

Simulation, Modeling, and Optimization of Intelligent Kidney Disease Predication Empowered with Computational Intelligence Approaches

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Abstract: Artificial intelligence (AI) is expanding its roots in medical diagnostics. Various acute and chronic diseases can be identified accurately at the initial level by using AI methods to prevent the progression of health complications. Kidney diseases are producing a high impact on global health and medical practitioners are suggested that the diagnosis at earlier stages is one of the foremost approaches to avert chronic kidney disease and renal failure. High blood pressure, diabetes mellitus, and glomerulonephritis are the root causes of kidney disease. Therefore, the present study is proposed a set of multiple techniques such as simulation, modeling, and optimization of intelligent kidney disease prediction (SMOIKD) which is based on computational intelligence approaches. Initially, seven parameters were used for the fuzzy logic system (FLS), and then twenty-five different attributes of the kidney dataset were used for the artificial neural network (ANN) and deep extreme machine learning (DEML). The expert system was proposed with the assistance of medical experts. For the quick and accurate evaluation of the proposed system, Matlab version 2019 was used. The proposed SMOIKD-FLS-ANN-DEML expert system has shown 94.16% accuracy. Hence this study



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concluded that SMOIKD-FLS-ANN-DEML system is effective to accurately diagnose kidney disease at initial levels.

Keywords: Fuzzy logic system; artificial neural network; deep extreme machine learning; feed-backward propagation; SMOIKD-FLS; SMOIKD-ANN; SMOIKD-DEML; SMOIKD-FLS-ANN-DEML

1 Introduction

Kidney is a bean-shaped organ located on either side of the spine, below the rib-cage, and behind the belly. The vital functions of kidney include the detoxification of harmful fluids and toxins (such as urea and creatinine), protection and retention of essential minerals, and maintenance of equilibrium between acidic and basic medium.

Numerous factors are producing influence in kidney dysfunction. Unhealthy dieting habits, over-the-counter painkillers or illegal drugs usage, and natural pollutants are under high consideration. Other medical conditions, such as hypertension, diabetes mellitus, glomerulonephritis, polycystic kidney disease, and kidney stones are susceptible factors that lead to kidney diseases. The impairment infiltration unit of kidney, nephron, may result in kidney failure [1].

There are two types of kidney failures according to duration of disease: Acute kidney failure and chronic kidney disorder (CKD). Acute kidney failure lasts for a few hours or days. This may lead to swollen legs, swollen feet, swollen ankles, decrease urine retention, itching, dyspnea, joint pain, decrease appetite, chest ache, stomachache, and backache. However, proper medical treatment could be functionally reversible the kidney state if there is no other serious medical problem such as hypertension, liver impairment, coronary artery disease, and diabetes, then [2].

Whereas, chronic kidney failure is long-lasting, remains for at least three months. This undergoes permanent kidney failure and patients need dialysis or transplantation of kidney [3]. CKD decreases the life expectancy of an individual by intensifying the risk of cardiovascular diseases, kidney failure, and other underlying complications. The clinical manifestations of early stages of CKD include proteinuria, acute kidney injury, infection, severe pain, kidney stones, and hepatitis C [4].

The frequently increase prevalence of CKD greatly marks the disease as a major issue around the globe. In 1990, CKD was at 27th rank for mortality rate worldwide. Unfortunately, in 2010, the position has risen to 18th rank [5]. Pakistan was affected greatly in 2017 and was at 8th rank. Currently, around 20,000 deaths are reporting every year [6].

The CKD has five stages of kidney damage based on estimated glomerular filtration rate (EGFR). This EGFR measures the extent of waste filtration by kidney nephrons [7]. In the early stages of CKD, kidneys effectively filter out the blood waste due to which symptoms of CKD do not appear. But at the later stages, kidneys work harder to filter out the waste and then stop functioning completely over time. A timely diagnosis of kidney disease makes it easier to cure it on time. The accuracy in diagnosis helps the medical practitioners to prescribe the best therapeutic strategy that greatly increases the chances of patient recovery.

Medical diagnosis is the foremost step in decision making of medical practitioners. For this, various new methods have been introduced by using AI that performs tasks by machines and expands its roots in medical diagnostics. In this FLS, ANN, and DEMML are included. The fuzzy logic controller is widely utilized in the field of medical sciences to design the diagnosis systems with the help of input parameters. These parameters are based on the symptoms of disease

mentioned by the medicinal practitioners. All of the parameters enter into fuzzy input sets to process by the fuzzy controller. These input variables convert into crisp outputs (input or output) which is the easily human-readable result. The fuzzy controller normally uses more than one parameter (symptoms of disease) to provide accuracy in results. It is a complete approach that processes inputs in the inference engine along with the composition [8].

