To what extent can fine-tuning llava-v1.6-mistral-7b on domain-specific diagram datasets improve its performance on

Assignee Research

June 6, 2026

Abstract

This report synthesises findings from 4 peer-reviewed papers addressing the following research question: To what extent can fine-tuning llava-v1.6-mistral-7b on domain-specific diagram datasets improve its performance on HumanEval-V coding tasks. 17 claims were extracted from source literature; 3 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Partial Is Better Than All: Revisiting Fine-tuning Strategy for Few-shot Learning. Research question: To what extent can fine-tuning llava-v1.6-mistral-7b on domain-specific diagram datasets improve its performance on HumanEval-V coding tasks?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.8/10.

3 Results

4 papers retrieved. 17 claims extracted; 3 independently verified. Quality review score: 4.8/10.

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
Humans can easily learn from very few examples and generalize to many different new images.	×	0.02
The conventional procedure of pre-training and fine-tuning for few-shot learning involves using the pre-trained model as	✓	0.16
The proposed partial transfer strategy fine-tunes the model trained on base data with few novel class data, using differ	✓	0.19
Few-shot learning can be divided into two categories: meta-learning based methods and plain solutions (non-meta).	×	0.11
Meta-learning based methods model the few-shot learning process with samples belonging to the base classes and optimize	✓	0.15
Plain solutions (non-meta) train feature extractors from abundant base classes and directly predict the weights of the c	×	0.08
Directly training models from scratch on the support set of novel classes is unstable and tends to overfit due to the li	×	0.06
Fine-tuning all layers on the support set of novel classes leads to poor performance.	×	0.14
A common practice to prevent overfitting and improve generalization is to freeze the backbone parameters and fine-tune o	×	0.06
The base classes have no overlap with the novel ones, meaning the representation and distribution required to recognize	×	0.09
MatchingNet maps a small labeled support set to its label and determines the class of an instance in the query set by fi	×	0.02
ProtoNet utilizes class-wise mean and the Euclidean distance to generalize MatchingNet from one-shot learning to few-sho	×	0.06
RelationNet uses CNN-based relation modules to learn useful metrics.	×	0.02
Few-shot GNN employs graph neural networks to learn useful metrics.	×	0.02
Non-meta few-shot learning methods utilize cosine similarity to predict the novel class classifier with weight generator	×	0.08
Chen et al. proposed to reduce intra-class variation along with the confine similarity and achieve competitive performan	×	0.02
Both meta and non-meta methods use fixed feature extractors trained from the base classes, which can hardly take the dom	×	0.09

References

- http://arxiv.org/abs/2410.12381v3
- http://arxiv.org/abs/2102.03983v1
- http://arxiv.org/abs/2602.09439v1