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Predicting Urgent Dialysis at Ambulance Transport to the Emergency Department Using Machine Learning Methods

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Abstract. Hemodialysis patients frequently require ambulance transport to the hospital for dialysis. Some patients require urgent dialysis (UD) within 24 hours of transport to hospital to avoid morbidity and mortality. UD is not available in all hospitals; therefore, predicting patients who need UD prior to hospital transport can help paramedics with destination planning. In this paper, we developed machine learning models for paramedics to predict whether a patient needs UD based on patient characteristics available at the time of ambulance transport. This paper presented a study based on ambulance data collected in Halifax, Canada. Given that relatively few patients need UD, a class imbalance problem is addressed by up-sampling methods and prediction models are developed using multiple machine learning methods. The achieved prediction scores are F1-score=0.76, sensitivity=0.76, and specificity=0.97, confirming that models can predict UD with limited patient characteristics.

Keywords. Dialysis, ambulance, machine learning, prediction model

1. Introduction

Predicting the need for an urgent clinical intervention, such as acute dialysis, surgery, transfer to the intensive care or hospital admission is important for prognostication and to ensure clinicians have a good awareness of which patients may require treatment to improve their overall health. Dialysis patients are especially susceptible to a number of poor health outcomes. Chronic hemodialysis patients have been shown to frequently require ambulance transport to the emergency department, they are at high risk of hospitalization and they are also at risk of needing timely dialysis subsequent to transport [1-4]. The ability to predict the need for timely, monitored, dialysis following ambulance transport to the hospital following paramedic assessment ("urgent dialysis") is of life saving importance. As urgent dialysis is not offered in all hospital facilities, understanding which patients may require it can help avoid re-transport, which in turn, can lead to needless and potentially harmful delays in care. The practical intent of the research is to provide a reliable model for paramedics to help them in making decisions about whether the patient being attended will need urgent dialysis on the basis of a

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limited number of available clinical markers in order to transport the patient to the appropriate hospital with urgent dialysis capabilities.

Both statistical and ML methods have been used to predict the probability of a number of health outcomes necessitating urgent care for both the general population and chronic dialysis population. Vinson et al. developed a risk prediction model for the outcome of urgent dialysis (defined as dialysis within 24 hours of transport to the Emergency Department (ED) by ambulance in a monitored setting, or among those with an initial potassium of >6.5 mmol/L) in a regional cohort of chronic dialysis patients who were transported to the ED. In this study, a risk prediction model incorporating presenting complaint, vital signs prior to transport, and time from last dialysis had very good discrimination (C-statistic 0.81, 95% CI: 0.76-0.86) for the primary outcome [1]. In subsequent work, Vinson et al. [5] used the clinical characteristics of hemodialysis patients to predict hyperkalemia using multivariable logistic regression. In a study of 704 patients, following ambulance transportation to the ED, 75 patients (11%) had severe hyperkalemia (≥6 mmol/L), and a risk prediction model that included prehospital vital signs, days from last hemodialysis and a prehospital electrocardiogram with features of hyperkalemia had an AUC of 0.82 for severe hyperkalemia. Ronksley et al. [6] used statistical methods to analyze ED utilization for chronic kidney disease patients in a large Canadian provincial population. Kang et al. [7] developed a five-layered neural network to predict the need for critical care using age, sex, vital sign, chief complaint, and symptoms at ED arrival, resulting in an AUC of 0.86. Raita et al. [8] used ML methods to predict high-risk patients and clinical outcomes after ED triage. Goto et al. [9] used lasso regression, random forest, gradient-boosted decision tree, and deep neural network to predict critical care outcomes and hospitalization using standard triage datasets and achieved better prediction performance compared to conventional triage approaches.

This research takes a Machine Learning (ML) approach to predict a patient's need for urgent dialysis at the time of ambulance transport to hospital. The ambulance transport data is analyzed for chronic hemodialysis patients, in Nova Scotia (Canada) over a 5-years period. Also a range of ML methods are investigated to develop an urgent dialysis prediction model. A key challenge addressed in the work was the class imbalance between urgent vs. non-urgent dialysis, where only 10% of the patients required urgent dialysis. The study resulted into a prediction performance of F1-score =0.78 and AUC=0.93—the prediction performance was noted to be better as compared with traditional biostatistical approaches [1].

2. Methods

The data for this study consists of all ambulance transports to the emergency department for a cohort of chronic hemodialysis patients, in a region of a Canadian province (Nova Scotia; catchment area of approximately 750,000 individuals) from 2014—2018. All of these patients were transported to the emergency department after being assessed by paramedics. Patient characteristics of relevance were those captured by paramedics at the time of transport including vital signs, demographics, chief complaint, and the number of hours from the last dialysis (which was collected using electronic medical records) prior to transport. The primary outcome was urgent dialysis, defined in a similar fashion to the study by Vinson et al., namely, dialysis in a monitored setting within 24 hours of ED arrival or dialysis within 24 hours with the first ED patient blood potassium level >6.5mmol/L. The cohort comprised of 879 ambulance transports of which 94 (11%) resulted in the need for urgent dialysis.

To develop the ML-based model for predicting urgent dialysis, the following challenges are addressed: (a) Outlier detection; (b) imbalance dataset, where the ratio between the two classes is 1:8; (c) missing data values; and (d) feature selection. Figure 1 illustrates the methodology for developing the dialysis prediction model.

