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Increasing the Effectiveness of Active Learning: Introducing Artificial Data Generation in Active Learning for Land Use/Land Cover Classification

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1 Abstract: In remote sensing, Active Learning (AL) has become an important technique to collect informative ground truth data “on-demand” for supervised classification tasks. In spite of its effectiveness, it is still significantly reliant on user interaction, which makes it both expensive and time consuming to implement. Most of the current literature focuses on the optimization of AL by modifying the selection criteria and the classifiers used. Although improvements in these areas will result in more effective data collection, the use of artificial data sources to reduce human-computer interaction remains unexplored. In this paper, we introduce a new component to the typical AL framework, the data generator, a source of artificial data to reduce the amount of user-labeled data required in AL. The implementation of the proposed AL framework is done using Geometric SMOTE as data generator. We compare the new AL framework to the original one using similar acquisition functions and classifiers over three AL-specific performance metrics in seven benchmark datasets. We show that this modification of the AL framework significantly reduces cost and time requirements for a successful AL implementation in all of the datasets used in the experiment.

15 Keywords: Active Learning; Artificial Data Generation; Land Use/Land Cover Classification;
16 Oversampling; SMOTE

17 1. Introduction

18 The technological development of air and spaceborne sensors, as well as the increasing number of remote sensing missions have allowed the continuous collection
19 of large amounts of high quality remotely sensed data. This data is often composed of multi and hyper spectral satellite imagery, essential for numerous applications, such
20 as Land Use/Land Cover (LULC) change detection, ecosystem management [1], agricultural management [2], water resource management [3], forest management, and
21 urban monitoring [4]. Despite LULC maps being essential for most of these applications,
22 their production is still a challenging task [5,6]. They can be updated using one of the
23 following strategies:

- 24 1. Photo-interpretation. This approach consists of evaluating a patch’s LULC class by
25 a human operator based on orthophoto and satellite image interpretation [7]. This
26 method guarantees a decent level of accuracy, as it is dependent on the interpreter’s
27 expertise and human error. Typically, it is an expensive, time-consuming task that
28 requires the expertise of a photo-interpreter. This task is also frequently applied to
29 obtain ground-truth labels for training and/or validating Machine Learning (ML)
30 algorithms for related tasks [8,9].

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- 35 2. Automated mapping. This approach is based on the usage of a ML method or a
36 combination of methods in order to obtain an updated LULC map. The develop-
37 ment of a reliable automated method is still a challenge among the ML and remote
38 sensing community, since the effectiveness of existing methods varies across applica-
39 tions and geographical areas [5]. Typically, this method requires the existence of
40 ground-truth data, which is frequently outdated or nonexistent for the required
41 time frame [1]. On the other hand, employing a ML method provides readily
42 available and relatively inexpensive LULC maps. The increasing quality of state-of-
43 the-art classification methods have motivated the application and adaptation of
44 these methods in this domain [10].
- 45 3. Hybrid approaches. These approaches employ photo-interpreted data to augment
46 the training dataset and improve the quality of automated mapping [11]. It at-
47 tempts to accelerate the photo-interpretation process by selecting a smaller sample
48 of the study area to be interpreted. The goal is to minimize the inaccuracies found
49 in the LULC map by supplying high-quality ground-truth data to the automated
50 method. The final (photo-interpreted) dataset consists of only the most informa-
51 tive samples, *i.e.*, patches that are typically difficult to classify for a traditional
52 automated mapping method [12].

53 The latter method is best known as AL. It is especially useful whenever there is a
54 shortage or even absence of ground-truth data and/or the mapping region does not
55 contain updated LULC maps [13]. In a context of limited sample-collection budget,
56 the collection of the most informative samples capable of optimally increasing the
57 classification accuracy of a LULC map is of particular interest [13]. AL attempts to
58 minimize the human-computer interaction involved in photo-interpretation by selecting
59 the data points to include in the annotation process. These data points are selected
60 based on an uncertainty measure and represent the points close to the decision borders.
61 Afterwards, they are passed on for photo-interpretation and added to the training dataset,
62 while the points with the lowest uncertainty values are ignored for photo-interpretation
63 and classification. This process is repeated until a convergence criterion is reached [14].

64 The relevant work developed within AL is described in detail in Section 2. This
65 paper attempts to address some of the challenges found in AL, mainly inherited from
66 automated and photo-interpreted mapping: mapping inaccuracies and time consuming
67 human-computer interactions. These challenges have different sources:

- 68 1. Human error. The involvement of photo-interpreters in the data labeling step
69 carries an additional risk to the creation of LULC patches. The minimum mapping
70 unit being considered, as well as the quality of the orthophotos and satellite images
71 being used, are some of the factors that may lead to the overlooking of small-area
72 LULC patches and label-noisy training data [15].
- 73 2. High-dimensional datasets. Although the amount of bands (*i.e.*, features) present in
74 multi and hyper spectral images contain useful information for automated classifi-
75 cation, they also introduce an increased level of complexity and redundancy in the
76 classification step [16]. These datasets are often prone to the Hughes phenomenon,
77 also known as the curse of dimensionality.
- 78 3. Class separability. Producing an LULC map considering classes with similar
79 spectral signatures makes them difficult to separate [17]. A lower pixel resolution
80 of the satellite images may also imply mixed-class pixels, which may lead to both
81 lower class separability as well as higher risk of human error.
- 82 4. Existence of rare land cover classes. The varying morphologies of different geo-
83 graphical regions naturally implies an uneven distribution of land cover classes [18].
84 This is particularly relevant in the context of AL since the data selection method
85 is based on a given uncertainty measure over data points whose class label is
86 unknown. Consequently, AL's iterative process of data selection may disregard
87 wrongly classified land cover areas belonging to a minority class.

88 Research developed in the field of AL typically focus on the reduction of human
89 error by minimizing the human interaction with the process through the development
90 of more efficient classifiers and selection criteria within the generally accepted AL
91 framework. Concurrently, the problem of rare land cover classes is rarely addressed.
92 This is a frequent problem in the ML community, known as the Imbalanced Learning
93 problem. This problem exists whenever there is an uneven between-class distribution in
94 the dataset [19]. Specifically, most classifiers are optimized and evaluated using accuracy-
95 like metrics, which are designed to work primarily with balanced datasets. Consequently,
96 these metrics tend to introduce a bias towards the majority class by attributing an
97 importance to each class proportional to its relative frequency [10]. As an example, such a
98 classifier could achieve an overall accuracy of 99% on a binary dataset where the minority
99 class represents 1% of the overall dataset and still be useless. A number of methods
100 have been developed to deal with this problem. They can be categorized into three
101 different types of approaches [20,21]. Cost-sensitive solutions perform changes to the
102 cost matrix in the learning phase. Algorithmic level solutions modify specific classifiers
103 to reinforce learning on minority classes. Resampling solutions modify the training data
104 by removing majority samples and/or generating artificial minority samples. The latter
105 is independent from the context and can be used alongside any classifier. Since we are
106 interested in the introduction of artificial data generation in AL, we will analyze the
107 state-of-the-art on resampling techniques (specifically oversampling) in Section 3.

