

Walia-LLM: Enhancing Amharic-LLaMA by Integrating Task-Specific and Generative Datasets

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Abstract

Large language models (LLMs) have received a lot of attention in natural language processing (NLP) research because of their exceptional performance in understanding and generating human languages. However, low-resource languages are left behind due to the unavailability of resources. In this work, we focus on enhancing the LLAMA-2-Amharic model by integrating task-specific and generative datasets to improve language model performance for Amharic. We compile an Amharic instruction fine-tuning dataset and fine-tuned LLAMA-2-Amharic model. The fine-tuned model shows promising results in different NLP tasks. We also explore the effectiveness of translated instruction datasets compared to the dataset we created. Our dataset creation pipeline, along with instruction datasets, trained models, and evaluation outputs, is made publicly available to encourage research in language-specific models¹.

1 Introduction

Large language models (LLMs) such as GPT series (Brown et al., 2020), LLAMA-2 (Touvron et al., 2023), Phi2 (Jawaheripi et al., 2023), Mistral (Jiang et al., 2023), Mixtral (Jiang et al., 2024), PaLM (Chowdhery et al., 2023), Gemini (Team et al., 2023), BLOOM (Workshop et al., 2022), have exhibited exceptional performance in understanding and generating human language, showcasing a range of capabilities from basic linguistic comprehension to complex text generation.

LLAMA-2 (Touvron et al., 2023), a family of pre-trained and fine-tuned large language models (LLMs), demonstrated impressive performance across multiple tasks, particularly in dialogue-based interactions. Regardless of these achieve-

ments, LLAMA-2 pre-training supports a small number of languages, which does not include low-resource languages like Amharic. This makes adapting LLMs to low-resource languages that are not included a significant challenge.

Adopting these LLMs to local languages requires the preparation of a quality instruction dataset. Amharic is one of the Semitic languages under the Afroasiatic language family spoken in Ethiopia with more than 57M speakers. There are numerous task-specific datasets for Amharic (Tonja et al., 2023) compared to other Ethiopian languages. This paper focuses on enhancing the LLAMA-2-Amharic (Andersland, 2024) model with quality datasets that are created by converting existing datasets in English into instruction-based Amharic datasets. Furthermore, we create new instruction datasets following the approach by Wei et al. (2022).

LLAMA-2-Amharic model by Andersland (2024) was created by pre-training LLAMA-2 7B model using open-source Amharic and translated corpus. After performing vocabulary expansion and pre-training, Andersland (2024) fine-tuned the created model by translating English instruction datasets into Amharic using commercial translation tools. In our research, we aim to improve the performance of the Amharic LLAMA model by integrating task-specific and generative datasets, as shown in Table 1. The contributions of this paper are as follows:

- Creating Amharic instruction fine-tuning data from existing NLP task-specific and generative datasets.
- Evaluating new and existing models' performance.
- Exploring the effect of carefully curated datasets by combining them with machine-translated instruction datasets.

¹For data generation pipeline, see <https://github.com/EthioNLP/afri-sft-data>. For models and datasets, refer to <https://huggingface.co/EthioNLP>.

- Exploring the effect of instructions on the model’s performance.
- Open-sourcing our dataset creation pipeline, instruction datasets, trained models, and evaluation outputs to promote language-specific studies on these models.

2 Related Work

The introduction of open-source LLMs like LLAMA-2 (Touvron et al., 2023) enabled the creation of several language models that focus on specific applications. This application gives more capabilities for these LLMs by teaching them to use tools (Schick et al., 2023), write code (Roziere et al., 2023), understand videos (Zhang et al., 2023a), or work for different languages (Cui et al., 2023). To achieve remarkable understanding and generation abilities, LLMs require large training data and huge compute resources (Hoffmann et al., 2022).

The work by Dong et al. (2023) explores how LLMs’ generation, natural language understanding, and problem-solving abilities relate to the data they are trained on and its composition. This work suggests that the amount of composition data is more important for these abilities to show in a low-resource scenario.

Using self-instructed fine-tuning, the work by Wei et al. (2022); Taori et al. (2023); Cui et al. (2023) showed a new approach to align the generation outputs of the generative models through the application of NLP tasks. These tasks are structured around natural language instruction templates, providing a novel means to guide the model’s generation process toward better adherence to task-specific requirements. LLAMA-Adapter (Zhang et al., 2023b) also shows that it is possible to reduce the fine-tuning time of LLAMA-7B by introducing lightweight adapters on top of the model.

