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HAR-MI with COSTE in Handling Multi-Class Imbalance

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Abstract—The class imbalance problem is a serious problem in machine learning. This problem can occur in two-class and multi-class problems. This problem can result in low accuracy and not obtaining information regarding the minority class. Approaches to overcome this problem often use a combination of the Data-Level Approach and Algorithm-Level Approach, which is often referred to as a Hybrid Approach. One of the Hybrid Approach methods to solve the multi-class imbalance problem is the Hybrid Approach Redefinition-Multiclass Imbalance (HAR-MI). The sampling method used in the HAR-MI is the Oversampling method. Oversampling tends to be chosen because Undersampling can eliminate useful information, but Oversampling often causes Over-Fitting. Therefore, this study will modify the HAR-MI approach by using the Complexity-based OverSampling TEchnique (COSTE). COSTE will rank the instances based on the measurement of complexity so that it will provide better results and prevent Over-Fitting. The results showed that HAR-MI with COSTE gave better results than the classic HAR-MI.

Keywords—Class Imbalance, Hybrid Approach, HAR-MI, Over-Fitting, COSTE

I. INTRODUCTION

The problem of class imbalance is a problem that is difficult to handle, even when using deep learning[1]. Class imbalance is manifested in the number of instances or samples that are unequal between majority and minority classes, and this often causes classification algorithms in machine learning to tend to provide more accurate results for majority classes. And ignore minority classes[2]. Most of the class imbalance problems are binary-class, although the problem sometimes is the multi-class problem[3].

Multi-class imbalance problems tend to be more difficult to handle than binary-class problems[4]. However, various approaches have been put forward to use the principle of decomposition in breaking the multi-class problem into a binary-class problem[5]. One approach that can be used is Dynamic Ensemble Selection[6].

There are several approaches to overcoming class imbalance problems, namely the data-level approach, algorithm-level approach, and cost-sensitive approach[7]. Hybrid Approach is an approach that combines using the Data-Level Approach with the Algorithm-Level Approach[8]. One of the Hybrid Approaches that is effective

in overcoming the problem of multi-class imbalance is the Hybrid Approach Redefinition-Multiclass Imbalance (HAR-MI)[9].

The HAR-MI method generally uses the Oversampling method[19]. Oversampling tends to be chosen because Undersampling can eliminate important information[10]. But sometimes, oversampling can lead to over-fitting[11]. This condition led to thinking about the importance of ranking each existing instance or classifier using the Complexity measurement. This is what underlies the Complexity-based OverSampling TEchnique (COSTE) method[12].

This study will use the COSTE approach to replace the SMOTE in HAR-MI, which is used in the preprocessing and processing stages[21]. The preprocessing stage will use Dynamic Ensemble Selection[13], and COSTE and the processing stage will use the Different Contribution Sampling and COSTE[14].

II. RELATED WORKS

A. Hybrid Approach

The pseudocode of the Hybrid Approach is as follows[15].

```
Input:  $D_T = \{x_1, x_2, \dots, x_n\}$  // Training Dataset  
N = Number of Classifier  
Output: Classification Prediction  $P$   
Method:  
Step 1 Preprocessing using Preprocessing Method  
Step 2 For  $t = 1$  to  $N$  do  
    I. Apply Machine Learning Classification Algorithm  
        on The Attributes of  $D_T$   
    II. Obtain Classification Prediction  $P_t$  from machine  
        learning classification algorithm  
End For  
Step 3 For  $t = 1$  to  $n$   
    Apply Preprocessing using Algorithm –  
    Level Approach and Data – Level Approach  
  
    Apply Processing using Algorithm –  
    Level Approach and Data – Level Approach  
End For
```

Based on pseudocode, it can be seen that the stages in the Hybrid Approach are generally divided into 2 (two), namely preprocessing and processing[20]. The preprocessing and processing stages will be carried out using the Data-Level Approach and Algorithm-Level Approach.

B. Dynamic Ensemble Selection

Dynamic Ensemble Selection is used to decompose multi-class problems into binary-class problems. The pseudocode of Dynamic Ensemble Selection is as follows[16].

```

Input:
S {Input Dataset}
K {Neighborhood Size}
Output:
Safe {Set of Safe Samples}
Borderline {Set of Borderline Samples}
Rare {Set of Rare Samples}
Outlier {Set of Outlier Samples}
For All  $Z_i \in S$  do
    Neighbors  $\leftarrow$  computeNeighbors ( $Z_i, S - \{Z_i\}, K$ )
    someClass  $\leftarrow$  countSomeClass ( $Z_i, \text{neighbors}$ )
    if someClass  $\geq$   $[0.8k]$  then
        safe  $\leftarrow$  safe  $\cup$   $\{Z_i\}$ 
    else
        if someClass  $\geq$   $[0.5k]$  then
            borderline  $\leftarrow$  borderline  $\cup$   $\{Z_i\}$ 
        else
            if someClass  $\geq$   $[0.2k]$  then
                rare  $\leftarrow$  rare  $\cup$   $\{Z_i\}$ 
            else
                Outlier  $\leftarrow$  Outlier  $\cup$   $\{Z_i\}$ 
            end if
        end if
    end if
end if
end for
    
```

Based on the pseudocode, it can be seen that Dynamic Ensemble Selection will be used to decompose multi-class problems into binary-class problems. There are 4 classes that will be generated, namely, Safe, Borderline, Rare, and Outlier.

