MINING ACUTE STROKE PATIENTS' DATA USING SUPERVISED MACHINE LEARNING

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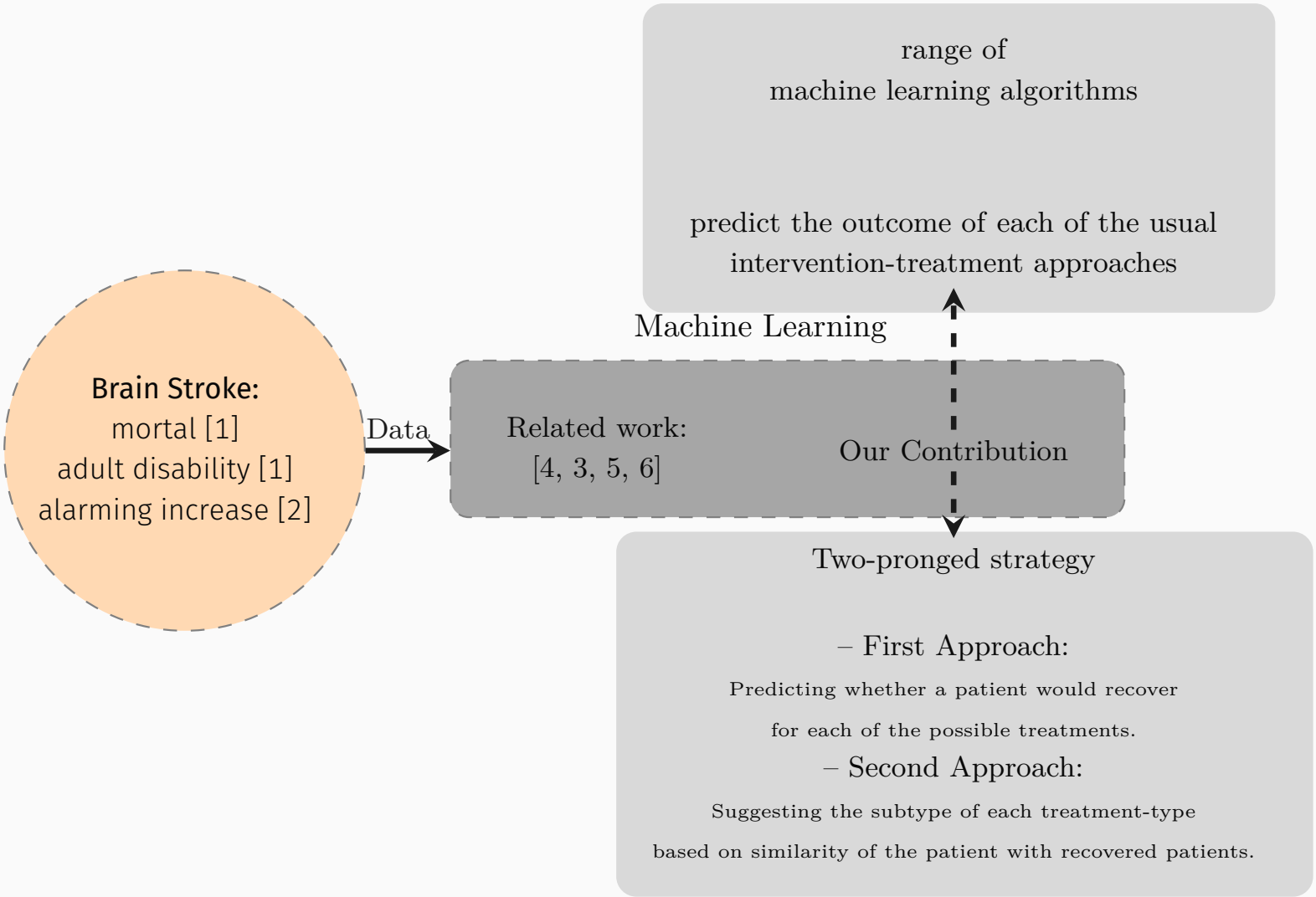
Outlines

