# Extending Italian Large Language Models for vision-language tasks

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## Abstract

With the growing evolution of Large Language Models, there has also been a rising interest in extending these models to incorporate non-textual signals. Specifically, Large Vision-Language Models have been developed, which extend Large Language Models to understand and process visual signals. This allows them to solve complex vision-language tasks, further extending their inherent abilities in text-only task resolution. However, for the Italian language, most works still focus on text-only solutions without extending them to multimodality. In this work, we extend Large Language Models for the Italian language to multimodality and benchmark the performance of these models when trained using the same experimental setting.

## Keywords

Large Language Models, Large Vision-Language Models, Multimodality

## 1. Introduction

In the last years, interest in Large Language Models (LLMs) has been growing steadily. The ability of these models to solve complex tasks, even when they have not been trained with that specific objective, makes them extremely useful for any natural language processing task. However, as it often occurs in the Natural Language Processing research field, the abundance of English data meant that the first openly released LLMs only supported the English language (e.g. LLaMA 2 [1]), limiting the applicability of these models to other languages. To cover this gap, several LLMs were trained to directly support the Italian language, using either a monolingual or multilingual strategy. Whichever the selected strategy, these models were obtained using one of the following methodologies: fine-tuning pre-existing models or training from scratch on datasets consisting mainly of Italian data. This trend allowed to extend LLMs not only to multiple underrepresented languages but also to new modalities. An example is represented by Large Vision-Language Models (LVLMs) that are LLMs extended with a technique enabling them to process visual inputs together with textual ones. Also in this case, there are training procedures that allow leveraging existing LLMs instead of training from scratch for vision-language inputs. This makes the process both more efficient, since the pre-training phase is skipped, and more effective, as the textual knowledge of the model is leveraged to learn how to perform vision-language tasks. Despite this, many open LLMs supporting the Italian language have not been extended to support multimodality. This is due to the limited availability of training data for vision-language tasks in Italian, whereas English training data often comprises multiple diverse and rich tasks. Furthermore, with the proliferation of Italian LLMs, like MINERVA [2] and VELVET[1], it becomes increasingly important to test their capabilities in the multimodal domain. This raises the question of whether it is possible to extend current LLMs trained for the Italian language for multimodality. Do these models perform well when extended to support it? In this work, we propose a study on the multimodal performance of Italian LLMs extended to LVLMs using a state-of-the-art approach.

Specifically, this work extends current literature as follows:

- We train several LLMs supporting the Italian language to extend them to LVLMs;
- We benchmark these models using datasets that are natively in Italian;
- We study the effect of different prompt formatting at inference time and showcase the length bias in the response of LVLMs.

[1]https://huggingface.co/Almawave/Velvet-14B

Finally, we want to underline that we are forced to use machine translation for training data due to the scarcity of large-scale multimodal data for non-English languages. However, we focus our evaluation on natively Italian multimodal datasets. Therefore, if a large-scale multimodal dataset natively in Italian were to be released, we can expect further improvements in performance since fewer machine translation errors would be present.

Furthermore, we release code and resources related to this study[2].

## 2. Related Works

For LVLMs, several methodologies have been designed to adapt LLMs. One of the most prominent approaches is the one introduced in LLaVA [3], where visual embeddings extracted from a Vision Transformer [4] are projected into the latent space of an LLM. This strategy has been further refined in LLaVA 1.5 [5], where the projection matrix is replaced with a Multi-Layer Perceptron, and LLaVA-OneVision [6], a LLaVA-based model enhanced to also perform multi-image and video tasks. Other approaches include the one used in BLIP-2 [7], leveraging a QFormer module to extract the most relevant features of images, and Flamingo [8], where cross-attention layers are added to the LLM and relevant visual tokens are extracted using a Perceiver Resampler module. Additionally, there is also LLaVA-NeXT [5] (also known as LLaVA 1.5 HD), which introduces a technique to process high-resolution images. The idea is to resize the image to a higher resolution than the one supported by the underlying vision encoder and split it into multiple images. Embeddings are then extracted for each image, as well as a resized version of the image to the supported resolution of the vision encoder to incorporate global details, and flattened into a single vector.

