Active Learning Augmentation

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1 Introduction

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2 Data Augmentation Methods

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3.1 Datasets

Dataset description.

Dataset	Features	Instances	Minority instances	Majority instances	IR	Classes
IMAGE SEGMENTATION	14	1155	165	165	1.0	7
MFEAT ZERNIKE	47	1994	198	200	1.01	10
TEXTURE	40	1824	165	166	1.01	11
WAVEFORM	40	1666	551	564	1.02	3
PENDIGITS	16	1832	176	191	1.09	10
VEHICLE	18	846	199	218	1.1	4
MICE PROTEIN	69	1073	105	150	1.43	8
GAS DRIFT	128	1987	234	430	1.84	6
AUTOUNIV AU7	5	1100	153	305	1.99	5
JAPANESE VOWELS	12	1992	156	323	2.07	9
USPS	256	1859	142	310	2.18	10
GESTURE SEGMENTATION	32	1974	200	590	2.95	5
FIRST ORDER THEOREM	51	1529	122	638	5.23	6
AUTOUNIV AU4	35	1250	98	587	5.99	3
CARDIOTOCOGRAPHY	21	1063	88	827	9.4	3
VOLKERT	147	1943	45	427	9.49	10
ASP POTASSCO	116	1076	19	212	11.16	11
STEEL PLATES	24	1941	55	673	12.24	7
BASEBALL	15	1320	57	1196	20.98	3
WINE QUALITY	11	1599	10	681	68.1	6

Table 1: Description of the datasets collected from each corresponding scene. The sampling strategy is similar to all scenes.

3.2 Machine Learning Algorithms

Classifiers and generators used.

3.3 Evaluation Metrics

Performance metrics.

3.4 Experimental Procedure

Experimental procedure.

3.5 Software Implementation

The experiment was implemented using the Python programming language, along with the Python libraries Scikit-Learn [1], Imbalanced-Learn [2], Geometric-SMOTE [3], Cluster-Over-Sampling [4], Research - Learn and ML-Research libraries. All functions, algorithms, experiments and results are provided in the GitHub repository of the project.