C. COSTE

The pseudocode from COSTE is as follows[12].

```

Input: Dataset  $N$  including the minority class instances
 $N_{\text{min}}$  and the majority class instances  $N_{\text{maj}}$ 
Output: Balanced Dataset  $N_{\text{bal}}$ 
 $\text{Array}_{\text{syn}} \leftarrow$ 
array for storing new synthetic instances

apply the min –
max normalization method to the dataset

for each instance  $X_i$  Calculate complexity using
Equation 1
    
$$\text{Complexity}_i = \sum_{j=1}^L \alpha_j x_j \quad (1)$$

rank  $X_i$  in the ascending order based on complexity
    
```

```

Calculate the number of new synthetic instances
needed  $T, T =$ 
 $\text{number}(N_{\text{maj}}) - \text{number}(N_{\text{min}})$ 
if  $T > \text{number}(N_{\text{min}}) - 1$  then
    for  $i = 1, 2, \dots, \text{number}(N_{\text{min}}) - 1$  do
        new synthetic instance  $X_{\text{new}} = (X_i + X_{(i+1)})/2$ 
        add  $X_{\text{new}}$  into  $\text{Array}_{\text{syn}}$ 
    end for
    update  $N_{\text{min}}$  by merging  $N_{\text{min}}$  and  $\text{Array}_{\text{syn}}$ 
    repeat Line 5
else
    for  $i = 1, 2, \dots, T - 1$  do
        new synthetic instance  $X_{\text{new}} = (X_i + X_{(i+1)})/2$ 
        add  $X_{\text{new}}$  into  $\text{Array}_{\text{syn}}$ 
    end for
    update  $N_{\text{min}}$  by merging  $N_{\text{min}}$  and  $\text{Array}_{\text{syn}}$ 
end if
return balanced dataset  $N_{\text{bal}}$  by merging  $N_{\text{min}}$  and  $N_{\text{maj}}$ 
    
```

The COSTE method is basically based on calculating complexity from each instance. It is used for ranking each instance. A higher ranking means less complex, and the instance with the highest ranking will be selected to be the classifier.

D. Classifier Performance

The classifier performance is measured by a number of parameters as follows.

1. Confusion Matrix

The Confusion Matrix can be seen in Table 1[17].

TABLE I. CONFUSION MATRIX

		Predictive Positive Class	Predictive Negative Class
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

2. Average Accuracy (AvAcc)

AvAcc can be calculated using the following equation[18].

$$TPR = \frac{TP}{TP+FN} \quad (2)$$

$$AvAcc = \frac{\sum_{i=1}^N TPR_i}{N} \quad (3)$$

3. Multi-Class G-Measure (mGM)

mGM can be calculated using the following equation[18]

$$Recall = TPR \quad (4)$$

$$mGM = \sqrt[N]{\prod_{i=1}^N recall_i} \quad (5)$$

III. PROPOSED METHOD

The research stages can be seen in Figure 1.

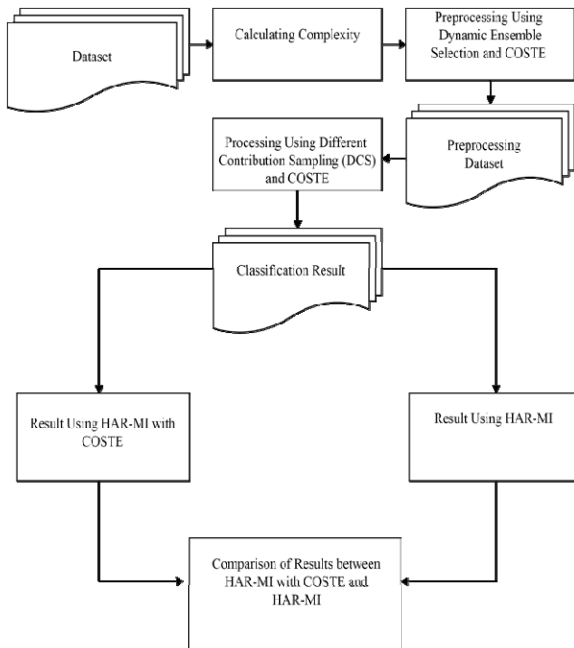


Fig. 1. Stage of Research Method

Based on Figure 1, it can be seen that the process begins with determining the dataset to be used. The dataset used is a multi-class imbalanced dataset. The first thing that will be done is the preprocessing stage, which is carried out using the Dynamic Ensemble Selection and COSTE. Dynamic Ensemble Selection is used to decompose multi-class problems into binary-class problems. This preprocessing stage will produce a preprocessed dataset. This preprocessed dataset will then undergo processing stages using Different Contribution Sampling (DCS) and COSTE. In this section, the Safe and Borderline classes will be grouped into majority class or negative samples, and rare and outlier classes will be grouped into minority class or positive samples. The results obtained will then be compared with the results obtained by the classic HAR-MI.

