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# DEVELOPMENT OF A COMPUTER SYSTEM TO SCREENING PATIENTS WITH CHRONIC KIDNEY DISEASE

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## ABSTRACT

This work aims to construct a computer system to aid in the early diagnosis of Chronic Kidney Disease (CKD) using noninvasive clinical data, exploring machine learning techniques. Data collection was performed at a referral center for treatment of chronic kidney disease. The database consists of 443 participants (instances), of whom 178 have no renal disease (control) and 265 have chronic kidney disease. The clinical data collected were: Gender, Age, Stature, Weight, Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP) and Diabetes. To classify chronic kidney disease, four classifier algorithms were tested: Random Forest (RF), Naive Bayes (NV), Support Vector Machine (SVM) and K-nearest neighbors (KNN). The classifier that obtained the best result was applied a graphical interface. Among the classifiers, the SVM showed more accurate results than the other classifiers with 93.18% of accuracy, the sensibility and specificity parameters were also higher than the other methods, 0.96 and 0.88, respectively. Thus, SVM was the classifier used to obtain the computer system that is available *online* for health professionals and the general population, presenting a low cost and easy execution alternative for screening patients with CKD.



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## INTRODUCTION

Chronic Kidney Disease (CKD) is defined as abnormalities in the structure or functions of the persistent kidneys for more than three months. This pathology affects more than 10% of the general population, decreasing the quality of life of millions of people, becoming one in the last years a public health problem at a global level (Eckardt *et al*., 2013). DRC is associated with the presence of comorbidities as cardiovascular diseases and stroke (Baumgarten *et al*., 2011). The main underlying diseases, prevalent in patients with CKD, are hypertension and diabetes, as well as obesity, which has been a worrying factor in recent decades (Baumgarten *et al*., 2011). Other risk factors are also associated with CKD, such as family history of kidney disease, advanced age, chronic use of anti-inflammatories, chronic glomerulonephritis, chronic pyelonephritis, prolonged acute kidney injury, autoimmune diseases, lifestyle (smoking, low water consumption, sedentary lifestyle, among others) (Chimwayi, 2017 and Draibe *et al*., 2014). DRC is classified in five stages based on the degree of reduction of the glomerular filtration rate, going from the normal/elevated condition to dialysis or transplantation (Draibe, 2014). Because it is asymptomatic in its early stages (Baumgarten *et al.,* 2011), the development of diagnostic and/or screening methods for the early detection of CKD is of great importance for public health. A computational tool that can identify in advance whether or not the patient has kidney disease, for example, may assist health professionals in the early diagnosis of this pathology, thus preventing the progression of the disease and preventing its complications. Following this line of prevention and early diagnosis, several studies have proposed methods of evaluating CKD, through computational models. Ho *et al*. (2012), for example, presented a computer-aided diagnostic tool based on ultrasound imaging used to detect and classify different stages of CKD. Estudillo-Valderrama *et al*. (2014), have suggested the feasibility study of a distributed approach for the management of alarms related to the monitoring of patients with CKD within the eNefro project. Rosmani *et al*. (2015), developed self-care guidelines for patients with CKD, and implemented a communication channel that assists patients in their daily self-care. Jun-Wei *et al*.(2014), have developed a system that evaluates in real time the patient's ultrasound images in order to verify the probability of having CKD. Other studies have used machine learning (ML) techniques, Singh *et al* (2014), used hierarchical methods for assessing CKD and heart failure through high dimensional data. Chiu *et al* (2012), proposed an intelligent model using artificial neural networks that detects and evaluates the severity of renal disease. Anantha Padmanaban (2016), obtained high accuracy in the early detection of CKD using Decision Tree as the classification method. Therefore, it is verified that ML methods are a solution to classification problems such as screening of patients with CKD. For, they offer a more accurate prediction about the health of the individual (Lenart, 2016). In the field of health care, this work aims to construct a classification model to assist in the early diagnosis of CKD using non-invasive clinical data, low cost and easy application, exploring machine learning techniques.