Acquiring and preparing a dataset for instruction fine-tuning presents a significant challenge due to the extensive labor and resources required. There are several ways of acquiring instruction data, including manual dataset creation, using generative models (Wang et al., 2022; Taori et al., 2023), or using machine translation instruction data for training LLMs for specific languages (Cui et al., 2023).

Fine-tuning LLMs such as LLAMA-2 for specific tasks is an area of exploration as well. Advanced language model-based translator (ALMA) (Xu

et al., 2023) outperformed state-of-the-art (SOTA) no language left behind (NLLB) (NLLB Team et al., 2022) model MT task. They worked on fine-tuning monolingual data and subsequent fine-tuning with parallel data. Apart from LLAMA-2, (Moslem et al., 2023) worked on Mistral 7B fine-tuning for medical domain machine translation, where they showed improvement in Spanish to English translation from baseline performance.

After the LLAMA-2 was released, researchers successfully adapted the model for other languages. The work by Cui et al. (2023) involved creating a unique tokenizer for Chinese, extending the pre-training phase, and then fine-tuning the model. This work incorporates secondary pre-training using Chinese data and fine-tunes the model with Chinese instruction datasets. The result shows a significant enhancement of the model’s ability to comprehend and execute instructions.

To the same approach of the work by Cui et al. (2023), LLAMA-2 was also adopted for Amharic (Andersland, 2024). During pre-training, Andersland (2024) used an open-source Amharic corpus with some translated corpus from English, and for fine-tuning, available English instruction datasets were translated to Amharic using the Google Translate API and SeamlessM4T. Following the increase of the LLAMA vocabulary size from 32k to 51k and subsequent pre-training with a large Amharic text corpus, they conducted supervised instruction fine-tuning using machine-translated datasets. Then, they evaluated their model using the MMLU (Hendrycks et al., 2020) multiple-choice English dataset by translating it into Amharic. The model is available without original Amharic evaluations because no instruction-based datasets exist for Amharic.

3 Dataset preparation

In this work, we have converted existing NLP task-specific datasets, like sentiment analysis and machine translation, into instruction datasets. We created an instruction template for each task and developed a data creation pipeline (Figure 1) that merges each template instruction with appropriate data from a pre-existing dataset. This pipeline helps us to create instruction datasets from pre-existing NLP task datasets. For the new NLP task, we focused on collecting a new dataset that can be converted into instruction data. We also created new datasets by tweaking existing datasets. Finally,

Data Source	Source Data			Is new	# Templates	Generated Data		
	train	val	test			train	val	test
Amharic QA	1723	595	299	NO	14	10000	595	299
MasakhaNews	11522	188	376	NO	11	7866	205	376
MT (amh-eng)	497739	1012	1012	NO	10	10000	997	1012
MT (eng-amh)	497739	1012	1012	NO	10	10000	997	1012
Summarization	5761	719	719	NO	9	10000	719	719
Text Expansion	5761	719	719	NO	9	10000	719	719
Sentiment Analysis (AfriSenti)	5984	1497	1999	NO	7	10000	1728	1999
NER	1750	500	250	NO	9	10000	500	250
News Title Generation	-	-	-	Yes	10	10000	5078	5078
Poem Generation	-	-	-	Yes	3	3885	69	70
Poem Completion	-	-	-	Yes	7	3885	69	70
Religious Lyrics Generation	-	-	-	Yes	3	4929	188	206
Religious Lyrics Completion	-	-	-	Yes	4	10000	1497	1728
Story generation	-	-	-	Yes	10	1665	24	25
Spelling Correction	-	-	-	Yes (modified)	9	10000	1438	1438
Non religious music Lyrics Generation	-	-	-	Yes	4	148	5	5
Non religious music Lyrics Completion	-	-	-	Yes	7	259	5	5
Total						122,637	14,911	15,011

Table 1: **Dataset** used for preparing instruction fine-tuning data. **Is new** = new custom dataset. Details of each data source are explained in Section 3. Figure 1 shows how a dataset is converted to instruction data using our Data processing Pipeline.

we included an instruction-tuning dataset converted into Amharic language using machine translation systems. Table 1 shows a detailed distribution of instruction task data.

3.1 Instruction dataset from existing datasets

We have used several existing datasets to create an instruction dataset from an existing one. The production of these datasets includes web scraping, human labeling, and verification. By collecting and using this dataset for instruction, we ensure the quality of our instruction dataset. The other benefit of working with these datasets is that we ensure similar prompts across all our models for testing, which eliminates prompt-related performance variance that is usually reported while evaluating the performance of this dataset in generative LLMs.

