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AI USING REAL-LIFE DATA, AN ADDITIONAL SCREENING TOOL FOR DOCTORS TO IDENTIFY PATIENT AT VERY HIGH RISK OF RENAL FAILURE

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BACKGROUND

Chronic renal failure (RF) is a major public health problem affecting 700 million people worldwide. Patients are often unaware of their renal disease, due to a lack of early diagnosis. Real-life data can be used to identify kidney disease at an early stage and reduce its burden.

OBJECTIVES

The objective of the study is to develop and validate a machine-learning algorithm for early detection of patients, at a very high-risk stage of RF based on patient history recorded in a real-life setting.

METHODS

Retrospective observational study using the ambulatory medicalized real-world THIN® France database. Patients were included from 2013 to 2023 if they had a history ≥ 3 year, a RF diagnosis (ICD10 N17, N18 N19), and eGFR /albuminuria value. Patients in stages G5, G4, G3b-A(2-3), G3a-A3 of the KDIGO classification are considered at very high-risk of RF. Ten machine learning algorithms were trained, tuned and validated in a training set, and the best model was tested in the testing set to avoid overfitting. As predictors, we included all variables related to treatment, comorbidities, procedures, vital sings, gender and age recorded at least one year prior to the event.

RESULTS

A total of 4,976 patients were included, 20.3 (1,017) % of them were at very high risk of RF. Patients were 71.4 years old, 41.5% were women, 78.3 % had hypertension, 39 % cardiovascular disease, 8.7 % heart failure and 42% diabetes. Patients overall had 12 years of back data. Patients at high risk of RF had a mean eGFR and albuminuria of 26.5 mL/min/1.73m2 and 245.2 mg/mmol and 52.1% of them were treated with analgesics. Patients at very high risk of Renal Failure are different from patients at low risk of renal failure ($p < 0.001$), with exception of the gender and coronary heart disease (table1).

Table1. Characteristic of patient (1,2)

At index date	Overall (N=4,995)	Very high risk of Renal Failure (N=1,017)	Low risk of Renal Failure (N=3,978)
Age in year	71.4±12.5	75.6±11.6	70.3±12.4
Female, no. (%)	2,071 (41.5)	410 (40.3)	1,661 (41.8)
BMI available			
no. (%)	3,733 (74.7)	684 (67.3)	3,049 (76.6)
Median	27.5	26.7	27.7
IQR	24.5, 31.1	24.1, 30.6	24.6, 31.2
Followed by GP (3), no. (%)	4,893 (98)	981 (96.5)	3,912 (98.3)
Back-data in years	12.1±6.2	11.5±5.8	12.3±6.2
History of renal failure in years	0.9±3.0	0.6±2.7	1±3
Diabetes mellitus, no. (%)	2,096 (42)	525 (51.6)	1,571 (39.5)
Hypertension, no. (%)	3,912 (78.3)	861 (84.7)	3,051 (76.7)
Cardiovascular disease, no. (%)	1,946 (39)	448 (44.1)	1,498 (37.7)
Heart failure, no. (%)	437 (8.7)	121 (11.9)	316 (7.9)
Coronary heart disease, no. (%)	148 (3)	34 (3.3)	114 (2.9)
Systolic blood pressure (SBP)	134.6±16.8	137.5±17.7	133.8±16.5
eGFR	56.3±91.2	26.5±11.8	63.9±100.7
uACR	92.8±1,459	245.2±601.1	53.9±1,604.1
Analgesics (N02), no. (%)	2,111 (42.3)	530 (52.1)	1,581 (39.7)
Acid related disorders (A02), no. (%)	2,915 (58.4)	670 (65.9)	2,245 (56.4)

(1) Data are mean ± SD, median [IQR] or number and percentage of patients.
(2) patients at very high risk of Renal Failure are different for patient at low risk of renal failure ($p < 0.001$), with exception of the gender and coronary heart disease.
(3) 2% of patients were followed by cardiologist, endocrinologist, rheumatologist, Hepatologist/Gastroenterologist, Gynecologist.
BMI: body mass index. IQR = inter quartile interval. GP: general practitioner. SBP: systolic blood pressure. DBP: diastolic blood pressure. eGFR: estimated glomerular filtration rate. uACR :Urine Albumin-Creatinine Ratio.

The accuracy of the ten models tested ranged from 0.79 to 0.97, and the F-score from 0.88 to 0.98. The best algorithm was the random forest which had accuracy and F-score both > 0.97. see table2.