## METHODOLOGY

**Database:** Data collection was performed at a referral center for the treatment of renal disease from July 2017 to July 2018. The present study is approved by the Research Ethics Committee of the Federal University of Maranhão, according to CAAE opinion: 67030517.5.0000.5087. The database consists of 443 adult patients (instances), aged between 20 and 80 years, of whom 178 presented no underlying disease (healthy) and 265presented CKD.

**Input variables:** The noninvasive data set presents seven attributes (characteristics): Gender, Age, Stature, Weight, Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP) and Diabetes. The attributes used in the data set are presented in Table 1.

**Table 1. Set of input attributes used in the experiment.**

| Variable | Type | Description |
|---|---|---|
| Gender | Binominal | M/F |
| Age | Interger | Age ofthepatient |
| Stature | Interger | Statureofthepatient |
| Weight | Interger | Body Mass of the patient |
| SBP | Numeric | SystolicBloodPressure |
| DBP | Numeric | DiastolicBloodPressure |
| Diabetes | Nominal | Yes or No |

**Proposed Method:** Four machine learning methods were used to predict the case of Chronic Kidney Disease with the aid of WEKA (Waikato Environment for Knowledge Analysis) software, written in Java, developed at Waikato University (Hall *et al*., 2009). The work methodology is shown in Figure 1.Figure 1 show which WEKA software was used to perform the classification experiments. The experiments consisted of two steps: training and testing of the classifiers using the respective 90% and 10% databases. After the classifier training phase, the 10-fold cross-validation method was used for testing. The best classifier result was an easy-to-use graphical interface to obtain DRC predictor software.

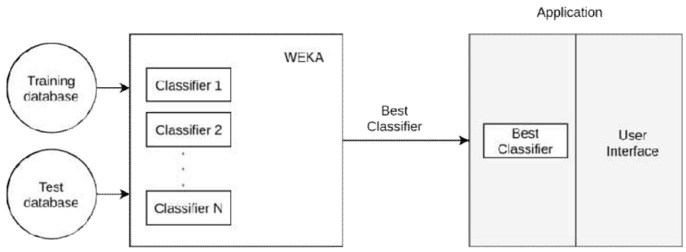


**Figure 1. Work methodology**

### Machine Learning Methods

**K-nearest neighbors:** The KNN algorithm is the supervised machine learning method used to classify unknown elements, seeking the similarity of the data in a standard space (Jun-Wei, 2014). The KNN calculates the distance between two points to predict the class, being more used the Euclidean distance, represented as:

$$d(x, y) = \sqrt{\sum_{i=1}^{k} (xi - yi)^2}$$

The euclidean distance d (x, y) measures the square root of the absolute distance between two points to find the examples of nearest k in a d-dimensional space. The unknown element class is identified by the closest category of its neighbor in common (Galit, 2010).

**Support Vector Machine:** The support vector machines (SVM) constitute the popular technique of data mining that aims at classification problem, predicting data class (Brereton, 2010). The SVM seeks to determine the optimal hyperplane, that is, a linear separator between two classes in the training data so that the distance is maximized between classes (Estudillo-Valderrama, 2014). The hyperplane generated by the SVM is determined by a subset of the points of the two classes, called support vectors (Ho, 2012).

**Naive Bayes:** The Naive Bayes algorithm is a simpler probabilistic classifier of the Bayesian networks, it uses only a formula to combine the previous probability and the conditional probabilities, so that it can calculate the probability of all the possible classes. To do this, the choice of the highest ranking of a given set of mutually exhaustive and exclusive classifications with previous probabilities and n attributes followed by the instance values (Dilli, 2017). The subsequent class probability that occurs for the specified instance can be shown as proportional to previous probabilities along with their respective values. In the assumption that if the attributes are independent, the value of the expression can be calculated using the product by calculating this product for each value from 1 to k, the highest value classification can be chosen (Dilli, 2017).

