**Detection of Chronic Kidney Disease using Neuro Fuzzy**

**Rule based Classifier**

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**ABSTRACT**

*Chronic kidney disease is as severe as cancer in today’s world. The disease may even lead to the permanent failure of kidney. The initial detection of this disease is needed for timely cure. In our present work, we present a neuro-fuzzy rule based classifier for detection of chronic kidney disease. We use blood test results of several patients for our research study. We compare our proposed classifier with some conventional classifiers such as MLP and decision tree. Several worthwhile statistical measures such as RMSE, kappa statistic, accuracy, true-positive rate (or recall), false-positive rate, precision, and f-measure are used for performing quantitative analysis. The result indicates that our proposed neuro-fuzzy rule based classifier performs better than the other classifiers used here.*

**Key words:** *Fuzzy Logic, Chronic Kidney Disease, Classification, Neuro Fuzzy Rule Based Classifier*

**1.0 INTRODUCTION**

Chronic Kidney Disease (CKD) [1] is a type of disease in which the functionality of kidney decreases over time. Chronic Kidney Disease is also called chronic renal failure, chronic renal disease, or chronic kidney failure. This disease also holds the risk of developing med- ical complications such as high blood pressure and anemia. This disease can be detected by blood test, various medical imaging and kidney biopsy test. This disease also holds the risks of permanent kidney failure which indicates severe medical condition of the patient. Thus timely and successful detection of CKD is recommended for early cure. In our work, we focus on using the blood test result for detecting CKD.

Data mining [2] [3] is a process of discovering of knowledge from large, real-world databases. Many data mining techniques have been applied to the domain of health care. Data mining techniques are applied for successful decision making in case of detecting a terminal illness by analyzing the database. This decision making is helpful in further diagnosis of the disease. In the field of health care data mining is usually used to predict a disease from analyzing the dataset. In the field of data mining, Classification [4] [5] is a data mining technique that is most widely used in the domain of health care.

Classification includes the process of predicting or making decision by learning from the previous result. This technique assigns items to a target class label. Conventional classi- fication techniques such as decision tree [6] [7], artificial neural network [8] [9] etc. have been widely used by researchers to correctly predict the correct target class label to predict different diseases in the domain of health science. Data classification is a two-step process.

Classification starts by selecting a mathematical model (i.e., classifier) suitable for the given problem. After selecting a suitable classifier, it is then trained using a sample dataset. This stage is the training that produces the first step in the classification process. After training, the classification procedure proceeds to step two known as the testing phase. In this step, the classifier is tested against a dataset with unknown target class label. The testing phase predicts the output class label and this predicted output is analyzed to measure the performance of the taken classifier. There are various classifiers that can be used to predict CKD. We have used blood test result as the dataset to classify CKD. Adaptive Neuro Fuzzy Inference System (ANFIS) [10] based on Takagi-Sugeno Fuzzy Inference System (FIS) model is used in our work to classify the blood test result dataset. Our work mainly focuses in classifying the dataset to correctly predict whether the given patient is having chronic kidney disease or not. Rest of the paper is organized as follows. Section 2 describes the literature review on this work. Section 3 describes the dataset and section 4 describes the classifier that is used in our work. Section 5 describes the work flow. In section 6 and 7 result and conclusion are discussed respectively.

**2.0 RELATED WORKS**

There are various literatures available in the context of using classification in predicting various health disorder and diseases of which some are mentioned here. Lakshmi et al [11] implemented Artificial Neural Network (ANN), Decision Tree and Logical Regression Learning classification algorithms to classify a dataset on kidney dialysis. They used Tana- gra, a data mining tool and 10-fold cross-validation to perform classification. They showed a performance comparison among these classifiers of which ANN gives better results than the other two.

Vijayarani and Dhayanand [12] performed classification to predict kidney disease. In their work they used a dataset to predict four types of kidney diseases. They illustrated that SVM is much more accurate but slower than Native Bays classifier.

