
23	50	1	0	0	0	3.43	10.80	179	710	7.60	7	6.842	7.07
24	60	1	0	0	0	2.09	7.10	169	180	33.70	5	5.352	5.27
25	29	0	0	1	0	1.76	7.80	185	360	13.80	7	6.385	6.51
26	62	1	0	0	0	2.65	10.80	172	550	9.70	7	6.764	6.96
27	55	1	0	0	0	0.06	13.00	176	130	52.90	4	4.124	4.08

28	60	1	2	1	0	2.00	12.80	236	80	91.63	2	2.09	2.22
29	60	0	1	1	0	1.90	11.50	141	84	63.87	3	3.578	3.5
30	48	1	1	1	0	2.30	9.80	275	200	33.13	5	5.47	5.26
31	45	1	0	2	0	1.20	9.80	195	390	15.52	6	6.383	6.46
32	35	1	0	0	0	2.13	14.20	161	1300	4.07	7	7.016	7.27
33	56	1	1	1	0	1.37	15.00	172	110	64.20	3	3.676	3.47
34	60	0	2	0	0	0.04	11.40	165	140	35.51	5	5.175	5.15
35	55	1	0	1	0	0.56	11.50	173	210	30.51	5	5.453	5.46
36	75	1	2	0	0	0.57	10.30	185	450	11.86	7	6.646	6.85
37	50	0	3	2	0	1.85	9.20	188	220	29.52	5	5.803	5.5
38	25	0	0	1	0	1.89	11.60	196	88	72.70	3	3.049	2.91
39	55	0	3	1	0	0.87	12.10	180	88	61.90	3	3.88	3.59
40	50	1	0	0	0	0.66	12.00	182	370	16.10	6	6.436	6.44
41	65	1	0	0	0	0.68	8.80	186	240	25.20	6	5.91	5.86
42	31	1	0	1	0	1.10	13.00	168	105	76.60	3	3.145	2.75
43	21	0	0	1	0	0.45	13.00	185	88	75.30	3	2.872	2.77
44	42	0	1	1	0	0.27	12.60	172	85	67.80	3	3.311	3.23
45	60	0	1	1	0	2.10	8.20	163	290	15.3	6	6.368	6.54
46	40	1	0	1	0	0.44	12.60	164	310	43.1	5	4.723	4.59
47	51	0	1	1	0	1.87	10.20	206	80	13.4	7	6.395	6.64
48	45	0	0	1	0	0.91	8.40	190	510	8.4	7	6.705	6.98
49	42	1	0	0	0	1.20	9.20	188	270	36.5	5	5.138	5.01
50	59	1	2	0	0	1.90	8.80	190	105	33.6	5	5.301	5.27

Table 5.Architecture and Specification of the generated ASNN

No. of nodes in the input layer	10
No. Of nodes in the hidden layer	8
No. of nodes in the output layer	1
Seedvalue	78
Activationfunction	Logistic 1/(1+exp(-x))

Table 6 Statistical comparison of classification of kidney dysfunction obtained using ASNN and PNN

Data set	ASNN				PNN	
	R^2	Q^2	RMSE	R^2	Q^2	RMSE
Training	0.987	0.969	0.2508	0.955	0.955	0.3038
Testing	0.951	0.934	0.4084	0.958	0.954	0.3436

After the training process the ability of classifications of the model is estimated from an external set data which is not included in the set of training data. The test data includes 50 instances. The output of the trained neural network is computed from the input test data. The computed classification of kidney dysfunction based on the GFR (for 50 patients) using the ASNN given in Table-4. From theTable-4, it is observed that,0 patient is in Class-1, 1patient is in Class-2, 11 patients are in Class-3, 3 patients are in Class-4, 12 patients are in Class-5, 7 patients are in Class-6, 16 patients are in Class-7.

The data set used in ASNN is also applied to Polynomial Neural Network (PNN) for comparative study. The PNN represents a new challenge for development of medical data prediction methods. It should be noted that, predictive ability of the PNN model is enhanced by varying number of variables in the polynomials. Numbers of iterations are increased until

convergence is achieved. Degree of polynomial represents number of terms in the polynomial equation that will be used in model selection. The present work involves second order polynomial equation to produce the best result. This result is achieved in 50 iterations.