For sentiment analysis data, we used *AfriSenti* (Muhammad et al., 2023), a sentiment analysis benchmark dataset for 14 African languages where Amharic is among the ones. The dataset is labeled with three sentiment classes: positive, negative, and neutral. The number of train, test, and val sets are shown in Table 1. We used the Amharic version of the classes for the test cases, and tests were done to check if the model gives one of the sentiment classes during generation.

We also worked with *MasakhaNews* (Adelani et al., 2023), a benchmark dataset for news topic classification covering 16 languages widely spoken in Africa. It provides an evaluation of baseline models from classical machine learning models and fine-tunes several language models.

To test if our model has the ability to identify

names from sentences, we modified *MasakhaNER* (Adelani et al., 2021), which is a dataset for named entity recognition (NER) in ten African languages. We created questions to extract only personal names for this work, and we plan to include more in our future works.

AmharicQA (Abedissa et al., 2023) is a publicly available Amharic open-ended question-answering dataset. It is a crowdsourced 2,628 question-answer pairs over 378 Wikipedia articles. These question-answer pairs are supplemented with context that the language model can use to answer the questions. We have also used this dataset to evaluate our models by converting it into an instruction dataset.

For tasks like Amharic text summarization, we used *XL-Sum* (Hasan et al., 2021), a comprehensive and diverse dataset comprising 1M annotated article-summary pairs. The dataset covers 44 languages, ranging from low to high-resource ones. We utilized the Amharic portion of the dataset in two ways. First, we took the text and prepared an instructional dataset to test our model’s ability to summarize the text. We also created a text expansion task where our model takes the shorter sentence and produces a detailed explanation of the text, the inverse of the text summarization task.

Finally, we used the dataset by Barrault et al. (2019); NLLB Team et al. (2022) to prepare training, validation, and testing for machine translation. Our training dataset is from WMT19 (Barrault et al., 2019), and validation and testing are from (NLLB Team et al., 2022).

The *Amharic spell correction* dataset is designed to assess the effectiveness of models in correcting

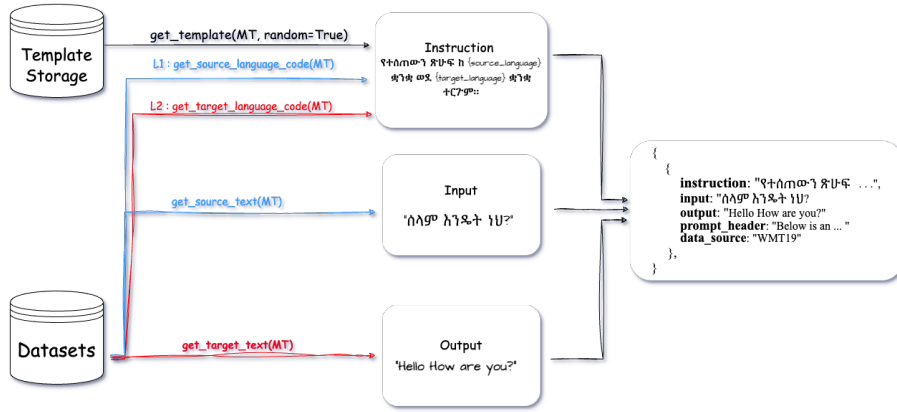


Figure 1: Data processing Pipeline. The pipeline creates instruction data from existing task datasets, and from generative datasets, we collected. All instructions, input, and output are in Amharic except for the MT case, as shown in the picture. The data source will not be used during training.

Amharic spelling errors, covering common misspellings to advance NLP tools for the language. We leveraged Amharic BBC news texts from XL-Sum (Hasan et al., 2021) for this task. We also leveraged the text augmentation library nlpaug (Ma, 2019). We introduced some random character augmentations, including *insertion*, *substitution*, *swapping*, *deletion*, and *word cropping*. This augmentation is done randomly and applied to part of the dataset.

After preparing each dataset, we found that the machine translation dataset we have was significantly larger than the other tasks, so we set a maximum threshold of 10k instructions randomly for the training split of each dataset. For validation and testing, we only used one template per task, and we did not expand the data sizes. More dataset examples and explanations are found in the Appendix B.

3.2 New Custom Datasets

Most of the task datasets we prepared in Section 3.1 did not focus on generation tasks. Generation tasks are less explored for low-resource languages like Amharic, so we created original datasets collected from publicly available sources.

