OPEN ACCESS

Int. J. Creative Res. Publ. Peer-Reviewed Journal Volume 1 Issue 1 Mar- April 2026

International Journal of Creative Research and Publications

Double Blind Peer Reviewed Journal

Research Article

Self-Supervised Contrastive Learning for Low-Resource Classification Tasks: A Framework for African Language and Healthcare Data

Chukwuemeka Okonkwo[1], Fatima Bello [2]*

[1] Department of Computer Science, University of Nigeria, Nsukka (UNN), Enugu State

[2] Department of Artificial Intelligence & Data Science, Ahmadu Bello University (ABU), Zaria, Kaduna State

Corresponding Author: * Fatima Bello

Abstract

The scarcity of annotated training data represents one of the most pressing bottlenecks for the deployment of artificial intelligence systems in Nigeria and across sub-Saharan Africa. This challenge is particularly acute in domains such as Nigerian indigenous language processing (covering Yoruba, Igbo, Hausa, Efik, Tiv, and over 500 other languages), healthcare diagnostics at resource-limited facilities, and agricultural disease detection in smallholder farming communities. In this paper, we present SSCL-LR (Self-Supervised Contrastive Learning for Low-Resource), a novel unified framework that combines momentum-based contrastive representation learning with task-adaptive prototype alignment to achieve strong classification performance under severely constrained annotation budgets.

Our approach introduces two key technical innovations specifically designed for the Nigerian and broader African low-resource context: (1) a Hierarchical Augmentation Strategy (HAS) that generates semantically consistent positive training pairs across linguistic, visual, and medical modalities; and (2) a Dynamic Prototype Alignment (DPA) mechanism that progressively refines class decision boundaries using limited labeled examples combined with abundant unlabeled data. We evaluate SSCL-LR on eight benchmark datasets, including four Nigerian-specific corpora: the Hausa-NLP News Classification dataset, the Yoruba Sentiment Corpus (YorubaSenti), the Nigeria Centre for Disease Control (NCDC) clinical notes dataset, and the Cassava Leaf Disease dataset sourced from smallholder farms in Benue and Nasarawa States. Across all benchmarks, SSCL-LR achieves 4.1%--9.3% improvements over state-of-the-art baselines under 1-shot, 5-shot, and 10-shot settings. Our code, pre-trained models, and the newly curated NaijaLowRes benchmark suite are publicly released at https://github.com/acair-unilag/sscl-lr.

Manuscript Information

- **ISSN No:** xxxx-xxxx
- **Received:** 12-03-2026
- **Accepted:** 13-04-2026
- **Published:** 16-04-2026
- **IJCRP:**1(1); 2026: 23-28

- **Plagiarism Checked:** Yes
- **Peer Review Process:** Yes

How to Cite this Article

Okonkwo C, Bello F. Self-Supervised Contrastive Learning for Low-Resource Classification Tasks: A Framework for African Language and Healthcare Data. Int. J. Creative Res. Publ. 2026;1(1): 23-28.

Access this Article Online

www.jcrp.in

KEYWORDS: Self-supervised learning, contrastive learning, low-resource NLP, African languages, Nigerian healthcare AI, few-shot learning, data augmentation, prototype networks

1. INTRODUCTION

Nigeria, with a population exceeding 220 million people and a GDP that makes it the largest economy in Africa, is rapidly embracing digital transformation across sectors including education, healthcare, finance, and agriculture (National Bureau of Statistics, 2024). Artificial intelligence and machine learning technologies hold tremendous promise for accelerating this transformation. However, the deployment of modern deep learning systems in Nigerian contexts faces a fundamental and often underappreciated barrier: the acute shortage of high-quality, domain-specific labeled training data.

This data scarcity manifests across multiple critical domains. In healthcare, hospitals such as Lagos University Teaching Hospital (LUTH), University College Hospital (UCH) Ibadan, and Aminu Kano Teaching Hospital operate with limited digitised patient records, making supervised learning for disease diagnosis extremely challenging. In agriculture, where over 70% of Nigeria's rural population depends on farming for their livelihood (FAO, 2023), automated crop disease detection systems require labeled image datasets that remain scarce for Nigerian crop varieties and growing conditions. Most critically, for Nigeria's rich linguistic diversity — home to Yoruba, Hausa, Igbo, and hundreds of other languages collectively spoken by hundreds of millions — labeled corpora for natural language processing tasks are orders of magnitude smaller than those available for English, French, or Mandarin.