Furthermore, the previous study reveals that in medical diagnosis artificial neural network (ANN) provides a high level of accuracy in the diagnosis. ANN is simulated as a human brain to analyze the complication that previously difficult by a human to evaluate. The automatic update programming of neural network has high accuracy as compared to the previously reported models. But, the forward technique of neural network processes the data differently. In errors, it automatically propagates back and updates back neurons to process data with high accuracy [9–11]. Besides all these, deep extreme machine learning is considered as another approach that accurately diagnoses the disease. It is an advanced version of a neural network. DEML processes the data by utilizing the technique of a neural model with more than one layer in its processing phase to produce more accurate outcomes [12].

2 Literature Review

Various advanced methods have been introduced by using AI to perform tasks by machines and expanding its roots in medical diagnostics. In the pattern recognition process, dealing with uncertainties is a common problem that has been introduced by using a fuzzy set theory [13].

In medical diagnosis, the application of different algorithms and techniques of artificial intelligence have been used. For the diagnosis of hepatitis disease, Karlik [14] investigated the neural Networks and Naive Bayes and suggested that both classifiers produce highly reliable diagnostic performance. Moreover, the Adaptive neuro-fuzzy inference system (ANFIS) is used to invoke neural networks that provided structures for the Fuzzy inference engine (FIE) to diagnose hepatitis B [15]. For cardiomyopathy, a machine learning based expert system has been introduced [16].

Ahmed et al. [17] developed a system for the diagnosis of kidney functionality by using fuzzy logic. The selected input variables in their study were alcohol intake, weight, blood sugar, age, nephron functionality, systolic, and diastolic blood pressure. The impairment of the kidney is measured between the ranges of 0–10 scale. However, the proposed system had some limitations such as, various vital medical factors (glomerular disease, water consumption level, electrolyte level, drugs, inherited kidney disease, and a child born with kidney disease) was not included in the system that produces a significant effect on the kidney functioning directly or indirectly.

Vijayarani et al. [18] designed a classification process that classified kidney disease infection by comparatively analysed SVM and ANN algorithms. Furthermore, Kumar et al. [19] described three ANN algorithms to diagnose kidney stones. They used multilayer perceptron with two hidden layers and the back-propagation algorithm in their proposed model.

However, there was a still essential need to develop computerized models that diagnose kidney disease at earlier stages with accuracy to avert chronic kidney disease and renal failure. In this study, different computational intelligence approaches were applied to diagnose kidney diseases. These computational methods will greatly assist physicians to diagnose renal disorders at its initial levels and even in a non-symptomatic state of patients to prevent them from kidney failure.

3 Proposed Model

The proposed system designed with a trained algorithm to diagnose kidney disease. In first step of SMOIKD-FLS-ANN-DEML system model, data acquisition layer, the raw data was passed on to the pre-processing layer for handling, merging, and normalization. Then the portable standard applied to exclude irregularities in the data from all three layers.

The second step of model, i.e., in prediction layer, the FLS, ANN, and DEML were used as shown in Fig. 1. FLS enabled the system to acquire accurate results from the large data and entailed logical rules. These rules defined by the assistance of medical practitioners. Fuzzy rules were applied to inputs of fuzzy sets and that converted to a fuzzy output. In the ANN and DEML, backpropagation is used to ensure existence of kidney disorder. ANN provided the computational results based on the structure and biological functions of neural networks and employed non-linear and statistical modeling tools for computing the complex relation among inputs and outputs. ANN included several neurons that specifically organized. Neurons were the essential parts of an ANN and had handling features that cooperated to overcome the targeted issue. Whereas, DEML was based on artificial neural networks and algorithms for computer systems to perform a certain task with greater accuracy and certainty.

Followed by data acquisition and prediction layer, performance evaluation layer performed to determine accuracy and miss rates. At last, in the decisive area, the conclusion was made about the diagnosis.

3.1 Fuzzy Based System Model

The SMOIKD-SL-MFIS adroit system consisted of seven input parameters, i.e., Blood urea, Serum creatine (N), Serum sodium, Serum uric acid (M), Serum potassium (A), Chloride, and Total Protein. Each of the parameters coded with two options, i.e., “Yes” and “No” to diagnose the kidney disease shown in Fig. 2.

