Image Classification Under Class-Imbalanced Situation

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Abstract. Image classification technology processes and analyzes image data to extract valuable feature information to distinguish different types of images, thereby completing the process of machine cognition and understanding of image data. As the cornerstone of image application field, image classification technology involves a wide range of application fields. The class imbalance distribution is ubiquitous in the application of image classification and is one of the main problems in image classification research. This study summarizes the literature on class-imbalanced image classification methods in recent years, and analyzes the classification methods from both the data level and the algorithm level. In data-level methods, oversampling, under sampling and mixed sampling methods are introduced, and the performance of these literature algorithms is summarized and analyzed. The algorithm-level classification method is introduced and analyzed from the aspects of classifier optimization and ensemble learning. All image classification methods are analyzed in detail in terms of advantages, disadvantages and datasets.

Keywords: Image Classification; Class Imbalance; Data Processing; Data Level; Algorithm Level.

1. Introduction

Image classification is one of the hot research directions in the field of computer vision. Although the emergence of deep learning technology has promoted the development of the image field, with the continuous breakthrough of deep learning in the field of computer vision, the deep neural network has improved various evaluation indicators of image recognition with its powerful learning ability, [1]. However, in the massive data, different image datasets have their own different problems, which limit their recognition ability. In addition, the imbalance problem in image classification tasks is also very common in real-world applications, and has become one of the prominent problems in the field of machine learning and data mining [2]. The classification network guides training based on the training set samples, and then classifies the test samples according to the trained classification network [3].

The classification of unbalanced high-dimensional image data still faces huge challenges, especially in the case of very limited samples of some minority classes, the difficulty of the problem is greatly increased [4]. It is worth noting that many data in real life are prone to the phenomenon of category imbalance, that is, the number of samples in different categories is quite different. This phenomenon is called the imbalance problem, which has been a problem that has long plagued academia and industry. a problem. In a class-imbalanced dataset, the majority class carries more samples than the minority class. The class distribution in data collected from many applications is often uneven, such as network intrusion detection [5], credit card fraud detection [6], and disease diagnosis [7], etc. This unbalanced distribution of data can lead to classification difficulties, as the classifier will tend to deal with the majority class and will misclassify the minority class [8]. At present, with the efforts of many scholars, a variety of excellent classification algorithms have emerged, and some practical results have been achieved. However, most of the existing classification algorithms are designed for datasets with balanced class distribution, and the actual performance of existing classification algorithms is poor when the training dataset presents an unbalanced distribution. Therefore, in these imbalanced classification tasks, how to improve the classification performance of the minority class while ensuring the classification performance of the majority class is a difficult task [9].

Among the existing reviews of imbalanced data classification methods, most of them are based on two-class imbalanced problems, and there are only a handful of reviews on dealing with class imbalanced problems. S Belharbi mainly introduces the method of combining data preprocessing technology and neural network, but only summarizes some multi-class imbalance methods, and its perspective and review content are not comprehensive [10]. S Huang analyzed the application and performance of various Boosting ensemble methods on multi-class imbalanced datasets, but did not describe and analyze other types of multi-class imbalanced classification methods [11]. M Barstugan introduced the sampling method, decomposition technology, neural network and ensemble method of multi-class unbalanced data, but only introduced the method itself, and did not study and analyze the specific model and algorithm [12]. The literature summarizes the methods in recent years from the perspectives of decomposition methods and ad hoc methods, and collectively refers to methods such as cost-sensitive, ensemble learning, and deep networks as ad hoc methods, and summarizes commonly used evaluation metrics in multi-class imbalanced problems. In the existing reviews, most of the studies are too one-sided, and no researchers have comprehensively described and analyzed multi-class imbalanced data classification methods. introduce.

This paper summarizes and introduces the classification literature of class imbalanced data published in recent years. Different from the existing review, this paper conducts a comprehensive analysis and summary from two aspects of data preprocessing methods and algorithm-level classification methods. The techniques and performance used by the various algorithms are elaborated and described in detail. The relevant solutions currently involved will be summarized and divided into data level and algorithm level. The specific division is shown in Figure 1.