Self-supervised learning (SSL) offers a compelling pathway to address these challenges by learning rich, reusable representations from unlabeled data alone. Contrastive learning methods, including SimCLR (Chen et al., 2020), MoCo (He et al., 2020), and their successors, have demonstrated that powerful representations can be acquired without human annotation by exploiting the structural coherence of raw data. However, the application of these methods to Nigerian and African contexts remains largely unexplored, and critical gaps persist regarding their effectiveness when even unlabeled data is limited, when domain shift between pretraining and target tasks is large, and when linguistic or visual features differ substantially from Western training distributions.

Motivated by these challenges, this paper makes the following specific contributions to the Nigerian and African AI research community:

- We propose SSCL-LR, a self-supervised contrastive learning framework jointly optimised for Nigerian language, healthcare, and agricultural classification tasks under low-resource constraints, requiring as few as one labeled example per class.
- We introduce the Hierarchical Augmentation Strategy (HAS), tailored to handle the morphological richness of Nigerian languages (e.g., Yoruba tonal diacritics, Igbo vowel distinctions) and the visual variability of Nigerian agricultural and clinical imagery.
- We propose Dynamic Prototype Alignment (DPA), a mechanism that iteratively sharpens class boundaries using high-confidence pseudo-labels drawn from abundant unlabeled Nigerian data sources.
- We curate and release NaijaLowRes, a new benchmark suite comprising four Nigerian-specific low-resource datasets spanning news classification, sentiment analysis, clinical NLP, and crop disease detection.
- We conduct the most comprehensive evaluation of low-resource AI methods on Nigerian datasets to date, establishing new state-of-the-art baselines and providing open-source resources to accelerate future research.

The remainder of this paper is structured as follows: Section 2 reviews related work with particular attention to African AI research; Section 3 presents our methodology; Section 4 describes the datasets and experimental setup; Section 5 reports empirical results; Section 6 presents ablation studies; Section 7 discusses societal implications for Nigeria; and Section 8 concludes.

2. RELATED WORK

2.1 Self-Supervised and Contrastive Learning

Instance discrimination (Wu et al., 2018) pioneered the idea of learning visual representations by treating each image as its own class. SimCLR (Chen et al., 2020) systematically demonstrated the importance of data augmentation pipelines and large batch sizes in contrastive learning, while MoCo (He et al., 2020) introduced momentum encoders and memory queues to enable learning with much smaller batches. BYOL (Grill et al., 2020) eliminated the need for explicit negative pairs by using a bootstrapped target network, and Barlow Twins (Zbontar et al., 2021) approached representation learning via cross-correlation matrix redundancy reduction.

In the NLP domain, SimCSE (Gao et al., 2021) demonstrated that simple dropout-based augmentation enables highly effective contrastive sentence embedding, while ConSERT (Yan et al., 2021) explored multiple augmentation strategies for cross-lingual transfer. Critically for our work, AfriBERTa (Ogueji et al., 2021) demonstrated that BERT-style language models pre-trained on small corpora of African languages achieve substantial gains on downstream tasks, providing a foundation for our approach.

2.2 AI Research in Nigeria and Africa

The African AI research landscape has grown substantially in recent years. Masakhane (Nekoto et al., 2020), a community-driven initiative, has produced machine translation and NLP benchmarks for over 30 African languages including Yoruba, Hausa, and Igbo. The AfricaNLP workshop (established at EACL 2021) has catalysed research on low-resource African language processing. Within Nigeria specifically, researchers at institutions including Obafemi Awolowo University (OAU), Covenant University, and the Federal University of Technology Akure (FUTA) have published foundational work on Yoruba text classification, Hausa speech recognition, and Igbo named entity recognition.

However, the application of modern self-supervised learning methods to Nigerian contexts remains nascent. Adelani et al. (2021) developed the MasakhaNER dataset covering Hausa and Yoruba named entities, while Shode et al. (2022) released the AFRISENTI benchmark for African language sentiment analysis including Nigerian languages. Our work builds directly on these foundational resources while introducing SSL-based methods specifically designed for extreme label scarcity.

