MEDINFO23

8 – 12 JULY 2023 | SYDNEY, AUSTRALIA

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

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Background

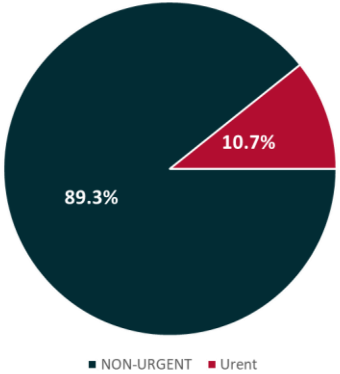
- Predicting the need for an urgent clinical intervention is important for prognostication and care planning
- Chronic hemodialysis patients frequently require ambulance transport to the Emergency Department (ED)
- Predicting the need for urgent dialysis by paramedics is of life saving importance
- Urgent dialysis is not offered in all hospitals—knowing which patients may require it can help avoid re-transport and harmful delays in care

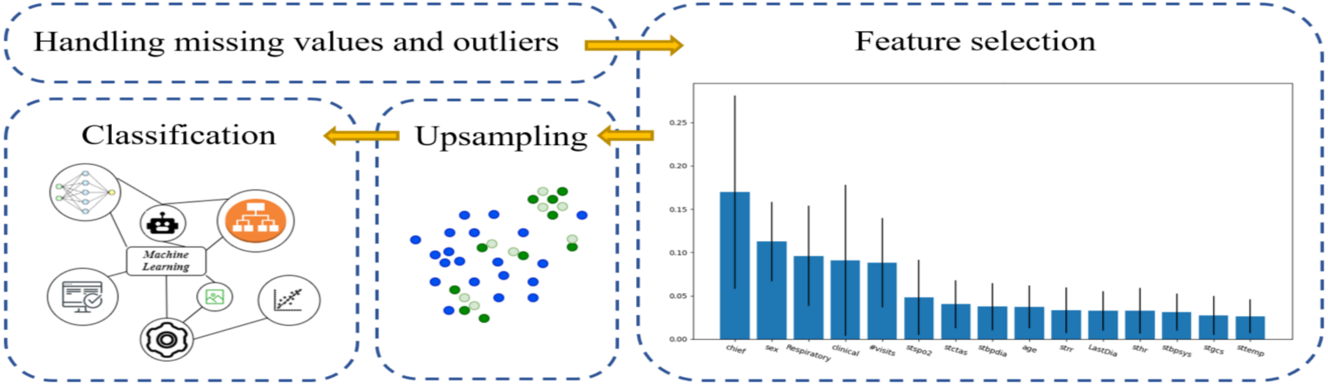
Objectives and Approach

- To help paramedics decide whether dialysis patients transported to the ED will require timely, monitored dialysis ("urgent dialysis")
    - To transport the hemodialysis patient to the appropriate hospital
- To develop a Machine Learning (ML) based prediction model to predict need for urgent dialysis using clinical markers available to paramedics
- Data
    - Ambulance transport data for chronic hemodialysis patients, in Nova Scotia (Canada) over a 5-years period (2014-2018)
    - 879 ambulance transports of which 94 (11%) needed urgent dialysis
    - Patient characteristics available to paramedics (21 variables): vital signs, demographics, chief complaint, and the number of hours from the last dialysis
    - The primary outcome was urgent dialysis

Methodology

- ML-based model for predicting urgent dialysis
  - Imbalance dataset--ratio between the urgent and non-urgent classes is 1:8
  - Missing data values
  - Feature selection
  - Prediction model development





Data Imputation

- Classification
  - Non-linear support vector regression
  - One nearest neighbour
- Density plots for pre- and post-imputation feature values are similar