For Italian LLMs, several models have been released which incorporate a great quantity of natively Italian training data. Minerva [2] is the first family of models trained from scratch on an open data mixture consisting of only English and Italian data. It has several checkpoints with different parameter counts, that are 1B, 3B and 7B. The 7B model was trained on a total of 2.48 trillion tokens of Italian, English and code. EuroLLM [9] is a family of LLMs developed in Europe to support all the 24 official European Union languages. Its two available checkpoints have 1.7B and 9B parameters. The models are pre-trained on a total of 4 trillion tokens, where 50% of the data is in English, 5% is code, and the remaining 45% are other languages (including Italian). Velvet is a family of LLMs trained on a balanced mixture of six languages, with particular emphasis on Italian (which

**Table 1**

Training hyperparameters used for the two steps of the LLaVA NeXT methodology

| Parameter | Stage | |
|---|---|---|
| | Pre-Train | Fine-Tune |
| Batch Size | 256 | 128 |
| Learning Rate | 1e-3 | 1e-5 |
| Weight Decay | 0. | 0. |
| Warmup Ratio | 0.03 | 0.03 |
| Epochs | 1 | 1 |

makes 23% of the data). The two available checkpoints for Velvet have 2B and 14B parameters.

FastwebMIIA[3] (Italian Artificial Intelligence Model) is a 7-billion-parameter autoregressive model developed by Fastweb. Based on a decoder-only architecture with rotary positional embeddings, it has been trained on about 3 trillion tokens, with a strong focus on Italian. It uses a custom tokenizer optimised for Italian, English and programming languages, with a vocabulary of 50,000 tokens. It supports a context window of 16k tokens and has been trained in a distributed pipeline on NVIDIA H100 GPUs via MLDE and LLMFoundry.

Furthermore, at the time of writing, LLaVA-NDiNO [10] is the only family of multimodal models extensively trained for the Italian language only, further showcasing the need for a more in-depth investigation of the current landscape of Italian LLMs and their extension to LVLMs.

For LLM evaluation in Italian, many efforts have been carried out to extensively evaluate Italian LLMs. For example, Bacciu et al. [11] introduced an open LLM leaderboard for the Italian language, Moroni et al. [12] released ITA-Bench, a comprehensive evaluation suite for Italian LLMs consisting of both machine-translated and natively Italian benchmarks, Attanasio et al. [13] released CALAMITA, a dynamic and growing benchmark for the Italian language.

Finally, we also highlight that there are novel works that showcase how non-trivial it is to evaluate LLMs. For example, Wang et al. [14] found mismatches between the generated output and output obtained using log-likelihood for next token prediction. Additionally, several works started to use a LLM-as-a-judge approach where the LLM is used as a model for evaluation [15].

## 3. Methodology

As mentioned in the introduction, our aim is to extend existing Italian LLMs with multimodal capabilities. We

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Listing 1: Mistral chat template used for base models. {user} and {assistant} are placeholders for the user and assistant messages respectively.

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<s>[INST] {user} [/INST] {assistant}</s>
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chose MINERVA, EUROLLM, VELVET and FASTWEBMIIA, since they are among the most recently released LLMs supporting the Italian language and clearly define the amount of Italian data used in training. For each model, we evaluate both its base and instruct variants at their largest available parameter scale. The only exception is represented by VELVET, for which only the instruct version is available.

For the vision backbone, we use the vision transformer of the CLIP [16] model, specifically, we focus on the large checkpoint with patch size 14 and image size 336.[4] We use this model since it is often used in the state-of-the-art research as the visual backbone for LVLMs [3].

To train the models, we use the methodology of LLaVA NEXT, because of both its performance and its open code-base, which allows for easier reproducibility of this study. This methodology is made of two steps: *pre-training* to warm up the multi-layer perceptron projector and *visual instruction tuning* to teach the model how to solve vision-language tasks. For both steps, training is performed using the next token prediction objective, implemented as cross-entropy loss. We report hyperparameters used for both steps in Table 1. For base models, we apply the Mistral chat template reported in Listing 1, since they do not have a chat template associated with them, while for instruct models we apply their own chat template.