108 In this paper, we propose a novel AL framework to address two limitations com-
109 monly found in the literature: minimize human-computer interaction and reduce the
110 class imbalance bias. This is done with the introduction of an additional component
111 in the iterative AL procedure (the generator) that is used to generate artificial data to
112 both balance and augment the training dataset. The introduction of this component
113 is expected to reduce the number of iterations required until the classifier reaches a
114 satisfactory performance.

115 This paper is organized as follows: Section 1 explains the problem and its context,
116 Sections 2 and 3 describe the state of the art in AL and Oversampling techniques, Section
117 4 explains the proposed method, Section 5 covers the datasets, evaluation metrics, ML
118 classifiers and experimental procedure, Section 6 presents the experiment's results and
119 discussion and Section 7 presents the conclusions drawn from our findings.

120 2. Active Learning Approaches

121 As the amount of unlabeled data increases, the interest and practical usefulness of
122 AL follows that trend [22]. AL is used as the general definition of frameworks aiming to
123 train a learning system in multiple steps, where a set of new data points are chosen and
124 added to the training dataset each time [11]. Typically, an AL framework is composed of
125 the following elements [11,13,23]:

- 127 1. Unlabeled dataset. Consists of the original data source (or a sample thereof). It
128 is used in combination with the chooser and the selection criterion to expand the
129 training dataset in regions where the classification uncertainty is higher. Therefore,
130 the unlabeled dataset is used for both producing the initial training dataset by
131 selecting a set of instances for the supervisor to annotate (discussed in point 3) and
132 calculating the uncertainty map to augment the training dataset.
- 133 2. Supervisor. A human annotator (or team of human annotators) to which the
134 uncertainty map is presented to. The supervisor is responsible for annotating
135 unlabeled instances to be added to the augmented dataset. In remote sensing,
136 the supervisor is typically a photo-interpreter, as is the case in [24]. Some of the
137 research also refers to the supervisor as the *oracle* [11,25–27].
- 138 3. Initial training dataset. It is a small, labeled sample of the original data source used
139 to initiate the first AL iteration. The size of the initial training sample normally
140 varies between no instances at all and 10% of the unlabeled dataset [28].

- 141 4. Current and expanded training dataset. It is the concatenation of the initial training
 142 dataset and the datasets labeled by the supervisor in past iterations (discussed in
 143 point 2).
 144 5. Chooser (classifier). Produces the class probabilities for each unlabeled instance.
 145 6. Selection criterion. It quantifies the chooser's uncertainty level for each instance
 146 belonging to the unlabeled dataset. It is typically based on the class probabilities
 147 assigned by the chooser. In some situations, the chooser and the selection criterion
 148 are grouped together under the concept *acquisition function* [11] or *query function* [13].
 149 Some of the literature refers to the selection criterion by using the concept *sampling
 150 scheme* [12].

151 Figure 1 schematizes the steps involved in a complete AL iteration. For a better
 152 context within the remote sensing domain, the prediction output can be identified as
 153 the LULC map. This framework starts by collecting unlabeled data from the original
 154 data source. It is used to generate a random initial training sample and is labeled by
 155 the supervisor. In practical applications, the supervisor is frequently a group of photo-
 156 interpreters [22]. The chooser is trained on the resulting dataset and is used to predict the
 157 class probabilities on the unlabeled dataset. The class probabilities are fed into a selection
 158 criterion to estimate the prediction's uncertainty, out of which the instances with the
 159 highest uncertainty will be selected. This calculation is motivated by the absence of
 160 labels in the uncertainty dataset. Therefore, it is impossible to estimate the prediction's
 161 accuracy in the unlabeled dataset in a real case scenario. The iteration is completed when
 162 the selected points are tagged by the supervisor and added to the training dataset (*i.e.*,
 163 the augmented dataset).

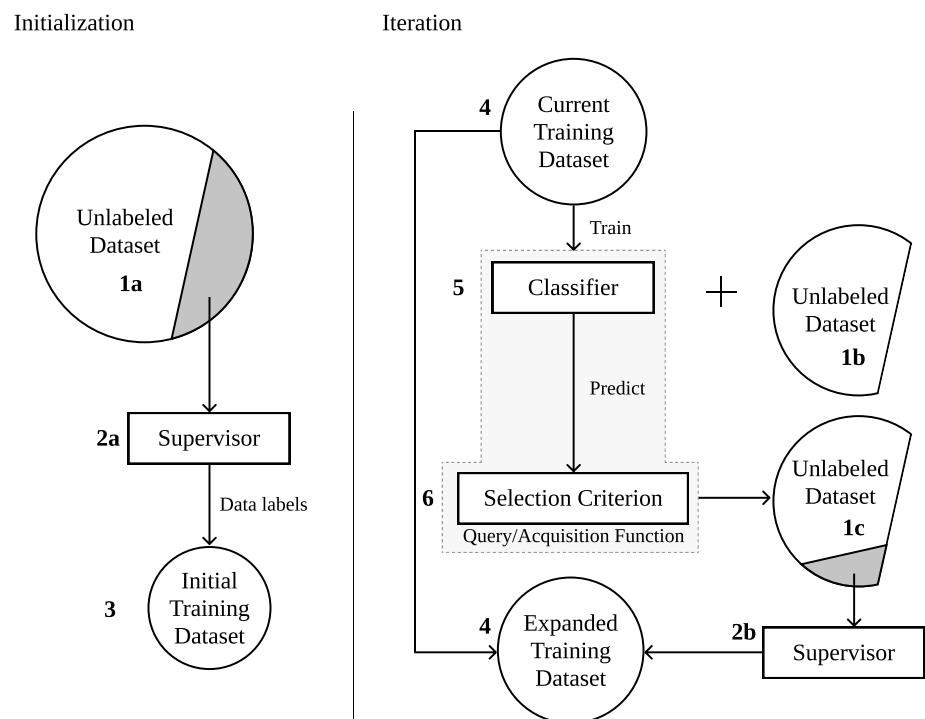


Figure 1. Diagram depicting the typical AL framework.

164 A common challenge found in AL tasks is ensuring the consistency of AL over
 165 different initializations [22]. There are two factors involved in this phenomenon. On one
 166 hand, the implementation of the same method over different initializations may result in
 167 significantly different initial training samples, amounts to varying accuracy curves. On
 168 the other hand, the lack of a robust selection criterion and/or classifier may also result in

169 inconsistencies across AL experiments with different initializations. This phenomenon
170 was observed and documented in a LULC classification context in [29].

171 The classification method plays a central role in the efficacy of AL. The classifier
172 used should be able to generalise with a relatively small training dataset. Specifically,
173 deep learning models are used in image classification due to its capability of producing
174 high quality predictions. Although, to make such models generalizable the training set
175 must be large enough, making its suitability for AL applications an open challenge [30–
176 32]. Some studies in the Remote Sensing domain were developed to address this gap.
177 In [30,32], the authors propose a deep learning-based AL approach by training the
178 same Convolutional Neural Network incrementally across iterations and smoothen the
179 decision boundaries of the model using the Markov Random Field model and a Best-
180 versus-Second Best labelling approach. This allows the introduction of additional data
181 variability in the final training dataset. Another study [31] combined transfer learning,
182 active classification and segmentation techniques for vehicle detection. By combining
183 different techniques, they were able to produce a classification mechanism that per-
184 formed well when the amount of training data is limited. However, the exploration
185 of advanced deep learning classifiers in AL is still limited. In [33], the authors show
186 that deep learning classifiers performs well on LULC classification, but are still not
187 generalizable for different geographical regions or periods. Specifically, AL methods are
188 still incapable of providing generalizable deep learning classifiers, which benefit from
189 multiple advantages. The development Convolutional Neural Networks with both 2 and
190 3-dimensional convolutions was explored in [34] and reported superior classification
191 performance on benchmark datasets. However, a large amount of training data was
192 used to produce the final classification map.