In Amharic, music, stories, and poems represent fascinating cultural artifacts. We have created three new datasets to facilitate the training and evaluation of models’ capabilities in processing these tasks. The first track we considered is *religious music lyrics generation*. We included several types of music lyrics in this dataset. We collected the above 2k Amharic spiritual song lyrics from WikiMez-

mur². Despite the popularity of non-religious music in Ethiopia, finding a freely available source to include this in our data was difficult; hence, our non-religious music data was smaller than the others. To expand this dataset, we split the lyrics into verses and created a new completion task where the input is the first verse and the output is the remaining whole verse.

To understand the story generation abilities of different models, we created a dataset for *Ethiopian folktales*: We collected several Ethiopian folktales from EthiopianFolkTales³. These stories are collected from all Ethiopian regions. Given that the dataset comprises traditional Ethiopian stories, there is no copyright restriction on them, and our usage is only for research purposes. We also collected *Amharic poem* from several public telegram channels.

For *news title generation*, we collected 50k news title and body pairs from different Amharic news sources such as BBC News⁴, Deutsche Welle (DW) news⁵, Sheger FM⁶, Addis Admass Newspaper⁷, and VOA Amharic⁸. To save GPT-4 credits, we did our testing only on the first 1300 items of this data.

3.3 Translated instruction fine-tuning dataset

During LLAMA model self-instructed fine-tuning (Touvron et al., 2023), instruction datasets like Alpaca (Taori et al., 2023) and dolly (Conover et al.,

²<https://wikimezmur.org/am>

³<https://www.ethiopianfolktales.com/am>

⁴<https://www.bbc.com/amharic>

⁵<https://www.dw.com/am>

⁶<https://www.shegerfm.com/>

⁷<https://www.addisadmassnews.com/>

⁸<https://amharic.voanews.com>

2023) have been widely used. In the work Andersland (2024), machine translation systems were used to translate these datasets into Amharic instruction fine-tuning data. This method is used by most papers that try to adopt LLAMA models for their language, like (Cui et al., 2023). For Amharic versions of alpaca and dolly datasets, we used datasets used by LLAMA-2-Amharic (Andersland, 2024) training. We explored the effect of training a model by using only our relatively clean and human-verified data alone and in combination with this machine translation data.

4 Experiments

We followed Chinese LLAMA (Cui et al., 2023) experiments to perform supervised fine-tuning (SFT) on our dataset using different types of the dataset we created. Figure 2 shows the full training pipeline that summarizes the overall experiment steps we followed. We used codes available on the Chinese-LLAMA-Alpaca⁹ repository. We used 4 A100 GPUs with the default parameters in the repository. All training is done for three epochs. All models and evaluation codes will be available in our repository. For the MT task, we also worked on M2M100 (Fan et al., 2021) and NLLB (NLLB Team et al., 2022) models.

During the evaluation of the models, we used gpt-4-0613 for GPT-4. For our LLAMA-based models, we used fixed generation parameters across the models. We also evaluated various models that purportedly support this language but excluded them due to their inability to perform the required tasks. This is further discussed in Appendix A.

Our main experiment includes:

- Evaluating existing models on our dataset.
- Fine-tuning the model using a dataset detailed in Table 1, referred to as **Walia (task data)**. Unlike the approach taken in the LLAMA-2-Amharic model (Andersland, 2024), this experiment did not incorporate machine-translated instructional data.
- Fine-tuning the model using **Walia (combined data)**, which consists of our prepared dataset along with the machine-translated instructional data previously utilized in the LLAMA-2-Amharic model (Andersland, 2024).

⁹<https://github.com/ymcui/Chinese-LLaMA-Alpaca>

- Fine-tuning **Walia MT**, the MT model we trained to perform the machine translation task in our dataset. In this experiment, we used only MT datasets from Table 1 and scaled them to 200k data rather than 20k as shown in the table.

4.1 Datasets

The first set of experiments we conducted involved evaluating the base LLAMA-2-Amharic model on our custom test set, which was created from different NLP task datasets. This will provide us with a baseline performance for Amharic tasks. The next set of experiments used different NLP task datasets that were converted into an instruction dataset by our data generation pipeline. We used LLAMA-2-Amharic model (Andersland, 2024), which is pre-trained using the LLAMA-2 model for the Amharic language and performed supervised instruction fine-tuning on the task datasets. This ensures our model only has access to quality datasets that were adopted from verified NLP tasks. Finally, we combined our instruction dataset with the machine-translated instruction datasets. In the different datasets above, we have capped our training dataset to a maximum of 10k data from individual tasks, as shown in Table 1. We kept fixed instruction and data frequency in our validation and test set to avoid any performance variation because of instruction differences. For machine translation experiments, we created additional data that contains 200k data points from Barrault et al. (2019) and NLLB Team et al. (2022).