4 Results & Discussion

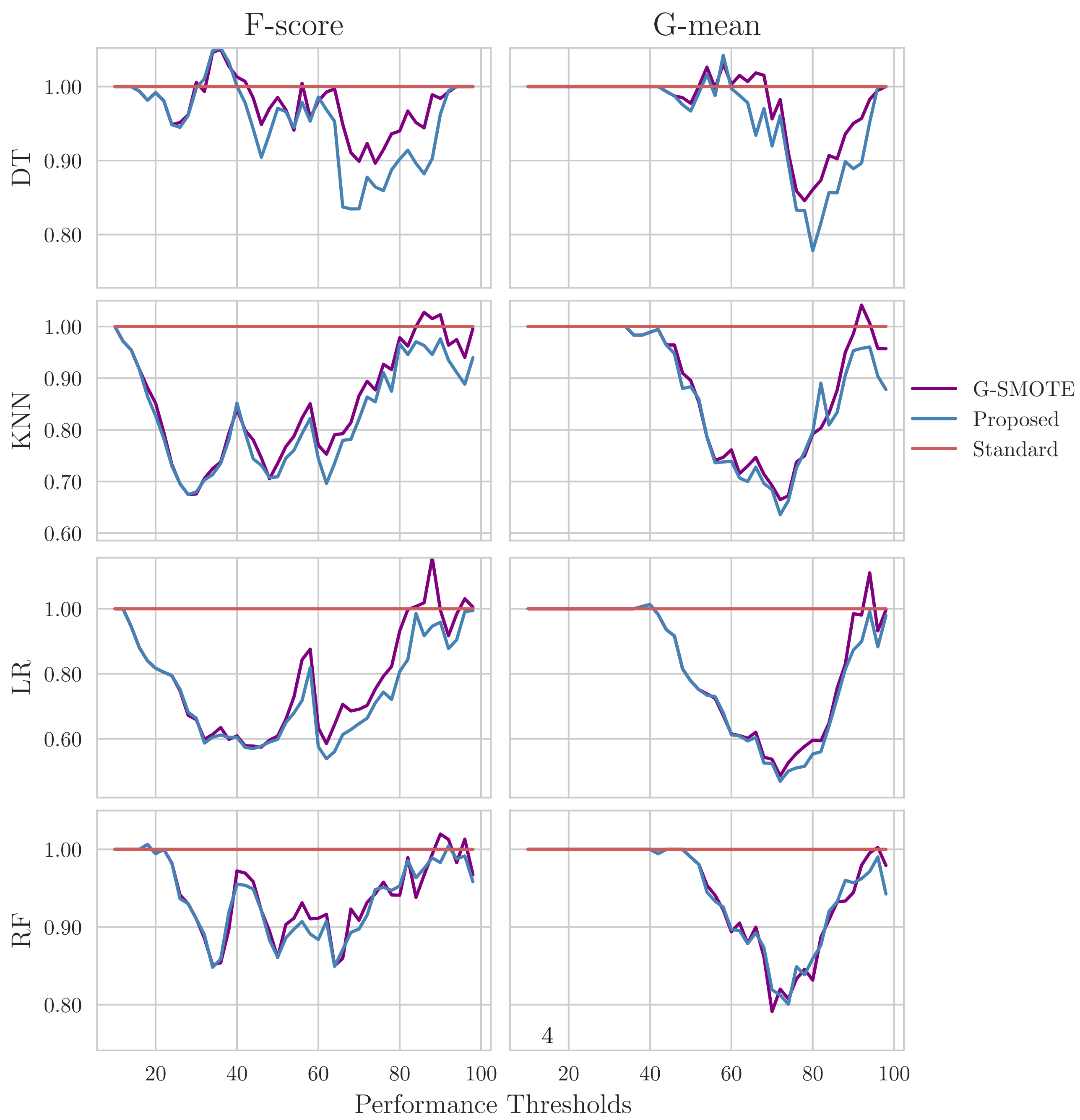
4.1 Results

Classifier	Evaluation Metric	Standard	G-SMOTE	Proposed
DT	Accuracy	2.50 ± 0.81	2.20 ± 0.4	**1.30 ± 0.64**
DT	F-score	2.50 ± 0.81	2.10 ± 0.3	**1.40 ± 0.8**
DT	G-mean	2.70 ± 0.64	2.00 ± 0.45	**1.30 ± 0.64**
KNN	Accuracy	2.40 ± 0.8	1.90 ± 0.54	**1.70 ± 0.9**
KNN	F-score	2.60 ± 0.66	1.80 ± 0.4	**1.60 ± 0.92**
KNN	G-mean	2.80 ± 0.4	1.70 ± 0.46	**1.50 ± 0.81**
LR	Accuracy	2.60 ± 0.66	2.10 ± 0.54	**1.30 ± 0.64**
LR	F-score	2.80 ± 0.4	2.00 ± 0.45	**1.20 ± 0.6**
LR	G-mean	2.80 ± 0.4	2.00 ± 0.45	**1.20 ± 0.6**
RF	Accuracy	2.60 ± 0.66	1.90 ± 0.54	**1.50 ± 0.81**
RF	F-score	2.60 ± 0.66	2.00 ± 0.45	**1.40 ± 0.8**
RF	G-mean	2.80 ± 0.4	**1.60 ± 0.49**	**1.60 ± 0.8**

Table 2: Mean rankings of the AULC metric over the different datasets (7), folds (5) and runs (3) used in the experiment. This means that the use of G-SMOTE almost always improves the results of the original framework.