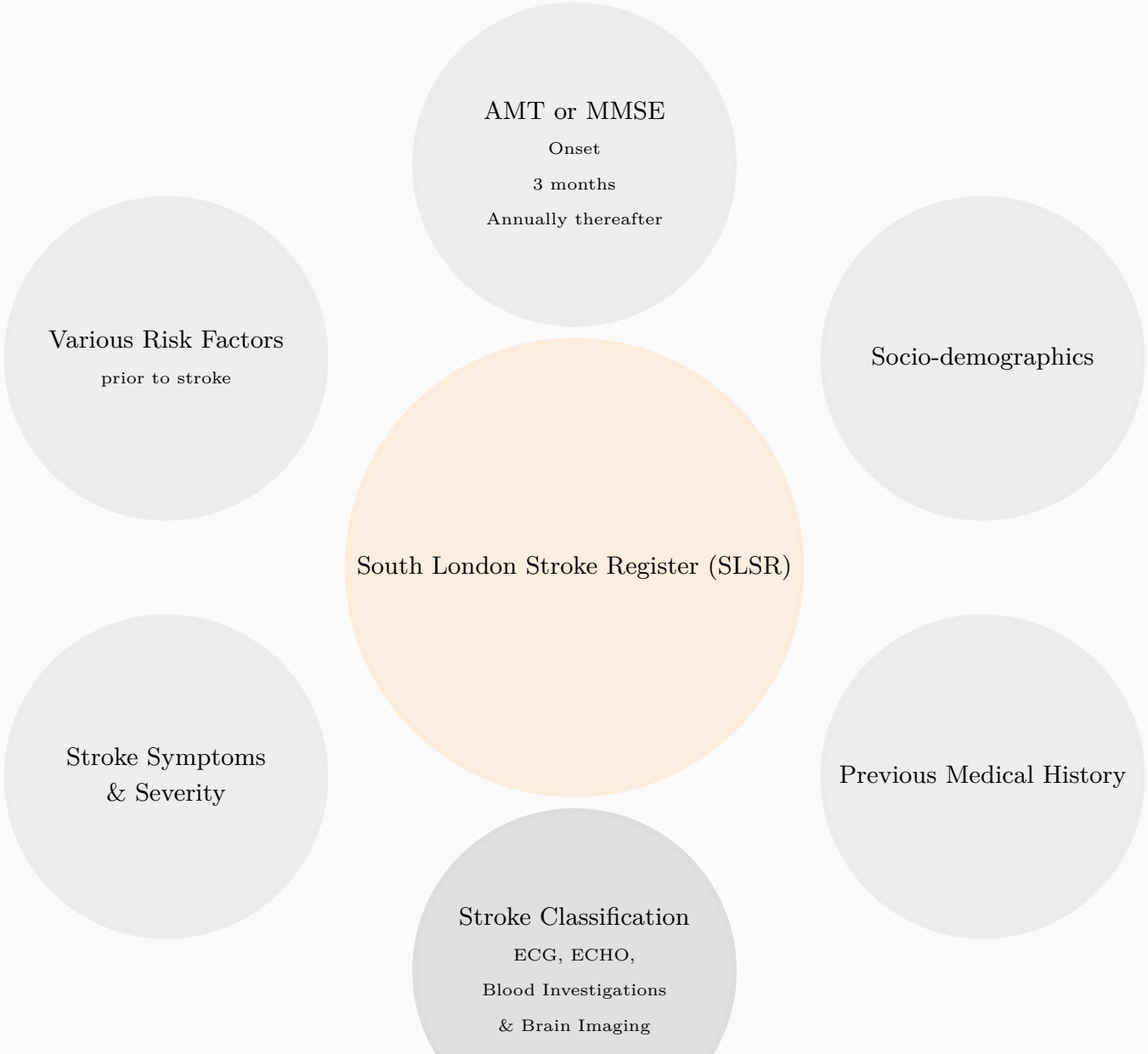
INTRODUCTION

Motivation


range of
machine learning algorithms
predict the outcome of each of the usual
intervention-treatment approaches
Machine Learning
Brain Stroke:
mortal [1]
adult disability [1]
alarming increase [2]
Data
Related work:
[4, 3, 5, 6]
Our Contribution
Two-pronged strategy
– First Approach:
Predicting whether a patient would recover
for each of the possible treatments.
– Second Approach:
Suggesting the subtype of each treatment-type
based on similarity of the patient with recovered patients.