4.2 Evaluation Metrics

For selected NLP tasks in this paper, we used different evaluation metrics. For *sentiment analysis* and *news classification* tasks, we have used the weighted f1 score. For these classification tasks, we also keep track of the number of times the model returns output that cannot be classified as one of the classes.

For *generation tasks*, we used Rogue (Lin, 2004) scores. We used Rogue scores to evaluate *xlm-summarization*, *reverse summarization*, and *AmharicQA* tasks. We reported Rogue1, Rogue2, and RogueL metrics for generation tasks, but we heavily rely on RogueL for analysis since it focuses on the longest common subsequence rather than n-grams. We observed that most of our generation outputs do not share common n-grams when n is greater than 2, and the generations from systems

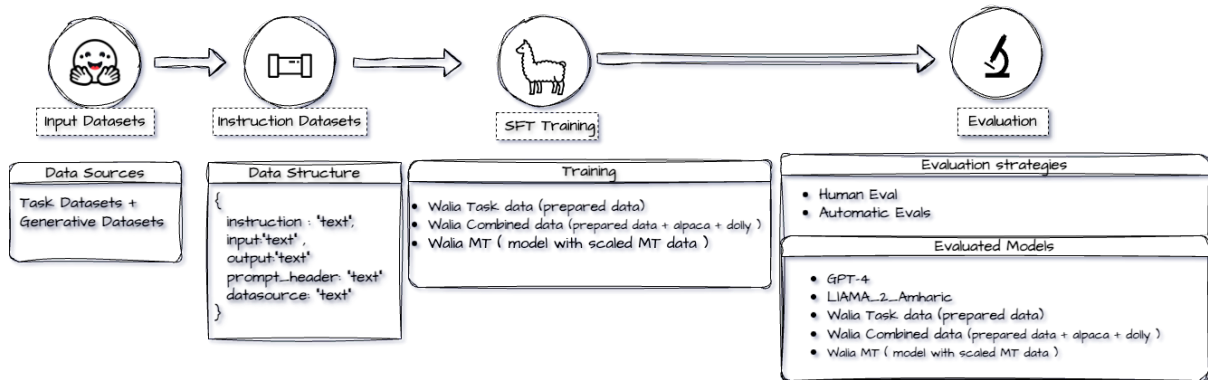


Figure 2: Full training pipeline that summarizes the work done.

like GPT-4 tend to be longer where the n-gram comparison methods express the results less. Additionally, we used character-based evaluation metrics, chrF++ (Popović, 2017) automatic evaluation metrics for MT tasks. We focused on character-based metrics (chrF++) because, for low-resource languages with complex morphologies, chrF++ offers a more robust and adaptable metric compared to word-based metrics like SacreBLEU.

Finally, we performed human evaluation for generative tasks such as music, poetry, and story generation. We sampled 120 individual items and conducted blind reviews using three people for each question. We created a rating system from 1 to 5 with detailed instructions and reported the average rating per task and model.

We did several evaluations for some tasks that were hard to evaluate, e.g., we used accuracy and SacreBLEU scores as evaluation metrics for AmharicQA following the suggestion by Abedissa et al. (2023); Lee et al. (2021). For tasks that require specific text output, we performed character normalization and text cleaning on the outputs before evaluation to avoid analysis because of typos and formatting issues.

In addition to the evaluation methods mentioned above, we explored the possibility of using GPT-4 for evaluation purposes, following the work from the Chinese LLAMA (Cui et al., 2023). Our assessment covered various generation tasks, showing that GPT-4 performs well in most areas. However, it shows inconsistency in scoring due to differences in the rating scale it assigns during each run. In addition, it struggles with evaluating poem and music generation tasks, as it does not fully understand Amharic poetic structure. Additionally, it encounters some challenges in evaluating machine transla-

tion, often missing grammatical details in Amharic sentences. Despite these limitations, GPT-4 has the potential for evaluating tasks if it is coupled with manual checks to ensure consistency. We expect similar difficulties in other low-resource languages based on our preliminary findings. While we did not include GPT-4 scores in our current reports due to time and cost constraints, we plan to include them in future research.