The risk evaluation of CKD is classified into 7 classes. In class1 (GFR> =105) the kidney filtration rate is high and increased GFR.In class 2(GFR 90-104) where there is a damage to the kidney with increased or normal level of GFR is treated with conditions of comorbid. In comorbid treatment conditions the course of therapy is with interventions in such a way that the progression of the disease is suppressed simultaneously reducing the risk factors of cardiac diseases. In class 3 (GFR 60-89) the kidney is damaged with mildly decreased GFR, it indicates the estimation of diseases progression. At class 4 (GFR 45-59) it shows moderately decreased GFR and class5 (GFR 30-44) which indicates moderate-severedecrease inGFR. At that stage, it results in assessment and therapy for the disease complication.In class 6 (GFR 15-29) it points out a severely affected GFR and there is a need for preparation for kidney transplantation. In class 7 (GFR < 15) it is a clear indication of permanent damage of failure of kidney. Kidney transplantation is recommended also in cases of uremia.

The key factors that give a room for kidney related diseases are hypertension and diabetes mellitus. When detected at an earlier stage in cases of diabetes with hypertension we have better medical procedures that can recover the patient from progressive renal failures. The medications used for lowering hypertension, suppresses the advancement of renal diseases. The medicines like ACE (Angiotensin converting enzyme) and ARBs (Angiotensin Receptor Blockers) have demonstrated the effective suppression of disease advancement. Patients undergoing the antihypertensive therapy are advised to have diet with low protein in order to slow down or recover the patient from CKD. For diabetic patients with initial stage of CKD control of blood sugar level using medications was observed to have better results in controlling CKD. In Patients where there is no control of advancement of CKD even with above suggestive course of therapies the only way out is the transplantation of kidney.

Performance evaluation

The developed model is evaluated for its stability using leave one out cross validation method of statistical analysis. The square of correlation coefficient of cross validation (q^2) is used to measure the models classification ability. A good correlation is obtained with LOO correlation co-efficient q^2 =0.969 for training and 0.934 for testing. So the classification power of the ASNN model is very significant. The cross-validated results are included in Table 6.

The accuracy of classification is evaluated by using four parameters squared correlation co-efficient (R^2), Mean Square Error, root mean square errors (MSE and RMSE) and classification accuracy.MSE is the average of the square of the variation between the output and targets. Lower the value, better the results and a zero value indicates no error. The squared correlation co-efficient (R^2) measures how well the predicted values from the output of the network “fit" with the actual data. The value of R^2lies between 0 and 1. A correlation co-efficient greater than 0.9, is generally described as strong model, whereas a

correlation co-efficient less than 0.5, is generally described as weak model. High value ofR^2 and low value of RMSE or MSE indicated a more stable model. The classification accuracy Ai of a model depends on the number of data items correctly classified and is evaluated by the formula:

$$Ai = \frac{t}{n} \times 100$$

External validation

After the Cross-validation process, predictive ability of the developed model is estimated from peripheral test set that was not included in the set of training data. The classification using ASNN is given in Table 4. The quality of classification is evaluated by using two parameters: squared correlation co-efficient (R^2) and RMSE. The high value of R^2 and low value of RMSE indicated a more stable model. The statistical performance of the Associative Neural Network is summarized in Table 6. The Root mean square errors of ASNN model for training and testing are 0.2508 and 0.4084 respectively. Figure 4 and 5 show scatter plot of the ASNN actual versus Predicted classification for training and test set. Squared coefficient of correlation (R^2) of 0.987for training and 0.951for testing confirms the suitability of the ASNN model and shows a good agreement of ASNN classification with actual one.