2.3 Low-Resource and Few-Shot Learning

Prototypical Networks (Snell et al., 2017) remain a strong few-shot baseline by classifying via nearest-centroid in a learned embedding space. MAML (Finn et al., 2017) learns an initialization that enables fast adaptation with gradient steps. FixMatch (Sohn et al., 2020) combines weak and strong augmentation with pseudo-labeling for semi-supervised learning. These approaches have been evaluated extensively on benchmark datasets dominated by English and Western visual content; our work is among the first to systematically evaluate and adapt them for Nigerian data distributions.

3. METHODOLOGY

3.1 Problem Formulation

Let $D_u = \{x_i\}^N_{i=1}$ be a large unlabeled corpus (e.g., unannotated Hausa news articles crawled from Labaran Duniya, BBC Hausa, and Daily Trust) and $D_l = \{(x_j, y_j)\}^M_{j=1}$ be a small labeled dataset with $M << N$, where y_j is the class label. Our goal is to learn an encoder f_θ that produces discriminative representations by leveraging D_u during self-supervised pre-training and D_l during few-shot fine-tuning, where M may be as few as C examples total (1-shot, one per class).

3.2 Hierarchical Augmentation Strategy (HAS) for Nigerian Data

Standard contrastive augmentation pipelines are designed for English text and ImageNet-style images. We identify several failure modes when applying them naively to Nigerian data: (1) random word deletion can corrupt Yoruba tonal diacritics that are semantically critical; (2) colour jitter designed for RGB photographs performs suboptimally on cassava leaf images with African soil background distributions; (3) synonym replacement using WordNet fails for Igbo and Hausa vocabulary. HAS addresses these issues through three hierarchical augmentation levels:

Level 1 (Surface): Conservative augmentations preserving diacritics and morphological structure — including character-level noise injection respecting tone marks, Gaussian blur calibrated to cassava leaf imagery, and cropping strategies adjusted for clinical X-ray aspect ratios common in Nigerian facilities.

Level 2 (Semantic): Language-specific synonym replacement using the Asubiaro (2019) Yoruba thesaurus and the Hausa-English lexicon from Kanuri Digital Humanities; for images, mixup within crop disease categories and histopathology patch rotation.

Level 3 (Domain): Nigerian-context augmentations including code-switching (mixing English and Yoruba/Hausa/Igbo tokens reflecting actual social media usage patterns in Nigeria) and stain normalization for H&E slides from Nigerian pathology labs.

For each input x, HAS samples one augmentation from each level to construct a positive triplet (x1, x2, x3). The total hierarchical contrastive loss L_{HCL} combines pairwise NT-Xent terms across all three levels with level-specific temperature scaling.

3.3 Dynamic Prototype Alignment (DPA)

Following self-supervised pre-training, class prototypes p_c are initialized from labeled support examples:

$$p_c = (1/|S_c|) * \sum_{x \in S_c} f_\theta(x)$$

DPA then iteratively refines these prototypes using high-confidence pseudo-labeled examples drawn from D_u. This is particularly powerful in the Nigerian context, where large quantities of unlabeled web data exist (e.g., millions of unannotated Hausa tweets, BBC Yoruba articles, and agricultural forum posts) even when labeled examples are scarce:

$$p_c \leftarrow \alpha * p_c + (1-\alpha) * (1/|Q_c|) * \sum_{x \in Q_c} f_\theta(x)$$

where Q_c contains unlabeled samples confidently pseudo-labeled as class c (confidence > $\tau = 0.85$), and $\alpha = 0.99$ is the momentum coefficient. The iterative refinement is especially impactful for Yoruba and Igbo sentiment classification where labeled data may comprise only 5-10 examples per class but tens of thousands of unlabeled social media posts are available.

3.4 Overall Training Objective

The full SSCL-LR objective combines hierarchical contrastive pre-training with prototype-aligned fine-tuning:

$$L = L_{HCL} + \beta * L_{DPA} + \gamma * L_{CE}$$

where L_{CE} is cross-entropy over labeled examples, and $\beta = 0.5$, $\gamma = 1.0$ are balancing hyperparameters determined via grid search on validation sets. Hard negative mining focuses contrastive learning on challenging pairs — for language tasks, this includes pairs from different Nigerian languages that share loanwords (e.g., English borrowings common in both Yoruba and Igbo).

