Diagnosis of Chronic Kidney Disease Using ANFIS, FF-ANFIS and GWO-ANFIS Algorithms

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Abstract
Chronic kidney disease (CKD) has subtle characteristics in its early stages that may delay identification. Early identification can assist to slow or stop kidney disease from progressing. The current study introduces an expert based on adaptive neuro-fuzzy inference system (ANFIS) to predict the presence or absence of CKD. Furthermore, the suggested system's training parameters were fine-tuned using the firefly (FF) and grey wolf optimization (GWO) algorithm to improve its accuracy. The results show that the GWO optimised ANFIS model is more effective at predicting CKD, with a 95.83% accuracy rate and a root mean square error (RMSE) of 0.2236.

Keywords:
Chronic Kidney Disease, Infinite Feature Selection, Adaptive Neuro-fuzzy Inference System, Firefly, Grey wolf optimization.

1. INTRODUCTION

The kidney is a vital body organ that filters all wastes and water from the human body to produce urine. Chronic Kidney Disease (CKD), also known as chronic renal disease or chronic kidney failure, is a life-threatening condition caused by the kidney's inability to fulfill its normal functions. It is a worldwide health concern that causes a constant decline in Glomerular Filtration Rate (GFR) for a period of 3 months or longer. Hypertension and hyperglycemia are the leading causes of the disorder. If CKD has progressed to the end stage, the only options for saving a patient's life are dialysis or a kidney transplant [1].

With the advancement of computer technology, intelligent approaches and algorithms have begun to play an increasingly important role in difficult and unpredictable medical tasks like disease diagnosis. The literature on the use of intelligent approaches in medicine has seen an immense number of similar studies during the previous decade [2]. Computer-assisted applications and methods for patient diagnosis and therapy appear to be a more recent topic of focus. Furthermore, because medical diagnosis is fraught with uncertainty, health professionals are turning to computerized technologies to aid with diagnosis and opinions. Fuzzy logic and neural networks, on the other hand, are effective approaches for coping with these uncertainties [3]. As mentioned in [3] both of them have advantages over traditional methods when dealing with ambiguous data or prior information. Individual application of these two strategies, however, can result in various flaws, as documented in [3]. At this moment, neuro-fuzzy integration is a hybrid intelligent system that blends the strength of fuzzy logic's human-like reasoning approach with neural networks' connectionist architecture.

When the literature is investigated, it can be easily seen that there exist limited number of studies based on ANFIS methodology. **Yadollahpour et al [4]** introduced an expert medical decision support system (MDSS) based on ANFIS to predict the timeframe of kidney failure. The MDSS's main system was an ANFIS model of the Takagi-Sugeno type that predicted Glomerular filtration rate (GFR) values as a biological marker of kidney failure. The model was built using 10-year patient information of clinically diagnosed CKD patients and a GFR threshold of 15 cc/kg/min/1.73 m2 as a biomarker of kidney failure. The ANFIS model used the weight, diastolic blood pressure, and diabetes mellitus as underlying diseases, and present GFR (t) as the variables of the predicting model to forecast GFR levels at future intervals after evaluating 10 parameters. The model was then given a user-friendly graphical user interface in MATLAB, where the user can input physical indicators acquired from patient observations to calculate the kidney failure time as an output. When the MDSS was tested against real data from male and female CKD patients, it was shown that it could accurately estimate GFR fluctuations in all sequential periods of 6, 12, and 18 months, with a normalized mean absolute error of less than 5%. **Damodara et al. [5]** demonstrated an early prediction model for kidney diseases using ANFIS. This model determines the phases of kidney disease so that appropriate treatment can be given based on the severity of the disease. The ANFIS CKD stage estimation model developed in the MATLAB has a 94% accuracy rate in terms of actual output to predicted output. **Subhashini and Jeyakumar [6]** introduced E-ANFIS (Enhanced Adaptive Neuro-fuzzy Inference Systems), an artificial intelligence technique that combines ALO and ANFIS to overcome the incidence of local minima and maxima in identifying kidney disease development. The Ant Lion Optimizer was used to increase the performance of ANFIS. This improved ANFIS was utilized to determine the stage of CKD progression. The proposed technique was tested on the MATLAB/Simulink platform and evaluated against ANFIS, fuzzy, and ANN, which are all known techniques. When comparing the newly presented E-ANFIS to other already existing algorithms, the acquired performance in terms of accuracy, recall, precision, F-measure, and specificity revealed that the newly introduced E-ANFIS is the preferred approach. **Kerian et al. [7]** applied Neuro-fuzzy algorithm to determine the risk of CKD in patients. The accuracy of predictions made with neuro-fuzzy was 97%. Prediction for CKD disease was accomplished utilizing selected variables in order to determine the risks. The prediction's results were grouped to determine the percentage of subjects with high risk of kidney disease that also had a higher chance of being diabetic. Three clusters were generated using hierarchical clustering, indicating a substantial link between CKD and diabetes. **Tangri et al. [8]** used demographic, clinical, and laboratory information from two separate Canadian patient cohorts with CKD stages 3 to 5 who were sent to nephrologists to create and validate prediction models. Models were constructed using Cox proportional hazards regression techniques, and discrimination, calibration plots, and the Akaike Information Criterion for fit of the model, and net reclassification improvement were assessed at 1, 3, and 5 years using C statistics and incorporated discrimination advancement. Age, sex, predicted GFR, albuminuria, serum calcium, serum phosphate, serum bicarbonate, and serum albumin were all included in the most appropriate prediction. The said model was more reliable in the validation cohort than a simpler model that included age, sex, estimated GFR, and albuminuria. ANFIS has been widely used in predicting the status or progression of CKD, according to a review of recent literature. These studies found that using ANFIS in conjunction with clinical specialist knowledge and diagnosis can significantly decrease diagnostic errors.