193 Selecting an efficient selection criterion is particularly important to find the instances
194 closest to the decision border (*i.e.*, instances difficult to classify) [35]. Therefore, many
195 AL related studies focus on the design of the query/acquisition function [13].

196 2.1. Non-informed selection criteria

197 Only one non-informed (*i.e.*, random) selection criterion was found in the literature.
198 Random sampling selects unlabeled instances without considering any external informa-
199 tion produced by the chooser. Since the method for selecting the unlabeled instances is
200 random, this method disregards the usage of a chooser and is comparatively worse than
201 any other selection criterion. However, random sampling is still a powerful baseline
202 method [27].

203 2.2. Ensemble-based selection criteria

204 Ensemble disagreement is based on the class predictions of a set of classifiers. The
205 disagreement between all the predictions for a given instance is a common measure for
206 uncertainty, although computationally inefficient [11,14]. It is calculated using the set of
207 classifications over a single instance, given by the number of votes assigned to the most
208 frequent class [35]. This method was implemented successfully for complex applications
209 such as deep active learning [11].

210 Multiview [36] consists on the training of multiple independent classifiers using
211 different views, which correspond to the selection of subsets of features or instances
212 in the dataset. Therefore, it can be seen as a bootstrap aggregation (bagging) ensemble
213 disagreement method. It is represented by the maximum disagreement score out of set
214 of disagreements calculated for each view [35]. A lower value for this metric means a
215 higher classification uncertainty. Multiview-based maximum disagreement has been
216 successfully applied to hyper-spectral image classification in [37] and [38].

217 An adapted disagreement criterion for an ensemble of k -nearest neighbors has been
218 proposed in [14]. This method employs a k -nearest neighbors classifier and computes
219 an instance's classification uncertainty based on the neighbors' class frequency using
220 the maximum disagreement metric over varying values for k . As a result, this method is

221 comparable to computing the dominant class' score over a weighted k -nearest neighbors
222 classifier. This method was also used on a multimetric active learning framework [39].

223 Another relevant ensemble-based selection criterion is the binary random forest-
224 based query model [13]. This method employs a one-versus-one ensemble method
225 to demonstrate an efficient data selection method using the estimated probability of
226 each binary random forest and determining the classification uncertainty based on the
227 probabilities closest to 0.5 (*i.e.*, the least separable pair of classes are used to determine
228 the uncertainty value). However, this study fails to compare the proposed method with
229 other benchmark methods, such as random sampling.

230 2.3. *Entropy-based criteria*

231 A number of contributions have focused on entropy-based querying. The applica-
232 tion of entropy is common among active deep learning applications [26], where the
233 training of an ensemble of classifiers is often too expensive.

234 Entropy query-by-bagging (EQB), also defined as maximum entropy [12], is an
235 ensemble approach of the entropy selection criterion, originally proposed in [40]. This
236 strategy uses the set of predictions produced by the ensemble classifier to calculate those
237 many entropy measurements. The estimated uncertainty measure for one instance is
238 given by the maximum entropy within that set. EQB was observed to be an efficient
239 selection criterion. Specifically, [35] applied EQB on hyper-spectral remote sensing im-
240 agery using Support Vector Machines (SVM) and Extreme Learning Machines (ELM) as
241 choosers, achieving optimal results when combining EQB with ELM. Another study suc-
242 cessfully implemented this method on an active deep learning application [12]. Another
243 study improved over this method with a normalized EQB selection criterion [41].

244 2.4. *Other relevant criteria*

245 Margin Sampling is a SVM-specific criterion, based on the distance of a given point
246 to the SVM's decision boundary [35]. This method is less popular than the remaining
247 methods because it is limited to one type of chooser (SVMs). One extension of this
248 method is the multiclass level uncertainty [35], calculated by subtracting the instance's
249 distance to the decision boundaries of the two most probable classes [42].

250 The Mutual Information-based (MI) criterion selects the new training instances
251 by maximizing the mutual information between the classifier and class labels in order
252 to select instances from regions that are difficult to classify. Although this method is
253 commonly used, it is frequently outperformed by the breaking ties selection criterion [43,
254 44].

255 The breaking ties (BT) selection criterion was originally introduced in [45]. It
256 consists of the subtraction between the probabilities of the two most likely classes.
257 Another related method is Modified Breaking Ties scheme (MBT), which aims at finding
258 the instances containing the largest probabilities for the dominant class [44,46].

259 Another type of selection criteria identified is the loss prediction method [25]. This
260 method replaces the selection criterion with a predictor whose goal is to estimate the
261 chooser's loss for a given prediction. This allows the new classifier to estimate the
262 prediction loss on unlabeled instances and select the ones with the highest predicted
263 loss.

264 Some of the literature fails to specify the strategy employed, although inferring it is
265 generally intuitive. For example, [47] successfully used AL to address the imbalanced
266 learning problem. They employed an ensemble of SVMs as the chooser, as well as
267 an ensemble-based selection criterion. All of the research found related to this topic
268 focused on the improvement of AL through modifications on the selection criterion
269 and classifiers used. None of these publications proposed significant variations to the
270 original AL framework.

271 3. Artificial Data Generation Approaches

272

273 The generation of artificial data is a common approach to address imbalanced learning
 274 tasks [21], as well as improving the effectiveness of supervised learning tasks [48]. In
 275 recent years some sophisticated data generation approaches were developed. However,
 276 the scope of this work is to propose the integration of a generator within the AL frame-
 277 work. To do this, we will focus on heuristic data generation approaches, specifically,
 278 oversamplers.

279

280 Heuristic data resampling methods employ local and/or global information to
 281 generate new, relevant, non-duplicate instances. These methods are most commonly
 282 used to populate minority classes and balance the between-class distribution of a dataset.
 283 The Synthetic Minority Oversampling Technique (SMOTE) [49] is a popular heuristic
 284 oversampling algorithm, proposed in 2002. The simplicity and effectiveness of this
 285 method contributes to its prevailing popularity. It generates a new instance through
 286 a linear interpolation of a randomly selected minority-class instance and one of its
 287 randomly selected k -nearest neighbors. The implementation of SMOTE for LULC clas-
 288 sification tasks has been found to improve the quality of the predictors used [50,51].
 289 Despite its popularity, its drawbacks motivated the development of other oversampling
 290 methods [52].