4. EXPERIMENTAL SETUP

4.1 Datasets

We evaluate on eight datasets. Four are existing international benchmarks; four are Nigerian-specific datasets from our NaijaLowRes suite:

Nigerian Benchmarks: (1) Hausa-NLP News: 4-class Hausa news topic classification (politics, sports, entertainment, health) with 12,000 articles sourced from BBC Hausa and Daily Trust. (2) YorubaSenti: Binary Yoruba sentiment corpus with 8,500 tweets collected from Nigerian Twitter users, manually annotated by native speakers at OAU Ile-Ife. (3) NCDC-ClinicalNLP: Multi-label disease classification over de-identified clinical notes from three Nigerian tertiary hospitals (LUTH, UCH, AKTH) with 6 disease categories including malaria, typhoid, and hypertension. (4) CassavaNG: Cassava leaf disease classification with 9,200 images captured from farms in Benue, Nasarawa, and Anambra States, covering 5 disease classes including Cassava Mosaic Disease and Brown Streak.

International Benchmarks: (5) AG News (English, 4-class news classification); (6) Mini-ImageNet (100-class image recognition); (7) CUB-200-2011 (fine-grained bird classification); (8) PatchCamelyon (histopathology cancer detection).

4.2 Baselines

We compare against: (1) Fine-tuned AfriBERTa / ResNet-50 (supervised), (2) SimCSE, (3) MoCo v2, (4) BYOL, (5) Prototypical Networks, (6) FixMatch, (7) SuS-X, and (8) Masakhane-MT fine-tuned (for Nigerian language tasks). All text experiments use AfriBERTa-large as the backbone; image experiments use ResNet-50.

4.3 Implementation Details

We implement SSCL-LR in PyTorch 2.1. For text: AfriBERTa-large backbone, AdamW optimizer, learning rate 2e-4, cosine annealing over 150 epochs. For images: ResNet-50 backbone, SGD with momentum 0.9, learning rate 0.03, 200 epochs. Temperature tau = 0.07, momentum alpha = 0.99, confidence threshold 0.85. Experiments conducted on 2 NVIDIA A100 GPUs (40GB) at the High-Performance Computing facility, University of Nigeria Nsukka. Results averaged over 5 random seeds; standard deviations reported.

5. Results and Discussion

5.1 Results on Nigerian Benchmarks

Table 1 shows classification accuracy (%) on Nigerian-specific benchmarks under 1-shot, 5-shot, and 10-shot settings. SSCL-LR achieves the best performance across all datasets and settings, with particularly notable gains on the NCDC clinical notes dataset where annotated medical records are extremely scarce.

Method	Hausa-NLP 1-shot	Hausa-NLP 5-shot	YorubaSenti 1-shot	YorubaSenti 5-shot	NCDC-Clinical 5-shot	CassavaNG 5-shot
Fine-tuned AfriBERTa	44.2±2.6	61.8±2.1	56.3±2.8	72.4±2.2	49.7±2.9	58.3±2.4
SimCSE	48.7±2.3	65.4±1.9	60.1±2.5	76.2±2.0	53.8±2.6	61.9±2.2
Prototypical Net	51.3±2.1	68.2±1.7	63.4±2.3	78.7±1.8	57.2±2.4	65.4±2.0
FixMatch	54.6±1.9	71.3±1.6	66.8±2.1	81.4±1.6	61.5±2.2	69.1±1.8
SuS-X	56.2±1.8	73.1±1.5	68.5±2.0	83.0±1.5	63.4±2.1	71.6±1.7
SSCL-LR (Ours)	63.7±1.4	80.8±1.1	76.9±1.6	89.4±1.2	72.8±1.7	79.2±1.4

Table 1: Classification accuracy (%) on Nigerian benchmark datasets. Best results in bold.

The improvement on YorubaSenti (5-shot: +6.4% over SuS-X) is particularly noteworthy given the challenges posed by Yoruba tonal orthography. We attribute this to the Level 1 HAS augmentation which preserves diacritical marks during contrastive pair generation, preventing the model from learning spurious representations based on corrupted tone markers. Similarly, the 9.4% gain on NCDC clinical notes reflects the effectiveness of DPA when large volumes of unlabeled clinical text from Nigerian hospitals are available to anchor prototype refinement.

5.2 Results on International Benchmarks

Table 2 presents result on international benchmarks, confirming that SSCL-LR is competitive across data distributions.

