University of Ottawa CSI 5155 Machine Learning Assignment 1 – Report

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GitHub: https://github.com/kmock930/Drug-Consumption-Machine-Learning-analysis.git

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Introduction

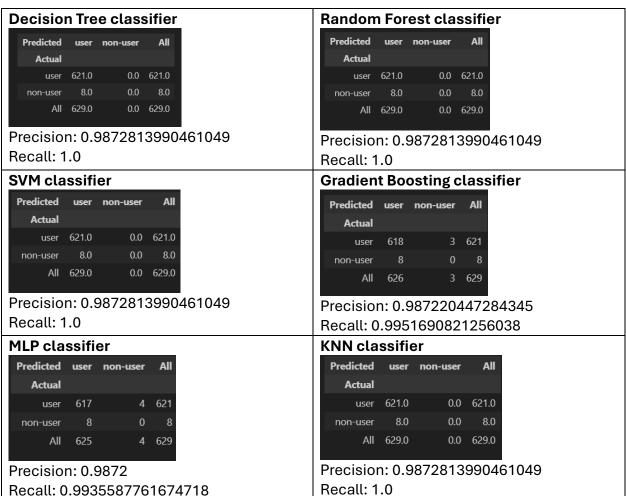
In the given classification problem, I applied a machine learning pipeline with 6 different classifiers on 2 datasets respectively based on the following approaches: classifying with fined tuned parameters (from the *Random Search* algorithm), classifying with undersampled data, classifying with over-sampled data, and classifying with a combination of data from both sampling methods.

In this report, I am going to show their performances with *confusion matrices*, some insightful metrics (including the *recall* and the *precision*) of each classifier, as well as *Receiver-Operating Characteristic curves (ROCs)* which show the performances of each classifier in terms of an *Area Under Curve (AUC)*.

Models Evaluation

Classification without sampling

Chocolate Dataset



Decision Tree classifier

Predicted	user	non-user	All
Actual			
user	170	451	621
non-user	2		8
All	172	457	629

Precision: 0.9883720930232558 Recall: 0.9883720930232558

Random Forest classifier

Predicted	user	non-user	All
Actual			
user	221	400	621
non-user	4	4	8
All	225	404	629

SVM classifier

Predicted	user	non-user	All
Actual			
user	236	385	621
non-user	4	4	8
All	240	389	629

Gradient Boosting classifier

Predicted	user	non-user	All
Actual			
user	211	410	621
non-user	5	3	8
All	216	413	629

Precision: 0.9768518518518519 Recall: 0.3397745571658615

MLP classifier

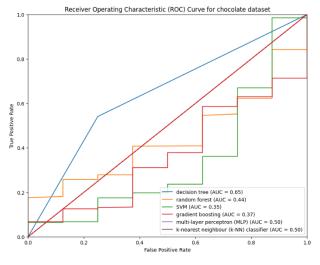
Predicted	user	non-user	All	
Actual				
user	222	399	621	
non-user	4	4	8	
All	226	403	629	

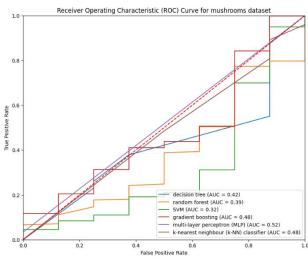
Precision: 0.9823008849557522 Recall: 0.357487922705314

KNN classifier

111111 0140011101			
Predicted	user	non-user	All
Actual			
user	239	382	621
non-user	4	4	8
All	243	386	629