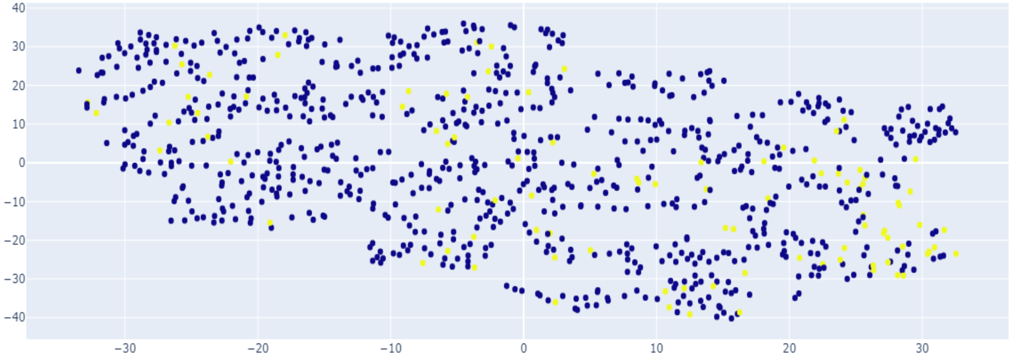
input

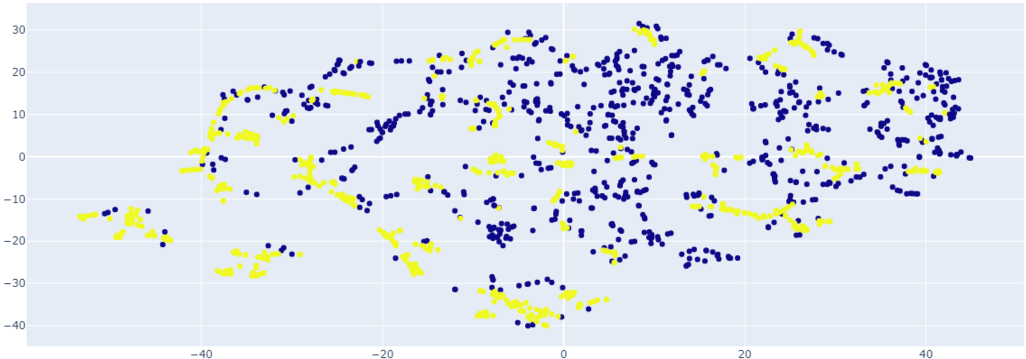
target

age	sex	ciden	fcomp	alimpre	stctas	stbpsys	stbpdia	sthr	strr	sttemp	stspo2	stgcs	stgluc	oflast	ehscta	urgentdialys
56	0	#####	Other	kness/Ma	2	70	40	102	16	39	84	14	11	#####	1 or 2	1
74	1	#####	espirato	espirator	3	150	90	92	30	37	84	15		#####	3,4 or 5	0
74	1	#####	espirato	espirator	3	126	42	63	20	37	99	15	8	#####	3,4 or 5	0
75	1	#####	Cardiac	rdiovascu	3	140	70	68	18	37		15	5	#####	3,4 or 5	0
58	1	#####	Cardiac	rdiovascu	2	80	40	146	20	37	96	15	20	#####	1 or 2	0
82	1	#####	trointest	GI/GU	3	182	62	100	16	36	96	15	8	#####	3,4 or 5	0
53	0	#####	trointest	GI/GU	2	96	60	106	18	39	97	15	10	#####	1 or 2	0
53	0	#####	trointest	GI/GU	3	144	80	74	24	37	100	15	6	#####	3,4 or 5	0
43	0	#####	Cardiac	rdiovascu	2	110	60	72	16	37	98	15	6	#####	1 or 2	0
79	1	#####	ness/Ma	kness/Ma	2	100	58	76	36	37	93	12	7	#####	1 or 2	1
65	1	#####	Other	skeletal/	2		50	70	18	36	97	15	6	#####	1 or 2	0
67	1	#####	skeletal	skeletal/	3	110	60	110	20	37	97	15		#####	3,4 or 5	0
67	1	#####	Other	Other	3	122	88	108	18	37	98	15	5	#####	3,4 or 5	0
67	1	#####	skeletal	skeletal/	3	118	62	82	20	36	96	15	7	#####	3,4 or 5	0
68	1	#####	skeletal	skeletal/	3	96	56	83	18		98	15		#####	3,4 or 5	1
52	0	#####	Other	ical/psyc	3	124	76	62	16	37	100	15	4	#####	3,4 or 5	0
33	1	#####	espirato	espirator	2	84	30	120	36	39	56	15	6	#####	1 or 2	0
33	1	#####	Other	Other	3	90	60	90	16	37	99	15		#####	3,4 or 5	0
33	1	#####	trointest	GI/GU	2	148	76	78	20	38	100	15		#####	1 or 2	0
34	1	#####	trointest	GI/GU	3	116	70	86	16	37		15		#####	3,4 or 5	0
35	1	#####	trointest	GI/GU	2	110	60	86	28	38	99	15	5	#####	1 or 2	1
36	1	#####	trointest	kness/Ma	3	116	80	90	20	37	100	15	6	#####	3,4 or 5	1
36	1	#####	espirato	espirator	2	110	80	80	18	37	94	15		#####	1 or 2	0
36	1	#####	trointest	GI/GU	2	80	50	105	24	37	95	15		#####	1 or 2	0

Class Imbalance

- Experimented with up-sampling and down-sampli
  methods
- Up-sampling the minority class (i.e. urgent dialys
  - Adaptive Synthetic Sampling Method (ADASYN)
  - Synthetic Minority Over-Sampling Technique (SMOTE)
  - Borderline SMOTE





