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Revisiting self-supervised contrastive learning for imbalanced classification

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ABSTRACT

Class imbalance remains a formidable challenge in machine learning, particularly affecting fields that depend on accurate classification across skewed datasets, such as medical imaging and software defect prediction. Traditional approaches often fail to adequately address the underrepresentation of minority classes, leading to models that exhibit high performance on majority classes but have poor performance on critical minority classes. Self-supervised contrastive learning has become an extremely encouraging method for this issue, enabling the utilization of unlabeled data to generate robust and generalizable models. This paper reviews the advancements in self-supervised contrastive learning for imbalanced classification, focusing on methodologies that enhance model performance through innovative contrastive loss functions and data augmentation strategies. By pulling similar instances closer and pushing dissimilar ones apart, these techniques help mitigate the biases inherent in imbalanced datasets. We critically analyze the effectiveness of these methods in diverse scenarios and propose future research directions aimed at refining these approaches for broader application in real-world settings. This review serves as a guide for researchers exploring the potential of contrastive learning to address class imbalances, highlighting recent successes and identifying crucial gaps that need addressing.

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1. INTRODUCTION

Class imbalance significantly challenges machine learning, particularly in fields requiring precise class predictions such as medical imaging, image recognition, and software defect prediction [1]. In these domains, the disproportionate representation of classes often biases algorithms towards the majority class, compromising the detection of less prevalent, but often more critical, minority classes [2]. Traditional classifiers typically excel with balanced datasets but struggle with skewed distributions, leading to poor generalization of real-world data [3], [4].

To circumvent the limitations of labelled datasets, self-supervised learning has become a reliable option, enabling models to pre-train on immense quantities of unlabeled data and then fine-tune them on smaller, tagged datasets, improving subsequent task performance [5]. This learning paradigm is exceptionally valuable where data annotation is costly or impractical [6], [7]. Among various self-supervised techniques, contrastive learning has been notably effective in managing class imbalances. Contrastive learning techniques help to better represent under-represented classes by enhancing the process of learning representations by pulling similar samples closer and pushing dissimilar ones apart in the feature space, which has shown promise in handling imbalanced classification tasks. It enhances model performance by utilizing a contrastive loss function that accentuates the distinctiveness and similarities between samples, thus enhancing the model's capacity to generalize across diverse data scenarios [8].

Considering the recent improvements in self-supervised contrastive learning for imbalance learning, we examine how these emerging advancements can enhance the field of imbalance classification. The purpose of this work is to examine self-supervised contrastive learning approaches that have been created in the past five years to address the issue of imbalanced classification. The aim is to offer direction to academics who are interested in exploring this research topic in the context of class imbalance.

The structure of this paper is as follows: in section 2, we provide a concise overview of the prominent self-supervised contrastive learning methods and imbalance approaches that have been devised. Then, we provide the methods used in conducting this review. Section 4 provides an extensive examination of the self-supervised contrastive learning methods that have been created to address the challenge of imbalanced categorization. Section 5 provides a conclusion to the report, offering valuable insights on potential future research.

2. LITERATURE REVIEW

2.1. Self-supervised learning

Self-supervised learning (SSL) has garnered significant interest lately as a viable method to train deep neural networks without requiring an enormous amount of labelled data. SSL involves a model that can predict specific attributes or relationships inside the data without depending on external annotations. This enables the model to acquire valuable representations that can be refined for particular duties in the future [9], [10].

2.1.1. Principles of self-supervised learning

Figure 1 illustrates the overall process of self-supervised learning, where x represents raw data, y represents labels. During the first phase, convolutional neural networks (ConvNet) are trained to resolve a specific pretext task. The pseudo labels for pretext tasks are created depending on particular data features. The ConvNet gets trained to acquire knowledge of entity characteristics related to the pretext task [11]. During training, shallower blocks of the ConvNet primarily detect low-level general features, while deeper blocks concentrate on identifying higher levels, task-specific characteristics like objects, scenarios, and parts of things [12]. Once the self-supervised training is complete, visual characteristics obtained can be efficiently utilized for downstream tasks, particularly in cases with sparse data. Pre-trained models improve performance and mitigate the issue of over-fitting. Only the visual characteristics from the initial layers are conveyed for training the supervised downstream task [13]. This strategy significantly enhances downstream tasks' performance compared to training the models from the beginning [14], [15]. Huang *et al.* [16] categories self-supervised learning techniques into three groups: generative, contrastive and predictive. Most visual categorization problems benefit from contrastive learning [17]. The contrastive loss function increases the similarity of images that belong to the same object class. It reduces the similarity between those that belong to distinct classes, which is especially advantageous for downstream object detection and classification tasks [18].