290

291 Geometric SMOTE (G-SMOTE) [52] introduces a modification of the SMOTE al-
 292 gorithm in the data generation mechanism to produce artificial instances with higher
 293 variability. Instead of generating artificial data as a linear combination of the parent
 294 instances, it is done within a deformed, truncated hyper-spheroid. G-SMOTE gener-
 295 ates an artificial instance \vec{z} within a hyper-spheroid, formed by selecting a minority
 296 instance \vec{x} and one of its nearest neighbors \vec{y} , as shown in Figure 2. The truncation
 297 and deformation parameters define the shape of the spheroid's geometry. The method
 298 also modifies the selection strategy for the k -nearest neighbors, accepting the generation
 299 of artificial instances using instances from different classes, as shown in Figure 2d. The
 300 modification of both selection and generation mechanisms addresses the main draw-
 301 backs found in SMOTE, the generation of both noisy data (*i.e.*, generate minority class
 302 instances within majority class regions) and near-duplicate minority class instances [52].
 303 G-SMOTE has shown superior performance when compared with other oversampling
 304 methods for LULC classification tasks, regardless of the classifier used [53].

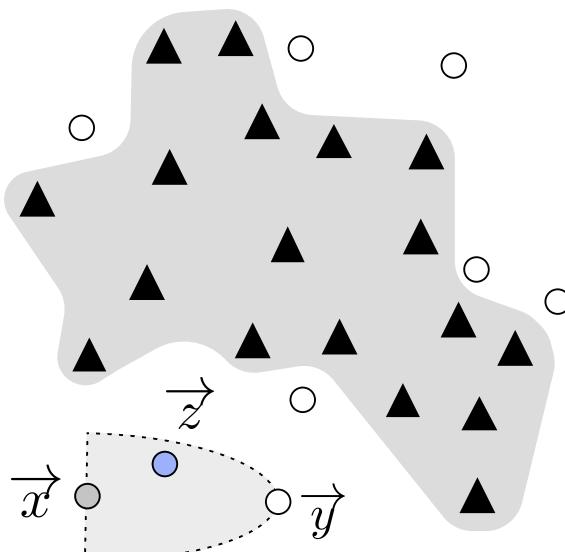


Figure 2. Example of G-SMOTE's generation process. G-SMOTE randomly selects instance \vec{x} and one of its nearest neighbors \vec{y} to produce instance \vec{z} .

304 **4. Proposed method**

305

306 Within the literature identified, most of the work developed in the AL domain
 307 revolved around improving the quality of classification algorithms and/or selection
 308 criteria. Although these methods allow earlier convergence of the AL iterative process,
 309 the impact of these methods are only observed between iterations. Consequently, none
 310 of these contributions focused on the definition of decision borders within iterations. The
 311 method proposed in this paper modifies the AL framework by introducing an artificial
 312 data generation step within AL's iterative process. We define this component as the
 313 generator and is intended to be integrated into the AL framework as shown in Figure 3.

314 This modification, by using a new source of data to augment the training set,
 315 leverages the data annotation work conducted by the human operator. The artificial
 316 data that is generated between iterations reduces the amount of labeled data required
 317 to reach optimal performance and lower the amount of human labor required to train
 318 a classifier to its optimal performance. This process lowers the annotation and overall
 319 training costs by translating some of the annotation cost into computational cost.

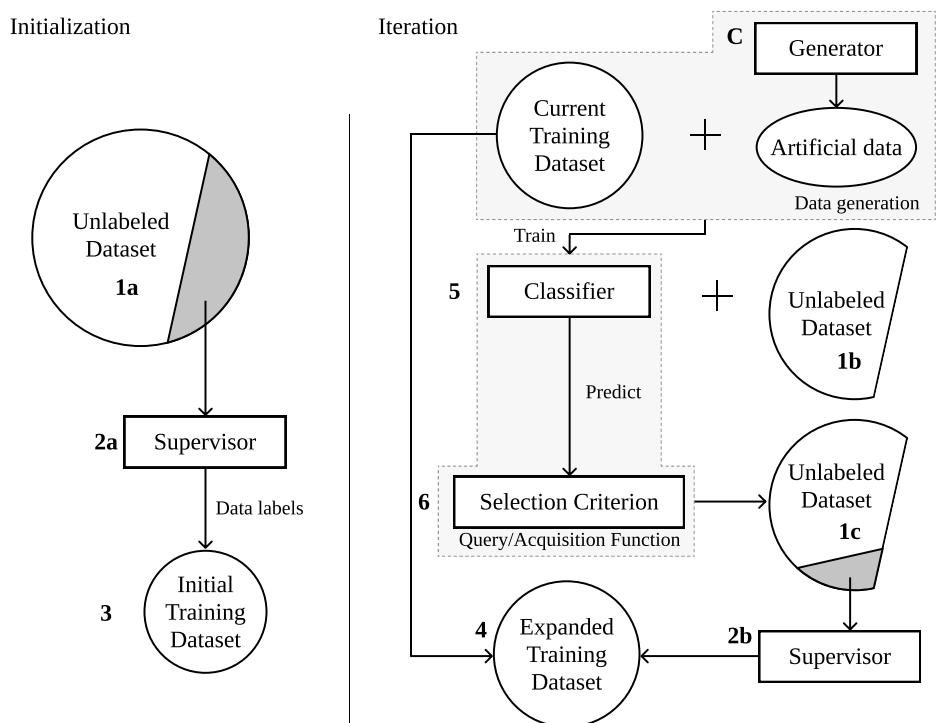


Figure 3. Proposed AL framework. This paper's contribution comprises a change in the AL framework through the introduction of a data generation mechanism, represented as the generator (marked with C), which is used to add artificial instances to the training dataset.

320

321 This method leverages the capability of artificial data to introduce more data vari-
 322 ability into the augmented dataset and facilitate the chooser's training phase with a
 323 more consistent definition of the decision boundaries at each iteration. Therefore, any
 324 algorithm capable of producing artificial data, be it agnostic or specific to the domain,
 325 can be employed. The artificial data is only used to train the classifiers involved in the
 326 process and is discarded once the training phase is completed. The remaining steps in
 327 the AL framework remain unchanged. This method addresses the limitations found in
 328 the previous sections:

329

1. The convergence of classification performance should be anticipated with the clearer definition of the decision boundaries across iterations.

- 330 2. Annotation cost is expected to reduce as the need for labeled instances reduces
 331 along with the early convergence of the classification performance.
 332 3. The class imbalance bias observed in typical classification tasks, as well as in AL is
 333 mitigated by balancing the class frequencies at each iteration.

334 Although the performance of this method is shown within a LULC classification
 335 context, the proposed framework is independent from the domain. The high dimension-
 336 ality of remotely sensed imagery make its classification particularly challenging when
 337 the availability of labeled data is scarce and/or comes at a high cost, being subjected to
 338 the curse of dimensionality. Consequently, it is a relevant and appropriate domain to
 339 test this method.

340 5. Methodology

341 In this section we describe the datasets, evaluation metrics, oversampler, classifiers,
 342 software used and the procedure developed. We demonstrate the proposed method's
 343 efficiency over 7 datasets, sampled from publicly available, well-known remote sensing
 344 hyperspectral scenes frequently found in remote sensing literature. The datasets and
 345 sampling strategy are described in Subsection 5.1. On each of these datasets, we apply
 346 3 different classifiers over the entire training set to estimate the optimal classification
 347 performance, the original AL framework as the baseline reference and the proposed
 348 method using G-SMOTE as a generator, described in Subsection 5.2. The metrics used to
 349 estimate the performance of these algorithms are described in Subsection 5.3. Finally,
 350 the experimental procedure is described in Subsection 5.4.