DATASET

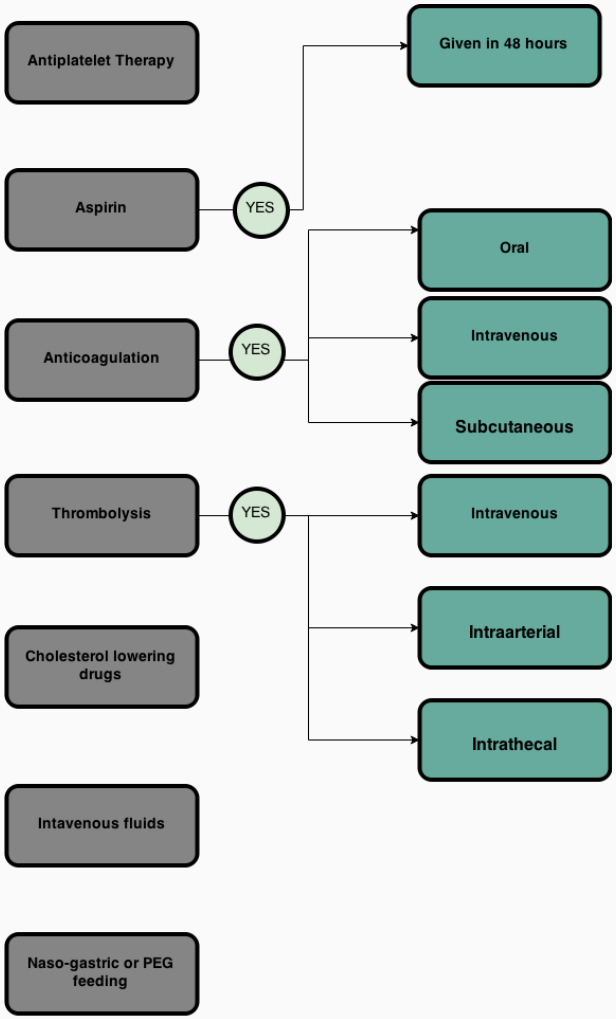
Dataset


AMT or MMSE
Onset
3 months
Annually thereafter
Various Risk Factors
prior to stroke
Socio-demographics
South London Stroke Register (SLSR)
Stroke Symptoms
& Severity
Previous Medical History
Stroke Classification
ECG, ECHO,
Blood Investigations
& Brain Imaging

METHODOLOGY

Classifications Criteria

Treatment Types:



First Approach

- Each sub-type of the main treatment types : treatment-class
- Predict if a treatment-class leads to recovery or not

Second Approach

- For each treatment type, suggest its subtype
- Use similarity with the recovered patients

Preprocessing of Data

Labelling *Recovered* and *not-recovered*:

- Scores accessing cognitive impairment:
  - Abbreviated Mental Test: Threshold - 7
  - Mini-Mental State Examination: Threshold - 24
- Used AMT (or scaled MMSE accordingly)
- Moving average: window of 3

Cleaning Up:

- Numerical to nominal
- Feature selection

Selected Treatment-classes

Index	Type of treatment
1	Antiplatelet therapy
2	Aspirin
3	Anticoagulation-subcutaneous
4	Anticoagulation-oral
5	Thrombolysis-oral
6	Cholesterol lowering drugs
7	Naso-gastric or PEG feeding
8	Intavenous fluids