**Decision tree:** The decision tree is a machine learning technique where a complex problem is decomposed into simpler subproblems, and presents as the main advantage the "decision making" taking into account the attributes that are considered more relevant, according to the metric chosen, besides of being understandable to people (Gama, 2000). The most important attribute is presented in the tree as the first node, and the least important attributes, according to the used criteria, are shown in the subsequent nodes. By choosing and presenting attributes in order of importance, Decision Trees allow users to know which factors most influence their work.

According to Garcia (2000), Decision Trees consist of:

- nodes that represent the attributes,
- arcs (branches) from the nodes and which receive the possible values for these attributes (each descending branch corresponds to a possible value of this attribute) and
- leaf nodes (tree leaves), which represent the different classes of a training set, that is, each leaf is associated with a class.
- Each path in the tree (from root to leaf) corresponds to a classification rule.

**Statistical analysis:** In the evaluation and comparison of the algorithms regarding the rate of correctness in the classification, the area values under the ROC curve, Kappa Satisitc, accuracy, sensitivity and specificity with the support of WEKA 3.8 software (Massad, 2004).

**Implementation of the computational system:** All the tests were implemented in the Python programming language with the help of the machine learning libraries: Scikit-Learn (Pedregosa, 2011) and Auto-Sklearn (Pedregosa, 2011) and the Django web development framework (http://www. djangoproject.com/)

## RESULTS AND DISCUSSION

The characteristics of the sample composed of 443 patients are shown in Table 2, which consists of 178 negative for CKD and 265 positive for CKD, with a total of 296 women and 147 males, with age, height and mean weight (48.69 - 1.58 - 74.27) for the negative group and (61.2 - 1.55 - 63.94) for the positive group. The mean systolic (SBP) and diastolic (DBP) pressure of the negative group were 122.71 and 77.61, respectively, and for the positive group 141.72 (SBP) and 82.75 (DBP). The presence of diabetes observed in the CKD positive group showed a total of 96 cases. The performance of the four classifier algorithms are compared using area under ROC curve, Kappa statistics and Precision, which can be observed in Table 3.The Receiver Operational Characteristic Curve (ROC) graphically represents the exchange between false positive and false negative. The area under the curve evaluates the performance of the classifiers based on: excellent (0.90-1), good (0.80-0.90), regular (0.70-0.80), poor (0.60- 0.70) and failure (0.50-0.60). Table 3 shows that the SVM and Random Forest classifiers have higher ROC values of 0.93 and 0.90, respectively, considered excellent in the classification scale. The KNN and Naive Bayes also provide satisfactory measurements, so it can be said that for the selected dataset all the classifiers showed the characteristics of a good classifier. From Table 3, it is observed that all classifiers presented K value greater than zero which represents a chance agreement. Among all classifiers the SVM has a higher value of K = 0.85, which means the perfect agreement between the classifier and the fundamental truth for the given data. Regarding precision, the SVM showed again superior to the others with 93%.The accuracy of the machine learning techniques trained and tested by the proposed method are compared among the classifiers shown in Figure 2.

**Table 2. Sample characteristics of the negative and positive group for Chronic Kidney Disease (CKD) database**

| Variables | Negative CKD (n=178) | Positive CKD (n=265) |
|---|---|---|
| Gender | | |
| Female (total) | n= 123 | n= 173 |
| Male (total) | n= 55 | n= 92 |
| Age (years) | 48,69 ± 11,66 | 61,2 ± 11,54 |
| Height (meter) | 1,58 ± 0,09 | 1,55 ± 0,08 |
| Weight (Kg) | 74,27 ± 13,71 | 63,94 ± 11,72 |
| SBP (mmHg) | 122,71 ± 11,49 | 141,72 ± 25,11 |
| DBP (mmHg) | 77,61 ± 7,76 | 82,75 ± 14,90 |
| Diabetes (total) | 0 | 96 |

**Table 3. Classifier performance for the selected dataset**

| Classifier Algorithms | Área ROC | Kappa statistic (K) | Precicion (%) |
|---|---|---|---|
| SVM | 0,93 | 0,85 | 93 |
| KNN | 0,87 | 0,71 | 87 |
| Random Forest | 0,90 | 0,65 | 83,9 |
| Naive Bayes | 0,85 | 0,56 | 81,8 |

Abbreviations: SVM: Support Vector Machines, KNN: K-nearest neighbors, ROC-Receiver operating characteristics curve.