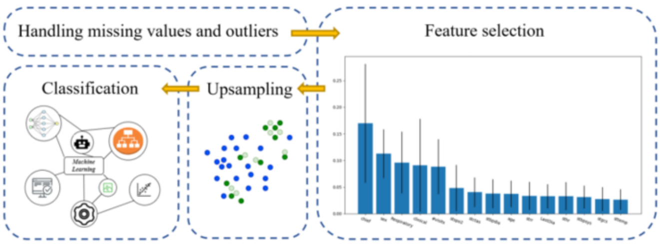

Figure 1. Methodology for developing urgent dialysis prediction models

Outlier detection and removal for each feature was performed using Inter Quartile [10]. Missing numerical values were imputed using nonlinear support vector regression which ensures that the imputed value is calculated using multiple features. [11, 12], and missing values for categorical features were calculated using one-nearest-neighbor model. The density plots for pre- and post-imputation feature values was noted to be similar, thus confirming that imputation did not change the data distribution. Feature selection was performed to determine feature importance using the extra trees classifier and Pearson correlation matrix, which resulted in the removal of some variables (i.e. the patient's Glasgow Coma Scale score and categories for the Canadian Triage and Acuity Scale score), and paramedic clinical impression [13]. To predict urgent dialysis, multiple ML methods are investigated—i.e. Logistic Regression (as the base model), Support Vector Machine (SVM) with different kernels, Neural Networks (NN), K-nearest neighbors (KNN), and ensemble methods of XG-boost (XGB) and Random Forest (RF) [13]. The initial prediction performance results (shown in Table 1) were unsatisfactory largely due to the inherent class imbalance between the classes urgent dialysis and not urgent dialysis. To improve prediction performance, both data up-sampling and down-sampling methods were experimented to balance the class distribution. Up-sampling the minority class (i.e. urgent dialysis) using Adaptive Synthetic Sampling Method (ADASYN), Synthetic Minority Over-Sampling Technique (SMOTE), and Borderline SMOTE provided better prediction accuracy [14]. The up-sampled dataset was plotted using t-distributed stochastic neighbor embedding (t-SNE) to confirm clear separation between the two classes. An UD prediction model was developed by experimenting with the ML methods using the balanced dataset. A 5-fold cross-validation was applied to train the ML models, to avoiding overfitting.

3. Results

A cross-validation approach is used to evaluate prediction performance, reporting False Negative (FN), False Positive (FP), and F1-score for each model. XG-Boost offered the best prediction amongst the other ML models—it performed 18% better than the base model of logistic regression, however the prediction performance in general was not high enough to be used for any decision making. Table 1 presents the prediction performance of the ML models with the original data having a class imbalance.

Table 1. Prediction performance and Classification results after training models with selected features on the original dataset

methods	Classification Results		
RF	FP=26	FN=9	F1_score =0.43
KNN	FP=41	FN=5	F1_score =0.45
SVM	FP=10	FN=12	F1_score =0.52
NN	FP=14	FN=12	F1_score =0.50
XG-Boost	**FP=12**	**FN=9**	**F1_score =0.58**
LR	FP=39	FN=8	F1_score =0.40

Table 2 shows the prediction performance of the ML-models using the up-sampled dataset. RF produced the highest prediction performance—i.e. F1_score=0.76, sensitivity=0.76, specificity=0.97, and area under the curve (AUC)=0.95. We note a significant increase in the prediction performance, with no overfitting, after balancing the class distribution. Figure 2 shows the AUC comparison for the different ML models.

Table 2. Classification results after training models with up-sampled data

Methods	FN	FP	F1-score	Sensitivity	Specificity
RF	**3**	**3**	**0.76**	**0.76**	**0.97**
XGB	2	9	0.66	0.84	0.91
KNN	1	25	0.47	0.77	0.92
SVM	1	13	0.49	0.92	0.79
NN	2	13	0.59	0.84	0.88
LR	5	21	0.38	0.61	0.80

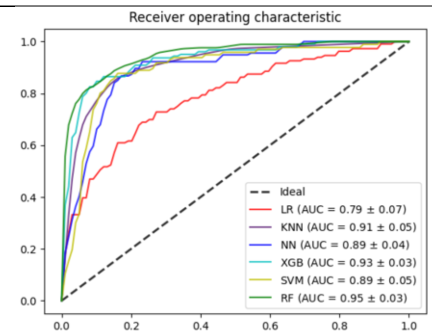

Figure 2. ROC curve for final classification models

4. Discussion

Developing an understanding of who may or may not need transport to a facility capable of providing monitored dialysis is an issue of clinical importance. Not all hospital facilities can provide monitored dialysis and transporting a patient to a facility that cannot provide this service will inevitably lead to a second transport (which may be associated with patient morbidity, or an increase in healthcare system cost). Knowing who would require urgent dialysis will ensure that patients are sent to the right tertiary care facility. This study utilized a regional dataset of chronic hemodialysis patients who were transported to the emergency department to predict those who required timely dialysis in a monitored setting following transport. The ML-modelling approach addressed (a) the class imbalance between urgent and non-urgent dialysis where almost 90% of patients do not require urgent dialysis; and (b) limited number of clinical markers available to paramedics at the time of ambulance transport. Based on the decision curve analysis, the ML methods showed superior performance in comparison with the conventional logistic regression model. Moreover, ML methods were better at predicting urgent dialysis compared to biostatistical approaches [1].

5. Conclusions

Much ML based prediction modeling is focused on predicting in-hospital interventions, risks and outcomes. In this research, we focused on providing decision support to assist paramedics during the critical period between home to hospital transport. The use of ML methods offers a new approach to investigate the predictability of patients' needs for urgent dialysis during ambulance transportation. In developing ML based prediction models offering high accuracy for predicting patients who need urgent dialysis. This study addressed the class imbalance problem, which is quite common in clinical datasets, and demonstrated the ability of ML models to provide high prediction performance even with a limited number of patient features. The future research plan is to develop a decision support application incorporating the urgent dialysis prediction model to help paramedics make timely decisions about patients dialysis needs. In addition, ML models will be developing to predict other important outcomes, including, hospitalization related to dialysis.

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