The value of all seven parameters used to form a lookup table. The proposed intelligent identification of kidney disease by using Mamdani fuzzy inference based adroit system is mathematically written for t-norm as follows:

$$(\mu_{DK}(dk)) = t \left[\left(\mu_{bloodurea}(a), \mu_{\substack{serum \\ creatine}}(b), \mu_{\substack{serum \\ sodium}}(c), \mu_{\substack{serum \\ uricacid}}(d), \mu_{\substack{serum \\ potassium}}(e), \mu_{chloride}(f), \right. \right. \\ \left. \left. \mu_{\substack{total \\ protein}}(g) \right) \right]$$

$$(\mu_{DK}(dk)) = \min \left[\left(\mu_{bloodurea}(a), \mu_{\substack{serum \\ creatine}}(b), \mu_{\substack{serum \\ sodium}}(c), \mu_{\substack{serum \\ uricacid}}(d), \mu_{\substack{serum \\ potassium}}(e), \mu_{chloride}(f), \right. \right. \\ \left. \left. \mu_{\substack{total \\ protein}}(g) \right) \right]$$

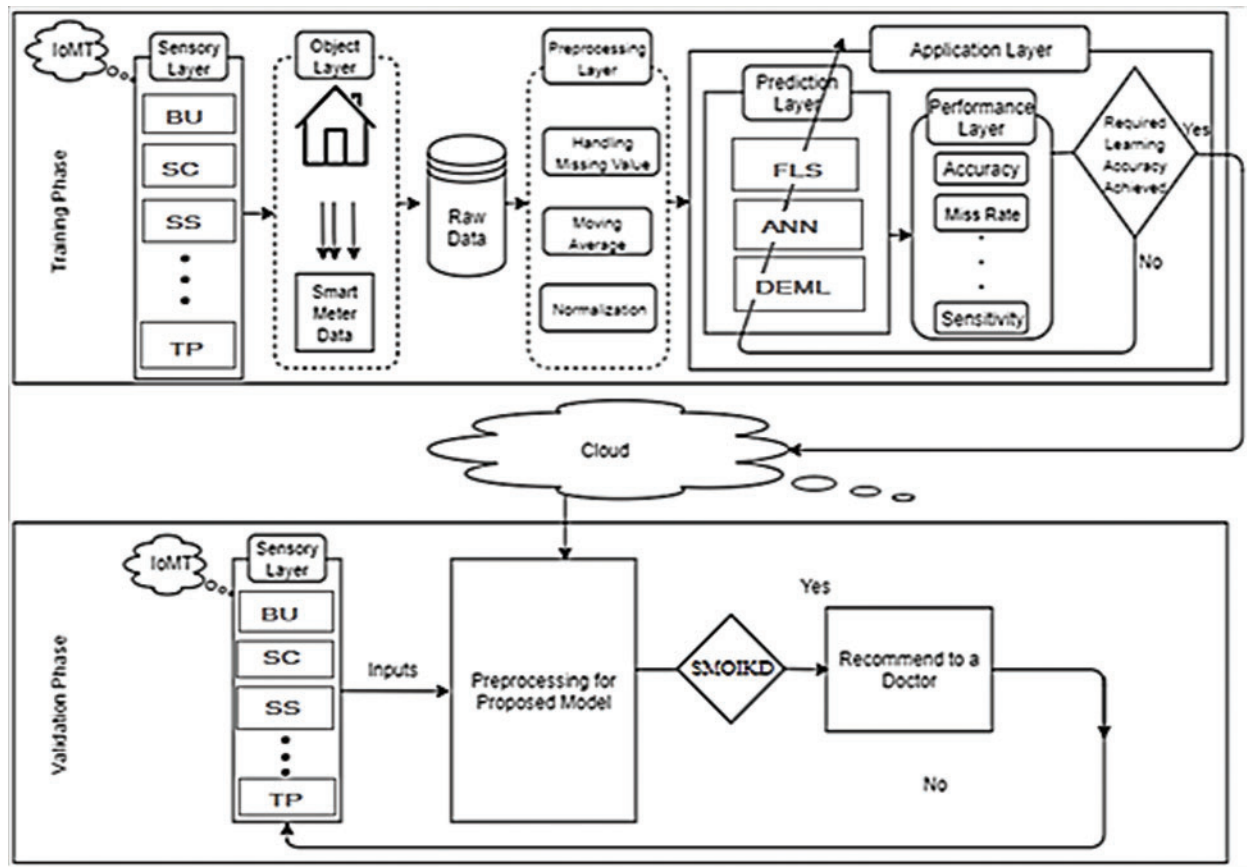


Figure 1: Proposed SMOIKD-FLS-ANN-DEML system model

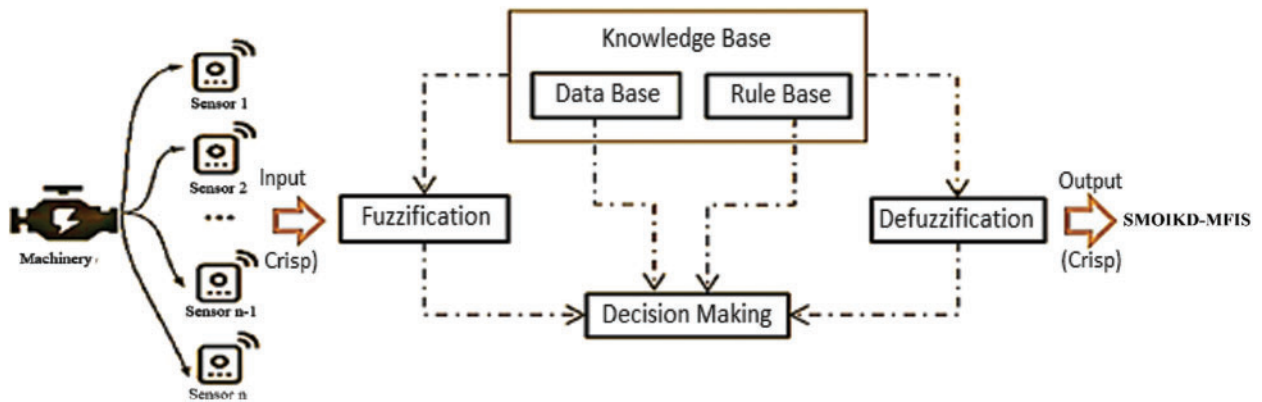


Figure 2: Proposed SMOIKD-SL-MFIS system model

3.1.1 Input Variables

The seven different types of input variables in a different set of ranges were employed. All of these value-driven analytical standards were utilized to evaluate the disease.

3.1.2 Output Variables

In this research, a single layer adroit system was used. The output parameter of proposed model was SMOIKD-SL-MFIS that divided into three categories for diagnosis: Negative, Borderline, and Positive that is shown in [Tab. 1](#).

Table 1: Output variables of proposed SMOIKD-SL-MFIS adroit system

Sr #	O/P parameters	Semantic sign
1	SMOIKD-MFIS	NT BL PT

NT=Negative, BL=Borderline, PT=Positive

3.1.3 Membership Functions