It is observed in Figure 2 the results associated to the four classifiers, where it shows that the SVM classifier presented greater accuracy in relation to the others with 93.18%, while, while KNN, Random Forest (RF) and Naive Bayes (NB) can provide accuracy of 86.36%, 84.09% and 81.81%, respectively.

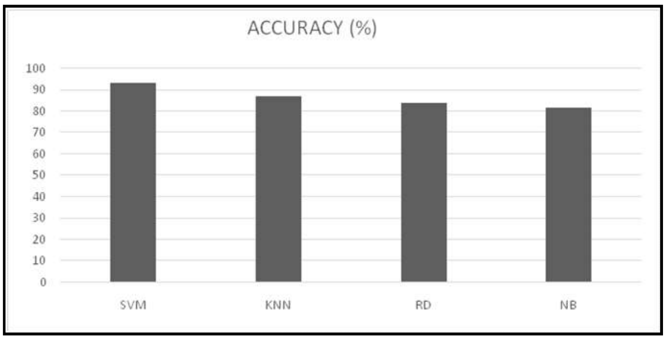


**Figure 2.Acuraccy of classifier algorithms**

Calculating the accuracy is relevant, because although evaluating the general effectiveness of the algorithm, if the classifier demonstrates an incorrect prediction, it can bring harm to the patient. Therefore, the sensitivity and specificity value is used in the experiments to evaluate the performance of the proposed methods.

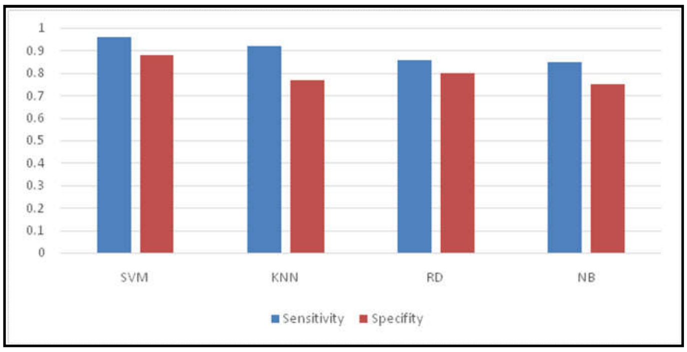


**Figure 3. Comparison between sensitivity and specificity of the classifiers**

**Table 4. Comparison of results with previous surveys**

| Authors | Database | Instances | Attributes | Methods | Acuraccy (%) |
|---|---|---|---|---|---|
| Kusiak, *et al.* (2005) | UIHC | 188 | 50 | RS | 75 |
| | | | | DT | 57 |
| Abhishek, *et al.* (2012) | Hospitals | 1199 | 7 | BPA | 81 |
| | | | | RBF | 62 |
| | | | | SVM | 60 |
| Chiu, *et al.* (2012) | HEC | 430 | 6 | BPN GFNN | 94,75 |
| | | | | MNN | 86,63 |
| | | | | | 93,23 |
| Vijayarani and Dhayanand (2015) | KFT | 583 | 6 | ANN | 87 |
| | | | | SVM | 76 |
| Anusorn, *et al.* (2016) | UCI | 400 | 24 | SVM | 98,3 |
| | | | | KNN | 98,1 |
| | | | | LR | 96 |
| | | | | DT | 94 |
| Anantha and Parthiban (2016) | CDC | 600 | 13 | DT | 91 |
| | | | | NB | 86 |
| Tazin, *et al.* (2016) | UCI | 400 | 15 | DT | 99 |
| | | | | SVM | 98 |
| | | | | KNN | 97 |
| | | | | NB | 96 |
| Kerina, *et al.* (2017) | UCI | 400 | 25 | Neuro-Fuzzy | 97 |
| Our study | HUUFMA | 442 | 7 | SVM | 93 |
| | | | | KNN | 86 |
| | | | | RD | 84 |
| | | | | NB | 81 |