Early detection of CKD is critical for slowing or even stopping the progression of kidney impairment. We require a comprehensive model to accurately anticipate the disease's progression because of the CKD's covert character in early stages, the uncertainty regulating CKD's status, and progression caused by dynamic elements of the human body.

To our knowledge, no study has used the firefly (FF) and grey wolf optimization (GWO) algorithms to fine-tune the parameters of ANFIS in order to construct a decision support system for predicting the presence or absence of CKD. As a result, we propose three decision support systems for identifying CKD and NON-CKD participants in this study: ANFIS, FF-based ANFIS (FF-ANFIS), and GWO-based ANFIS (GWO-ANFIS).

The paper is organized as follows: Section 2 elaborates the data analysis of this work and describes the detailed methodology of the proposed firefly (FF) and grey wolf optimization (GWO) based ANFIS models. In section 3, the results of the developed models are discussed, as well as their comparison in terms of accuracy and RMSE. Section 5 contains the study's concluding remarks.

2. MATERIALS AND METHODOLOGY

2.1 Dataset

In this study, we used data from the University of California, Irvine (UCI) data repository known as Chronic_kidney_disease Dataset [9]. The dataset contains 400 observations with missing or noisy data. There are 250 CKD patients records and 150 NON-CKD patients records in the database. Therefore, 62.5 % of subjects have CKD, while 37.5 % do not. The dataset was recorded from the subjects ranging in the age from 2 to 90 years. Therefore, there are 24 characteristics in the CKD dataset containing 11 numeric and 13 nominal features, as well as the 25th feature that indicates the CKD status. A description of the CKD dataset is shown in table 1.

Table 1: Description of CKD dataset.

S. No.	Attribute	Description	Type	Permissible values
1.	Age	Patient's age	Numerical	in years
2.	Bp	blood pressure	Numerical	in mm/Hg
3.	Sg	specific gravity	Nominal	(1.005,1.010,1.015,1.020,1.025)
4.	Al	Albumin	Nominal	(0,1,2,3,4,5)
5.	Su	Sugar	nominal	(0,1,2,3,4,5)
6.	Rbc	red blood	nominal	normal,

		cells		abnormal
7.	Pc	pus cell	nominal	normal, abnormal
8.	Pcc	pus cell clumps	nominal	present, not present
9.	Ba	Bacteria	nominal	present, not present
10.	bgr	blood glucose random	numeric al	in mgs/dl
11.	Bu	blood urea	numeric al	in mgs/dl
12.	Sc	serum creatinine	numeric al	in mgs/dl
13.	sod	Sodium	numeric al	in mEq/L
14.	pot	potassium	numeric al	in mEq/L
15.	hemo	haemoglobi n	numeric al	in gms
16.	pcv	packed cell volume	numeric al	in cells/cumm
17.	Wc	white blood cell count	numeric al	in cells/cumm
18.	Rc	red blood cell count	numeric al	millions/cm m
19.	Htn	hypertensio n	nominal	yes, no
20.	Dm	diabetes mellitus	nominal	yes, no
21.	Cad	coronary artery disease	nominal	yes, no
22.	appet	Appetite	nominal	good, poor
23.	Pe	pedal edema	nominal	yes, no
24.	Ane	anaemia	nominal	yes, no
25.	class	Class	nominal	CKD, NON-CKD