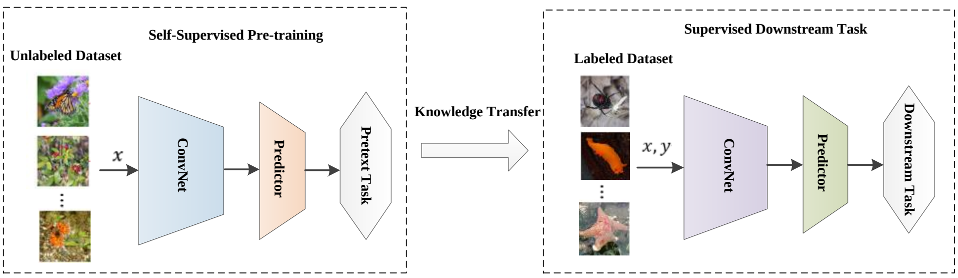

Figure 1. The flow of self-supervised learning

2.1.2. Contrastive learning frameworks

Contrastive learning is a new popular self-supervised method and has demonstrated exceptional performance across various computer vision tasks, resulting in widespread success in image [19], [20], text

[21], [22], audio [23], [24], and video [25], [26]. Contrastive learning extracts comparable or dissimilar representations from data arranged in pairs based on their similarities or differences. An applied loss function for contrastive learning, known as InfoNCE, is:

$$\mathcal{L}_{q,k+,\{k^-\}} = -\log \frac{\exp(q \cdot k^+/\tau)}{\exp(q \cdot k^+/\tau) + \sum_{k^-} \exp(q \cdot k^-/\tau)} \quad (1)$$

where q represents the query representation, k^+ is the representation of positive key samples and k^- denotes negative key samples, with τ denoting a temperature hyper-parameter. Equation (1) encourages the model to closely align the depictions of positive pairs and distance those of negative pairs.

Contrastive methods [27] implement the approach suggested in reference [28] that dense contrastive learning facilitates self-supervised visual pre-training by attracting positive sample pairings and repelling negative ones. Momentum contrast (MoCo) [10] utilizes unlabeled data to create pre-trained models that can be further refined with labelled data. Chen *et al.* [9] utilized SimCLR to attain similar results as a supervised ResNet-50 model by solely training a linear classifier on self-supervised representations from the entire ImageNet dataset. Chen *et al.* [20] upgraded MoCo to MoCo v2, enabling competitive results with short batch size training on the entire ImageNet [29]. BYOL [30] and SimSiam [31] aim to minimize the distance between pairs of positive samples and an asymmetric Siamese network. Figure 2 illustrates the popular frameworks. Figure 2(a) depicts the MoCo framework, Figure 2(b) shows the SimCLR framework, and Figure 2(c) illustrates the BYOL framework. Contrastive learning frameworks aim to improve the agreement between similar images while distinguishing them from dissimilar images using a contrastive loss function. This pre-training method forces the model to obtain efficient representations. Approaches differ in their techniques for generating positive and negative image pairs from unlabeled data and data selection in pre-training. Wang *et al.* [32] analyze contrastive learning in terms of the regularity and alignment of acquired representations. Kotar *et al.* [33] comprehensively analyze contrastive self-supervised learning techniques. It explores the effects of different training strategies and datasets on performance in various downstream tasks, concluding that these approaches significantly advance state-of-the-art representation learning.