A. Preprocessing using Dynamic Ensemble Selection and COSTE

The pseudocode of the preprocessing stage is as follows.

```

Input: Dataset  $N$  including the minority class instances  $N_{min}$ 
and the
majority class instances  $N_{maj}$ 
Output: Balanced Dataset  $N_{bal}$ 

For All  $Z \in S$  do
    Determine Safe, Borderline, Rare and Outlier
    Class
end for
for each instance  $X_i$  in Each class Calculate complexity

rank  $X_i$  in the ascending order based on Class
Calculate the number of new synthetic instances needed
 $T, T = \text{number}(N_{maj}) - \text{number}(N_{min})$ 
  
```

```

if  $T > \text{number}(N_{min}) - 1$  then
    for  $i = 1, 2, \dots, \text{number}(N_{min}) - 1$  do
        new synthetic instance  $X_{new} = (X_i + X_{(i+T)})/2$ 
        add  $X_{new}$  into  $Array_{syn}$ 
    end for
    update  $N_{min}$  by merging  $N_{min}$  and  $Array_{syn}$ 
    repeat Line 5
else
    for  $i = 1, 2, \dots, T - 1$  do
        new synthetic instance  $X_{new} = (X_i + X_{(i+T)})/2$ 
        add  $X_{new}$  into  $Array_{syn}$ 
    end for
    update  $N_{min}$  by merging  $N_{min}$  and  $Array_{syn}$ 
end if
return balanced dataset  $N_{bal}$  by merging  $N_{min}$ 
and  $N_{maj}$ 
  
```

B. Processing using Different Contribution Sampling and COSTE

The pseudocode of the processing stage is as follows.

```

Input: Preprocessed Dataset
Output: Result Dataset
Perform ESVM for Each Class
for All instances in Safe and Borderline do
    Deleting Noise in Sample  $SVSet_s$ 
    Perform COSTE for Sample in  $SVSet_s$ 
End for
for All instances in Rare and Outlier do
    Deleting Noise in Sample  $NSVSet_s$ 
    Perform COSTE for Sample in  $SVSet_s$ 
End for
for All instances in SVSet_s and NSV Set_s from Safe and Borderline do
    Create Negative Samples
End for
for All instances in SVSet_s and NSV Set_s from Rare and Outlier do
    Create Positive Samples
End for
for All instances in Negative and Positive Samples do
    Create Result Dataset
End for
  
```

IV. RESULT AND ANALYSIS

A. Dataset Description

The dataset used in this study can be seen in Table II.

TABLE II. DATASET DESCRIPTION

Dataset	#Ex	#Features	Distribution of Class	IR
Cleveland	1728	13	164/55/36/35/13	12.62
Contraceptive	1473	9	629/333/511	1.89
Dermatology	358	33	111/60/71/48/48/20	5.55
Lymphography	148	18	2/81/61/4	40.5
Vehicle	846	18	199/212/217/218	1.17
Wine	178	13	59/71/48	1.48

B. Testing Result

The test results can be seen in Table III.

TABLE III. TESTING RESULT

Dataset	HAR-MI with COSTE		HAR-MI	
	AvACC	mGM	AvACC	mGM
Cleveland	0.879	0.913	0.813	0.901
Contraceptive	0.913	0.892	0.921	0.903
Dermatology	0.817	0.821	0.856	0.837
Lypmography	0.826	0.821	0.818	0.819
Vehicle	0.842	0.837	0.823	0.821
Wine	0.867	0.873	0.851	0.871

Based on Table III, it can be seen that the Average Accuracy given by HAR-MI with COSTE is better than HAR-MI. Only on the Contraceptive Dataset, the results provided by HAR-MI are better than HAR-MI with COSTE. In general, the number of Features and also the Imbalance Ratio are the factors that most influence the Average Accuracy. The same result is shown by mGM where the results given by HAR-MI with COSTE are better than that of HAR-MI.

C. Discussion

Based on the Average Accuracy (AvACC) test, it can be seen that the number of features and the imbalance ratio greatly influence the results obtained. In general, the results obtained by HAR-MI with COSTE are better than that of the classic HAR-MI. Only the Contraceptive Dataset shows that the classic HAR-MI is better than the HAR-MI with COSTE. The same result is shown by the multi-class G-Measure (mGM), which shows that HAR-MI with COSTE is better than HAR-MI.

V. RESULT AND ANALYSIS

Based on the research results, it can be seen that HAR-MI with COSTE gives better results when compared to classic HAR-MI both in terms of Average Accuracy (AvACC) and multi-class G-Mean (mGM) values. The results obtained are good, but there is a decrease in quality if the existing dataset has a large number of features or has a high imbalance ratio. Future Research should be able to improve the results obtained if there is a dataset with a large number of features and also a high imbalance ratio.

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