Method	AG News 1-shot	AG News 5-shot	Mini-ImageNet 5-shot	CUB-200 5-shot	PatchCamelyon 5-shot
SimCLR / SimCSE	55.8±1.9	72.1±1.5	62.4±1.7	57.3±2.0	63.8±1.9
MoCo v2	57.3±1.8	73.8±1.4	65.7±1.6	60.8±1.8	66.4±1.8
Prototypical Net	58.2±1.7	73.6±1.4	69.3±1.4	66.2±1.5	70.1±1.6
FixMatch	60.4±1.6	75.3±1.3	72.6±1.3	69.7±1.4	73.5±1.5
SuS-X	61.7±1.5	76.8±1.2	74.1±1.2	71.3±1.3	75.2±1.4
SSCL-LR (Ours)	67.0±1.2	82.3±0.9	79.1±1.0	77.5±1.1	81.7±1.2

Table 2: Classification accuracy (%) on international benchmarks.

6. Ablation Study

We conduct ablation experiments on YorubaSenti (5-shot) and CassavaNG (5-shot) to isolate contributions of each proposed component.

Configuration	YorubaSenti 5-shot	CassavaNG 5-shot
Baseline (AfriBERTa + Prototype)	78.7±1.8	65.4±2.0
+ HAS Level 1 only	82.4±1.6	69.8±1.8
+ HAS Levels 1+2	85.1±1.5	73.2±1.7
+ HAS All 3 Levels	86.8±1.4	75.6±1.6
+ DPA only (no HAS)	84.3±1.5	72.9±1.7
Full SSCL-LR (HAS + DPA)	89.4±1.2	79.2±1.4

Table 3: Ablation results on Nigerian datasets. Each row adds one component cumulatively.

The results confirm that diacritic-preserving Level 1 augmentation alone provides a 3.7% gain on YorubaSenti, demonstrating that standard augmentation pipelines that ignore tonal marks constitute a meaningful performance bottleneck. Domain-level augmentation (Level 3), which incorporates code-switching patterns, provides an additional 1.7% gain reflecting the prevalence of Naija (Nigerian Pidgin) and English-Yoruba mixing in the social media corpus. DPA provides the largest individual gain (+5.6% over HAS-only on YorubaSenti), validating the hypothesis that abundant unlabeled Nigerian social media data can be effectively harnessed for prototype refinement.

7. Societal Implications for Nigeria

The deployment of SSCL-LR in Nigerian contexts has direct practical implications across several nationally significant domains. In healthcare, the NCDC-ClinicalNLP results suggest that AI-assisted diagnosis of malaria, typhoid, and hypertension — three of Nigeria's leading causes of morbidity — is feasible even at primary healthcare centres that lack the resources to generate large labeled datasets. Collaboration with the Federal Ministry of Health and the Nigerian Medical Association could enable pilot deployments at state-level facilities.

In agriculture, accurate cassava disease detection with as few as 5 labeled images per disease class could be embedded in mobile applications for smallholder farmers across the cassava belt spanning Benue, Kogi, and Enugu States. Given that Nigeria is the world's largest cassava producer (FAO, 2023), even modest improvements in early disease detection could have substantial economic impact for rural farming households.

For linguistic inclusion, the demonstrated effectiveness of SSCL-LR on Yoruba, Hausa, and Igbo — Nigeria's three major languages — establishes a template for extension to smaller languages such as Efik, Ibibio, Kanuri, and Tiv, potentially enabling digital services in languages that have historically been excluded from AI technology. We call on the National Information Technology Development Agency (NITDA) and TETFund to prioritise funding for such extensions as part of Nigeria's National Digital Economy Policy and Strategy (NDEPS) 2020-2030.

We acknowledge that the deployment of AI systems in sensitive Nigerian contexts raises important ethical considerations. The NCDC clinical dataset was processed under ethical approval from the Health Research Ethics Committees of all three participating hospitals. All patient data was de-identified prior to model training. We urge future researchers using NaijaLowRes to adhere to the Nigerian Data Protection Regulation (NDPR) 2019 and the National Health Act 2014.

8. CONCLUSION

We presented SSCL-LR, a self-supervised contrastive learning framework designed for low-resource classification with specific attention to Nigerian linguistic, healthcare, and agricultural data. By introducing the Hierarchical Augmentation Strategy — calibrated to the morphological richness of Nigerian languages and local imagery distributions — and Dynamic Prototype Alignment that leverages abundant unlabeled Nigerian web data, our method achieves 4.1%--9.3% improvements over competitive baselines on eight benchmarks including four newly curated Nigerian datasets.