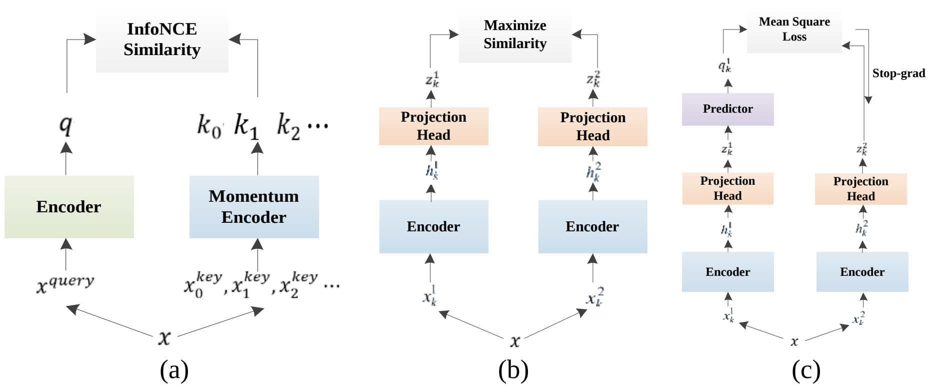

Figure 2. Illustration of the contrastive learning frameworks (a) MoCo, (b) SimCLR, and (c) BYOL

2.2. Imbalance learning

2.2.1. Data-level

Data-level techniques encompass the utilization of over-sampling and under-sampling. The data-level technique involves altering the training data to achieve an equitable distribution of classes. The under-sampling method balances the data by deleting samples of the majority class, which may reduce some helpful information in the datasets. On the contrary, the over-sampling method balances the data by augmenting the minority class with additional samples by repeating or generating new instances, which causes the learner to overfit. Chawla *et al.* [34] created synthetic minority over-sampling technique (SMOTE) to overcome these concerns by generating new instances of the minority class based on the k-nearest neighbors. When the minority class consists of numerous small separate clusters, using SMOTE can lead to more class overlap and raise the complexity of the classification task [35]. Various solutions have been suggested to tackle these shortcomings by either incorporating both classes during generation or as a subsequent cleaning process.

The researcher proposed Borderline-SMOTE [36], which only oversamples or strengthens the borderline minority samples. Adaptive Synthetic sampling approach (ADASYN) [37] utilizes a weighted distribution to allocate various minority samples based on the level of learning complexity. Safe-level-SMOTE

[38] and noise reduction a priori synthetic over-sampling technique (NRAS) [39] are meant to minimize the chance of introducing disruptive artificial data points within the main class area. The sampling with the majority (SWIM) [40] approach uses Mahalanobis distance to locate synthetic samples based on both classes' samples. Radial-based oversampling (RBO) [41] generates minority objects using radial basis functions and potential estimation. Combined cleaning and resampling (CCR) [42] method cleans minority object decision borders and guides synthetic oversampling. Several works have explored how to improve the synthetic oversampling method to be suitable for multi-class imbalance issues. Mahalanobis distance-based over-sampling (MDO) [43] used the same Mahalanobis distance as the class mean of each inspection. Zhu *et al.* [44] proposed k-NN-based synthetic minority oversampling (SMOM), which balances minority sample direction to build new prototypes. Synthetic oversampling with the minority and majority classes (SOMM) [45] use synthetic oversampling to create synthetic samples for minority and majority classes.

2.2.2. Algorithm-level

The imbalance problem is solved at the algorithm level, utilizing varying misclassification costs to make classifiers prioritize the minority class [46]. In the imbalance issue, a false negative prediction should cost more than a false positive if the minority class is positive in classification outcomes. Classificational methods can include these expenses during model training to reduce imbalanced data. The classic Ada-boost algorithm reduces classifier generation error. Sun *et al.* [47] studied meta-techniques for unbalanced data. They combined cost-sensitive learning with AdaBoost to develop three cost-sensitive boosting methods to improve positive class categorization. Besides, Lin *et al.* [48] proposed the loss function of Focal Loss, in which a penalty is applied for each category utilizing a cost matrix. Increase the weight of the minority class to reduce the possibility of the class being misclassified. Class-balanced (CB) focal loss [49] adds a class-balanced factor for class dispersion. This recalibration ensures that the model prioritizes classes based on their data representation, lowering the influence of the majority class. progressive margin loss (PML) [50] weights decision border samples because they define class separations. Long-tailed multi-label datasets are complex enough to optimize with single-label assumptions. The empirical findings illustrate that the improvement of the precision of the loss function varies with different datasets. Algorithm-level approaches lack flexibility compared to data-level alternatives [51].