Prediction Modeling

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

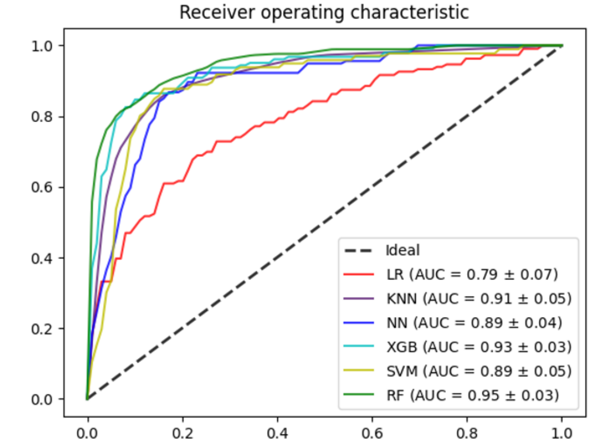
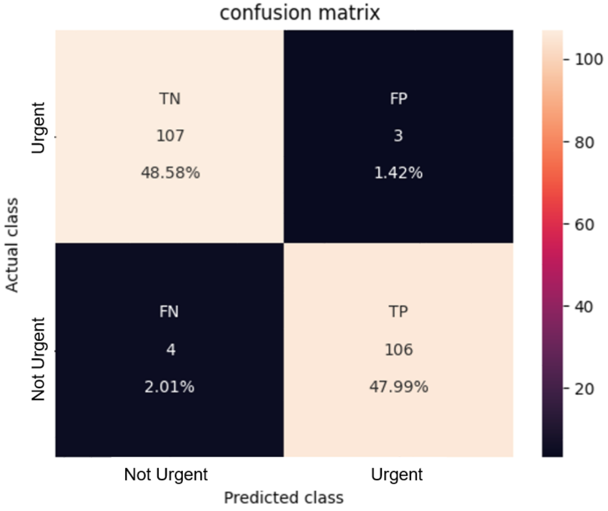
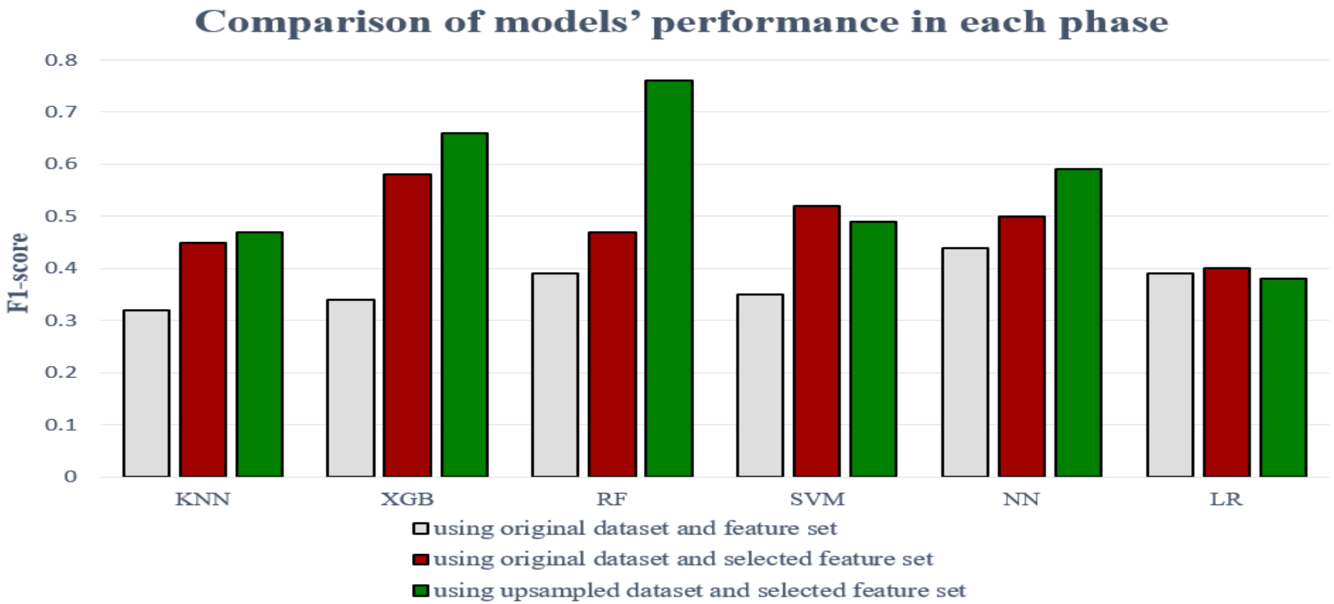


Figure 2. ROC curve for final classification models



Result Comparison



Concluding Remarks

- Pre-hospital patient data analysis to determine appropriate care options
- Decision support to assist paramedics during the critical period between home to hospital transport
- ML methods can be used to predict patients' needs for urgent dialysis during ambulance transportation
  - Addressed the class imbalance problem which is quite common in clinical datasets
  - Achieved high prediction performance using patient features available to paramedics

Thank you