This work represents a step toward AI systems that are built by Nigerians, for Nigerian needs, using Nigerian data. The NaijaLowRes benchmark and open-source codebase are intended to lower barriers for AI researchers at Nigerian universities and provide a common evaluation framework for the growing Nigerian AI research community. Future work will extend SSCL-LR to Nigerian Pidgin (Naija), additional minority languages such as Kanuri and Nupe, multimodal healthcare applications, and real-time deployment on edge devices appropriate for Nigerian infrastructure constraints.

ACKNOWLEDGEMENTS

This research was supported by the Tertiary Education Trust Fund (TETFund) under Research Grant No. TETF/DR&D/CE/UNN/2024/RP/VOL.I, and by the African Development Bank (AfDB) AI for African Development Initiative. Computational resources were provided by the

University of Nigeria Nsukka High-Performance Computing Centre, established with support from the World Bank Africa Higher Education Centres of Excellence (ACE) project. The authors thank Dr. Amina Yusuf of NCDC and the clinical informatics teams at LUTH and UCH for their support in curating the clinical notes dataset. We also acknowledge the Masakhane community for their foundational contributions to African NLP resources.

REFERENCES

1. Adelani DI, et al. MasakhaNER: Named entity recognition for African languages. Trans Assoc Comput Linguist. 2021;9:1116–31.
2. AfricaNLP Workshop Organisers. Proceedings of the 2nd Workshop on African Natural Language Processing. EACL; 2021.
3. Asubiaro TV. A Yoruba lexical resource for NLP applications. In: Proc Afr Lang Technol Workshop, LREC; 2019.
4. Chen T, Kornblith S, Norouzi M, Hinton G. A simple framework for contrastive learning of visual representations. In: Proc Int Conf Mach Learn (ICML); 2020. p. 1597–607.
5. Food and Agriculture Organization of the United Nations. Nigeria: Agricultural sector review. Rome: FAO; 2023.
6. Finn C, Abbeel P, Levine S. Model-agnostic meta-learning for fast adaptation of deep networks. In: Proc ICML; 2017. p. 1126–35.
7. Gao T, Yao X, Chen D. SimCSE: Simple contrastive learning of sentence embeddings. In: Proc EMNLP; 2021. p. 6894–910.
8. Grill JB, et al. Bootstrap your own latent: A new approach to self-supervised learning. In: Proc NeurIPS; 2020. p. 21271–84.
9. He K, Fan H, Wu Y, Xie S, Girshick R. Momentum contrast for unsupervised visual representation learning. In: Proc CVPR; 2020. p. 9729–38.
10. National Bureau of Statistics. Nigerian Gross Domestic Product Report Q3 2024. Abuja: NBS; 2024.
11. Nekoto W, et al. Participatory research for low-resourced machine translation: A case study in African languages. In: Findings of EMNLP; 2020. p. 2144–60.
12. National Information Technology Development Agency. National Digital Economy Policy and Strategy (2020–2030). Abuja: NITDA; 2020.
13. Ogueji K, Zhu Y, Lin J. Small data? No problem! Exploring pretrained multilingual models for low-resource African languages. In: Proc ACL MultilingualNLP; 2021.
14. Shode I, Akinjobi D, Afolabi A, Adelani D, Dossou B, Emezue C. AFRISENTI-SEMEVAL: Sentiment analysis for low-resource African languages using Twitter data. In: Proc SemEval; 2023.
15. Snell J, Swersky K, Zemel R. Prototypical networks for few-shot learning. In: Proc NeurIPS; 2017.
16. Sohn K, et al. FixMatch: Simplifying semi-supervised learning with consistency and confidence. In: Proc NeurIPS; 2020.
17. Udandarao V, Gupta A, Albanie S. SuS-X: Training-free name-only transfer of vision-language models. In: Proc ICCV; 2023.
18. Wu Z, Xiong Y, Yu SX, Lin D. Unsupervised feature learning via non-parametric instance discrimination. In: Proc CVPR; 2018. p. 3733–42.
19. Yan Y, et al. ConSERT: A contrastive framework for self-supervised sentence representation transfer. In: Proc ACL; 2021. p. 5065–75.
20. Zbontar J, Jing L, Misra I, LeCun Y, Deny S. Barlow Twins: Self-supervised learning via redundancy reduction. In: Proc ICML; 2021. p. 12310–20.