352 Our methodology focuses on two objectives: (1) Comparison of optimal classifi-
 353 cation performance among active learners and traditional supervised learning and (2)
 354 Comparison of classification convergence efficiency among AL frameworks.

355 5.1. Datasets

356 The datasets used were extracted from publicly available repositories containing
 357 hyperspectral images and ground truth data. Additionally, all datasets were collected
 358 using the same sampling procedure. The description of the hyperspectral scenes used in
 359 this study is provided in Table 2. These scenes were chosen because of their popularity
 360 in the research community and their high baseline classification scores. Consequently,
 361 demonstrating an outperforming method in this context is particularly challenging and
 362 valuable.

Dataset	Sensor	Location	Dimension	Bands	Res. (m)	Classes
Botswana	Hyperion	Okavango Delta	1476 x 256	145	30	14
Salinas A	AVIRIS	California, USA	86 x 83	224	3.7	6
Kennedy Space Center	AVIRIS	Florida, USA	512 x 614	176	18	16
Indian Pines	AVIRIS	NW Indiana, USA	145 x 145	220	20	16
Salinas	AVIRIS	California, USA	512 x 217	224	3.7	16
Pavia University	ROSIS	Pavia, Italy	610 x 610	103	1.3	9
Pavia Centre	ROSIS	Pavia, Italy	1096 x 1096	102	1.3	9

Table 2: Description of the hyperspectral scenes used in this experiment. The column “Res. (m)” refers to the resolution of the sensors (in meters) that captured each of the scenes.

364 The Indian Pines scene [54] is composed of agriculture fields in approximately
 365 two thirds of its coverage, low density buildup areas and natural perennial vegetation
 366 in the remainder of its area (see Figure 4a). The Pavia Centre and University scenes

367 are hyperspectral, high-resolution images containing ground truth data composed of
 368 urban-related coverage (see Figures 4b and 4c). The Salinas and Salinas A scenes contain
 369 at-sensor radiance data. As subset of Salinas, the Salinas A scene contains contains the
 370 vegetables fields present in Salinas and the latter is also composed of bare soils and
 371 vineyard fields (see Figures 4d and 4e). The Botswana scene contains ground truth data
 372 composed of seasonal swamps, occasional swamps, and drier woodlands located in the
 373 distal portion of the Delta (see Figure 4f). The Kennedy Space Center scene contains a
 374 ground truth composed of both vegetation and urban-related coverage (see Figure 4g).

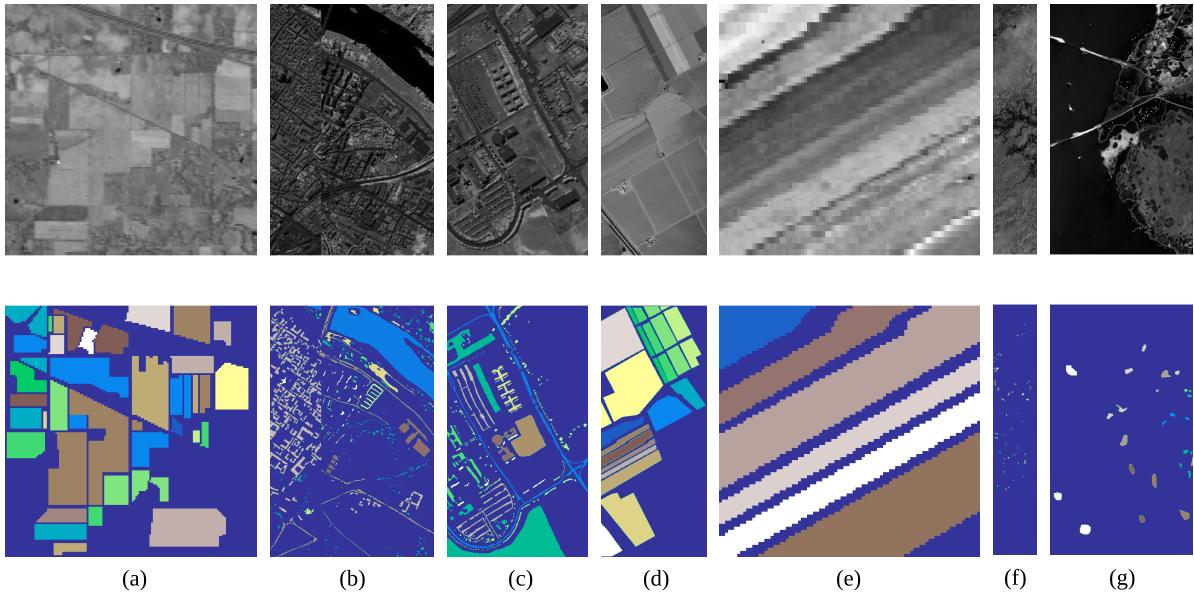


Figure 4. Gray scale visualization of a band (top row) and ground truth (bottom row) of each scene used in this study. (a) Indian Pines, (b) Pavia Centre, (c) Pavia University, (d) Salinas, (e) Salinas A, (f) Botswana, (g) Kennedy Space Center

375 The sampling strategy is similar to all datasets. The pixels without a ground
 376 truth label are first discarded. All the classes with cardinality lower than 150 are also
 377 discarded. This is done to maintain feasible Imbalance Ratios (IR) across datasets
 378 (where $IR = \frac{count(C_{maj})}{count(C_{min})}$). Finally, a stratified sample of 1500 instances are selected for
 379 the experiment. The resulting datasets are described in Table 3. The motivation for
 380 this strategy is three fold: (1) reduce the datasets to a manageable size and allow the
 381 experimental procedure to be completed within a feasible time frame, (2) ensure the
 382 relative class frequencies in the scenes are preserved and (3) ensure equivalent analyses
 383 across datasets and AL frameworks. In this context, a fixed number of instances per
 384 dataset is especially important to standardize the AL-related performance metrics.

Dataset	Features	Instances	Min. Instances	Maj. Instances	IR	Classes
Botswana	145	1500	89	154	1.73	12
Salinas A	224	1500	109	428	3.93	6
Kennedy Space Center	176	1500	47	272	5.79	12
Indian Pines	220	1500	31	366	11.81	12
Salinas	224	1500	25	312	12.48	16
Pavia University	103	1500	33	654	19.82	9
Pavia Centre	102	1500	27	668	24.74	9

Table 3: Description of the datasets collected from each corresponding scene. The sampling strategy is similar to all scenes.

385 5.2. Machine Learning Algorithms

386

387 We use two different types of ML algorithms. A data generation algorithm, used
388 to form the generator, and classification algorithms, used to calculate the classification
389 uncertainties in the unlabeled dataset and predict the class labels in the validation and
390 test sets.

391 Although any method capable of generating artificial data can be used as a generator,
392 the one used in this experiment is an oversampler, originally developed to deal with
393 imbalanced learning problems. Specifically, we chose G-SMOTE, a state-of-the-art
394 oversampler.

