ARS Generalization and Pass@1 Performance in Few-Shot Code Generation

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: Can ARS generalize to few-shot code generation tasks like HumanEval, and how does it affect pass@1 scores compared to baseline models without suppression. 14 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Self-Supervised Learning For Few-Shot Image Classification. Research question: Can ARS generalize to few-shot code generation tasks like HumanEval, and how does it affect pass@1 scores compared to baseline models without suppression?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.8/10.

3 Results

13 papers retrieved. 14 claims extracted; 0 independently verified. Quality review score: 2.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The MiniImageNet dataset contains 60,000 images from 100 classes, with 600 images per class.	×	0.03
The MiniImageNet data split strategy used samples 64 classes for training, 16 classes for validation, and 20 classes for	×	0.05
The CUB-200-2011 dataset contains 200 classes of birds with a total of 11,788 images.	×	0.01
The CUB-200-2011 evaluation split consists of 100 classes for training, 50 for validation, and 50 for testing.	×	0.03
CropDiseases, EuroSAT, ISIC, and ChestX are the four datasets proposed in [9] for cross-domain few-shot learning evaluat	×	0.10
The similarity to MiniImageNet decreases across the cross-domain datasets in the order: CropDiseases, EuroSAT, ISIC, Che	×	0.04
The proposed method uses the AMDIM SSL training framework to pre-train the feature embedding network.	×	0.14
The AmdimNet architecture used has parameters ndf=192, ndepth=8, and nrkhs=1536.	×	0.01
On the MiniImageNet 1-Shot 5-Way task, the 'Ours Mini80 SSL' method achieved an accuracy of 64.03 $\pm$ 0.20%.	×	0.04
On the MiniImageNet 5-Shot 5-Way task, the 'Ours Image900 SSL' method achieved an accuracy of 90.98 $\pm$ 0.10%.	×	0.04
On the CUB dataset 1-Shot 5-Way task, the 'Ours CUB150 SSL' method achieved an accuracy of 71.85 $\pm$ 0.22%.	×	0.04
On the CUB dataset 5-Shot 5-Way task, the 'Ours Image1K SSL' method achieved an accuracy of 89.18 $\pm$ 0.13%.	×	0.04
MatchingNet with a 4 Conv embedding net achieved 43.56 $\pm$ 0.84% accuracy on the MiniImageNet 1-Shot 5-Way task.	×	0.03
LEO with a Wide-ResNet28 embedding net achieved 77.59 $\pm$ 0.12% accuracy on the MiniImageNet 5-Shot 5-Way task.	×	0.04

References

- http://arxiv.org/abs/2410.12381v3
- http://arxiv.org/abs/2409.03868v1
- http://arxiv.org/abs/1911.06045v3