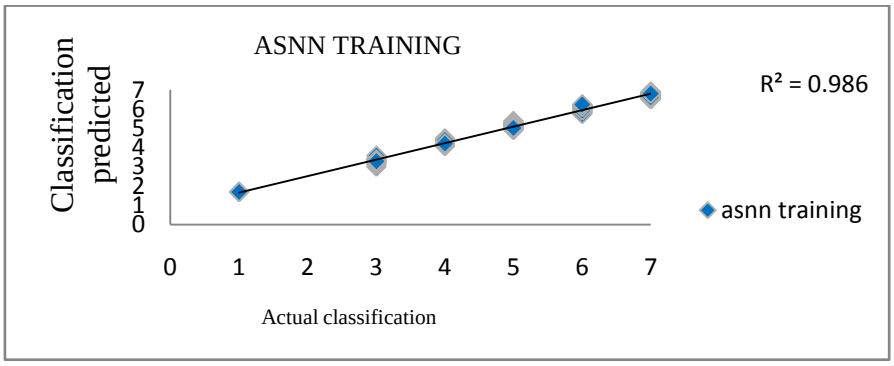

Fig 4. Actual vs predicted values of ASNN training set

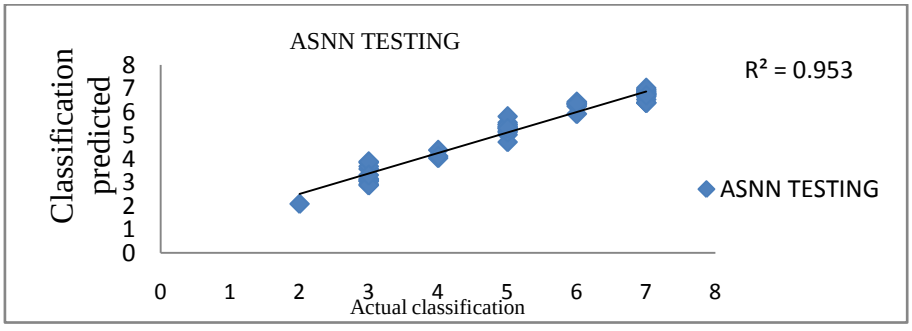

Fig5. Actual vs predicted values of ASNN testing set

The data set used in ASNN is also applied to Polynomial Neural Network (PNN) for comparative study. The PNN represents a new challenge for development of medical data prediction methods. It should be noted that, predictive ability of the PNN model is enhanced by varying number of variables in the polynomials. Numbers of iterations are increased until convergence is achieved. Degree of polynomial represents number of terms in the polynomial equation. The present work involves second order polynomial equation which

includes 22 square and cross terms of input data produce the best result. This result is achieved in 50 iterations.

Table 3 and 4 gives the classification for training and test set using the best fitted polynomial equation. Figure 6 and 7 shows actual classification and PNN classification for both Training and Test set. The statistical performance of PNN analysis is included in Table 6. Squared correlation coefficient of 0.955for training and 0.958 for testing confirms the classification ability of PNN but accuracy is less compared to ASNN classification model.

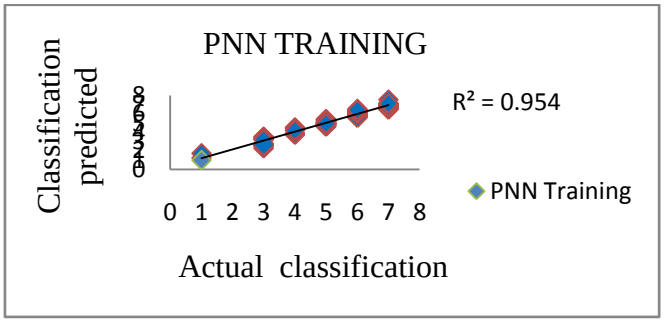

Fig6. Actual vs predicted values of PNN training set

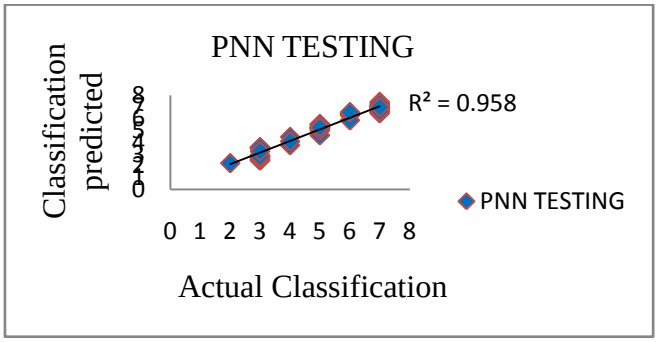

Fig7. Actual vs predicted values of PNN testing set

CONCLUSION

The results in this paper clearly show the diagnosis and classification of kidney dysfunction with better statistics than other models reported in other literatures. The ASNN with 10-8-1 architecture produces low classification error. By using ASNN statistically significant classification model with the squared correlation coefficient (R^2) values of 0.987 for testing and 0.951 for testing. On the same data another classification model is developed on PNN which classify kidney dysfunction into five stages based on severity levels of CKD with squared correlation coefficient (R^2) 0.955for training and 0.958for testing. The obtained results in this study reveal that the ASNN classification is better than PNN. The results of this work indicate that it is possible to diagnosis and classify Kidney disease patients and give treatment accordingly. It is also proved that the diagnosis and classification using the ASNN and PNN are more ideal, dependable and trustworthy to the doctors for getting clinical clues and ideas regarding the therapy and medications according to the severity of suffered patients and progression of CKD.

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