Van Eyck et al [13] used data mining to predict the acute injury of kidney after cardiac surgery. Anu Chaudhary et al. [14] used Apriori and K-means algorithm to predict heart disease and kidney failure. They used Apriori and K-means along with some machine learn- ing tools for correct and accurate classification of data. They used several plots such as ROC curve to analyze the algorithm. Ruey Kei Chiu et al [15] used different types of neural network to detect the stage of chronic kidney disease. They used Back propagation Net- work, Generalized Feed Forward Neural Network and Modular Neural Network to classify the dataset. They illustrated that Back propagation gives higher accuracy among the three. Manish Kumar [16] implemented random forest machine learning algorithm to predict chronic kidney disease. In this work six classifiers were used. They were namely Random Forest (RF) classifiers, Sequential Minimal Optimization (SMO), Nave Bayes, Radial Basis Function (RBF) and Multilayer Perceptron Classifier (MLPC) and Simple Logistic (SLG) along with 10-fold cross-validation. In this work it was proved that RF classifier works much better that rest of the classifiers. Parul Sinha and Poonam Sinha [17] used SVM and KNN to classify chronic kidney disease. In their work they showed that KNN performed better than SVM to classy this problem.

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**3.0 ABOUT THE DATASET**

The dataset have been collected from UCI machine leaning repository [18]. This dataset contains 25 attributes (24 input attributes and 1 class label attribute). This dataset gives us a full summery of the blood test that was performed on the patient. Analysing this blood test we can derive a conclusion that whether this patient has Chronic Kidney Disease or not. This dataset contains attributes that describes the physical condition of the patient. All the attributes are explained in table 1.

Table 1 illustrates the attribute description for the dataset. This dataset contains missing values that has been marked by ' ?'. These missing values are replaced using the following data cleaning techniques that considers arithmetic mean for each cluster (group) of data. For each attribute all the tuples are grouped into two groups depending on the class label (25th attribute). We consider each group at a time and consider the weighted mean for each attribute and replace the missing value with this mean. This makes the tuples retain the property to which class label it belongs to. This dataset contains 400 tuples. The training and testing datasets are prepared from this dataset using *10-fold cross-validation.*

**4.0 PROPOSED METHOD USING NEURO FUZZY RULE-BASED CLASSIFIER**

Neuro Fuzzy Rule based classification system [19] have been a keen topic for research. In this section we describe the Fuzzy Rule Based Classifier that we will use in our work to classify the considered problem. This type of classifiers considers Fuzzy set theory to build rules based on the training dataset. Fuzzy set theory implies that there is no crisp boundary

for a set. This gives us flexibility; decide the boundaries for generating each of the rules. In

our work we implement Adaptive Neuro Fuzzy Inference System (ANFIS) based on Sugeno Fuzzy Inference System (FIS) to classify our given problem.

A fuzzy set considers a set of ordered pair of the variable and its membership function. The membership function defines a curve that describes the mapping of the variable to the membership values between 0 and 1. This membership function decides the values that are in the fuzzy set. In our work we use gaussian curve membership function to the attributes. Thus based on this set theory and reasoning we can define Fuzzy Inference model as a computing platform that performs a mapping from a given input to output using fuzzy logic. In our work we consider Sugeno FIS which generates if ∙∙∙ then rules. Such a rule can be illustrated as in equation 1.

if i is X then j is f(i) (1)

In equation 1, the variable i is a crisp input and if it belongs to the fuzzy set X then the output corresponds to f(i). Such types of rules are generated in Sugeno FIS. When an adaptive network has a similar functionality to This type of FIS then the resulting model that is constructed is known as ANFIS.