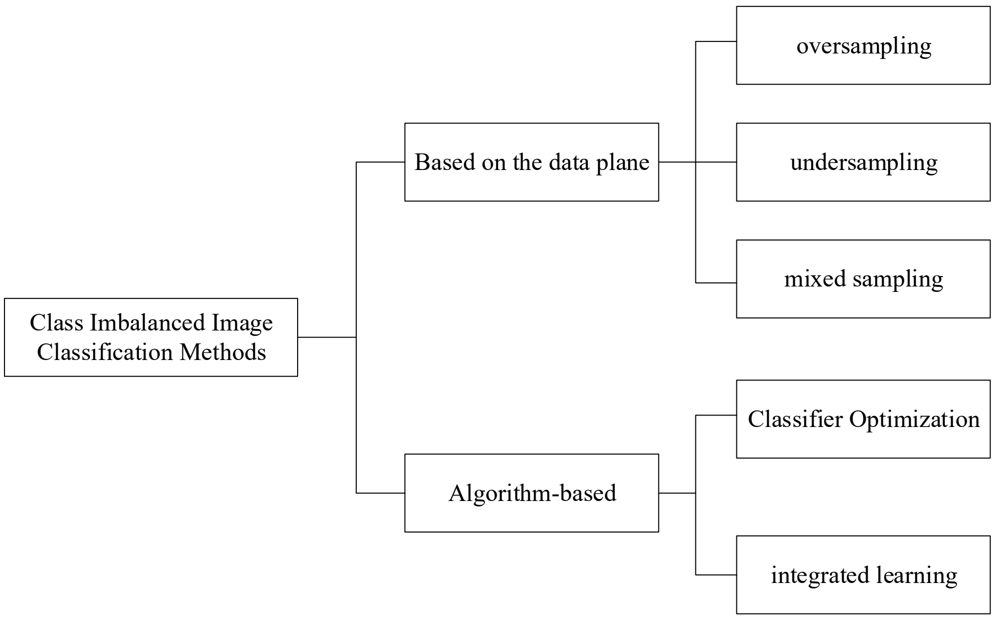

Figure 1. Class Imbalanced Image Classification Method

2. Class Imbalanced Image Data Level Classification Method

The data-dependent classification algorithm balances the class distribution of the training set by data sampling or data generation. The following will introduce several typical data-level algorithms.

2.1 Oversampling Algorithm

Oversampling is the most commonly used method in multi-class imbalanced data preprocessing techniques, which solves the multi-class imbalance problem by introducing new minority class instances, thereby realizing the rebalancing of the original skewed data [13]. However, random copying of samples does not introduce new information, and excessive copying of minority class samples will generate a large number of repeated samples, making the network overfitting. Oversampling is the most commonly used method in multi-class imbalanced data preprocessing techniques.

Oversampling is the simplest image classification algorithm. It expands the number of minority class samples by randomly copying the minority class samples to ensure the class balance of the training data. However, random oversampling does not introduce new information to the minority class, and simple replication leads to overfitting problems in the classification algorithm. To solve the overfitting problem of random oversampling algorithm, Chawla proposed a minority class sample synthesis method SMOTE. First, a minority class sample is randomly selected as the main sample, then the K nearest neighbor samples of the main sample are selected from the remaining minority class samples, and finally a minority class sample is randomly selected from the nearest neighbor samples, and the sample is randomly connected to the main sample. Sampling, and use the sampled points as synthetic minority class samples. However, due to the generation of wrong samples, the minority class is over-generalized to the majority class region, compromising the learnability of minority class samples [14]. In view of the shortcomings of existing SMOTE methods, some researchers have improved them. Wang Xiao proposed a synthetic minority oversampling algorithm SSCMIO based on k-nearest neighbors. When processing data, the k-nearest neighbor direction of each instance is assigned a selection weight, and the adjacent direction that may cause severe over-generalization is given a smaller selection weight. This method selects safer neighboring directions to synthesize instances, and applies NBDOS clustering to avoid calculating the selection weights of some minority class instances. At the same time, two loop filtering is used to reduce the calculation of the distance between a large number of instances [15]. SSCMIO also proposes a mechanism to avoid over-generalization, over-sampling based on the safety factor of instance neighborhoods, and assigns smaller weights to regions that may cause over-generalization. Different from the SMOM algorithm, SSCMIO adopts the reverse nearest neighbor sampling safety factor to prevent newly generated instances from intruding into the area of other classes, which can effectively reduce the occurrence of class overlap. HDSMOTE guides the direction of synthetic samples by comparing the Hellinger distance in the neighborhood of minority class instances, and proposes a sampling quality assessment strategy based on Hellinger distance to evaluate synthetic instances, which effectively solves the problems of over-generalization and class overlap [16].