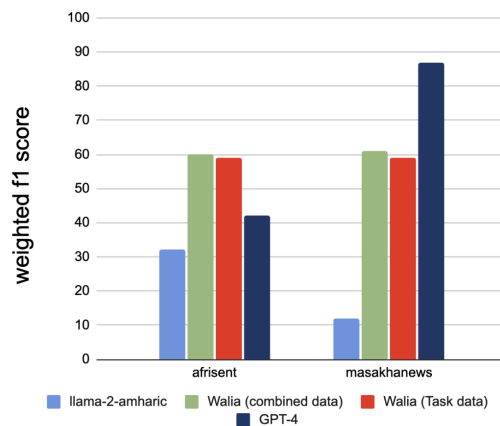


Figure 3: Generation scores: weighted f1 scores for AfriSenti and MasakhaNews (left) and SacreBLEU score for Amharic QA (right)

Tasks	GPT-4	LLAMA-2-Am	Walia I	Walia II
Text summarization	3.34	0.62	1.13	0.80
Text expansion	3.10	3.22	2.05	2.82
Amharic QA	28.23	2.83	5.37	6.25

Table 2: I = Walia (task data), II = Walia (combined data). ROUGEL scores for text summarization, Text expansion and Amharic QA.

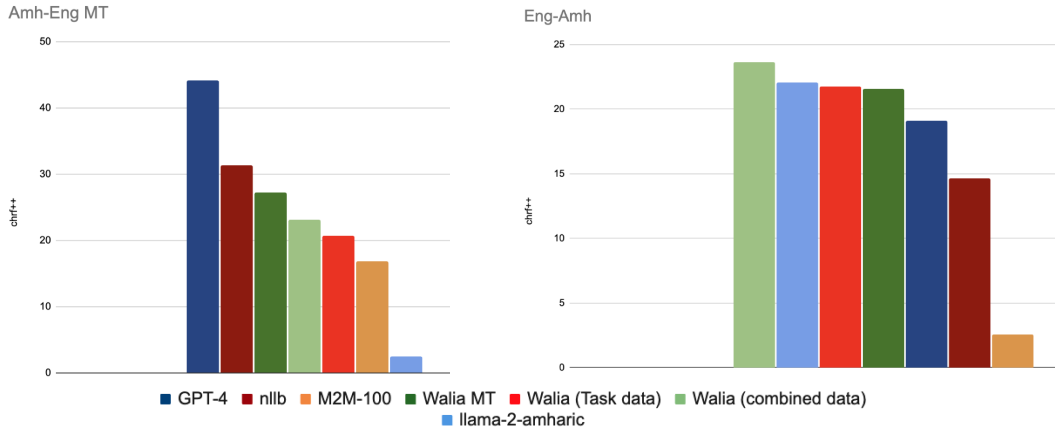


Figure 4: chrF++ scores for **machine translation**. Amharic to English translation scores (Right) and English to Amharic translation scores(left).

5 Results

Below, we discuss the performance of each model we tested by task type and evaluation strategy.

5.1 Classification Results

In our dataset, 2 out of 17 tasks can be considered classification tasks. Examining the weighted F1 score metrics in Figure 3 , we observe two key points. First, comparing our models with the LLAMA-2-Amharic model (Andersland, 2024), we see significant improvements in both the AfriSenti and MasakhaNews tasks for Amharic. This demonstrates that our dataset, as shown in Table 1, can enhance our models’ capabilities across various tasks. Secondly, we observe that GPT-4 performs well on Amharic tasks, indicating that we can develop models with similar capabilities using our dataset.

5.2 Generation Results

As explained in Section 4.2, we focus on RougeL metrics for our analysis. Across text summarization and AmharicQA, GPT-4 takes the lead, showing the model’s generation ability is very high. We were able to improve the LLAMA-2-Amharic model’s ability for this task using our data, as shown in Table 2. We cant tell if our data or combined data have that much effect in overall tasks but we can observe working with only machine translated instruction tuning dataset cant give us this abilities.

We conducted a human evaluation for the models that do not have fixed gold labels, as shown in Table 3. Table 3 result shows that the generation ability of LLLAMA-2-Amharic can be enhanced by

adding generation-specific datasets. Walia lacks an understanding of the specific formatting of texts because of the limitations in our pre-processing. However, it shows significant improvement where the LLAMA-2-Amharic fails to understand the query. Overall, we can see the benefits of not relying solely on machine-translated instruction datasets and the advantages of utilizing a diverse dataset.

