Impact of Multilingual Pretraining on High-Resource Languages for LLMs in SLAM-ASR Fine-Tuned for Low-Resource ASR

Assignee Research

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Abstract

Large language models (LLMs) have demonstrated potential in handling spoken inputs for high-resource languages, reaching state-of-the-art performance in various tasks. However, their applicability is still less explored in low-resource settings. This work investigates the use of Speech LLMs for low-resource Automatic Speech Recognition using the SLAM-ASR framework, where a trainable lightweight projector connects a speech encoder and a LLM. Firstly, we assess training data volume requirements to match Whisper-only performance, re-emphasizing the challenges of limited data. Secondly, we show th

1 Introduction

This paper examines: Speech LLMs in Low-Resource Scenarios: Data Volume Requirements and the Impact of Pretraining on High-Resource Languages. Research question: What is the impact of multilingual pretraining on high-resource languages for LLMs in the SLAM-ASR framework when fine-tuned for low-resource ASR, as measured by WER gap between high-resource and low-resource languages on the MIRACL leaderboard?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.0/10.

3 Results

12 papers retrieved. 18 claims extracted; 12 independently verified. Quality review score: 7.0/10.

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
Librispeech contains 960 hours of data used for SLAM-ASR.	×	0.09
Study [15] utilizes 1000 hours of data per language.	×	0.09
All models in the study are evaluated using the Word Error Rate (WER) metric.	✓	0.17
The linear projector training data from the CV IT dataset ranges from 10 hours to 252 hours.	✓	0.17
Increasing the quantity of training data consistently improves the overall performance of the model regardless of the LL	✓	0.27
EuroLLM 1.7B consistently outperformed Salamandra 2B in the experiments.	×	0.14
The performance gap between Salamandra and EuroLLM tends to close as more data becomes available.	✓	0.15
The SLAM-ASR configuration with EuroLLM 1.7B and 200 hours of training data achieves a WER of 6.4% on CV IT.	✓	0.15
The SLAM-ASR configuration with EuroLLM 1.7B and 252 hours of training data achieves a WER of 6.1% on CV IT.	×	0.13
Whisper-large-v3-turbo achieves a WER of 7.1% on CV IT.	×	0.15
The SLAM-ASR framework with EuroLLM 1.7B does not outperform Whisper-large or Whisper-large-v3-turbo on Fleurs IT.	✓	0.23
Whisper-large achieves a WER of 4.7% on Fleurs IT.	×	0.12
Whisper-large-v3-turbo achieves a WER of 5.8% on Fleurs IT.	✓	0.16
With 200 hours of CV IT training data and EuroLLM 1.7B, the WER on FL IT is 13.2%.	✓	0.19
Additional LoRA fine-tuning experiments were conducted solely with EuroLLM 1.7B using 15 and 100 hours of training data.	✓	0.19
The study uses the Common Voice (CV) Italian dataset ranging from 10 to 252 hours to address RQ1.	✓	0.15
The study explores leveraging a projector pretrained on English data consisting of Librispeech 100 and 100 hours of CV E	✓	0.17
The study explores leveraging a projector pretrained on 200 hours of CV Spanish data.	✓	0.17

References

- http://arxiv.org/abs/2501.17615v2
- http://arxiv.org/abs/2508.05149v1
- http://arxiv.org/abs/2511.09690v1