Table 1: Attribute Description

|  |  |  |
| --- | --- | --- |
| **Attribute Name** | **value** | **Description** |
| Age | Continuous | Age of the patient |
| Blood Pressure | Continuous | Blood pressure of the patient in mm/Hg |
| Specific Gravity | Discrete | Specific Gravity measured in the test |
| Albumin | Discrete | Albumin value in blood |
| Sugar | Discrete | Sugar level value in blood |
| Red Blood Cells | Discrete | Indicates whether Red Blood Cells count is normal or abnormal |
| Pus Cell | Discrete | Indicates whether Pus Cells are normal or abnormal |
| Pus Cell clumps | Discrete | Indicates whether pus cell clumps are present or not |
| Bacteria | Discrete | Indicates whether bacteria is present or not |
| bgr | discrete | blood glucose random |
| Blood Urea | Continuous | Blood Urea value in mgs/dl |
| Serum Creatinine | Continuous | Serum Creatinine value in mgs/dl |
| Sodium | Continuous | Sodium value in mEq/L |
| Potassium | Continuous | Potassium value in mEq/L |
| Hemoglobin | Continuous | Hemoglobin value in gms |
| Packed Cell Volume | Continuous | Value of Packed Cell Volume |
| White Blood Cell Count | Continuous | White Blood Cell Count in cells/cumm |
| Red Blood Cell Count | Continuous | Red Blood Cell Count in millions/cmm |
| Hypertension | Discrete | Indicates whether the patient has Hypertension or not |
| Diabetes Mellitus | Discrete | Indicates whether the patient has Diabetes Mellitus or not |
| Coronary Artery Disease | Discrete | Indicates whether the patient is suffering from Coronary Artery Disease or not |
| Appetite | Discrete | Indicates whether the patient is having normal Appetite or not |
| Pedal Edema | Discrete | Indicates whether the patient has Pedal Edema or not |
| Anemia | Discrete | Indicates whether the patient is suffering from Anemia or not |
| Class | Discrete | Indicates whether the patient has Chronic Kidney Disease or not |

ANFIS is an adaptive network that has the similar functionality to a Sugeno FIS. A simple

ANFIS model that utilizes two input variables and one output variable is illustrated in Figure 1. There are many variations of ANFIS that is available. A typical ANFIS contains five different layers. Each of the layers are described below.

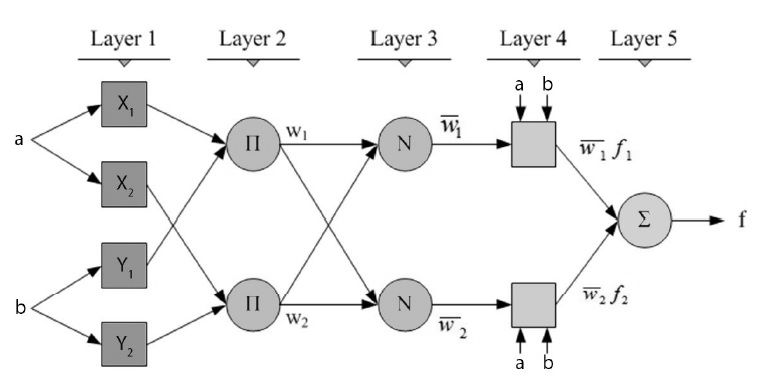


Figure 1: ANFIS model for two input variable with two fuzzy rules

**Layer 1:** Each of the node i in this layer is defined with a membership function depending on the given input. Each of the nodes contains a membership function associated with the input variable that was generated in Sugeno FIS. The membership functions satisfy each of the input variables. The premise parameters used in this step to calibrate and generate the membership functions.

For each -th node in layer 1 is an adaptive node having the node function as:

(2)

where or is the input variable to node and each node is assigned a linguistic label or to it. Here denotes the membership function for *A* and can be any valid parameterized function that depends on a parameter set. This parameter set can also be called as premise parameters.The membership function [i.e., in the generalized form] here denotes the generalized bell-shaped MF which depends upon three different parameters a, *b,* and *c* as given by the equation

 (3)

**Layer 2:** Each of the node in this layer is assigned a fixed label . This layer calculates the

firing strength of each of the individual rules in each nodes. This firing strength is calculated by calculating the product of all membership function associated to a rule.

In this layer, the work considers a fixed node label denoted by for which the output for the incoming signal can be defined by:

(4)

This output represents the firing strength of a rule.

**Layer 3:** In this layer the rule firing strength is normalized. The normalized firing strength for ith node is calculated as the ratio of firing strength of ith rule from previous layer to the sum of all firing strengths.