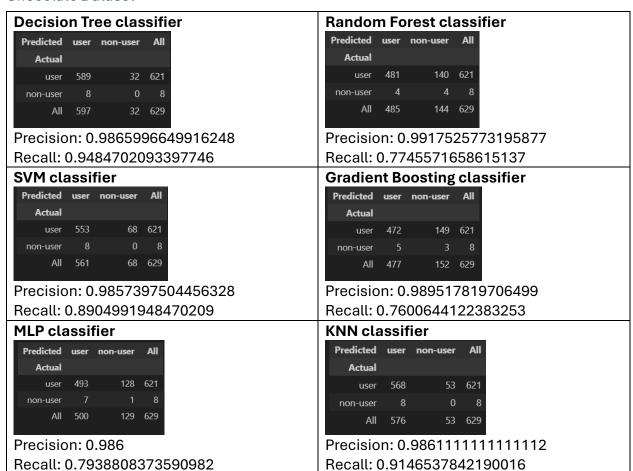
Precision: 0.9835390946502057 Recall: 0.38486312399355876





Classification with the Under-sampling method

Chocolate Dataset





Precision: 0.9879310344827587 Recall: 0.9227053140096618

Random Forest classifier			
Predicted	user non-user		All
Actual			
user	481	140	621
non-user	4	4	8
All	485	144	629

Precision: 0.9917525773195877 Recall: 0.7745571658615137

SVM classifier

Predicted	user	non-user	All
Actual			
user	553	68	621
non-user	8	0	8
All	561	68	629

Precision: 0.9857397504456328 Recall: 0.8904991948470209

Gradien	t Boo	sting
Predicted	user	non-us

Predicted	user	non-user	All
Actual			
user	470	151	621
non-user	5	3	8
All	475	154	629

Precision: 0.9894736842105263 Recall: 0.7568438003220612

MLP classifier

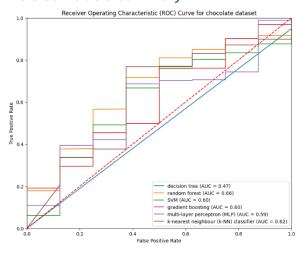
Predicted	user	non-user	All
Actual			
user	494	127	621
non-user	7	1	8
All	501	128	629

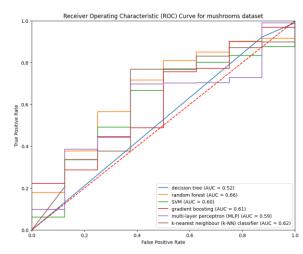
Precision: 0.9860279441117764 Recall: 0.7954911433172303

KNN classifier

KININ CLASSIFICI			
Predicted	user	non-user	All
Actual			
user	568	53	621
non-user	8	0	8
All	576	53	629

Precision: 0.9861111111111112 Recall: 0.9146537842190016





Classification with the Over-sampling method

Chocolate Dataset

Predicted user non-user All Actual user 456 165 621 non-user 7 1 8 All 463 166 629

Precision: 0.9848812095032398 Recall: 0.7342995169082126

Random Forest classifier			
Predicted	user	non-user	All
Actual			
user	427	194	621
non-user	6	2	8
All	433	196	629

Precision: 0.9861431870669746 Recall: 0.6876006441223832

SVM classifier

Predicted	user	non-user	All
Actual			
user	481	140	621
non-user	7	1	8
All	488	141	629

Precision: 0.985655737704918 Recall: 0.7745571658615137

Gradient Boosting

	_	
user	non-user	All
415	206	621
6	2	8
421	208	629
	415 6	6 2

Precision: 0.9857482185273159 Recall: 0.6682769726247987

MLP classifier

Predicted	user	non-user	All
Actual			
user	466	155	621
non-user	5	3	8
All	471	158	629

Precision: 0.9893842887473461 Recall: 0.750402576489533

KNN classifier

Predicted	user	non-user	All
Actual			
user	421	200	621
non-user	4	4	8
All	425	204	629

Precision: 0.9905882352941177 Recall: 0.677938808373591

Decision Tree classifier

			_
Predicted	user	non-user	All
Actual			
user	431	190	621
non-user	4	4	8
All	435	194	629

Precision: 0.9908045977011494 Recall: 0.6940418679549114

Random Forest classifier

Predicted	user	non-user	All
Actual			
user	428	193	621
non-user	5	3	8
All	433	196	629