2.2.3. Ensemble learning

Ensemble learning enhances predicted accuracy by combining predictions from many models. Ensemble learning includes bagging, boosting, and stacking methods [52]. Ensemble methods are frequently employed to address the issue of class imbalance. For example, Chawla *et al.* [53] proposed SMOTEBagging, which uses bagging and SMOTE to build multi-classifiers to diversify fake samples. SMOTEBoost generates synthetic minority class samples throughout each boosting iteration using SMOTE and a boosting technique. Seiffert [54] introduced RUSBoost, a method that utilizes random undersampling. RUSBoost can decrease training time while utilizing AdaBoost to enhance performance. Lv *et al.* [55] implemented the over-sampling SMOTE and AdaBoost algorithm to balance credit card consumption data. Evidence shows that SMOTE-AdaBoost exceeds AdaBoost. Ileberi *et al.* [56] suggested a machine learning approach for identifying instances of credit card fraud, and the dataset was rebalanced using SMOTE. Su *et al.* [57] proposed a model that utilizes SMOTE-AdaBoost. The results demonstrate enhanced identification of the intended objective of the combat target in the presence of disproportionate data. Edward *et al.* [58] present a novel rebalancing framework, incorporating SMOTE and cluster-based undersampling technique (SCUT), and recursive feature elimination (RFE) for improved multi-class classification performance in addressing the challenges of imbalanced medical datasets. Gao *et al.* [59] explore the effectiveness of combining SMOTE with convolutional neural network models and the boosting method to address imbalanced image classification tasks. The boosting ensemble technique is generally more effective than using a single classifier to address the issue of class imbalance. It shows superior performance in resolving this issue.

3. RESEARCH METHOD

The research techniques part primarily focuses on the planning, execution, and presentation of the review findings. Initially, the relevant research questions on self-supervised contrastive learning methods for handling imbalanced data are formulated and defined. Second, the relevant literature and related facts are extracted by searching various databases. Finally, a systematic review of the results report is written.

3.1. Research questions

The initial stage in carrying out a systematic review involves identifying the research question. This phase should be concise and straightforward. These are the research inquiries within the scope of this study:
Q1: What is the present status of research on self-supervised contrastive learning for imbalanced data?

Q2: What is the most effective approach using self-supervised contrastive learning to address imbalanced data classification?
Q3: What are the most critical gaps and shortcomings in the reviewed research?

3.2. Search strategy

The search was conducted using specific terms, such as "Imbalance" combined with the "AND" operator and "contrastive learning" along with various synonyms, as indicated in Table 1. To ensure the survey included only relevant scientific works, additional modifications were implemented in each search engine. These modifications excluded any publications other than journal and conference papers, thereby refining the search results.

3.3. Criteria for inclusion and exclusion

Criteria for inclusion were established to categorize articles retrieved from scientific databases, ensuring the collection of pertinent information related to the research inquiries. Only documents that met these specific criteria, as outlined in Table 2, were considered for further analysis. This approach helped to focus the review on relevant publications that directly addressed the research questions.

3.4. Conducting review process

This section details the practical execution of the review depicted in Figure 3. The process entailed the identification, screening, assessment of eligibility and inclusion. This straightforward graphic clearly shows the methodical approach to choosing relevant studies for review. A time frame of up to five years was set to capitalize on new research findings and incorporate additional useful information into the study. Initially, the 842 papers obtained from the ACM Digital Library, IEEE Explore, ScienceDirect, SpringerLink, and Scopus databases were refined based on the specified criteria for inclusion and exclusion. Ultimately, a total of 798 articles were deemed ineligible and excluded, while 44 articles met the criteria and were considered admissible.