2.2 Infinite Feature Selection (IFS) method

The IFS method is utilized for choosing the optimal feature vectors. A preliminary step of IFS is choosing a fitting length l and energy scores e_l (i) for every feature vector, which is expressed in the equation (1).

$$e_l(i) = \sum_{j\in v} \sum_{p\in p^l_{i,j}} \prod_{k=0}^{l-1} a_{vk,vk+1} = \sum_{j\in v} A^l(i,j) \tag{1}$$

Where, $P^l_{i.\ j}$ corresponds to the set of all paths of length l among the nodes j and i, A^l is characterized as the matrix's power iteration, $A$and$v$ is signified as vertices of the feature vectors. By broadening the path length to infinity, the probability of feature vectors is standardized [10]. Hence, another energy score for each featurefi considers all path lengths including infinity, which is mathematically characterized in the equation (2).

$$e(i)= [\ (\sum_{l=0}^{\infty} \quad A^l)- I\ ]\bar{1} \tag{2}$$

where I is denoted as identity matrix and $\bar{1}$ is represented as column vectors of ones.

In matrix algebra, $\sum_{k=0}^{\infty} \quad X^l$ is represented as the geometric series of matrix X. this series converges to $(I - X)^{-1}$ if p(X)<1, where p(X) is represented as the highest magnitude of the Eigen value of X. Utilizing this property, the standardized energy score for every feature vector is calculated by the equation (3).

$$e^{'}(i)\ [(\ (\sum_{l=0}^{\infty} \quad r^l A^l)- I)\ \bar{1}]_I = [((I-rA)^{-1} - I)\bar{1}]_i \tag{3}$$

The calculation of matrix's power iterations in the equation (1) is decreased by calculating $((I-rA)^{-1} - I)$. The achieved feature values are specified as the inputs for a proposed algorithm.

2.3 GWO algorithm

GWO is an ideological strategy established by Mirjalili in 2014 that shows the hunting mechanism of grey wolves. Grey wolves are members of the Canidae species that loves to stay in packs. The leaders, known as alpha (α), are either male or female and are strictly controlled by society. Betas (β) and delta (δ) wolves are the second order wolves which help alpha wolves in making decisions. The last order of wolves is omega (ω) maintains the relationship and takes care of younger ones.

During the hunting process, the grey wolves are surrounding their prey. Equation (4) and (5) [11] are mathematical models of surrounding behavior:

$$\vec{D} = \vec{C}.\vec{X}_p(t) - \vec{X}(t) \tag{4}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{5}$$

where,

t= Current iteration

$\vec{D}$= Surrounding prey vector

$\vec{A}$, $\vec{C}$= Co-efficient vector

$\vec{X}$= A Grey wolf's position vector

$\vec{X}_p$ = Position vector of the prey

The following equations (6) and (7) demonstrate the calculation of vectors $\vec{A}$ and $\vec{C}$ [12]:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{6}$$

$$\vec{C} = 2.\vec{r_2} \tag{7}$$

where $\vec{r_1}$ and $\vec{r_2}$ are the vectors whose values lies randomly between [0, 1] and $\vec{a}$ components are linearly reduced from 2 to 0 in the iterations [12].

The three optimum outcomes will be recognizedduring the repetitions, and the calculation for the next iteration will be modified based on the earlier three optimum responses. The expressions characterized by equation (8), (9) and (10) [12], [13]:

$$\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| \\ \vec{D}_\beta &= \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta &= \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \end{aligned} \tag{8}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right) \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right) \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \end{aligned} \tag{9}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{10}$$

The convergence of the required optimum solution calculates the recurrence termination of the GWO calculation. Calculating the alpha value achieves the optimal solution, and the value of the resulting alpha location is the variable that will be utilized in the subsequent calculation or stage. If the issue has no constraints, the solution can be acquired by ending the iterative methodology by setting the utmost iteration (t) at the beginning of the calculating process [14].