395 Three classification algorithms are used. We use different types of classifiers to
396 test the framework's performance under varying situations: neighbors-based, linear
397 and ensemble models. The neighbors-based classifier chosen was K-nearest neighbors
398 (KNN) [55], a logistic regression (LR) [56] is used as the linear model and a random
399 forest classifier (RFC) [57] was used as the ensemble model.

400 The acquisition function is completed by testing three different selection criteria.
401 Random selection is used as a baseline selection criterion, whereas entropy and breaking
402 ties are used due to their popularity and independence of the classifier used.

403 5.3. Evaluation Metrics

404

405 Since the datasets used in this experiment have an imbalanced distribution of
406 class frequencies, metrics such as the *Overall Accuracy* (OA) and *Kappa coefficient* are
407 insufficient to accurately depict classification performance [58,59]. Instead, metrics such
408 as Producer's Accuracy (or *Recall*) and User's Accuracy (or *Precision*) can be used. Since
409 they consist of ratios based on True/False Positives (TP and FP) and Negatives (TN
410 and FN), they provide per class information regarding the classifier's classification
411 performance. However, in this experiment, the meaning and number of classes available
412 in each dataset varies, making these metrics difficult to synthesize.

413 The performance metric *Geometric mean* (G-mean) and *F-score* are less sensitive to
414 the data imbalance bias [60,61]. Therefore, we employ both of these scorers. G-mean
415 consists of the geometric mean of $Specificity = \frac{TN}{TN+FP}$ and $Sensitivity = \frac{TP}{TP+FN}$ (also
416 known as *Recall*) [61]. Both metrics are calculated in a multiclass context considering a
417 one-versus-all approach. For multiclass problems, the *G-mean* scorer is calculated as its
418 average per class values:

$$G\text{-mean} = \sqrt{Sensitivity_i \times Specificity_i}$$

419 The F-score performance metric is the harmonic mean of *Precision* and *Recall*. The
420 two metrics are also calculated considering a one-versus-all approach. The *F-score* for
421 the multi-class case can be calculated using its average per class values [62]:

$$F\text{-score} = 2 \frac{Precision \times Recall}{Precision + Recall}$$

422 The comparison of classification convergence across AL frameworks and selection
423 criteria is done using 2 AL-specific performance metrics. Particularly, we follow the
424 recommendations found in [22]. Each AL configuration is evaluated using the *Area*
425 *Under the Learning Curve* (AULC) performance metric. It is the sum of the classification
426 performance values of all iterations. To facilitate the analysis of the results, we fix the
427 range of this metric between [0, 1] by dividing it with the total amount of iterations (*i.e.*,
428 the maximum performance area).

429 The *Data Utilization Rate* (DUR) [63] metric consists of the ratio between the number
430 of instances required to reach a given G-mean score threshold by an AL strategy and
431 an equivalent baseline strategy. For easier interpretability, we simplify this metric by

432 using the percentage of training data used by an AL strategy to reach the performance
 433 threshold, instead of presenting these values as a ratio of the baseline strategy. The DUR
 434 metric is measured at 9 different performance levels, between 0.6 and 0.95 G-mean scores
 435 at a 0.05 step.

436 *5.4. Experimental Procedure*

437
 438 A common practice in methodological evaluations is the implementation of an
 439 offline experiment [64]. It consists of using an existing set of labeled data as a proxy for
 440 the population of unlabeled instances. Because the dataset is already fully labeled, the
 441 supervisor's typical annotation process involved in each iteration is done at zero cost.
 442 Each AL and classifier configuration is tested using a stratified 5-fold cross validation
 443 testing scheme. For each round, the larger partition is split in a stratified fashion to form a
 444 training and validation set (containing 20% of the original partition). The validation set is
 445 used to evaluate the convergence efficiency of active learners; the chooser's classification
 446 performance metrics and amount of data points used at each iteration are used to
 447 compute the AULC and DUR. Additionally, within the AL iterative process, the classifier
 448 with optimal performance on the validation set is evaluated using the test set. In
 449 order to further reduce possible initialization biases, this procedure is repeated 3 times
 450 with different initialization seeds and the results of all runs are averaged (*i.e.*, each
 451 configuration is trained and evaluated 15 times). Finally, the maximum performance
 452 lines are calculated using the same approach. In those cases, the validation set is not
 453 used. The experimental procedure is depicted in Figure 5.

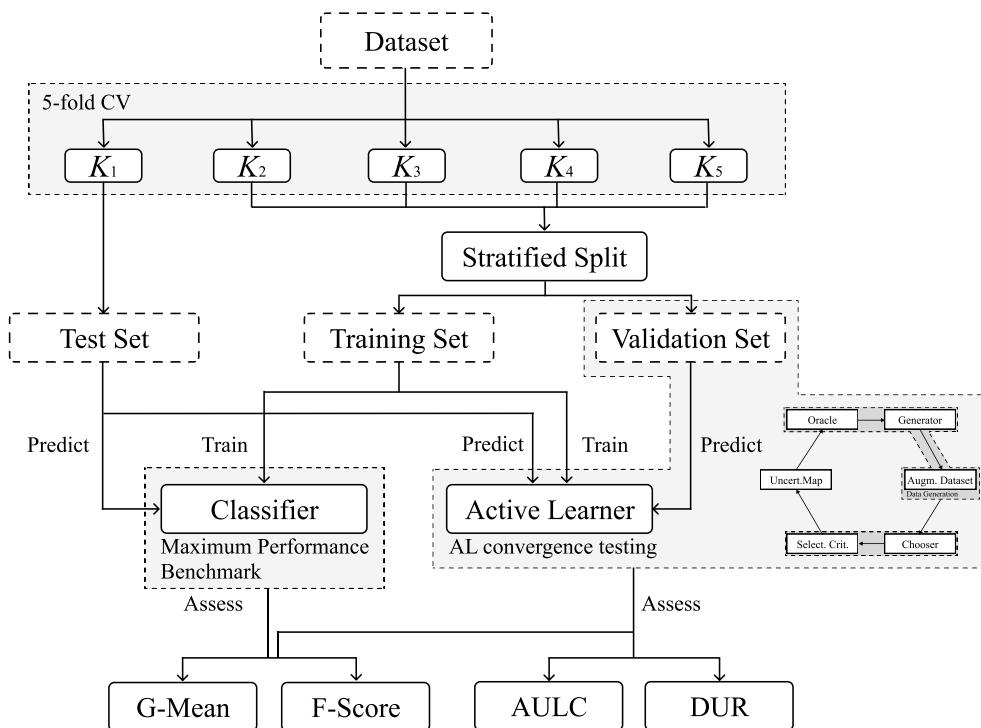


Figure 5. Experimental procedure. The datasets extracted from hyperspectral scenes are split in 5 folds. 1 of those (*e.g.*, K_1) is used to test the optimal performance of AL algorithms and the classification without AL. The training set is used to iterate AL algorithms and train classifiers. The validation set is used to test the convergence of AL algorithms. The results are averaged over the 5 folds across each of the 3 different initializations of this procedure.

454 To make the AL-specific metrics comparable among active learners, the configura-
455 tions of the different frameworks must be similar. For each dataset, the number of
456 instances is constant to facilitate the analysis of the same metrics.