2.2 Undersampling Algorithm

Undersampling, as opposed to oversampling, maintains the balance between classes by reducing the number of samples of the majority class [17]. In multi-class imbalanced data, the existence of class overlap problem will cause the classifier to fail to identify class boundaries effectively, thus reducing the performance of the classifier. Hartono proposed an undersampling method based on class overlap, LOFCUS, which uses the LOF local outlier factor and boxplot to clean the noise samples in the training data set, and extracts the samples that play a key role in the classification according to the class overlap. Undersampling, thereby maximizing the maintenance of the original data distribution, improves the accuracy of the classifier [18]. Clustering methods combined with undersampling can effectively handle majority classes in imbalanced datasets. Krawczyk proposed a clustering-based undersampling method CUS. After clustering the majority class instances, then undersampling the instances with the largest amount of information to form multiple balanced datasets. Experiments show that this method is effective in the classification of majority class and minority class instances have achieved high accuracy [19]. The general sampling method of multi-class imbalanced data first balances the data set, and then trains the classifier. Different from existing methods, Arefeen adopts the multi-class unbalanced data processed in a training-and-balanced manner, and proposes a two-stage algorithm OCSV-US [20] that combines undersampling and genetic algorithm. In the first stage, M single-class classifiers are trained according to the number of multi-classes, and each classifier will return a set of class instances with the highest informative value for sampling in the next stage. In the second stage, multiple random undersampled data subsets are created according to the class instances in the previous step, and the subsets are evolved by applying the genetic algorithm until the fitness function of the subsets can no longer be improved. The best dataset for classification. The results show that the two-stage strategy implemented by this method can improve the computational time efficiency and classification accuracy.

2.3 Hybrid Sampling Algorithm

In the class imbalanced data preprocessing method, the oversampling algorithm and the undersampling algorithm have their own advantages and disadvantages. Some researchers combine the two kinds of sampling and process the majority class and the minority class at the same time to reduce the imbalance of the data [21].

Combining SMOTE with other undersampling techniques is a common approach in mixed sampling schemes. In dealing with the problem of class overlap, Hartono proposes a hybrid sampling method that minimizes overlapping selection, which balances multiple classes according to the overlap of classes, and uses minority-based oversampling (M-SMOTE) and editing nearest neighbors. (ENN) to sample the minority and majority classes separately. Experiments show that this method has better effects on indicators such as recall rate [22]. Some researchers believe that the disadvantage of SMOTE overfitting is unavoidable, especially when the dataset is extremely imbalanced, so they propose a new oversampling scheme in mixed sampling. Xu proposes a sample-based similarity oversampling and undersampling preprocessing method, firstly undersampling the most influential majority class samples, and then oversampling the most important minority class samples by analyzing the safety level produced by their neighboring regions. It turns out that the proposed algorithm can reduce the generation of noisy samples or overlapping samples [23]. Random Balance is a two-class unbalanced data preprocessing strategy that uses random class ratios to randomly undersample and SMOTE oversample data. Based on this, Janicka proposed the Multi Rand Bal method, which uses randomly generated priors for sampling instead of class proportions [24]. Rodríguez combined dynamic ensemble selection with Multi Rand Bal in his proposed HAR-MI method, maintaining the diversity of data and classifiers, and using a small number of classifiers to achieve higher performance. The classifier-based method combined with oversampling has demonstrated its advantages in solving unbalanced problems with its powerful learning ability [25].

2.4 Comparison and Summary of Data-level Algorithms

The class-imbalanced data-level image classification methods are introduced from three aspects: oversampling, undersampling and mixed sampling. To further explore the performance of data preprocessing methods on multi-class imbalanced datasets, Table 1 analyzes and compares algorithms using the same dataset.

