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# Diabetes Patients at Risk of Developing Kidney Disease: Application of Classification Algorithms

*Completed Research Paper*

*Extended Abstract*

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## Abstract

The study aims to identify the Type 2 Diabetes patients who are at risk of developing diabetic Kidney Disease (DKD). This study compares the performance of classification algorithms that are commonly used to identify patients at risk of developing DKD when predicting for short, medium and long terms. We used 5,097 records at 36 clinics from 2005 to 2017. Syntactic minority oversampling and random undersampling were used to create a balanced dataset. Our findings show that the performance of classification algorithms depends on both the period and purpose of prediction, whether the prediction is to identify people who will not develop DKD or determine at-risk patients. Undersampling as opposed to oversampling improved performance. 19 predictors and their importance in short, medium and long terms were identified. This study provides guidelines for an automated system to prompt type-2 diabetes patients for screening, which offers a potential reduction of the burden placed upon the clinical settings.

**Keywords**

Predictive analytics, chronic disease, artificial neural networks, multi-task learning, regression

## Extended Abstract

One of the major complications of Type 2 Diabetes (T2D) is diabetic kidney disease (DKD). The T2D prevalence is increasing worldwide (World Health Organization, 2016) from 382 million in 2013 to 592 million people in 2035 (Aguiree et al., 2013). Landray et al. (2010) have reported that 25-40% of patients with T2D develop chronic kidney disease. DKD is associated with the increased mortality among T2D patients (Afkarian et al., 2013). While out of five stages of DKD, the identification of patients at early stages of 1-3 is important for the treatment; typically signs and symptoms of DKD do not show up until later stages (Ware, 2018). The rise in the number of T2D patients and the fact that T2D is the leading cause of chronic kidney disease (Subramanian and Hirsch, 2018) make it imperative to identify T2D patients at risk of DKD early. This enables targeted disease management in order to prevent the progression of DKD.

There are two approaches for preventing DKD progression among T2D patients. In the first approach, every T2D patient is targeted by public health policies, which is highly costly (Jain and Mottl, 2015). In the second approach, a subpopulation of T2D patients is predicted as "at-risk" using machine learning classification algorithms. Machine learning techniques have the potential to recognize the complex patterns in electronic medical records (EMR) and identify patients at risk of developing diseases (Capan et al., 2017; Ferroni et al., 2017; Lagani et al., 2013; Uyar et al., 2015) such as DKD. Advances in the field of machine learning allow for better predictions of target groups with the risk of DKD progression (Low et al., 2017). Prediction of DKD offers the promise of prioritizing diagnostic and therapeutic processes in the context of overwhelming patient demand. On an individual patient care basis, physicians are well-equipped to identify those at risk of DKD. However, when attempting to issue proactive, appropriate notification to patients to schedule an appointment for laboratory screening across a patient panel of thousands, the choice of good classification algorithm is an important challenge; that is the topic of this article.

The current study aims to answer the following research questions (RQ):

RQ1: Is there any difference in performance of classification algorithms to identify patients at risk of DKD progression when predicting for short, medium, or long-term and using random sampling, SMOTE, or RUS?

RQ2: What are the predictors of DKD? Does the importance of each predictor change when predicting for short, medium, or long term?

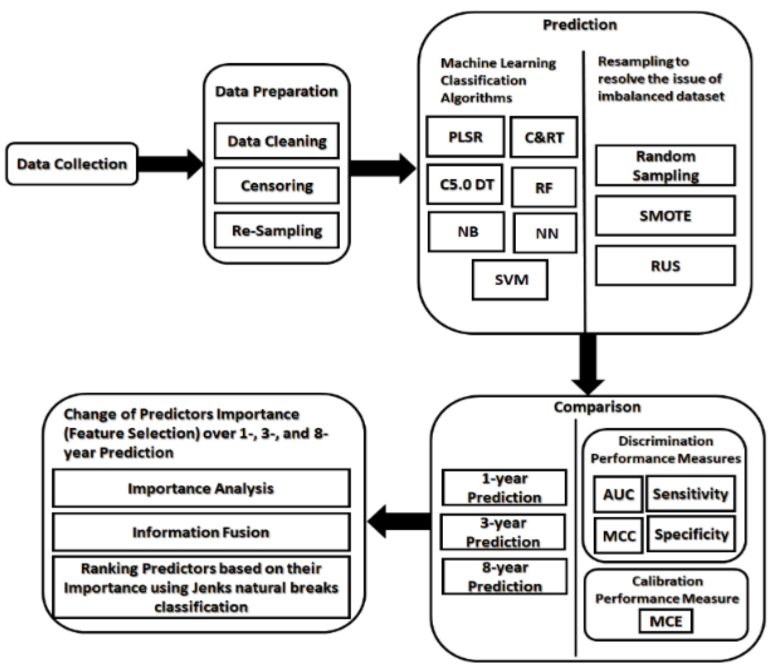


**Figure 1. Methodology**

In order to answer to the above questions, the current study runs the classification algorithms used in previous literature (Leung et al., 2013); namely partial least square regression (PLSR), classification and regression tree (C&RT), C5.0 decision tree (C 5.0 DT), random forest (RF), naïve Bayes (NB), neural network (NN) and support vector machine (SVM) for the linked daily generated EMRs collected from 36 general practice offices. The resampling techniques were no resampling, SMOTE, and RUS. In addition, the analysis was conducted for 1 year, 3 years and 8 years of prediction. Our findings show that the performance of predictive techniques to predict DKD depends on 1) the period of prediction being short, medium, or long-term and 2) whether the purpose of prediction is to identify T2D patients at risk of developing DKD or those that are not at risk. Figure 1 presents the methodology used in this study.

Our findings show that both discrimination and calibration performances of predictive technique are not only related to the period of prediction (short, medium, and long-term), but also depends on the purpose of prediction, whether the prediction is an attempt to identify T2D people who will not develop DKD or identify T2D patients at risk of developing DKD. For instance, in the short term, NN-RUS shows better performance as measured by AUC and MCC and MCE particularly when the prediction is looking for T2D patients who are going to develop DKD, measured by sensitivity. However, the results show that C 5.0 DT-RUS better predicts T2D patients who are not at risk of DKD, since its specificity is higher than other predictive methods. When predicting for the medium and long terms, the choice of technique, we can similarly observe that RF-RUS has the best performance, unless the objective is to identify T2D patients who are not at risk of developing DKD. Although in 8-year prediction RF-SMOTE showed better MCE compared to RF-RUS, the difference was not statistically significant and as such, it can be treated similarly to RF-RUS. We have incorporated these results in full paper.

This is the first time in literature that the change of predictors' importance for developing DKD among T2D patients has been examined through different predicting periods (1, 3, and 8-year predictions).