457 In most practical AL applications it is assumed that the number of instances in the
458 initial training sample is too small to perform hyperparameter tuning. Consequently,
459 in order to ensure realistic results, our experimental procedure does not include hyper-
460 parameter optimization. The predefined hyperparameters are shown in Table 4. They
461 were set up based on general recommendations and default settings for the classifiers
462 and generators used.

463 The AL iterative process is set up with a randomly selected initial training sample
464 with 15 initial samples. At each iteration, 15 additional samples are added to the training
465 set. This process is stopped after 49 iterations, once 50% of the entire dataset (*i.e.*, 78% of
466 the training set) is added to the augmented dataset.

Classifier	Hyperparameters	Values
LR	maximum iterations	10000
	solver	sag
	penalty	None
	# neighbors	5
KNN	weights	uniform
	metric	euclidean
	maximum tree depth	None
RF	# estimators	100
	criterion	gini
Generator		
G-SMOTE	# neighbors	5
	deformation factor	0.5
	truncation factor	0.5

Table 4: Hyper-parameter definition for the classifiers and generator used in the experiment.

467 5.5. Software Implementation

468 The experiment was implemented using the Python programming language, along
469 with the Python libraries [Scikit-Learn](#) [65], [Imbalanced-Learn](#) [66], [Geometric-SMOTE](#),
470 [Cluster-Over-Sampling](#) and [Research-Learn](#) libraries. All functions, algorithms, experi-
471 ments and results are provided in the [GitHub repository of the project](#).

472 6. Results & Discussion

473 The evaluation of the different AL frameworks in a multiple dataset context should
474 not rely uniquely on the mean of the performance metrics across datasets. [67] recom-
475 mends the use of mean ranking scores, since the performance levels of the different
476 frameworks varies according to the data it is being used on. Consequently, evaluating
477 these performance metrics solely based on their mean values might lead to inaccurate
478 analyses. Accordingly, the results of this experiment are analysed using both the mean
479 ranking and absolute scores for each model. The rank values are assigned based on the
480 mean scores resulting from three different initializations of 5-fold cross validation for
481 each classifier and active learner. The goal of this analysis is to understand whether the
482 proposed framework (AL with the integration of an artificial data generator) is capable
483 of using less data from the original dataset while simultaneously achieving better classi-
484 fication results than the standard AL framework, *i.e.*, guarantee a faster classification
485 convergence.

487 6.1. Results

488

489 Table 5 shows the average rankings and standard deviations across datasets of the
490 AULC scores for each active learner.

Classifier	Evaluation Metric	Standard	Proposed
KNN	F-score	2.00 ± 0.0	1.00 ± 0.0
KNN	G-mean	2.00 ± 0.0	1.00 ± 0.0
LR	F-score	1.71 ± 0.45	1.29 ± 0.45
LR	G-mean	2.00 ± 0.0	1.00 ± 0.0
RF	F-score	1.86 ± 0.35	1.14 ± 0.35
RF	G-mean	2.00 ± 0.0	1.00 ± 0.0

Table 5: 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.

491 The mean AULC absolute scores are provided in Table 6. These values are computed
492 as the mean of the sum of the scores of a specific performance metric over all iterations
493 (for an AL configuration). In other words, these values correspond to the average AULC
494 over 7 datasets \times 5 folds \times 3 initializations.

Classifier	Evaluation Metric	Standard	Proposed
KNN	F-score	0.762 ± 0.131	0.794 ± 0.123
KNN	G-mean	0.864 ± 0.079	0.886 ± 0.073
LR	F-score	0.839 ± 0.119	0.843 ± 0.116
LR	G-mean	0.907 ± 0.074	0.911 ± 0.071
RF	F-score	0.810 ± 0.109	0.819 ± 0.1
RF	G-mean	0.890 ± 0.068	0.901 ± 0.059

Table 6: 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.

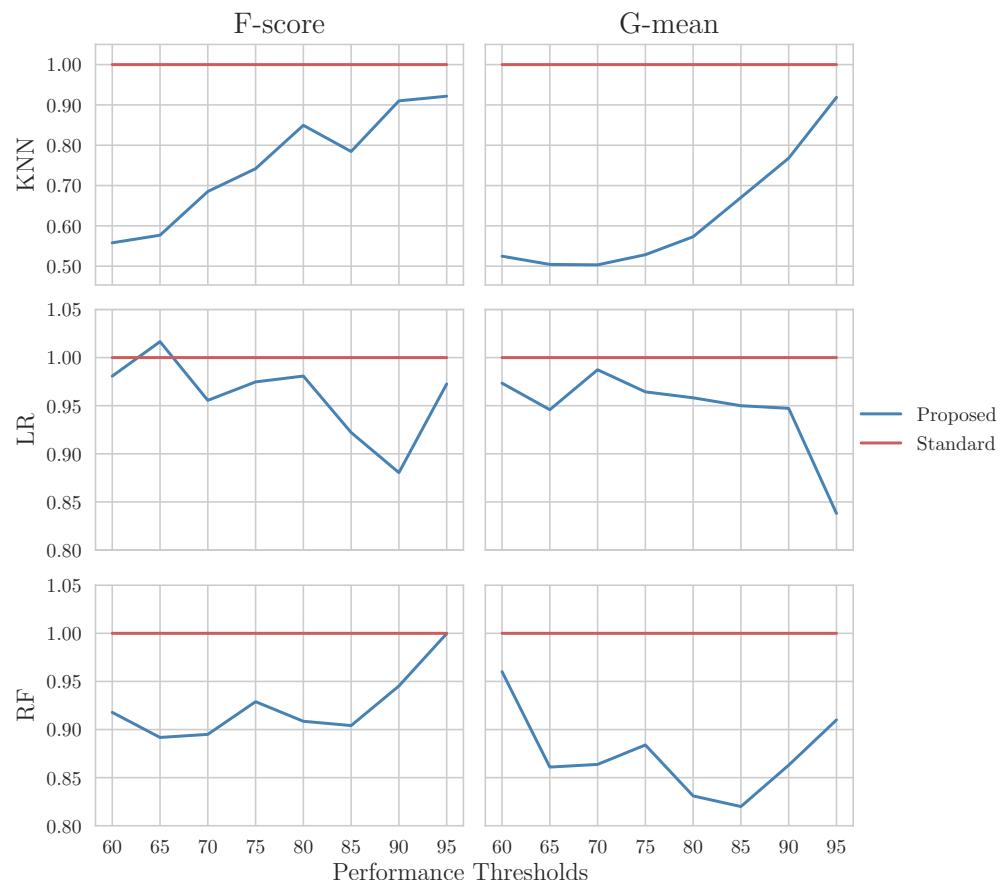
495 The average DURs are shown in Table 4. They were calculated for various G-mean
496 scores thresholds, varying at a step of 5% between 60% and 95%. Each row shows the
497 percentage of training data required by the different AL configurations to reach that
498 specific G-mean score.