Abbreviations: University of Iowa Hospitals and Clinics (UIHC), Clinic Foundation Heart Disease (CHD), Synthetic renal function (KFT), Rear Propagation Algorithm (BPA), Radial Base Function (RBF), Support Vector Machine (SVM), Reed-Solomon (RS), Decision tree (DT), Back-propagation network (BPN), generalized feeding neural networks (GRNN), modular neural networks (MNN), Naive Bayes (NB), University of California Irvine (UCI), Decision Tree (C4.5), K-nearest neighbors (KNN), Logistic Regression (LR), Minimal Sequential Optimization (SMO), Radial Basis Function (RBF), Multilayer Perceptron Classifier (MLPC) Simple Logistic (SLG).

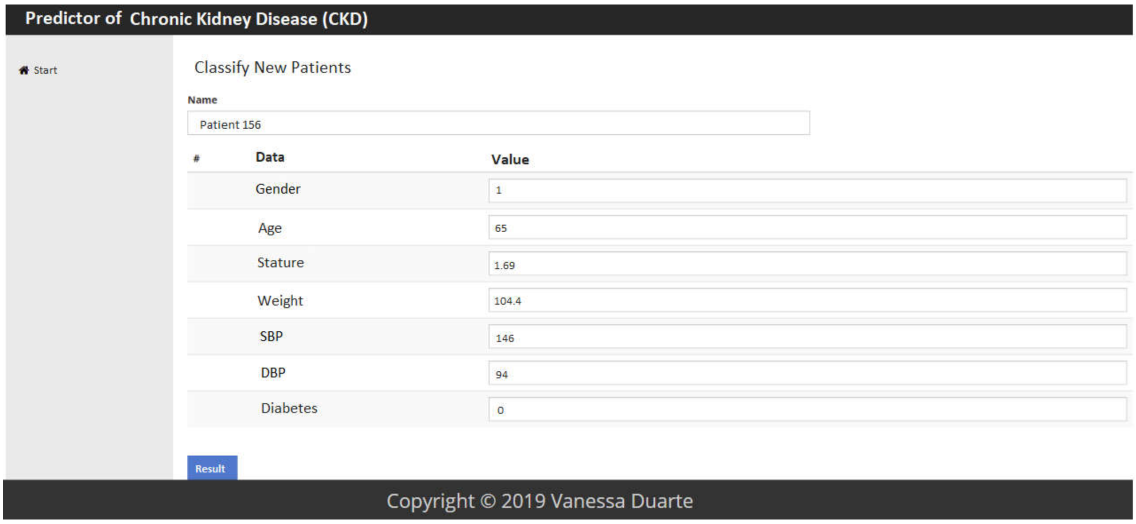


**Figure 4. Predicting software for CKD running**

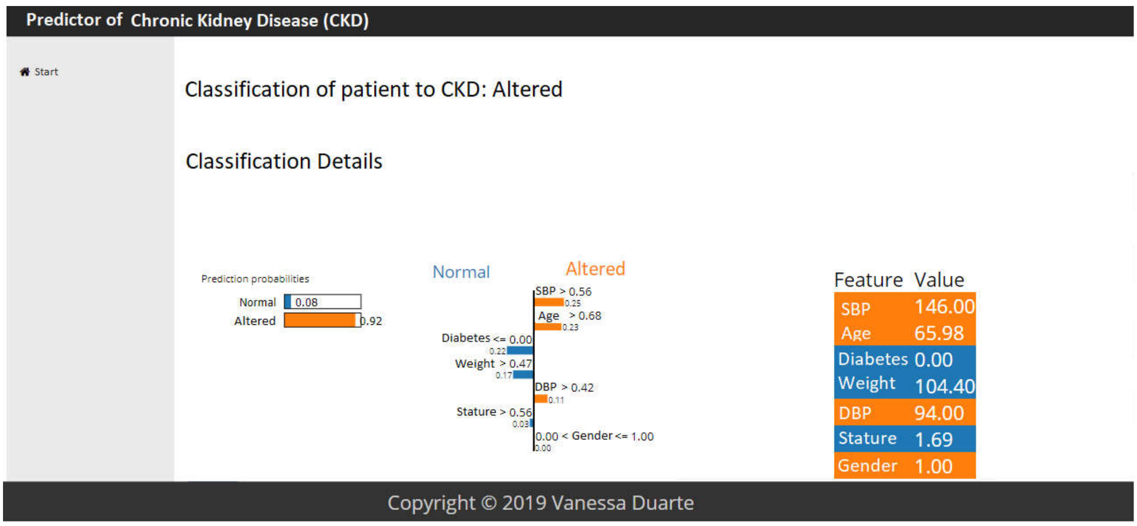


**Figure 5. Result of Predicting software for CKD**

Figure 3 illustrates the sensitivity and specificity parameters of the classifiers used in the experiment. The SVM classifier indicates slightly higher values of sensitivity of 0.96 compared to KNN with 0.92. The sensitivity values of the Random Forest (RF) and Naive Bayes (NB) classifiers were lower with 0.86 and 0.85, respectively. Regarding the specificity value, the SVM classifier also presented slightly higher than the other methods in 0.88, Random Forest (RF), KNN and Naive Bayes (NB) showed specificity of 0.80, 0.77 and 0.75, respectively. Several investigations using other methods of classification were applied in a set of data for diagnosis of chronic kidney disease and obtained good results of accuracy, it is worth noting that they used invasive clinical data as input to the classifier. Our study, compared to previous studies, can be seen in Table 4.In Table 4 it can be observed that in our study, compared to the results of Anusorn, *et al*. (2016) and Tazin, *et al*. (2016) on the prediction of CKD using the SVM classifier algorithm, were slightly similar with accuracy greater than 90%. Choosing the appropriate input variables is the most important feature of the model that can improve prediction accuracy, and our study, using noninvasive data, was possible to obtain high accuracy in relation to the other studies with invasive variables.