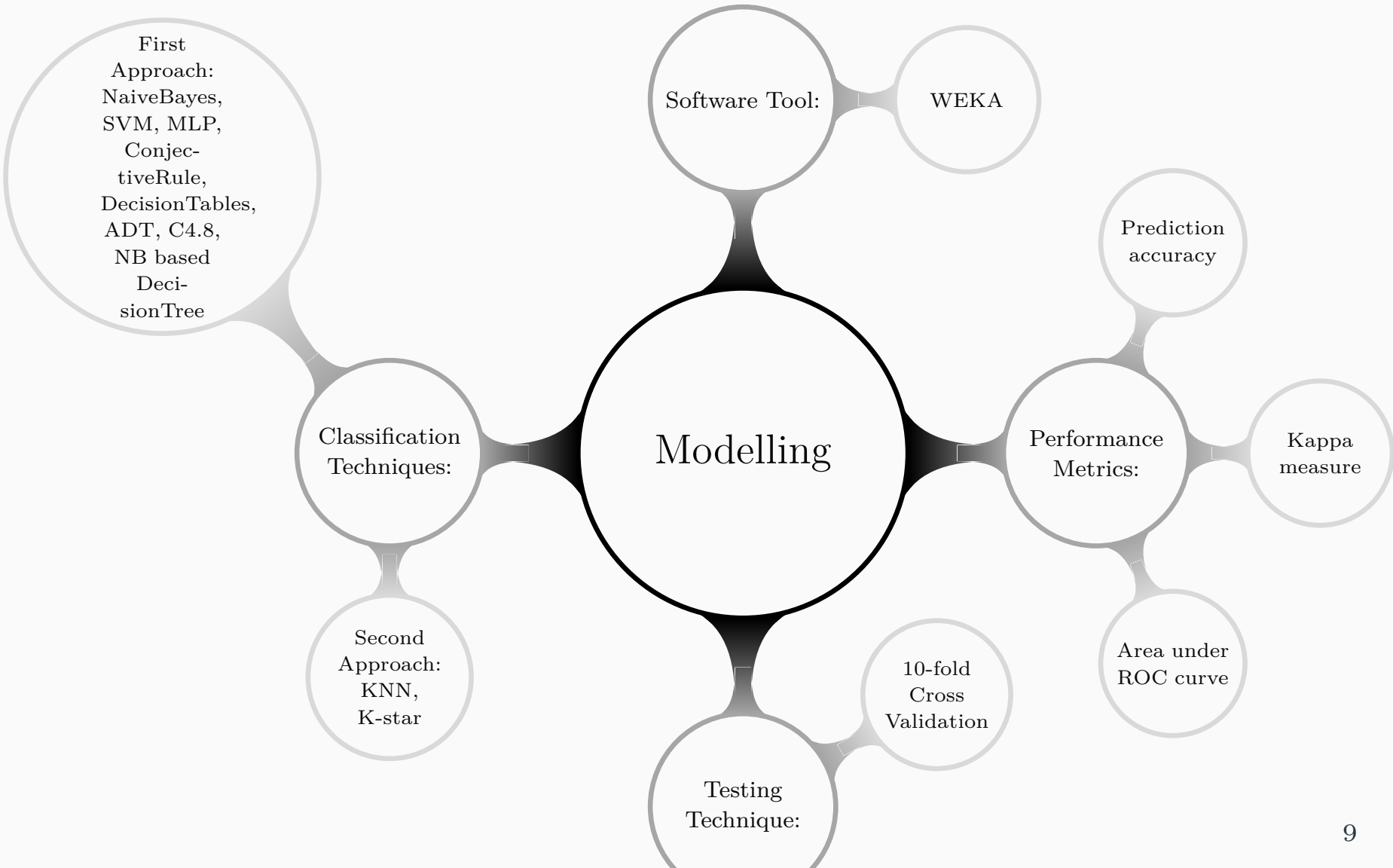
First Approach

- $n = 520$
- $Treatment - classes = 8$

Second Approach

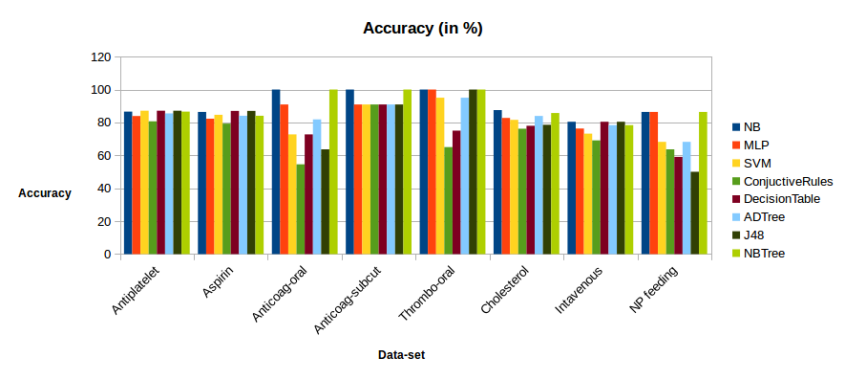
- $n = 390$
- $Treatment - classes = 7$ (merged 3 and 4)