Precision: 0.9884526558891455 Recall: 0.6892109500805152

SVM classifier

Predicted	user	non-user	All
Actual			
user	481	140	621
non-user	7	1	8
All	488	141	629

Precision: 0.985655737704918 Recall: 0.7745571658615137

Gradient Boosting classifier

Predicted	user	non-user	All
Actual			
user	411	210	621
non-user	6	2	8
All	417	212	629

Precision: 0.9856115107913669 Recall: 0.6618357487922706

MLP classifier

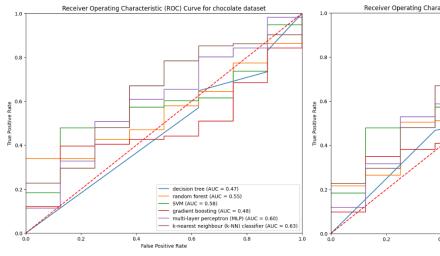
Predicted	user	non-user	All
Actual			
user	467	154	621
non-user	5	3	8
All	472	157	629

Precision: 0.989406779661017 Recall: 0.7520128824476651

KNN classifier

Predicted	user	non-user	All
Actual			
user	421	200	621
non-user	4	4	8
All	425	204	629

Precision: 0.9905882352941177 Recall: 0.677938808373591



Classification with a combination of sampling methods

Chocolate Dataset

Decision Tree classifierPredictedusernon-userAllActual302621non-user268All321308629

Precision: 0.9937694704049844 Recall: 0.5136876006441223

Random Forest classifierPredictedusernon-userAllActualuser435186621non-user628All441188629

Precision: 0.9863945578231292 Recall: 0.7004830917874396

SVM classifier

Predicted	user	non-user	All
Actual			
user	469	152	621
non-user	7	1	8
All	476	153	629

Precision: 0.9852941176470589 Recall: 0.7552334943639292

Gradient Boosting classifier

		_	
Predicted	user	non-user	All
Actual			
user	427	194	621
non-user	6	2	8
All	433	196	629

Precision: 0.9861431870669746 Recall: 0.6876006441223832

MLP classifier

Predicted	user	non-user	All
Actual			
user	473	148	621
non-user	5	3	8
All	478	151	629

Precision: 0.9895397489539749 Recall: 0.7616747181964574

KNN classifier

Predicted	user	non-user	All
Actual			
user	448	173	621
non-user	5	3	8
All	453	176	629

Precision: 0.9889624724061811 Recall: 0.7214170692431562

Decision Tree classifier

Predicted	user	non-user	All
Actual			
user	388	233	621
non-user	3	5	8
All	391	238	629

Precision: 0.9923273657289002 Recall: 0.6247987117552335

Predicted user non-user All Actual user 435 186 621 non-user 6 2 8

All 441

Random Forest classifier

Precision: 0.9863945578231292 Recall: 0.7004830917874396

188 629

SVM classifier

Predicted	user	non-user	All
Actual			
user	469	152	621
non-user	7	1	8
All	476	153	629

Precision: 0.9852941176470589 Recall: 0.7552334943639292

Gradient Boosting classifier

Predicted	user	non-user	All
Actual			
user	427	194	621
non-user	6	2	8
All	433	196	629

Precision: 0.9861431870669746 Recall: 0.9861431870669746

MLP classifier

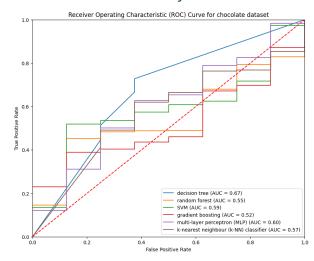
Predicted	user	non-user	All
Actual			
user	474	147	621
non-user	5	3	8
All	479	150	629

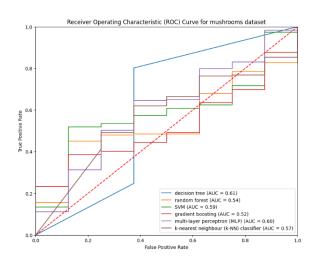
Precision: 0.9895615866388309 Recall: 0.7632850241545893