This was the first study performed with data from a population from the Brazilian Northeast, more precisely from the University Hospital of Maranhão, using a machine learning technique using less invasive data related to Chronic Renal Disease (CKD) with a high sensitivity value, which may be added to the health professionals in the aid to the early diagnosis and in the treatment of the patients. With the classifier implementation, seen in Figure 4 and 5, our model can be used as a central computational component in a medical decision support system, and assist physicians in making appropriate decisions. In Figure 4 shows the running Chronic Kidney Disease Predictor (CKD) software, where it is possible to enter the patient's name with their respective data for further evaluation. Figure 5 presents the software results regarding CKD patient classification, as well as the details of the classification, ie, the variables that most influenced the classifier in obtaining the result. The Software is available online at: <https://rins.picos.ufpi.br/> and is registered with the National Institute of Industrial Property (INPI) under process No.: BR512019001220-8.There is an extreme need to develop classification techniques that can accelerate and simplify the process of diagnosing chronic diseases. In this study, the objective was reached, in which the prediction of CKD can be made with noninvasive data related to the disease, in order to simplify the classification process and facilitate health professionals to manage their patients. In the future, other noninvasive parameters such as nutrition, physical activity, water consumption, smoking and alcoholism can be considered for the detection of CKD, as well as the performance of other classifiers such as Artificial Neural Networks, Fuzzy Logic and Logistical Regression can be compared using the WEKA tool for situations and dataset.

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**Conflicts of Interest:** The authors declare no conflict of interest.

**Conclusion**

According to the experimental results, the SVM classifier algorithm showed superior to the others in all evaluated parameters. Thus, SVM was the machine learning technique used to obtain software for predicting chronic kidney disease using noninvasive data. The software generated from the chosen classifier is available *on line*, presenting a low cost alternative and easy execution. From it, the medical team can effectively use with ability to assist in the early diagnosis of CKD without invasive exams and accurately treat patients. In addition, public users can take advantage of this model to conduct self-detection so that the necessary precaution can be taken in advance to avoid any risk of causing the disease or preventing it from worsening to later stages.

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