Table 1. Comparison of classification methods at the level of class imbalanced data

Reference	method	data set	advantage	shortcoming
SMOM [14]	Oversampling	Yeast[16], Vowel[18], Abalone[20] Ecoli[14], Winered[19]	Adopting a mechanism to avoid over-generalization, select safer neighboring directions to synthesize instances, and effectively identify minority classes.	Involving two loop filtering, the algorithm is difficult to implement, and it is only suitable for processingcontinuous attributes.
SSCMIO [15]	Oversampling	Ecoli[14], Yeast[16], Led7digit [21] , LEV[22], ERA	Using the local features and global features of the sample points to calculate the safety factor of the nearest neighbor sampling, it can avoid over-generalization and alleviate the problem of class overlap.	Only datasets with numerical attributes can be processed, no experiments were performed on datasets with nominal attributes.
HDSMOTE [16]	Oversampling	Ecoli[14], Yeast[16],	Secondary synthetic oversampling improves the classifier's ability to identify	The G-Mean and F values obtained by the algorithm need to be improved without

		Glass[17], Abalone[20] Page-bloc [23]	minority class samples and reduces overfitting.	comparing with the recent multi-class unbalanced algorithms.
LOFCUS [18]	Undersampling	Ecoli [14], Glass[17], Balance[15], User	Noise samples are efficiently processed and undersampled according to class overlap, maintaining the original class distribution.	The selected data set has a small number of categories and samples, and data with a highly imbalanced ratio is not analyzed.
OCSV-US [19]	Undersampling	Balance[15], Car, Cleveland, Wine[24] New-Thyro	First train M classifiers and return a set of class instances with the highest informative value, and then sample the best dataset, which significantly improves time efficiency and classification accuracy.	It is not compared with recent multi-class imbalanced algorithms and has high time complexity at training time.
CUS [20]	Undersampling	Ecoli[14], Yeast[16], Abalone[20] prima, poker	Good performance on datasets with high imbalance rate.	High-dimensional datasets are not processed.Simplified into a two-class problem, the sampling process will have the problem of losing the distribution information of multiple classes.
SCUT [22]	mixed sampling	Ecoli[14], Yeast[16], Autos, Wine[24] Thyroid	It performs better on large number of classes and highly imbalanced datasets, and can effectively deal with noise.	The threshold set when sampling a single class is the mean value of all class instances, and the class distribution correlation is not considered.
CIAR [23]	mixed sampling	AIV[29], CPA[27], Electronics, Video Games	The synthesized samples are further divided into subsets to train the base classifier, which improves time efficiency and classification performance.	Experiments are only conducted on the review dataset, other forms of datasets are not considered.
MOSHS [24]	mixed sampling	Wine[24] Flare, Pageblocks, Car[30]	Limit overfitting during sampling and consider handling of class overlap.	Only the undersampling algorithms are compared, and the advantages of the algorithms cannot be reflected.
RBWS-ADAM2 [25]	mixed sampling	FTP-PASV, Database[33], Wine[24]	Use random balanced sampling to construct multiple training sets with differences, and retain high-weight samples to enhance the generalization ability of the classifier.	No comparison with recent class-imbalanced algorithms and high time complexity at training time.

3. Types of Imbalanced Algorithm-Level Classification Methods

Algorithmic-level classification methods improve the accuracy of class prediction by optimizing the base classifier or classification model. At present, algorithm-level classification methods for multi-class imbalanced classification can be divided into two aspects: classifier optimization and ensemble learning [26].

3.1 Algorithm Classification based on Classifier Optimization

In the field of machine learning and deep learning, a variety of algorithms have been proposed for classification problems. However, for imbalanced multi-classification tasks, existing classifiers may not be able to adapt to this complex data environment. Therefore, some researchers focus on improving or adjusting the classifier to make it also have good classification ability and performance in the class imbalance classification scene.