KNN classifier

Predicted	user	non-user	All
Actual			
user	448	173	621
non-user	5	3	8
All	453	176	629

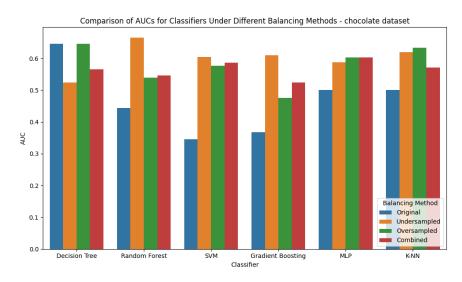
Precision: 0.9889624724061811 Recall: 0.7214170692431562

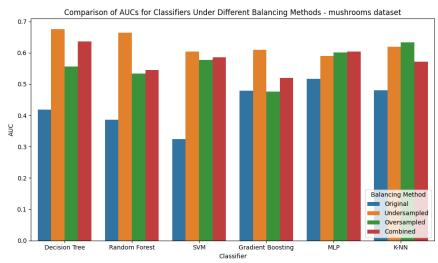




Further Analysis

Based on the above estimations, essentially the ROC curves, we have the AUCs which compares the performance of different classifiers under different sampling methods. Therefore, they are summarized in the following bar plots.





Lesson Learnt

Processes in the Pipeline

The pipeline begins with data preprocessing, followed by feature extraction. Six classifiers are then instantiated with custom parameters. *Random Search* was used for hyperparameter optimization. After splitting the datasets into training and test sets, classifiers were trained and evaluated using precision, recall, and AUC.

Analysis from the Evaluation Metrics

The primary analysis is mainly based on the *precision*, *recall*, and *AUC* scores from confusion matrices. In the original classification (without resampling), the Decision Tree achieved the highest scores across both datasets. With *under-sampling*, the Random Forest showed the highest precision in both datasets, while the Decision Tree had the highest recall and AUC in the chocolate dataset. For *oversampling*, KNN gave the highest precision and AUC in the chocolate dataset, and the SVM had the highest recall. Using *combined sampling*, the Decision Tree excelled in precision and AUC in both datasets, while MLP and Gradient Boosting had the highest recall. Overall, the **Decision Tree** is the best classifier which is also suggested in the bar plot regarding AUC comparisons across different sampling methods.

Issue in the Datasets

Why different sampling methods suggests the best classifier differently is because of the class imbalance issue. In the Chocolate dataset, we can clearly see that the number of "user" category sample (i.e., 621) is far more than that of "non-user" category samples (i.e., 8). In the Mushrooms dataset, we can also clearly see that the number of magic mushroom non-users (i.e., 386) is slightly more than that of users (i.e., 243). The imbalance of classes obviously leads to a biased conclusion. In other words, all techniques generally suggest decision tree the best classifier.

Addressing the Issue

Regarding the *class imbalance*, *Random Under Sampler* is used to under-sample the majority classes in both datasets; *SMOTE* is used to over-sample the minority classes; and a combination of techniques is used to make a fair sampling approach to the data. The advantage of that is obviously balancing the number of samples in each class. However, this may lead to other potential problems. For instance, after under-sampling the dataset, some data from the majority class are trimmed. This causes data loss. On the other hand, after over-sampling the minority class, some unnecessary data are added. Affirmatively, it reduces biases in the results, but it increases the variance of data.

Conclusion

According to the notion of "No Free Lunch" principle, no single algorithm is always the most accurate one. Therefore, the analysis here also considers using a combination of sampling methods to address the *class imbalance* issue fairly. The AUC comparison graphs suggests that:

The combination of methods has nearly an average AUC between both sampling methods; and,

By using any sampling techniques (including the combination of methods), it generally gives a higher AUC score from any classifier based on any dataset.

In conclusion, by using a sampling technique reduces biases from the class imbalance issue; and by using a combination of sampling techniques, a fair conclusion is drawn.