Membership functions were established with the help of medical experts of Shalimar Hospital Pathology Lab, Pakistan. Membership functions of the proposed automated SMOIKD-SL-MFIS adroit system were used to generate the curve values of positive, negative, and borderline output of disease. This dispensed a mathematical form of FLS that is used to compute input and output parameters. Membership functions were established with the help of medical experts of Shalimar Hospital Pathology Lab, Pakistan.

3.1.4 Rules Table

In the proposed SMOIKD-SL-MFIS rules table, the adroit system of 2187 input and output rules were used. All the rules were designed with the assistance of medical experts.

3.1.5 Rule-Based

The proposed input and output rules were based on the SMOIKD-SL-MFIS adroit system. All these rules were essential for input and output variables. The achievement of our adroit system was built by using these rules.

3.1.6 Inference Engine

The inference engine was another main component of this proposed adroit system. The fuzzy inference system was the core unit of a fuzzy-based adroit system that had decision ability.

3.1.7 De-Fuzzifier

De-fuzzifier was another key element of proposed adroit system that mainly comprised of various components. A centroid type of De-fuzzifier was used in this research. This model described the transformation of the fuzzy output (that generated by the inference engine) to frangible by using analogous membership functionalities in contrast to fuzzifier output. [Fig. 3](#) shown the De-Fuzzifier graphical illustrations of the proposed SMOIKD-SL-MFIS adroit system. In [Figs. 3a](#) and [3b](#), the graphical illustrations of the De-fuzzifier of the SMOIKD-SL-MFIS adroit system are presented.