In this layer, it is required to denote a fixed node label for every node as and then calculate its normalized firing strength. Typically, the normalized firing strengths for every -th node can be computed as the ratio between the firing strength of that layer to the sum of all firing rules in that layer as:

(5)

**Layer 4:** In this layer each node has a node function with a set of parameters. These parameters are known as consequent parameters. In each node of this layer computes the output of node function along with the rule firing strength.

In layer 4, it is necessary to compute the output considering the parameter set embedded in the membership function. The parameters in this set are referred as consequent parameters. For every ith node the node function can be given as:

(6)

**Layer 5:** In this layer a summation is performed of the entire previous layer. This summation is the resultant output of the classifier.

In the last layer (layer 5), each of the node is assigned with a fixed node label denoting a summation operation. Each node computes the summation of all incoming signals as outputs as:

(7)

ANFIS uses hybrid learning model in the training phase. ANFIS uses the training dataset and FIS to train the dataset. This classification model gives fuzzy output as the result. But this output cannot be compared with the target class label to obtain classification accuracy. In order to get crisp output, defuzzification is performed on the fuzzy result considering the membership function of the output.

**5.0 METHODOLOGY**

Our work mainly focuses on classifying the given problem using Neuro Fuzzy Rule based classifier (i.e. ANFIS). We have used Neuro Fuzzy Rule based classifier as our primary classifier and its performance is compared to secondary classifiers. For this purpose we have selected Multilayer Perceptron (MLP) and Decision Tree (DT) as our secondary classifier to which we will compare its performance. In case of Decision Tree we consider Classification and Regression Tree (CART) as our classifier. The work flow of our methodology is illustrated in Figure 2.

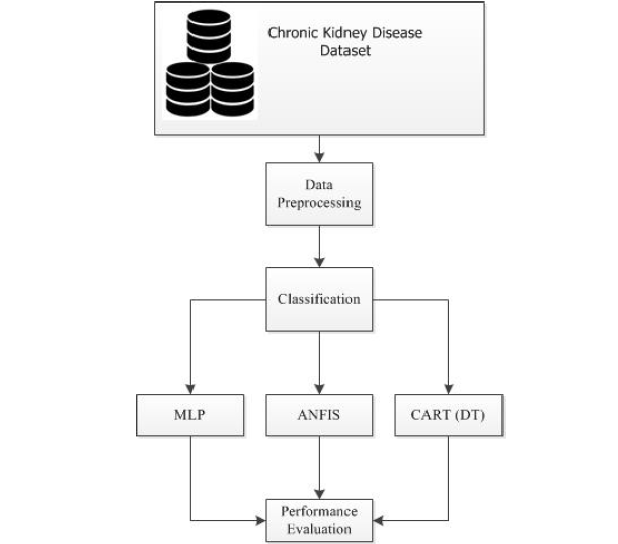
 Figure 2: workflow of our methodology

Figure 2 illustrates the actual work flow of our methodology that starts by taking the dataset as input. This dataset is the raw data that is needed to be processed. Data cleaning preprocessing is done on the dataset to clean and normalize the dataset. This step is also performed to remove or replace missing values. After the dataset is preprocessed, we perform 10-fold cross-validation on the dataset to generate two datasets namely: training dataset and testing dataset. First the training is performed on the selected classifiers using the training dataset. After training is performed we use the testing dataset to test the trained classifiers. This testing is performed by using the testing dataset. Testing is done to measure the performance of the selected classifiers. This is performed by comparing the predicted result to the actual result. This is further discussed in section 6.0

**6.0 RESULTS AND DISCUSSION**

The classifiers were applied to the dataset that was pre-processed to analyze the performance of each of the classifiers. The methodology and all the classifiers were implemented using MATLAB R2013a. The methodology was tested in a personal computer having AMD-FX-4300 (3.80 GHz) processor and 8 GB RAM. The dataset contains two target classes namely: 0 (= chronic kidney disease) and 1 (= no chronic kidney disease).

