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Early Prediction of Chronic Kidney Disease Using Machine Learning Supported by Predictive Analytics

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Abstract

© 2018 IEEE. Chronic Kidney Disease is a serious lifelong condition that induced by either kidney pathology or reduced kidney functions. Early prediction and proper treatments can possibly stop, or slow the progression of this chronic disease to end-stage, where dialysis or kidney transplantation is the only way to save patient's life. In this study, we examine the ability of several machine-learning methods for early prediction of Chronic Kidney Disease. This matter has been studied widely; however, we are supporting our methodology by the use of predictive analytics, in which we examine the relationship in between data parameters as well as with the target class attribute. Predictive analytics enables us to introduce the optimal subset of parameters to feed machine learning to build a set of predictive models. This study starts with 24 parameters in addition to the class attribute, and ends up by 30 % of them as ideal sub set to predict Chronic Kidney Disease. A total of 4 machine learning based classifiers have been evaluated within a supervised learning setting, achieving highest performance outcomes of AUC 0.995, sensitivity 0.9897, and specificity 1. The experimental procedure concludes that advances in machine learning, with assist of predictive analytics, represent a promising setting by which to recognize intelligent solutions, which in turn prove the ability of predication in the kidney disease domain and beyond.

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Keywords

Chronic Kidney Disease, Machine learning, Predictive analytics

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