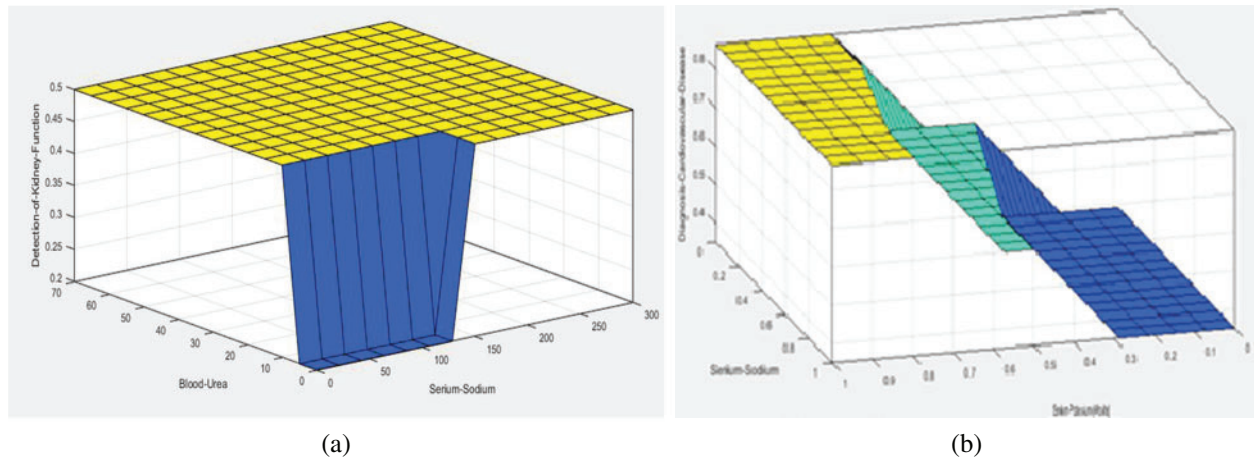


Figure 3: De-Fuzzifier graphical illustrations of proposed SMOIKD-SL-MFIS adroit system. (a) Rule surface for blood urea and serum sodium. (b) Rule surface for total protein and serum sodium

3.1.8 Lookup Diagram

Matlab 2019 tool was used for demonstrating, simulated, algorithm expansion, and prototyping. For the simulation of results, seven inputs and one output of SMOIKD were used. These are shown in Fig. 4.



Figure 4: Lookup diagram for proposed SMOIKD adroit system

3.2 ANN Based System Model

The dataset of kidney comprised of twenty-five variables wherein twenty-four were input variables and one was output variable. These variables were designed according to the symptoms of kidney disease. All the input variables were entered into ANN system. The input layer constituted 24 neurons, the hidden layers constituted 10 neurons and one output layer constituted 2 neurons.

ANN contained neurons that were used to form a complex model. An ANN used in an accurate system and the input system was referred to as the sensory system. The step by step designing of the proposed SMOIKD-ANN system model existed within the sensory system, which consisted of input parameters. To detect the occupancy point, the sensory system passed through the training of the neural system which was a state-of-the-art algorithm.

The neural networks were associated with each other, even in a precise sensory system. The single neuron which was used in the sensory system had segments with a peculiar weight and a single output. The neural network system used backward propagation to diagnose kidney disease. If the kidney disease was identified, then suspected patients referred to the emergency otherwise discarded.

3.3 Deep Extreme Machine Learning System Model

DEML is widely used in many fields for allocation and reversion purposes. DEML is well organized in the rate of computational complication which comprises of three layers, the first one is the input layer, the second is the hidden layer and the last one represents the output layer. The physical model of a DEML is shown in Fig. 5.