In order to improve the learning performance of the classical ELM algorithm for multi-class imbalanced data, LI proposes an efficient machine learning algorithm. The optimization analysis of the ELM classification algorithm is carried out. The GPELM algorithm based on the G mean and the mixed cost function uses the probability of a given training sample in each category to calculate the G mean, which is used to improve the classification accuracy of the minority class samples. After verification, it can be concluded that the The algorithm has achieved good results in data classification [27]. In order to improve the learning performance of the classical ELM algorithm on multi-class imbalanced data, some researchers have improved ELM and combined it with other advanced techniques. Raghuwanshi combines the Bayesian classifier with the ELM algorithm, and derives a new P-ELM algorithm, which is used to achieve accurate image classification. First, according to the characteristics of the Bayesian algorithm, the image data set is divided into k components, and then the divided training data set is sent to the corresponding k single-class ELM classifiers based on kernels, and each single-class classifier performs operations in parallel. . The output function of the P-ELM classifier constructs an estimate of the probability density. After analysis and verification, P-ELM has better classification accuracy and time efficiency [28]. Learning on multi-class imbalanced data streams also deserves attention, and some researchers have applied online learning to ELM. Yu uses sequential classifiers and ELM algorithms for optimization, and proposes a voting-based weighted online sequential extreme learning machine (VWOS-ELM). This method extends the weight matrix of WOS-ELM to multiple classes, and constructs several independent WOS-ELM-based networks to adapt to the incoming new data, and without storing previously learned samples, The class imbalance problem is handled in a one-by-one and block-by-block mode [29]. For the WOS-ELMK algorithm in dealing with the problem of imbalanced data classification, it does not consider the distribution characteristics of samples in different categories and the impact of the importance of each sample in the same category on the classification results. Using implicit kernel mapping instead of random feature mapping, by using kernel mapping, even if only a single classifier is used, it can adapt to some new data with random initialization and maintain the stability of the classifier. Additionally, WOS-ELMK implements a pinned memory scheme to save computational load on large unbalanced data streams [30].

3.2 Classification of Algorithms based on Ensemble Learning

Ensemble learning is a method for solving imbalanced multi-classification problems, which usually outperforms methods using a single classifier [31]. Ensemble learning combines multiple single classifiers after training, and generally adopts a majority voting mechanism for classification.

Some methods combine resampling techniques with ensemble learning methods to balance the training set by resampling before building the ensemble. Collell proposed a Hybrid Boosting Ensemble Model (HECMI) for handling multi-class imbalanced data with multiple majority and minority classes. For class imbalanced data, an experimental study of base classifier selection based on boosting algorithm is carried out. When analyzing class imbalanced data, the influence of the choice of base classifier on the classification effect of the ensemble algorithm deserves attention. The relevant data parameter indicates that the method can effectively handle and classify multi-class imbalanced data [32]. However, it performs poorly in the presence of noise and outliers. Therefore, Fernandes proposed an ensemble classifier based on sampling and genetic algorithms (SA-GABEC), which tries to find the best subset for a given sample, which is the most accurate in prediction. Finally, combining different classifiers to form an ensemble ensures the diversity of classifiers [33]. In order to explore the effect of combining different sampling techniques and ensemble classifiers on the prediction performance of classification models, Ndirangu conducted experiments on existing ensemble methods, and adopted two methods of combining sampling classifiers and ensemble classifiers, namely resampling ensemble The classifier and SMOTE integrate the classifier, and select different base classifiers to construct multiple combinations, which are trained and tested on a large multi-class imbalanced benchmark dataset. Experiments show that ensemble classifiers using random forests outperform any single classifier [34]. Unlike previous ensemble learning methods, some researchers have combined adaptive methods with hybrid ensembles. Vafaie proposes a nested approach of boosting and bagging to create a powerful ensemble structure (CIAR). The training set is first balanced by SMOTE and RUS techniques, which are then used to create the base learner in the bagging ensemble. Through experimental comparison, this model has the best predictive performance [35].

3.3 Comparison of Image Classification based on Algorithm

Table 2. Comparison of classification methods at the class imbalance algorithm level