Classifier	Evaluation Metric	Standard	G-SMOTE	Proposed
DT	Accuracy	0.733 ± 0.092	0.732 ± 0.087	**0.740 ± 0.087**
DT	F-score	0.695 ± 0.088	0.698 ± 0.09	**0.705 ± 0.092**
DT	G-mean	0.804 ± 0.065	0.811 ± 0.06	**0.816 ± 0.062**
KNN	Accuracy	0.816 ± 0.091	0.818 ± 0.088	**0.822 ± 0.091**
KNN	F-score	0.775 ± 0.102	0.784 ± 0.108	**0.788 ± 0.111**
KNN	G-mean	0.852 ± 0.084	0.866 ± 0.072	**0.869 ± 0.074**
LR	Accuracy	0.802 ± 0.091	0.812 ± 0.088	**0.821 ± 0.086**
LR	F-score	0.749 ± 0.112	0.773 ± 0.116	**0.784 ± 0.115**
LR	G-mean	0.839 ± 0.093	0.870 ± 0.065	**0.875 ± 0.064**
RF	Accuracy	0.861 ± 0.076	0.861 ± 0.075	**0.862 ± 0.077**
RF	F-score	0.823 ± 0.105	0.827 ± 0.105	**0.829 ± 0.105**
RF	G-mean	0.886 ± 0.077	**0.895 ± 0.063**	**0.895 ± 0.065**

Table 3: Average AULC of each AL configuration tested. Each AULC score is calculated using the G-mean scores of each iteration in the validation set. By the end of the iterative process, each AL configuration used a total of 750 instances of the 960 instances that compose the training set.



Classifier	Evaluation Metric	MP	Standard	G-SMOTE	Proposed
DT	Accuracy	0.809 ± 0.086	0.802 ± 0.089	0.806 ± 0.089	**0.812 ± 0.087**
DT	F-score	0.774 ± 0.107	0.772 ± 0.096	0.775 ± 0.101	**0.781 ± 0.103**
DT	G-mean	0.853 ± 0.081	0.854 ± 0.069	0.860 ± 0.067	**0.864 ± 0.068**
KNN	Accuracy	0.882 ± 0.085	**0.883 ± 0.087**	0.877 ± 0.087	0.881 ± 0.093
KNN	F-score	0.848 ± 0.116	0.849 ± 0.115	0.847 ± 0.118	**0.852 ± 0.121**
KNN	G-mean	0.896 ± 0.094	0.899 ± 0.09	0.904 ± 0.078	**0.907 ± 0.08**
LR	Accuracy	0.855 ± 0.074	**0.870 ± 0.073**	0.858 ± 0.077	**0.870 ± 0.076**
LR	F-score	0.812 ± 0.113	0.835 ± 0.105	0.825 ± 0.106	**0.838 ± 0.106**
LR	G-mean	0.875 ± 0.099	0.895 ± 0.075	0.899 ± 0.059	**0.907 ± 0.059**
RF	Accuracy	0.897 ± 0.08	0.905 ± 0.078	0.904 ± 0.078	**0.906 ± 0.077**
RF	F-score	0.867 ± 0.107	**0.877 ± 0.103**	0.875 ± 0.108	**0.877 ± 0.108**
RF	G-mean	0.911 ± 0.081	0.917 ± 0.078	0.923 ± 0.067	**0.925 ± 0.065**

Table 4: Optimal classification scores. The Maximum Performance (MP) classification scores are calculated using classifiers trained using the entire training set.

4.2 Statistical Analysis

Dataset	p-value	Significance
Baseball	2.6e-02	True
Gas Drift	2.0e-06	True
Image Segmentation	3.8e-05	True
Japanese Vowels	2.1e-02	True
Mfeat Zernike	9.5e-04	True
Mice Protein	1.5e-08	True
Pendigits	5.3e-05	True
Texture	5.4e-06	True
Vehicle	9.2e-03	True
Waveform	4.3e-03	True

Table 5: Adjusted p-values using the Wilcoxon signed-rank method. Bold values are statistically significant at a level of $\alpha = 0.05$. The null hypothesis is that the performance of the proposed framework is similar to that of the original framework.

4.3 Discussion

5 Conclusion

References

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