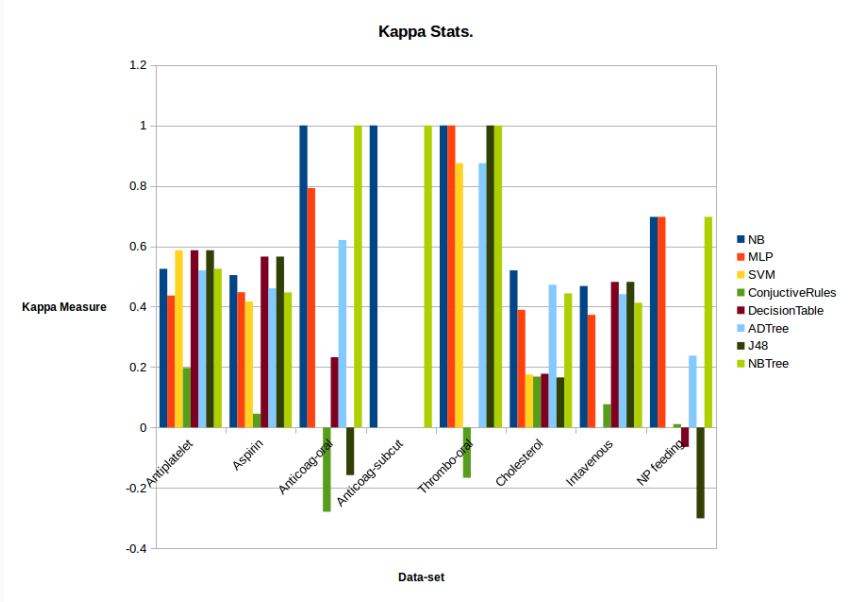
Modelling Data

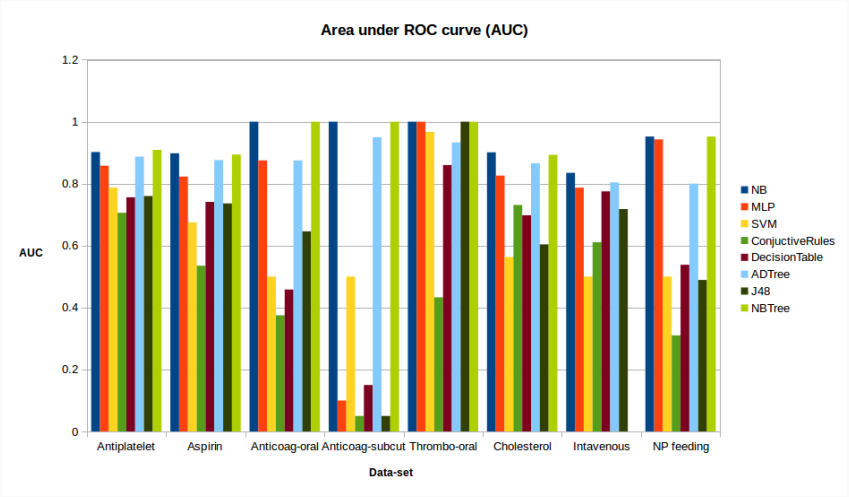


EVALUATION RESULTS AND COMPARISON

First Approach



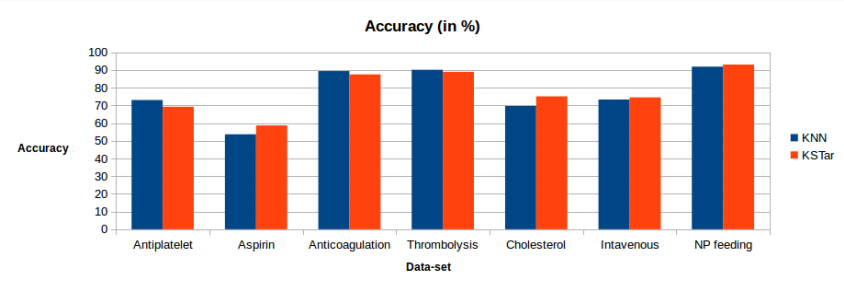


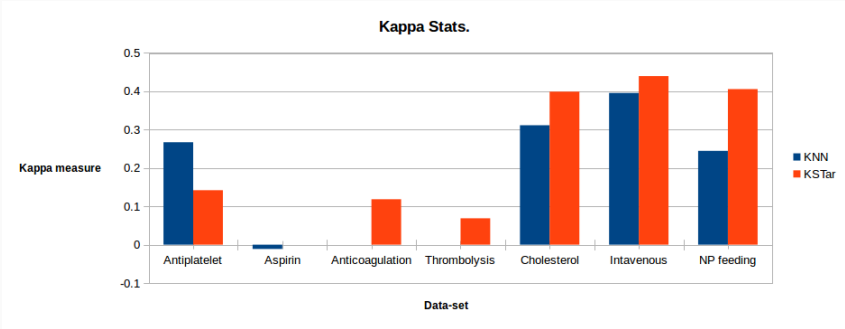


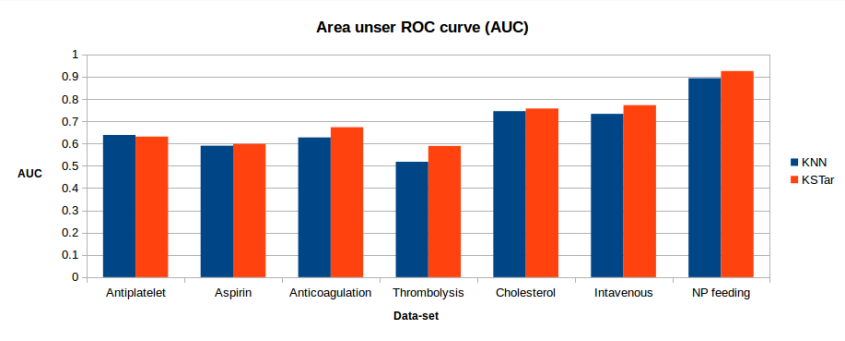
First Approach

	Accuracy (in %)	Kappa measure	Area under ROC
Antiplatelet	J48	J48	ADTree
	87.0968	0.578	0.871
Aspirin	ADTree	ADTree	NB
	85.7988	0.5375	0.846
Anticoag-subcut	All except SVM	NB, NBTree	NB, NBTree
	90.9091	0.6207	1
Anticoag-oral	MLP, ConjuctiveRules, ADTree, J48	NB, DecisionTable, NBTree	ADTree
	72.7273	0.2326	0.75
Thrombo-oral	NB, J48, NBTree	J48	NB, J48, NBTree
	90	0.76447	1
Cholesterol	ADTree	ADTree	ADTree, J48