2.4 FF algorithm

The FF algorithm is a meta -heuristic optimization procedurerecommended by Xin-She Yang,considered by the dazzling movement and the phenomena of bioluminescent interaction of fireflies, that can be employed to enhance the parameters like feed rate, spindle speed andcut depthetc. Since its initiation, FF has acknowledged a lot of consideration and has been utilized in anextensive range of applications. The FF method is both appropriate and easy to utilize. It can also be utilized in a parallel environment. FF algorithms are mainlydefined by: (1) Fireflies are unisexual among fireflies. (2) The attraction is equal to the strength, as all reduce with a range mounting. The lighter one then changes to one of two light bulbs brighter. If there is no lightning higher than a firefly, it can travel at random. (3) The target function setting determines the light of the firefly.

The generations of new solutions are in random fashion and fireflies' attraction [15]. The brilliance of the fireflies should be associated with the objective function of the related problem. Their brightness makes them capable to divide themselves into additional modest groups and each subgroup swarm around the nearby models. In this way, FF algorithm is suitable for optimization problems as specified by [16, 17].

The attractiveness, I of the firefly i on the firefly j depends on the level of the brightness of the firefly and the distance between the firefly i and j is r_{ij} as in equation (11).

$$I(r) = \frac{Is}{r^2} \tag{11}$$

Assume there are 'n' fireflies, and x_i corresponds to the solution for firefly i. The attractiveness of the fireflyisrelatedwiththeobjectivefunctionf(x_i). The attractiveness, I of a firefly is selected to make known its current position of its objective function or fitness value f (x) as in equation (12).

$$I_i = f(x_i) \tag{12}$$

The less attractive firefly is drawn in and moved to the more brilliant one and every firefly has a specific attractiveness value β. In any case, the attractiveness value β is relative dependent on the distance between fireflies. The attractiveness function of the firefly at r=0 is set up by equation (13).

$$\beta = \beta_0 e^{-\gamma r^2} \tag{13}$$

2.5 ANFIS

It is basically a mixture of Fuzzy inference system (FIS) and neural networks (NN), which blends the unambiguous knowledge bases of FIS with the learning ability of ANN. The major goal of ANFIS system is to combine the best characteristics of the fuzzy based systems and NN to provide efficient results. ANFIS is a data learning technique that utilizes Fuzzy Logic to change given inputs into an ideal output through highly interrelated Neural Network processing elements and information connections, which are weighted to map the statistical inputs into an output. It is supposed that the fuzzy inference system has two inputs and one output. The rule base contains the fuzzy if-then rules of Takagi and Sugeno's type [64] as follows:

In the event that x is A and y is B, z is f (x, y)

where A and B are the fuzzy sets in the predecessors and z = f (x, y) is a crisp set in the subsequent. The equivalent ANFIS structure is shown in figure 1.

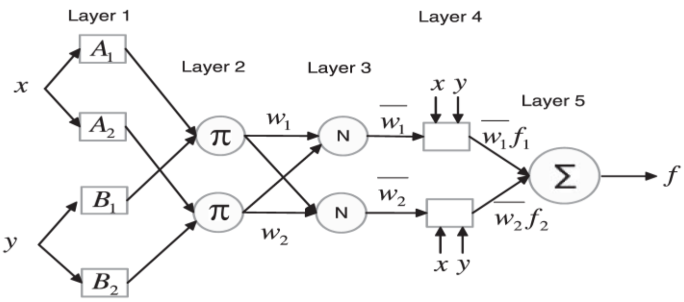

Figure 1: ANFIS structure

However, it has been also observed that the performance of ANFIS classifier may get affected by a variety of parameters which include size and training dataset quality, severity of integrated dataset and factors used as inputs [18]. The identification of CKD necessitates a dynamic framework that really can respond to variations made in the database.

To solve this issue, optimization algorithms can be used that improve the performance of these classifiers. Optimization algorithms help in the improvement of instances because these strategies are simple to use and provide extremely effective outcomes. A large number of optimization algorithms are available presently such as, Particle optimization algorithm (PSO), BAT, Ant colony optimization, grasshopper optimization algorithm, FF, GWO and so on. After conducting the through literature review, it was decided to apply FF and GWO because they are able the enhance the accuracy [19,20].

3. RESULTS AND DISCUSSION

In the data pre-processing phase, the empty cells and NAN values were replaced with the mean values of the rest of the data set. The string values were converted to numerical class to make them understandable for the classifier.