Table 1. Query for search

Main search string
("Imbalance" or "unbalance" or "skew") and ("classification" or "recognition") and ("Self-supervised" or "Unsupervised") and ("contrastive learning" or "contrastive method" or "contrastive technique")

Table 2. The criterion for selection

Inclusion	Exclusion	Criterion
English article	Non-English article	Whether the literature is in English
Since 2019	Before 2019	A timeline
Journal article and conference proceeding	Book and review	Genre of literature

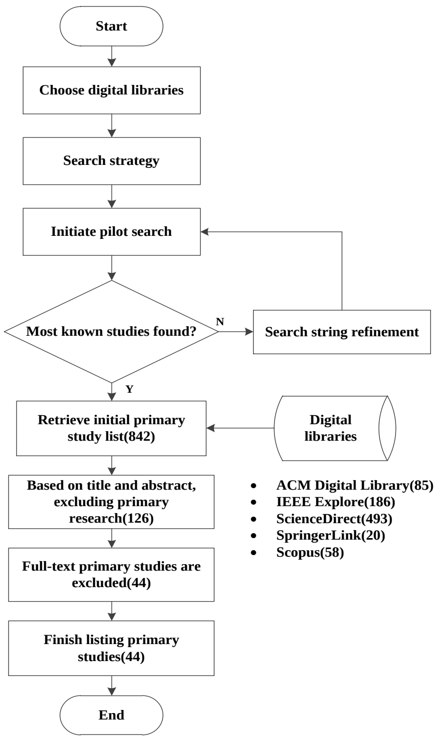

Figure 3. Flow diagram of the proposed search study

4. RESULTS AND DISCUSSION

4.1. Answering the research questions

This study analyses previous results to address the three research inquiries already outlined.

Q1: What is the current state of research on self-supervised contrastive learning for imbalanced data?

Self-supervised contrastive learning has acquired significant attention in the research community for efficiently learning representations from unlabeled data. Tu *et al.* [60] introduced AAG, which makes use of an auxiliary augmentation strategy and GNT-Xent loss. Similarly, Tian *et al.* [61] proposed constrained contrastive distribution learning for anomaly detection (CCD), an approach for anomaly detection in medical photos using limited contrastive distribution learning, which focuses on learning fine-grained feature representations through contrastive learning with pretext constraints. Gao *et al.* [62] proposed distilled contrastive learning (DisCo) as a way to mitigate the performance deterioration of SSL on lightweight models. Yao *et al.* [63] investigated SSL on electronic health records using graph kernel infomax, showcasing the success of contrastive learning in this domain. Furthermore, Kang *et al.* [64] focused on long-tailed learning and improving feature extractors and classifiers for imbalanced data through contrastive pretraining and feature normalization. Träuble *et al.* [65] introduced a novel contrastive loss for brain age prediction on 3D stiffness maps, aiming to improve generalization across non-uniformly distributed data in medical imaging data.

Q2: What is the most effective approach using self-supervised contrastive learning to address imbalanced data classification?

Based on contrastive SSL, researchers have proposed several innovative techniques and strategies to enhance representation learning. These approaches aim to improve the robustness of classifiers, particularly in the context of skewed category distributions. By addressing these challenges, they effectively contribute to solving imbalanced classification issues.

Various methods have been proposed to enhance self-supervised learning, such as devising sampling strategies that ensure minority classes are adequately represented in the contrastive learning process. For example, model-Aware K-center [66] improved contrastive learning on imbalanced seed data is also explored through an open-world sampling framework, which strategically selects unlabeled data from external sources to learn generalizable, balanced, and diverse representations. Yang *et al.* [67] suggested a novel hypergraph contrastive learning model (IS-HGCL) that utilizes hypergraphs to tackle the problems of imbalance and long-tail distribution in graduate development predictions.

Adjusting the margin or weighting the contrastive loss based on class distribution or sample hardness, makes the model sensitive to the learning difficulty of different classes. The SCoRe [68] framework introduces submodular combinatorial loss functions that effectively address the challenges posed by class imbalance. Empirical evidence demonstrates that these goals surpass the most advanced metric learners now available by as much as 7.6% in imbalanced classification tasks. Wang *et al.* [69] the novel focal CL was proposed with satellite images, and Alenezi *et al.* [70] introduced the innovative W-shaped CL model utilizing skin lesion photos as datasets. Similarly, Zhang *et al.* [71] applied contrastive learning with a weighted loss function to imbalanced datasets in the field of healthcare. Audibert *et al.* [72] introduce a new multi-label contrastive loss that adapts the conventional contrastive learning framework to handle datasets with a long-tailed distribution better.