	86.3095	0.4889	0.883
Intavenous	ADTree	ADTree	ADTree
	79.3814	0.4476	0.807
NP feeding	MLP	MLP	NB, NBTree
	81.8182	0.581	0.867

Second Approach



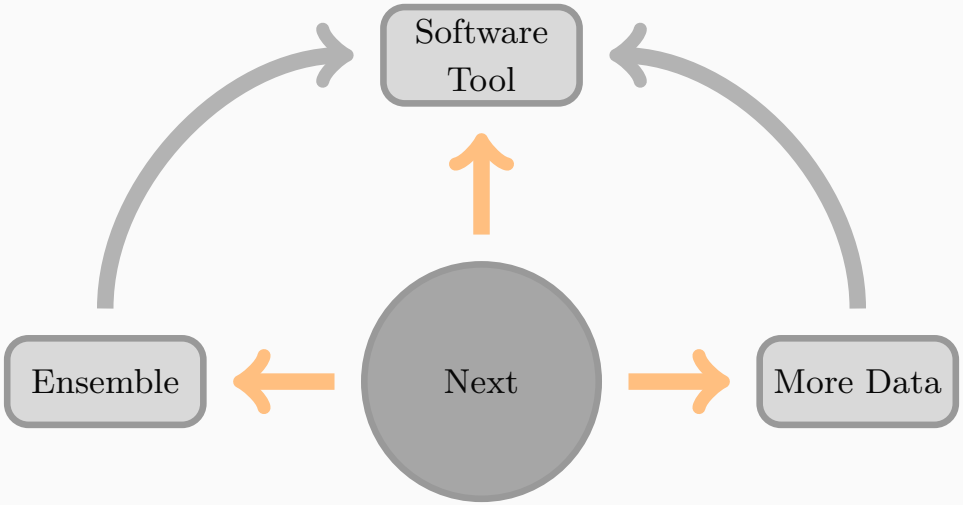




Second Approach

	Accuracy (in %)	Kappa measure	Area under ROC
Antiplatelet	Both	KStar	KStar
	65.019	0.168	0.612
Aspirin	KStar	KStar	KStar
	54.5455	0.2287	0.634
Anticoagulation	KNN	KStar	KStar
	88.9734	0.0504	0.565
Thrombolysis	KNN	KNN	KStar
	88.5496	0.0041	0.562
Cholesterol-oral	KNN	KNN	KNN
	64.9805	0.1647	0.68
Intavenous	KNN	KNN	KNN
	67.6113	0.2676	0.709
NP feeding	KNN	KStar	KNN
	91.8605	0.179	0.82

Conclusion



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Thank You!

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