Reference	method	data set	advantage	shortcoming
GPELM [27]	Classifier Optimization	Ecoli[14], Yeast[16], Wine[24] Thyroid, New-thyroid	The parameters of ELM are optimized through G-means and mixed cost function, which maintains the class distribution of the initial data and improves the performance of the classifier.	Poor performance on extremely imbalanced datasets.
WLGE-ELM [28]	Classifier Optimization	Yeast[16], Glass[17], Wine[24] Balance [15], New-thyroid	The weighted local generalization error is introduced as a loss function to suppress the output of hidden nodes sensitive to minority classes, and hyperparameters are selected through Bayesian optimization, which improves the learning ability of the classifier.	A lot of bad hidden layer nodes are introduced, and the approximate method to solve the problem increases the training time.
P-ELM Q-[29]	Classifier Optimization	Ecoli[14], Yeast[16], Glass[17], Wine[24]	Class labels can be determined by comparing the output values of k single-class classifiers, and this method has better time performance and classification accuracy.	Only comparisons with ELM-based algorithms were made.
GWOS-ELM [30]	Classifier Optimization	Ecoli[14], Yeast[16], Glass[17], Vehicle New-thyroid	The class overlap region is divided by Euclidean distance and mapped to high dimensions to make the classification. The algorithm finds the optimal hyperplane, which can effectively handle class overlap.	Fail to classify datasets with large number of instances effectively.
PT-bagging [32]	integrated learning	Ecoli[14], Yeast[16], Glass[17], Vehicle, New-thyroid	The natural class distribution of the data is preserved, resulting in well-calibrated posteriors, which improve the accuracy of the classifier.	The distribution of classes is not exploited during sampling.
EFSM [33]	integrated learning	Ecoli[14], Yeast[16], Glass[17], Vehicle	Heterogeneous ensemble models are constructed and exhibit good performance in outlier detection and classification.	The evaluation index is single, and the comparison algorithm is too outdated.
SA-GABEC [34]	integrated learning	Dermatology Satimage	Applying a genetic algorithm to the dataset to find the best subset for undersampling	The problem of noise in the dataset was not dealt with

			makes the method perform well on recall and extended G-means.	and was not compared with state-of-the-art algorithms.
Ada SS [35]	integrated learning	Ecoli[14], Yeast[16], Balance [15], Glass[17], New-Thyroid	With a small number of clusters and classifiers, the method is still robust and able to resolve highly imbalanced multiclass data.	It has not been compared with algorithms dealing with multi-class imbalance, and the evaluation index is single.

The two types of methods at the algorithm level introduced above are summarized. Table 2 summarizes and analyzes the multi-class unbalanced algorithm-level classification methods introduced in this chapter.

4. Conclusion

This paper reviews data-level approaches and algorithm-level approaches for class-imbalanced data. First, the methods of oversampling, undersampling and mixed sampling are introduced in the data method. Secondly, it summarizes the commonly used algorithm-level methods, and introduces and analyzes it in detail from the aspects of classifier optimization and ensemble learning. The main contributions of this paper are:

a) A comprehensive introduction to data-level methods in dealing with multi-class imbalanced problems, and a comparison and analysis of the experimental results of data-level methods using the same dataset.

b) For the first time, the algorithm-level classification methods for class-imbalanced data are elaborated and analyzed from the perspectives of base classifier optimization, ensemble learning and summation, and various algorithms for learning in multi-class imbalanced data streams are introduced.

c) Finally, this paper summarizes the current problems in the research field of class imbalanced data classification, and proposes corresponding solutions

At present, the algorithms and models proposed for multi-class imbalanced classification problems have made considerable progress and development, but there are still many problems to be solved, and further in-depth research and optimization of existing methods are needed. The current problems and future research directions for multi-class imbalanced classification are discussed below.

(1) Multi-class imbalance learning on data streams is a direction that is rarely researched at present, and most of the available data stream classification algorithms are developed for the two-class imbalance problem. Some researchers have studied multi-class imbalanced data flow and achieved good results. However, the problem of uncertainty that may exist in multi-class unbalanced data flow has not been solved, for example, after a period of time, the majority class may become the minority class, the minority class will become the majority class, and the new class will change with time. The class may also come. In response to these problems, future research can combine windowing techniques and dynamic selection ensembles to batch data, evaluate and remove weak classifiers in the ensemble, and retain more capable classifiers.

(2) The amount of data generated in real applications is large and the complexity is higher. In addition to the skewed class distribution, class overlap, and how many classes and how many classes in the class imbalanced data, there are also extreme imbalances and noise. And the case of concept drift. However, most of the existing multi-class imbalanced data processing methods only focus on solving one or two of these problems. More efficient and comprehensive methods for classification in this complex environment should be developed.

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