G-mean Score	Classifier	Standard	Proposed
0.60	KNN	4.0%	2.1%
0.60	LR	2.2%	2.1%
0.60	RF	2.2%	2.1%
0.65	KNN	5.6%	2.8%
0.65	LR	3.0%	2.7%
0.65	RF	3.1%	2.6%
0.70	KNN	7.9%	4.1%
0.70	LR	4.2%	4.1%
0.70	RF	4.5%	3.6%
0.75	KNN	13.5%	7.1%
0.75	LR	7.2%	6.6%
0.75	RF	6.6%	5.4%
0.80	KNN	24.4%	16.9%

G-mean Score	Classifier	Standard	Proposed
0.80	LR	13.1%	11.7%
0.80	RF	11.6%	9.2%
0.85	KNN	29.8%	23.6%
0.85	LR	19.8%	18.8%
0.85	RF	23.1%	17.3%
0.90	KNN	41.0%	36.1%
0.90	LR	28.1%	24.8%
0.90	RF	37.1%	30.3%
0.95	KNN	71.3%	69.1%
0.95	LR	45.8%	40.2%
0.95	RF	64.6%	62.2%

Table 4: Mean data utilization of AL algorithms, as a percentage of the training set.

The DUR of the proposed method relative to the baseline method is shown in Figure 6. A DUR below 1 means that the proposed framework requires less data to reach the same performance threshold (as a percentage, relative to the amount of data required by the baseline framework). For instance, in the upper left graphic we can see that the proposed framework achieves 90% classification using F-score while using 91% of the amount of data used by the traditional AL framework, in other words 9% less data.

**Figure 6.** Mean data utilization rates. The y-axis shows the percentage of data (relative to the baseline AL framework) required to reach the different performance thresholds.

505 The averaged optimal classification scores are shown in Table 5. The maximum
 506 performance (MP) classification scores are shown as a benchmark and represent the
 507 performance of the corresponding classifier using the entire training set.

Classifier	Evaluation Metric	MP	Standard	Proposed
KNN	F-score	0.838 ± 0.106	0.835 ± 0.115	0.843 ± 0.105
KNN	G-mean	0.907 ± 0.063	0.904 ± 0.069	0.912 ± 0.061
LR	F-score	0.890 ± 0.084	0.883 ± 0.096	0.887 ± 0.097
LR	G-mean	0.935 ± 0.052	0.931 ± 0.059	0.938 ± 0.055
RF	F-score	0.859 ± 0.083	0.866 ± 0.081	0.869 ± 0.08
RF	G-mean	0.918 ± 0.051	0.921 ± 0.051	0.930 ± 0.043

Table 5: Optimal classification scores. The Maximum Performance (MP) classification scores are calculated using classifiers trained using the entire training set.

508 6.2. Statistical Analysis

509
 510 The methods used to test the experiment's results must be appropriate for a multi-
 511 dataset context. Therefore the statistical analysis is performed using the Wilcoxon signed-
 512 rank test [68] as a post-hoc analysis. The variable used for this test is the data utilization
 513 rate based on the G-mean performance metric, considering the various performance
 514 thresholds from Table 4.

515 The Wilcoxon signed-rank test results are shown in Table 6. We test as null hypoth-
 516 esis that the performance of the proposed framework is the same as the original AL
 517 framework. The null hypothesis was rejected in all datasets.

Dataset	p-value	Significance
Botswana	3.8e-03	True
Indian Pines	2.3e-04	True
Kennedy Space Center	1.3e-04	True
Pavia Centre	4.3e-03	True
Pavia University	4.6e-05	True
Salinas	4.6e-05	True
Salinas A	3.0e-03	True

Table 6: 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.

518 6.3. Discussion

519 This paper expands the AL framework by adding an artificial data generator into its
 520 iterative process. This modification is done to accelerate the classification convergence
 521 of the standard AL procedure, which is reflected in the reduction of the amount of data
 522 necessary to reach better classification results.

523 The convergence efficiency of the proposed method is always higher than the
 524 baseline AL framework, with the exception of one comparison, as shown in Table 5 and
 525 Figure 6. This means the proposed AL framework using data generation was able to
 526 outperform the baseline AL in nearly all scenarios.

527 The mean AULC scores in Table 6 show a significant improvement in the per-
 528 formance of AL when a generator is used. The mean performance of the proposed
 529 framework is always better than the baseline framework. This improvement is explained
 530 by:

- 531 1. Earlier convergence of AL, *i.e.*, requiring less data to achieve comparable performance levels. This effect is shown in Table 4, where we found that the proposed framework always uses less data for similar performance levels, regardless of the classifier used.
- 532 2. Higher optimal classification performance, *i.e.*, reaching higher performance levels overall. This effect is shown in Table 5, where we found that using a generator in AL led to a better classification performance and was capable of outperforming the MP threshold.

533 Our results show statistical significance in every dataset. The proposed framework
534 had a superior performance with statistical significance on each dataset at a level of
535 $\alpha = 0.05$. This indicates that regardless of the context under which an AL algorithm is
536 used, the proposed framework reduces the amount of data necessary in the AL's iterative
537 process.

538 This paper introduces the concept of applying data a generation algorithm in the
539 AL framework. This was done with the implementation of a recent state of the art
540 generalization of a popular data generation algorithm. Although, since this algorithm
541 is based on heuristics, future work should focus on improving these results through
542 the design of new data generation mechanisms, at the cost of additional computational
543 power. In addition, we also noticed significant standard errors in our experimental
544 results (see Subsection 6.1). This indicates that AL procedures seem to be particularly
545 sensitive to the initialization method, which is still a limitation of AL, regardless of the
546 framework and configurations used. This is consistent with the findings in [22], which
547 future work should attempt to address. Although using a generator marginally reduced
548 this standard error, it is not sufficient to address this specific limitation.

549 7. Conclusion

550 The aim of this experiment was to test the effectiveness of a new AL framework
551 that introduces artificial data generation in its iterative process. The experiment was
552 designed to test the proposed method under particularly challenging conditions, where
553 the maximum performance line is naturally high in most datasets. The element that
554 constitute the Generator component was set up in a plug-and-play scheme, without
555 significant tuning of the G-SMOTE oversampler. Using a generator in AL improved
556 the original AL framework in all scenarios. These results could be further improved
557 through the modification and more intense tuning of the data generation strategy. In
558 our experiment, artificial data was generated only to match each non-majority class
559 frequency with the majority class frequency, strictly balancing the class distribution.
560 Generating a larger amount of data for all classes can further improve these results.

561 The high performance scores for the baseline AL framework made the achievement
562 of significant improvements over the traditional AL framework under these conditions
563 particularly meaningful. The advantage of the proposed AL framework is shown in
564 Table 4. In most of the presented scenarios there is a substantial reduction of data
565 necessary to reach a given performance threshold.

566 The results from this experiment show that using a data generator in the AL frame-
567 work will improve the convergence of the method. This framework successfully antici-
568 pate the predictor's optimal performance, as shown in Tables 5, 6 and 4. Therefore, in a
569 real application, the annotation cost would have been reduced since less iterations and
570 labeled instances are necessary to reach near optimal classification performance.

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575 G.D.; Validation, F.B., G.D.; Formal Analysis, J.F.; Writing - Original Draft Preparation, J.F.; Writing
576 - Review & Editing, F.B., G.D., J.F.; Supervision, F.B.; Funding Acquisition, F.B.

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