Artificial Intelligence in the Operating Room: evaluating traditional classifiers to predict patient readmission

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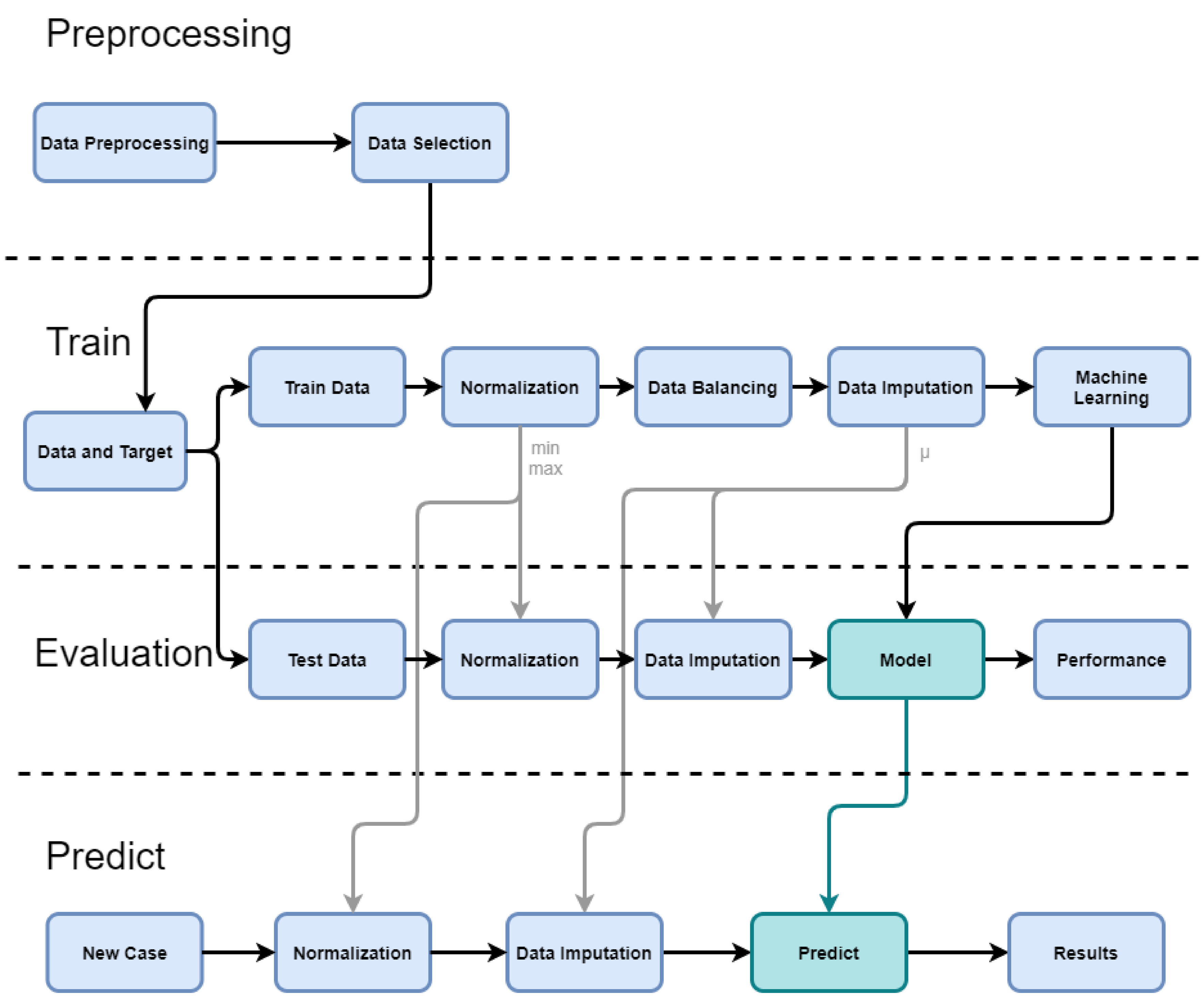
Motivation

The analysis of the number of readmissions is of uttermost importance since, in addition to the added expenses for the hospital and the implications for the patient, it is also a marker of quality of the service provided by the healthcare facility.

Methods



Dataset:
- 21,112 records from three Portuguese hospitals and contains 21,112 records
- To calculate which patients were readmitted, an interval of 30 days was considered

Pre-processing:
- Remotion of all instances for which the surgery had been cancelled

Data selection:
- 133 cases before surgery (79 non-readmissions and 54 readmissions)
- 8 095 cases after surgery (5 314 non-readmissions and 2 781 readmissions)

Data normalisation:
- Z-score normalization

Data balance:
- SMOTE (Synthetic Minority Over-sampling TEchnique)

Data imputation:
- Some of the variables were filled in with the value zero, since this value is not in the list for the designation of any attribute.
- For the variable ``Hour'', which only exists in the phase after the operation, the average calculated using only the training data, was used to fill both the training and test data

Classifiers:

Logistic Regression (LR)
Support Vector Machines (SVM)
K-Nearest Neighbour (kNN)
Decision Trees (DT)

Evaluation

A percentage of 30% was used for the test set, and the remaining was left for the train test.

Table 1: Precision, Recall and F1-Score before surgery

Precision	LR	SVM	kNN	DT
Not readmitted	0.64	0.63	0.68	**1.00**
Readmitted	0.85	0.68	0.87	**0.96**
Recall	LR	SVM	kNN	DT
Not readmitted	0.92	0.76	0.92	**0.96**
Readmitted	0.46	0.54	0.54	**1.00**
F1-Score	LR	SVM	kNN	DT
Not readmitted	0.75	0.69	0.78	**0.98**
Readmitted	0.59	0.60	0.67	**0.98**

Table 2: Precision, Recall and F1-Score after surgery

Precision	LR	SVM	kNN	DT
Not readmitted	0.82	0.84	0.80	**0.87**
Readmitted	0.55	0.55	0.65	**0.75**
Recall	LR	SVM	kNN	DT
Not readmitted	0.68	0.76	0.76	**0.86**
Readmitted	0.72	0.73	0.65	**0.75**
F1-Score	LR	SVM	kNN	DT
Not readmitted	0.74	0.80	0.78	**0.86**
Readmitted	0.62	0.67	0.62	**0.75**

Conclusion

The objective of this project was to develop a forecast model for the readmission of a patient before and after undergoing a surgical intervention. The existence of these models will have a high impact in the clinical practice. A patient predicted to be readmitted can be more carefully analysed by the healthcare staff and more tests and procedures can be performed before his release from the hospital in order to reduce the number of readmissions. Even after the release of the patient from the hospital, a closer monitoring of the recovery by phone calls or schedule appointments can be done to identify early possible problems.

Although the developed model is functional, there are improvements that could be made. The application of deep learning} techniques is a possibility. We note, however, that these type of models need to be carefully evaluated, being that simpler models are to be favoured in this context.