Table 2: Configuration Parameters of the MLP model

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| Number of hidden layers | One |
| Number of neurons in input layer | Element count in membership matrix |
| Number of neurons in output layer | Data classes present |
| Learning rule | Gradient descent with momentum |
| Transfer function used | Tan-sigmoid |

Here we have,

(8)

Where, H denotes the number of neurons in the hidden layer. I and O are the number of input and output attributes respectively. There are two main approaches to tree pruning: pre-pruning and post-pruning. As already specified, the research study employs CART for selection of splitting attribute and building the initial decision tree model. After tree construction, minimal cost complexity pruning algorithm is used which is a post-pruning approach. Configuration Parameters of the CART model are given below.

Table 3: Configuration Parameters of the CART model

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| Attribute selection measure | Gini index |
| Minimal number of instances at terminal nodes | 2 |
| Pruning approach used | Post-pruning approach |
| Pruning algorithm name | Minimal cost complexity pruning |
| Number of folds used | 5 |
| Random seed number | 1 |

For testing purpose we have taken MLP and CART algorithm for DT classifier. The performance comparison was performed based on classification accuracy, root-mean-square error (RMSE) [20], kappa statistic [21], true-positive rate (TP-Rate), false-positive rate (FP-Rate), precision, recall and F-measure values. These statistics were calculated by analysing the confusion matrix [22].

Table 4: Performance Evaluation based on predicted class label

|  |  |  |  |
| --- | --- | --- | --- |
| **Classifier** | **Accuracy** | **RMSE** | **Kappa Statistic** |
| MLP | 92.45% | 0.2723 | 0.8537 |
| ANFIS | 97.52% | 0.1581 | 0.9469 |
| DT | 91.66% | 0.2886 | 0.8188 |

The performance of each of the classifiers based on classification accuracy, RMSE and kappa statistics are given in Table 4. This table illustrates that ANFIS gives lower root mean square error and higher accuracy. And it also illustrates DT gives highest root mean square error and lowest accuracy. It can be observed from the table that both the classifiers (MLP and DT) have high accuracy (i.e. over 90%) but ANFIS performs far better than MLP and DT in this contrast. We can also observe that kappa statistic of ANFIS is greater than other two. This table illustrates the statistics that is obtained by comparing the predicted output to actual output.

Table 5: Performance Evaluation based on confusion matrix

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classifier** | **TP-Rate** | **FP-Rate** | **Precession** | **F-Measure** |
| MLP | 92.45% | 6.33% | 92.24% | 92.12% |
| ANFIS | 97.56% | 2.43% | 97.18% | 97.36% |
| DT | 92.44% | 7.55% | 90.70% | 91.31% |

Next we analyze the confusion matrix generated by each of the classifiers. We compute TP-rate, FP-rate, Precession and F-Measure from the confusion matrix. The result of each of the parameters for each classifier is given in Table 5. In this table we consider the result of weighted average of all the classes present (i.e. class 0 and class 1) for each of the statistics. From this table it can be observed that ANFIS performs better than each of the other classifiers resulting higher TP-rate and low FP-rate value than the rest. According to the above table , TP-rate of MLP and DT are very close but there is a significant difference in FP-rate. It can be also observed that ANFIS performs greater precession and F-Measure value than the other two. In fact, considering the division of training and testing datasets using *10-fold cross-validation* technique, ANFIS has given 5% better accuracy compare to the other classifiers.

**7.0 CONCLUSION**

Chronic kidney disease is a very severe disease as it may lead to the permanent kidney failure. Early detection of the disease followed by proper medical treatment might save many lives from danger. Indeed, it is a challenging task to detect the kidney disease at an initial stage. We propose here a neuro-fuzzy rule based classification method to detect the severity of kidney disease. We compare our method with some traditional classification techniques such as MLP and decision tree. We use blood test results of several patients for our research work. The present study uses some useful statistical measures such as RMSE, kappa statistic, accuracy, true-positive rate (or recall), false-positive rate, precision, and F-measure for performing quantitative analysis. The result shows that our proposed technique performs significantly better than the other conventional classification methods used here.

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