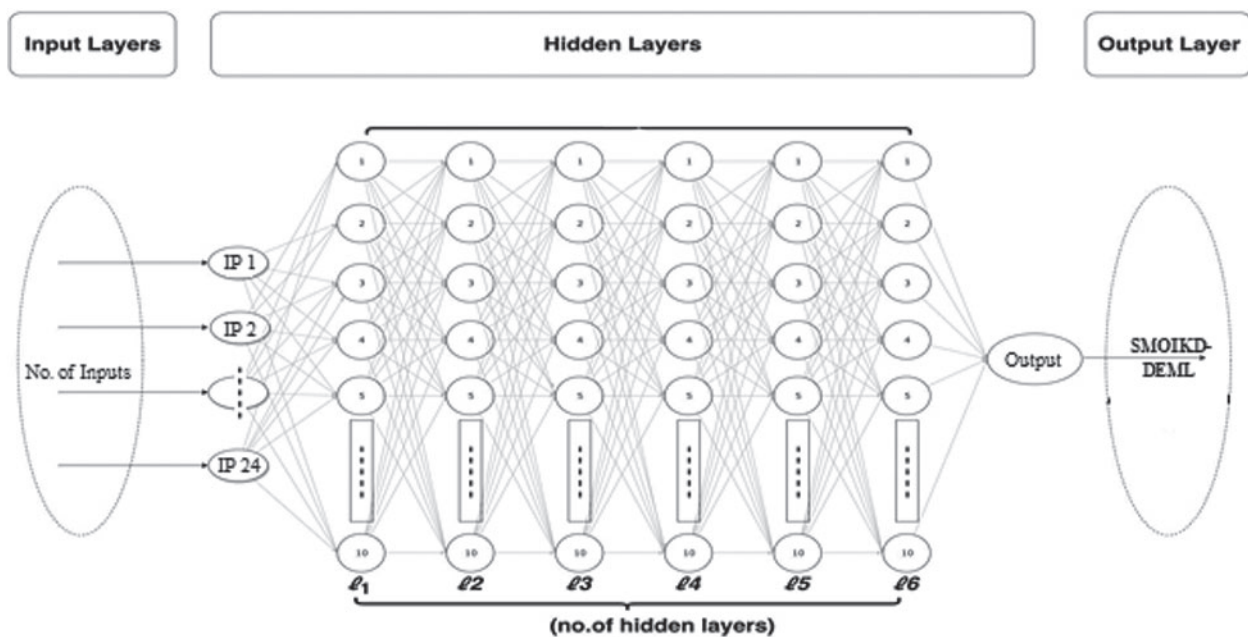


Figure 5: Proposed SMOIKD-DEML system model

In this study, the input layer, hidden layer, and output layer were used in the backpropagation process of the ANN. There were different steps in the backpropagation process, such as weight initialization, feedforward, backpropagation of error, and weight and bias updating. Every neuron in the hidden layer had the activation function $f(x) = \text{Sigmoid}(x)$. The sigmoid function for the first input layer is written as in Eq. (1), and the first layer output is written as in Eq. (2), and the suggested SMOIKD-DELM hidden layer for the sigmoid function is written as in Eq. (3). Activation feature for the output layer is described in Eq. (4).

Feedforward propagation for the input layer or first layer is written in Eq. (1), and the output of the first layer is written in Eq. (2).

$$\chi_j = b_1 + \sum_{i=1}^m (\psi_{ij} * o_i) \quad (1)$$

$$v_j = \frac{1}{1 + e^{-\chi_j}} \quad \text{where } j = 1, 2, 3 \dots o \quad (2)$$

Feedforward propagation for the second layer to the output layer is presented in Eq. (3).

$$\chi_{k^l} = b^l + \sum_{j=1}^n (z_{jk^l} * v_j^{l=1}) \quad (3)$$

The activation feature of the output layer is defined in Eq. (4).

$$v_{k^l} = \frac{1}{1 + e^{-\chi_{k^l}}} \quad \text{where } k = 2, 3 \dots o \quad (4)$$

$$\chi_{k^l} = b^l + \sum_{j=1}^n (z_{jk^l} * v_j^l) \quad \text{where, } l = 1, 2, 3 \dots 6 \quad (5)$$

Error in the back-propagation is written as in Eq. (6).

$$Err = \frac{1}{2} \sum_k (Target_k - v_{k^l=6})^2 \quad (6)$$

where $Target_k$ represents the desired output and v_k is a calculated output.

Eq. (7) reflects the rate of weight shift that is written for the output layer.

$$\Delta \psi \propto -\frac{\partial Err}{\partial \psi}$$

$$\Delta v_{j,k^l=6} = -\epsilon \frac{\partial Err}{\partial v_{j,k^l=6}} \quad (7)$$

It is written by adding the chain rule as in Eq. (8)

$$\Delta v_{j,k^l=6} = -\epsilon \frac{\partial Err}{\partial v_{k^l}} \times \frac{\partial v_{k^l}}{\partial \chi_{k^l}} \times \frac{\partial \chi_{k^l}}{\partial v_{j,k^l}} \quad (8)$$

After implementing the chain rule which substitutes all values of Eq. (8), it is possible to obtain the updated weight value as shown in Eq. (9).

$$\Delta v_{j,k^l=6} = \epsilon (Target_k - v_{k^l}) \times v_{k^l} (1 - v_{k^l}) \times (v_j^l)$$

$$\Delta v_{j,k^l} \in \xi_{k^l} v_j^l \quad (9)$$

where,

$$\xi_{k^l} = (Target_k - v_{k^l}) \times v_{k^l} (1 - v_{k^l})$$

$$\Delta \psi_{i,j^l} \propto - \left[\sum_k \frac{\partial Err}{\partial v_{k^l}} \times \frac{\partial v_{k^l}}{\partial \chi_{k^l}} \times \frac{\partial \chi_{k^l}}{\partial v_{j^l}} \right] \times \frac{\partial v_{j^l}}{\partial \chi_{j^l}} \times \frac{\partial \chi_{j^l}}{\partial \psi_{i,j^l}}$$

$$\Delta\psi_{i,j^l} = -\epsilon \left[\sum_k \frac{\partial Err}{\partial v_{k^l}} \times \frac{\partial v_{k^l}}{\partial \chi_{k^l}} \times \frac{\partial \chi_{k^l}}{\partial v_{j^l}} \right] \times \frac{\partial v_{j^l}}{\partial \chi_{j^l}} \times \frac{\partial \chi_{j^l}}{\partial \psi_{i,j^l}}$$

$$\Delta\psi_{i,j^l} = \epsilon \left[\sum_k (Target_k - v_{k^l}^l) \times v_{k^l} (1 - v_{k^l}) \times (v_{j^l}) \right] \times v_{k^l} (1 - v_{k^l}) \times q_i$$

$$\Delta\psi_{i,j^l} = \epsilon \left[\sum_k \xi_{k^l}(z_{j,k^l}) \right] \times v_{j^l} (1 - v_{j^l}) \times q_i$$

$$\Delta\psi_{i,j^l} = \epsilon \xi_{j^l} q_i$$

where,

$$\xi_{j^l} = \left[\sum_k \xi_{k^l}(z_{j,k^l}) \right] \times v_{j^l} (1 - v_{j^l})$$