Other effective strategy currently being used or actively researched include hybrid learning approaches and architectural innovations. Taher *et al.* [73] were assigned the goal of developing a framework that would improve performance by integrating contrastive and generative tasks to learn both global and local properties. Kallidromitis *et al.* [74] introduce a novel framework combining contrastive learning with neural processes to enhance time series forecasting without relying on pre-defined data augmentations, showing significant improvements in diverse datasets. Yang *et al.* [75] proposed prototypical contrastive learning (ProCL), which integrates contrastive learning with clustering and allocates weights to negative samples based on the distance to the prototype. Table 3 briefly overviews some of the most effective methods of research on self-supervised contrastive learning applications in imbalance classification.

Q3: What are the most critical gaps and shortcomings in the reviewed research?

Self-supervised contrastive learning with various strategies significantly enhances representation learning and addresses the imbalanced data classification problem. However, there are still notable gaps and deficiencies in these approaches that need to be addressed. These gaps are critical for ongoing research and the successful implementation of practical applications.

First, models based on self-supervised contrastive learning, especially those involving large-scale data augmentation and complex sampling strategies, can be computationally intensive and require many hardware resources [76]. Second, contrastive learning methods are susceptible to data quality. In cases where the data is noisy or contains many outliers, the effectiveness of contrastive learning may be reduced, so diverse data augmentation techniques are needed [77]. Lastly, models trained using self-supervised contrastive learning may overfit the characteristics of the training data, especially when using large amounts of augmentation or specific sampling strategies, which may hurt generalization [78].

Table 3. Summary of recent literature on contrastive SSL in imbalanced classification

Strategy	References	Dataset	Advantage	Disadvantage
Augmentation Strategy	MoCo-CXR Ref. [79]	CheXpert	Pre-training is particularly advantageous when there is a scarcity of labelled training data	The performance gains diminish as the quantity of labelled training data increases
Meta-Learning	MedAug Ref. [80]	CheXpert,	Utilize patient metadata for choosing positive pairs and 14.4% higher in the average AUC than baseline	selecting hard negative pairs using metadata did not yield improvements over the baseline
Hybrid Learning	MICLe Ref. [81]	Dermatology, CheXpert	The method significantly improves the accuracy of medical image classifiers	It may still require a substantial amount of unlabeled data to achieve optimal performance
Sampling Strategy	MAK Ref. [67]	ImageNet-100-LT	Effectively enhances the quality of learned representations by strategically selecting unlabeled data from external sources	challenges related to data imbalance and distraction from out-of-distribution samples
Adjusting contrastive loss	AFCL Ref. [82]	FMNIST, ISIC 2018	It outperforms CL and FCL in terms of both weighted and unweighted classification accuracies	It requires careful tuning of hyperparameters resulting in a complicated training process
Sampling Strategy	SDCLR Ref. [83]	CIFAR-10-LT, CIFAR-100-LT, ImageNet-LT	It focuses on difficult-to-learn samples, which enhances the model's ability to generalize better across various classes	It may lead to the exclusion of some useful information
Sampling Strategy	BCL Ref. [84]	CIFAR-10-LT, CIFAR-100-LT, ImageNet-LT, iNaturalist2018	Incorporates class averaging, which balances the gradient contributions from negative classes	It may require more computational resources and careful tuning of hyperparameters to achieve optimal performance
Adjusting contrastive loss	KCL Ref. [85]	ImageNet-LT, iNaturalist2018	Effectively balances the number of positive instances across classes	It may not fully leverage all available instances from the same class for positive pair construction
Sampling Strategy	CL Ref. [86]	ISIC2018, APTOS2019	Enhanced the cross-entropy method by effectively distinguishing minority and majority classes in the feature space.	The risk of overfitting, particularly when resampling is applied to minority classes
Architectural innovation	HCLe Ref. [87]	ISIC2020， BRACS, REFUGE	It acquires consistent characteristics of the dominant class and avoids being trained on the infrequent and varied minority.	It may limit its ability to generalize well to unseen minority class instances
Adjusting contrastive loss	TSC Ref. [88]	CIFAR-10-LT, CIFAR-100-LT, ImageNet-LT, iNaturalist2018	Enhances the separability of minority classes and leads to better generalization in long-tailed recognition tasks	May not yield the analytical optimal solution for points on a hypersphere
Architectural innovation	SSCL Ref. [89]	Salinas, Pavia University, and Botswana	Streamlines the training procedure by obviating the necessity for manual annotation	The effectiveness of the acquired representations is highly dependent on the formulation of the preliminary tasks
Hybrid Learning	Leverages Cross-domain CNN Ref. [90]	Hyperspectral images	Effectively captures transferable representations from large amounts of unlabeled hyperspectral images	A significant challenge arises in maintaining spectral homogeneity when using larger regions for pseudo-labeling
Architectural innovation	ISD Ref. [91]	ImageNet	Effectively utilizes a soft similarity approach for negative images	The iterative distillation procedure may necessitate additional computational resources.
Hybrid Learning	ProCo Ref. [92]	ISIC2018, APTOS2019	A comprehensive approach to address the issue of imbalance	It relies on a complex framework involving multiple modules