The unsupervised Infinite feature selection strategy examined the data in the feature extraction phase and calculated the weights of each feature, as shown in Table 2, using the alpha-factor, which in the proposed model was 0.82. The more informatics data columns were chosen based on weights. This was accomplished by specifying a weight threshold against which the weights were tested and the selected features were segregated. The mean of the weights of all features was used to define the threshold in the proposed work. The ranks and weights of 24 features are shown in Table 2. Out of the 24 features available, 15 were chosen for CKD prediction.

Table 2: Ranks and Weights of the Features

S. No.	Feature	Description	Rank	Weight
1.	Sc	serum creatinine	12	2.1276
2.	Htn	hypertension	19	0.9515
3.	Bu	blood urea	11	1.9008
4.	Al	albumin	4	1.8975

5.	Su	sugar	5	1.5060
6.	Wc	white blood cell count	17	1.5051
7.	Age	Patient’s age	1	1.3367
8.	Cad	coronary artery disease	21	1.3214
9.	Ane	anaemia	24	1.2615
10.	Bgr	blood glucose random	10	1.2495
11.	Pe	pedal edema	23	1.2164
12.	Pcc	pus cell clumps	8	1.1858
13.	Ba	bacteria	9	0.9964
14.	Bp	blood pressure	2	0.9515
15.	Pot	potassium	14	0.6289
16.	Pc	pus cell	7	0.0788
17.	Dm	diabetes mellitus	20	0.788
18.	Sod	Sodium	13	-0.4497
19.	Rbc	red blood cells	6	-0.4772
20.	Rc	red blood cell count	18	-0.7983
21.	Appet	appetite	22	-0.9822
22.	Pcv	Packed cell volume	16	-1.1657
23.	Sg	specific gravity	3	-1.1681
24.	Hemo	Haemoglobin	15	-1.2123

Following that ANFIS, FF-ANFIS and GWO-ANFIS classifiers were created using 70% training features and 30% testing features. After initial experimental research, Table 3 shows the various parameters and settings for the ANFIS, FF-ANFIS and GWO-ANFIS algorithms.

Table 3: Parameter Settings.

Parameter	Classifier		
	ANFIS	FF-ANFIS	GWO-ANFIS
Type	Sugeno	Sugeno	Sugeno
Number of Clusters	3	3	3
Input membership function type	Gaussmf	-	-
Output membership function type is	Linear	-	-
Exponent for the fuzzy partition matrix U	2	-	-
Maximum number of iterations	100	50	50
Population Size	-	20	50
Lower Bounds of the population	-	-25	-25
Upper Bounds of the population	-	+25	+25
Light Absorption Coefficient base value (gamma)	-	2	-
Attraction Coefficient (beta)	-	2	-
Mutation Coefficient	-	0.1	-

(alpha)			
Mutation Coefficient Damping Ratio	-	0.95	-
Minimum improvement in objective function between two consecutive iterations	1e-5	-	-
Inference method (AND)	PROD	PROD	PROD
Inference method (OR)	PROBOR	PROBOR	PROBOR
Inference method (Implication)	PROD	PROD	PROD
Inference method (aggregation)	SUM	SUM	SUM
Inference method (defuzzification)	WTAVER	WTAVER	WTAVER

The results achieved from the simulation performed in the MATLAB software for three algorithms i.e. ANFIS, FF-ANFIS and GWO-ANFIS were evaluated using accuracy and RMSE, as shown in table 4.

Table 4:

Performance Metrics	**ANFIS**	**FF-ANFIS**	**GWO-ANFIS**
Accuracy	90.8 %	94.1 %	95.83 %
RMSE	0.3838	0.241	0.2236

After examining the table, it is observed that the value of accuracy is highest in case of GWO-ANFIS algorithm whereas the RMSE value is lowest.

4. Conclusion

This study provided insight into the diagnosis of the CKD patients. The dataset was collected from 400 patients containing 24features. The IFS algorithm was used to select the most strongly representative features of the CKD. The selected features were fed into classification algorithms: ANFIS, FF-ANFIS and GWO-ANFIS. the GWO-ANFIS algorithm outperformed on all other algorithms, achieving an accuracy and RMSE value of 95.83 percent and 0.2236 respectively. In the future, we aim to validate our results by using big dataset or compare the results using another dataset that contains the same features.

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