The output and hidden layers in Eq. (10) are updating weights and biases between them.

$$z_{j,k^l=6}^+ = z_{j,k^l=6} + \lambda_{c^l=6} \Delta v_{j,k^l=6} \quad (10)$$

In Eq. (11), the weight and bias change between the input layer and the hidden layer is represented.

$$\psi_{i,j^l}^+ = \psi_{i,j^l} + \lambda_{c^l} \Delta \psi_{i,j^l} \quad (11)$$

λ_c is the learning rate of the SMOIKD-DEML and the value of λ_c is between 0 and 1. The convergence of SMOIKD-DEML depends upon the careful selection of the value λ_c .

4 Results and Discussions

The data of the proposed SMOIKD-SL-MFIS adroit system was obtained with the assistance of the medical experts at Pathology Lab of Shalimar Hospital, Pakistan. The effectiveness of the proposed technique was tested in a few records. The accuracy rate of SMOIKD-SL-MFIS for the detection of kidney disease was found to be 91.29% and the miss rate value was found to be 8.71%.

In many of the previously reported models, the dataset utilized to diagnose kidney disease was availed from UCI [20]. In the present study, Matlab 2019 tool was used for the dataset that contained 400 total instants. In this proposed ANN model, 70% data (280 samples) was used for training purposes and the remaining 30% data (120 samples) was used for the validation. The results were generated based on the training of data. The accuracy and miss rate of training and testing are shown in Tabs. 2 and 3 respectively. Three hidden neuron layers employed 15, 10, and 5 neurons respectively in all three methods of ANN such as Levenberg marquardt (LM), Bayesian regularization (BR), and Scaled conjugate gradient (SCG). In this research, ANN techniques (based on the LM) was achieved an accuracy of 93.70% and the miss rate was only 6.30%.

Table 2: Performance evaluation of proposed SMOIKD-ANN (training)

Algorithm (%)		
LM	Accuracy	95.80
	Misrate	4.20
BR	Accuracy	93.51
	Misrate	6.49
SCG	Accuracy	91.01
	Misrate	8.99

Table 3: Performance evaluation of proposed SMOIKD-ANN (testing)

Algorithm (%)		
LM	Accuracy	93.70
	Misrate	6.30
BR	Accuracy	92.09
	Misrate	7.91
SCG	Accuracy	89.44
	Misrate	10.56

Another machine learning technique in our proposed method was DEML that employed 400 instances. The accuracy was found to be 96.07% for the training by using 280 samples and misrate was found to be 3.93% for the validation by using 120 samples. DEML found the best arrangement model for the prediction of the kidney disease in different hidden layers, hidden neurons, and a combination of activation functions. In the proposed system, DEML shown outperformance compare to other techniques. The following statistical measures were used to measure the performance of the proposed DEML algorithm.

$$\text{Misrate} = \frac{O_1/C_0 + O_0/C_1}{C_0 + C_1} * 100\% \quad (12)$$

$$\text{Accuracy} = \frac{O_0/C_0 + O_1/C_1}{C_0 + C_1} * 100\% \quad (13)$$

$$\text{Sensitivity} = \frac{O_0/C_0}{O_1/C_0 + O_1/C_1} * 100\% \quad (14)$$

$$\text{Specificity} = \frac{O_1/C_1}{O_1/C_0 + O_1/C_1} * 100\% \quad (15)$$

$$\text{FPV} = [100 - \text{Specificity}]\% \quad (16)$$

$$\text{FNR} = [100 - \text{Sensitivity}]\% \quad (17)$$

$$\text{NPV} = \frac{O_1/C_1}{C_1} * 100\% \quad (18)$$

$$NPV = \frac{O_0/C_0}{C_0} * 100\% \quad (19)$$

For the kidney dataset in [20], the DEML approach was employed and the acquired outcomes are shown in Tabs. 4 and 5. The training accuracy of the proposed SMOIKD-DEML system with varying hidden layers during the prediction of kidney disease is shown in Tab. 4. Accuracy and miss rates were found to be 96.07% and 3.93% respectively. In the proposed system, there were two anticipated yields, infected (0) and not infected (1).

Testing accuracy of the proposed SMOIKD-DEML system with varying hidden layers during the prediction of kidney disease diagnosis is shown in Tab. 5. The proposed system achieved 94.16% accuracy and the miss rate was 5.84%.