5.3 Machine Translation (MT)

For the MT task, we evaluated two open-source sequence-to-sequence models (M2M100 (Fan et al., 2021) and NLLB (NLLB Team et al., 2022)), GPT-4, LLAMA-2-Amharic, and our models. Figure 4 shows chrF++ results for the above MT models.

For the Amharic to English results, we see that we were able to improve the LLAMA-2-Amharic ability in all our models. Our scaled Walia-MT model takes the lead compared to all our model varieties, but GPT-4 and NLLB (NLLB Team et al., 2022) lead in the overall comparison. All our trained models outperform the M2M100 (Fan et al., 2021) model.

When the target is changed to Amharic, the base model we compared our work with, LLAMA-2-Amharic, shows promising results. This can be attributed to the extensive Amharic data seen during the pretraining and supervised fine-tuning. All our models outperform GPT-4 and the open-source sequence-to-sequence models (M2M100 (Fan et al., 2021) and NLLB (NLLB Team et al., 2022)).

6 Conclusion and Future Works

In this work, we created Amharic instruction fine-tuning dataset, evaluated the performance of exist-

Tasks	GPT-4	LLaMA-2-Amharic	Walia (Task data)	Walia (combined data)
Story generation	2.93	1.00	<u>3.60</u>	1.73
Poem completion	2.53	1.46	1.73	<u>2.26</u>
Poem generation	2.13	1.00	<u>2.46</u>	2.00
Religious Lyrics Generation	2.86	1.46	<u>1.60</u>	1.46
Religious Lyrics Completion	3.60	1.40	<u>2.13</u>	1.93
Non religious Lyrics Generation	3.53	1.00	1.60	<u>2.06</u>

Table 3: Average blind **human evaluation** out of 5, for three people in each task. **(1)** empty or non Amharic text. **(2)** not written in task format. **(3)** written in task format but no consistent idea and spelling errors. **(4)** looks like that specific generation task but has spelling and grammar errors. **(5)** this looks like a perfect generation of the task. Underlined text indicates cases where we see improvement compared to LLaMA-2-Amharic.

ing and our fine-tuned models in the new dataset, and explored the effect of carefully curated datasets on the models’ performance. We observed a possibility of reusing task-specific datasets to improve the generation and task performance of the existing LLaMA-2-Amharic model. This shows the advantage of task dependant datasets in overall tasks.

Our data generation pipeline that generates instruction datasets from task datasets can be used for the generation of similar datasets for other languages given template instructions. We are working on this kind of dataset for all languages included in MasakaNER (Adelani et al., 2021), MasakhaNews (Adelani et al., 2023), AfriSenti (Muhammad et al., 2023) and more to improve multilingual LLaMA models. We plan to open-source the instruction datasets with the generation code.

Moving forward, we aim to improve both the quality and volume of the data utilized. Task-specific dataset creations are meant to complement, not replace, language-specific instruction dataset creations, and we plan to work on creating quality instruction datasets in addition to using existing task datasets. We also plan to explore the relevance of using LLMs for evaluation in low-resource languages like Amharic and incorporate LLMs to evaluate our LLMs.

7 Limitations

One limitation we observed in our work is the lack of reliable generation metrics for our tasks. The models tend to generate wordy and explained outputs despite our attempts to design the instruction template specifically. As a solution, we used several metrics that can express one task’s ability and reported the best-suited one.

In our current evaluation of all the models, we observed significant limitations while performing the spell correction and NER tasks. For Amharic spell correction all four generation models, includ-

ing GPT-4, try to generate other things related to the text, and the word error rate for all of them is close to 99%.

We have yet to explore the effect of using machine-translated instruction datasets for building language-specific LLMs with regard to introducing cultural bias.

Acknowledgments

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A Experimental details

We adopted our LLAMA-2 instruction tuning experimental code from Chinese-LLAMA-Alpaca¹⁰ repository by (Cui et al., 2023). we performed our instruction finetuning for three epochs on 4 A100 GPUs using the parameters in Table 4. In the generation phase, we used parameters in Table 5 for all models except GPT-4.

Parameter	Value
epoch	3
lr	1e-4
lora_rank	8
lora_alpha	32
lora_dropout	0.05
per_device_train_batch_size	1
per_device_eval_batch_size	1
gradient_accumulation_steps	8

Table 4: Training Parameters

Parameter	Value
seed	42
do_sample	True
min_length	None
top_p	1.0
temperature	1.0
top_k	5
repetition_penalty	5.0
length_penalty	1

Table 5: Configuration settings for token generation.