Table2. Comparison of model performance calculated in the training set

Algorithm	Accuracy	F-score
Random Forest (RF)	**0.973**	**0.983**
Light Gradient Boosted Machine (GBM)	0.964	0.978
Neural Networks (NNT)	0.928	0.956
K-Nearest Neighbors (KNN)	0.896	0.938
Extreme Gradient Boosting (XGBoost)	0.887	0.933
Support Vector Machine (SVM)	0.809	0.890
Naive Bayes	0.801	0.889
Penalized Logistic Regression(pLR)	0.797	0.887
Decision tree	0.797	0.887
Flexible discriminant analysis (FDA)	0.796	0,885

The most important predictors observed among others included age, BMI, number of weight records, SBP (figure 1). Accuracy and F-score of the final RF model calculated on the testing set (not used for training) is 0,89 and 0,79, respectively.

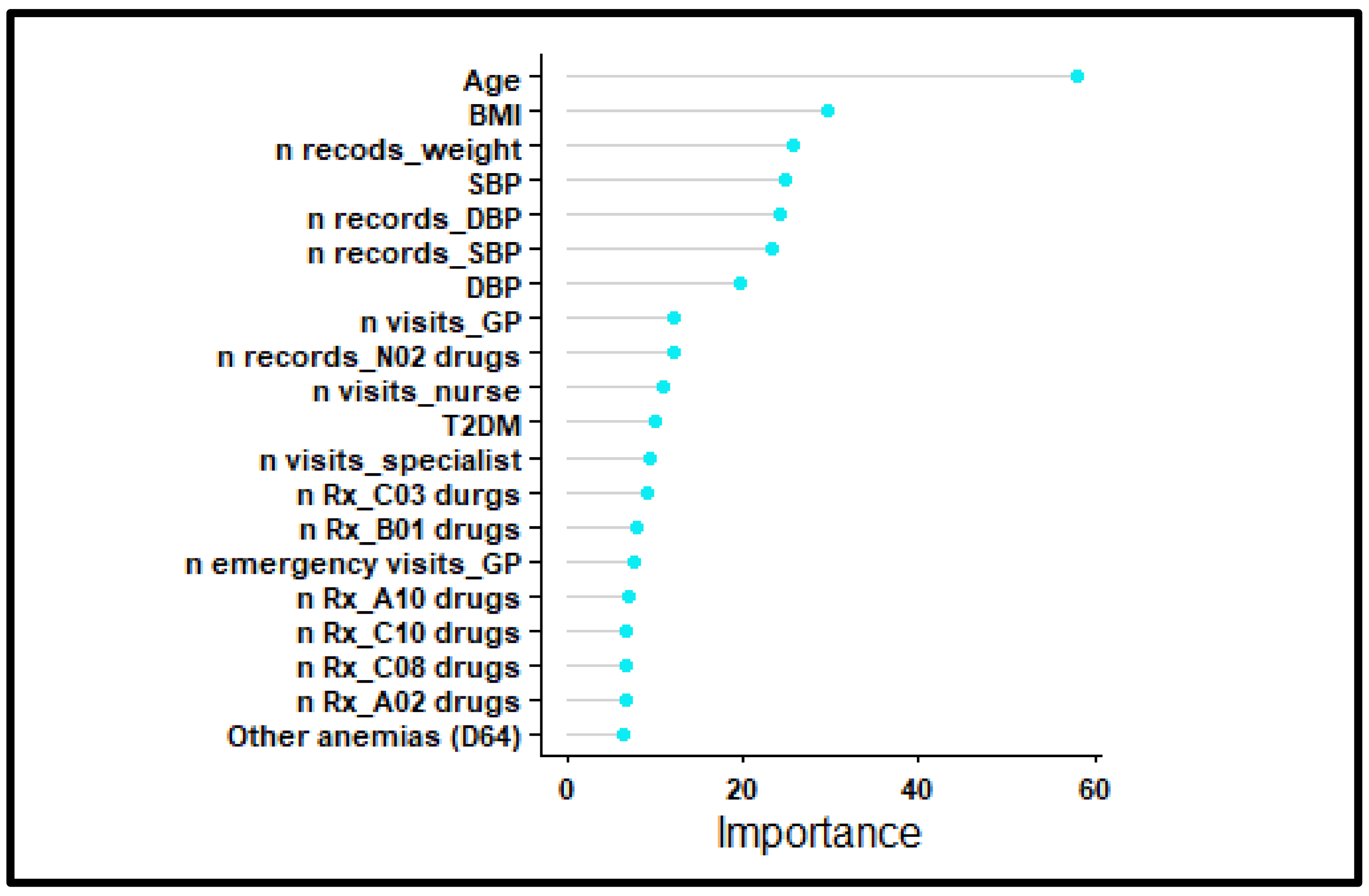

Figure 1. The twenty main predictors of the RF model

CONCLUSIONS

These results show by using a combination of AI and RWD, including medical wandering, medical decisions and patient loyalty to their physician, offers doctors a powerful additional tool for improving the early medical management of patients with kidney disease. In this study, we did not include electronic medical records for the year preceding the index year, although this would probably increase the model's performance, as we wanted to develop a tool for early detection to give the physician a one-year lead time to act before the patient reaches very high risk stage of renal disease.

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