Table 4: Training accuracy of proposed SMOIKD-DEML

N = 280 (No. of instances)	Result (Output) (O ₀ , O ₁)	
Expected Output (O ₀ , O ₁)	O ₀ (Infected)	O ₁ (Not Infected)
Input		
C ₀ = 175 _(Not Infected)	170	5
C ₁ = 105 _(Infected)	6	99

Table 5: Testing the accuracy of proposed SMOIKD-DEML

N = 120 (No. of instances)	Result (Output) (O ₀ , O ₁)	
Expected output (O ₀ , O ₁)	O ₀ (Infected)	O ₁ (Not Infected)
Input		
C ₀ = 75 _(Not Infected)	73	2
C ₁ = 45 _(Infected)	5	40

Tabs. 4 and 5 show the accuracy rate of proposed SMOIKD-DEML during the training and the validation. In training, the accuracy rate was found to be 96.07% and the error comes were found to be 3.93%. The validation was found accuracy and error of 94.16% and 5.84% respectively.

Final results are shown in Fig. 6 shows accuracy and miss rate of the proposed model methodologies. The currently proposed methodologies are also in line with the previous methodologies that were employed in the detection of a particular disease.

The other prototypes applied in the detection of kidney disease were FIS [17], ANN [18], SVM [18], and ANN [19]. The testing accuracy of these were found to be 86.70%, 87.70%, 76.30%, and 92.00% respectively, as shown in Fig. 6. Moreover, the SMOIKD-SL-MFIS, SMOIKD-ANN, and SMOIKD-DEML frameworks achieved an accuracy of 91.29%, 93.70%, and 94.16% respectively.

In the proposed system, we have presented a comparison for the performance of DEML with ANN and FLS and found that DEML outperformed compared to ANN and FLS.

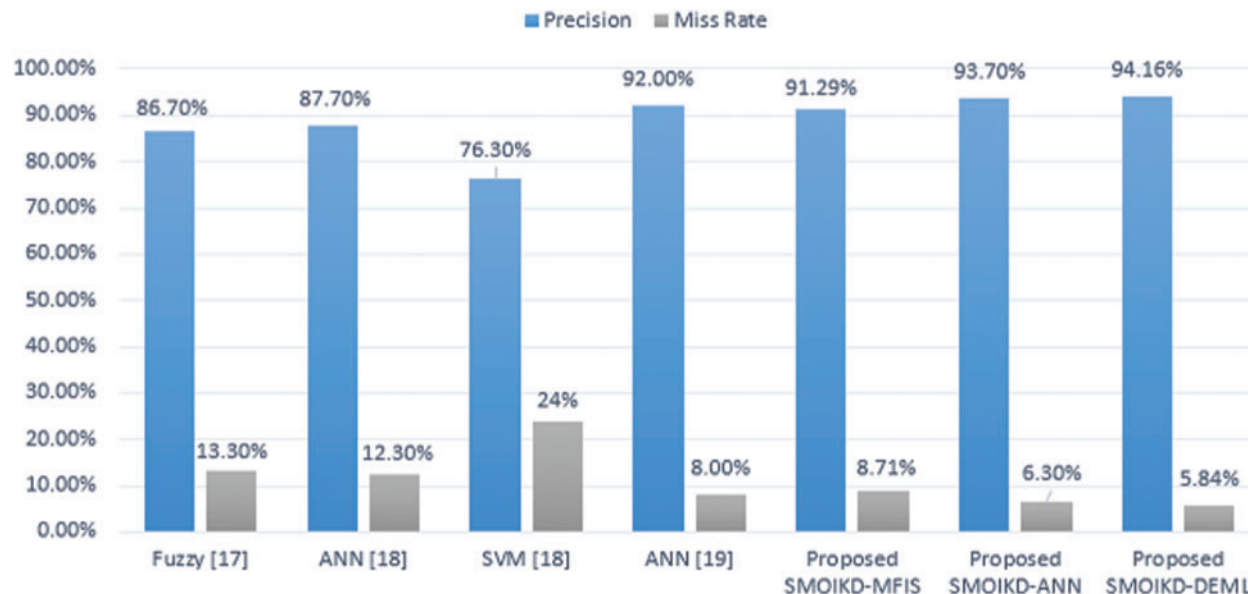


Figure 6: Comparison results of the proposed solutions with the previous methodology

5 Conclusion

The study concludes that computational intelligence approaches are effective and authentic methods to diagnose kidney diseases from its earlier stages. This method of diagnosis will assist medical practitioners to diagnose kidney disease in early stages even when symptoms not visible due to its accurate calculations. The proposed DEML provides better results in the disease prediction as compared to ANN and FLS and it also outperforms as compared to previously reported techniques in the same domain.

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