4.2. Results discussion

This study reviews the state-of-the-art self-supervised contrastive learning techniques involved in addressing imbalanced classification. The study investigates contrastive learning with different training methodologies in different downstream tasks, ultimately showing that self-supervised contrastive learning focuses on improving model robustness and generalization by effectively utilizing large quantities of unlabeled data, which is particularly beneficial in scenarios where labelled data for rare events or classes is scarce. Moreover, we cannot combine or make statistical comparisons of the impacts of each SSL technique on performance improvement. This is because the research included in our analysis utilizes distinct datasets, provides various performance indicators, and examines different aims.

Several suggestions for future research directions in imbalanced classification using self-supervised learning are recommended to focus more on these challenges. We suggest using contrastive SSL pre-training instead of generative SSL pre-training for the classification challenge. Previous analysis reveals that integrating re-sampling strategies with SSL techniques is particularly effective in scenarios of severe class imbalance and low data availability. The choice of sampling procedures can have an impact on contrastive SSL approaches, such as MoCo and SimCLR, that require a significant quantity of negative examples. Therefore, finding a solution to reduce the dependence on sample methodologies remains an attractive and unresolved issue. Hence, additional research is required to explore methods for generating negative samples and improving the integration of SSL with downstream tasks to boost the effectiveness of SSL approaches in imbalanced domains.

An additional aspect that requires further improvement is the modification of the contrastive loss function, which is crucial for enhancing the performance. The researchers have developed contrastive loss functions tailored for specific uses in imbalanced areas, such as multimodal learning, local representation learning, and multiscale learning. Lastly, integration with other SSL techniques, like pretext tasks or clustering-based approaches, can help better handle imbalanced data. Meantime, deeper integration with domain-specific applications and the development of new benchmarks that better reflect the challenges of imbalanced datasets in real-world settings.

5. CONCLUSION

Self-supervised representation learning has garnered considerable interest in recent years because to its ability to learn from unlabeled data efficiently. The study of imbalanced classification presents numerous significant and pressing challenges. Self-supervised contrastive learning is evolving rapidly, and its adaptation to imbalanced data is a promising area that bridges the disparity between unsupervised learning capabilities and supervised learning's need for labelled data.

This paper comprehensively reviews imbalance classification methods based on self-supervised contrastive learning, covering the most popular contrastive learning frameworks and construction mechanisms. In addition, we presented a concise summary of the issue of class imbalance and the latest approaches to address it. This literature review includes a reasonable search method, with a low probability of missing articles and high scientific value. We categorized the SSL approaches and extracted benefits and limits from existing literature to formulate recommendations for future research. The following studies should incorporate improved sampling and augmentation techniques, as well as an adaptive contrastive loss function, to expedite the identification of optimal methods. As research on high-dimensional imbalanced data is highly significant, we hope to guide researchers interested in exploring contrastive learning techniques to extend to more imbalance fields, such as object detection, and image segmentation.

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