B Dataset details

Figure 5 shows how we repurposed existing sentiment analysis data to convert it into an instruction dataset. We utilized a task template selected at random from our collection. The number of templates collected for each task is shown in the table.

To avoid instruction overfitting, we collected a variety of instructions, like the example shown in Figure 6. The example displays different instructions that can be paired with a machine translation dataset to create a machine translation instruction dataset. This step is repeated for all tasks, including tasks like poem generation, which we created by collecting from different websites.

Due to the difficulty we faced in evaluating generation tasks, we employed human evaluation. Figure 7 shows how evaluators scored each generation output for the case of the story generation task.

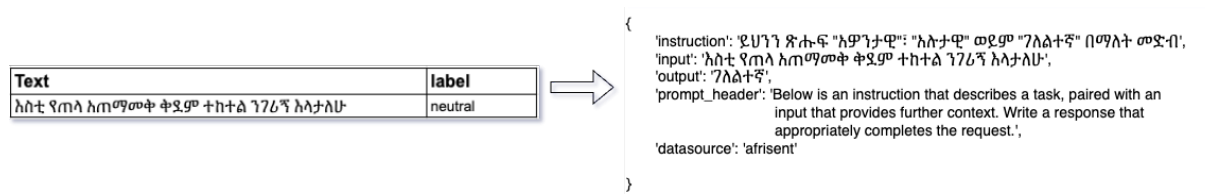


Figure 5: Example data output from our dataset creation pipeline. 1

ID	Instruction templates
	የተሰጠውን ጽሁፍ ከ {source_language} ቋንቋ ወደ {target_language} ቋንቋ ተርጉም::
1	(Translate the writing given in {source_language} into {target_language} text)
	የተሰጠውን የ{source_language} አረፍተ ነገር ወደ {target_language} ተርጉም
2	(Translate {source_language} sentence to {target_language} sentence)
	ደህ የ {source_language} ፅሁፍ በ{target_language} አንዱት ሊጻፍ ይቻላል
3	(This is {source_language} sentence , How can it be written in {target_language})

Figure 6: Example templates for machine translation task with English translation. By using random instructions for tasks, we ensure that the model does not fit the specific instructions for tasks.

¹⁰<https://github.com/ymcui/Chinese-LLaMA-Alpaca>

		output analysis
instructions	የተሰጠው ጽሑፍ አስተያየት ምን ዓይነት ነው? "አዎንታዊ"፣ "አሉታዊ" ወይም "ገለልተኛ" የምል ምላሽ ሰጥ።	
input	@user ክብር አና ምስጋና ለዓለማት ፈጣሪ ይሁን	
output	አዎንታዊ	
prompt_header	Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.	
GPT-4 output	ይህ የተሰጠው ጽሑፍ ዐዎንታዊ አስተያየት ነው።	correct
llama-2-amharic output	ጽሑፉ አዎንታዊ መልክነት ያስተላልፋል።	correct
Walia (combined data) output	አዎንታዊ	correct
Walia (task data) output	አዎንታዊ	correct
mala-500 output	(Ammohay) \amha-r', ammoroy': «assistant» - used for both males & females; e., '\amma roo/(father)-asstant or helper... more » Less • new window -- edit translation-- disclaimers * This dictionary does not contain any content that falls into these categoriesmore about this how do I know which category my entry belongsless About · Contact Us All'}	incorrect

		output analysis
instructions	የተሰጠው ጽሑፍ አስተያየት ምን ዓይነት ነው? "አዎንታዊ"፣ "አሉታዊ" ወይም "ገለልተኛ" የምል ምላሽ ሰጥ።	
input	@user @user አዎ አረ ቤቱ ይቆጠረው'	
output	አሉታዊ	
prompt_header	Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.	
GPT-4 output	አዎንታዊ	incorrect
llama-2-amharic output	ቤቱን ማንቀሳቀስ!	incorrect
Walia (combined data) output	ገለልተኛ	incorrect
Walia (task data) output	ገለልተኛ	incorrect
mala-500 output	\[Ancient Greek word for slave][1]] (or servant) or helper; used when there are many servants who assist their lord/lady of higher rank.[]. For example Assistant Ministers can be appointed by minister-of more senior ranks but not yet Prime minister himself They could also work at lower level positions like Manager /ator etc... In this context its meaning has evolved into one that means helping people out especially those less fortunate than'	incorrect

Figure 8: Example of analysis we did on the model outputs.