### 3.1. Training Mixture

For both training steps, we use a state-of-the-art machine translation model to translate popular vision-language English-only datasets to Italian. This is necessary since, at the time of writing, there is no large-scale vision-language dataset for instruction tuning in Italian. Therefore, we use MADLAD 400 3B [17], since it is one of the latest and best-performing machine translation models. For *pre-training*, we use the same dataset as LLaVA translated to the Italian language. During *pre-training*, the whole model is kept frozen, except for the multi-layer perceptron. Thanks to this approach, the multi-layer perceptron weights are initialized so that the vision embeddings are correctly projected into the LLM's space. For *visual instruction tuning*, we consider a combination of two datasets: *MultiInstruct* [18] and the *conversational* split of the LLaVA-INSTRUCT [3] dataset. The former is a collection of diverse vision-language tasks (e.g. Visual

Question Answering, Visual Grounding, ...), which allows the model to learn to correctly solve this type of task, while the latter is a multi-turn dataset generated by prompting GPT-4. Thanks to this training mixture, the model learns to both solve tasks and provide meaningful and complete responses to user prompts. For MultiInstruct, we perform some additional processing operations. Instructions are manually translated, therefore only the data instances (e.g. questions and answers in a visual question-answer task) are machine-translated. For tasks that use bounding boxes, we normalize the bounding box values to the [0, 1] range so that the values are consistent with the reference images and independent of their resolution. For tasks that provide options to choose from within the instruction, we format them as an ordered list using either numbers, uppercase or lowercase letters, or plain text. In such cases, we also replace the target text to be predicted with the corresponding identifier (e.g. if the option is a number, the target text is also converted to a number). Finally, we append a string to guide model responses, depending on the type of output that is expected: "Rispondi solamente con il numero dell'opzione corretta dalle scelte date." ("Answer with the option's number from the given choices directly." in English) when the options are identified by numbers, "Rispondi solamente con la lettera dell'opzione corretta dalle scelte date." ("Answer with the option's letter from the given choices directly." in English) when the options are identified by letters, "Rispondi usando una zona di delimitazione." ("Answer using a bounding box." in English) when the target text is a bounding box and, finally, "Rispondi usando una singola parola o frase." ("Answer the question using a single word or phrase." in English) for all other cases. In total, the training mixture combining these two datasets consists of 172,335 instances.

### 3.2. Hardware and Software Configuration

Our experimental setup was provided by Fastweb SpA via a high-performance computing cluster [5] composed of 31 NVIDIA DGX H100 systems, organized according to the NVIDIA DGX SuperPOD reference architecture. The cluster is deployed within a datacenter located in Lombardia, Italy, and offers a total of 248 NVIDIA H100 Tensor Core GPUs interconnected through high-bandwidth NVLink and InfiniBand, enabling low-latency communication and efficient scaling across nodes.

The training and evaluation of the models was conducted in a distributed manner through the Machine Learning Distributed Engine *MLDE*[6] platform, which enabled efficient parallelisation of workloads on DGX H100

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[4]https://huggingface.co/openai/clip-vit-large-patch14-336

[5]Fastweb Announcement

[6]https://www.hpe.com/us/en/software/marketplace/hpe-ml-development-environment.html

**Table 2**

We report results for the three benchmarks considered in this study. All benchmarks are evaluated using *exact match* as metric. The best result for each dataset and each formatting is in bold.

| Dataset | Type | Model | Formatting | | | | AVG |
|---|---|---|---|---|---|---|---|
| | | | Pre | Post | Pre-Swap | Post-Swap | |
| GQA-IT | base | Minerva-7B | .2867 | .3523 | .2523 | .2023 | .2734 |
| | | EuroLLM-9B | .2893 | .3917 | .4157 | .0973 | **.2985** |
| | | FastwebMIIA-7B | .1683 | **.4147** | .4043 | .0297 | .2543 |
| | instruct | Minerva-7B | .2653 | .3520 | .3120 | .0533 | .2457 |
| | | EuroLLM-9B | .0370 | .4140 | **.4187** | .0677 | .2344 |
| | | Velvet-14B | **.3007** | .2863 | .3107 | **.2843** | .2955 |
| | | FastwebMIIA-7B | .0933 | .3233 | .3227 | .0790 | .2046 |
| | | LLaVA-NeXT 8B | .0009 | .3106 | .3454 | .0849 | .1855 |
| MTVQA-IT | base | Minerva-7B | .0486 | .0577 | .0509 | .0373 | .0486 |
| | | EuroLLM-9B | **.1018** | .1097 | .1143 | .0792 | .1013 |
| | | FastwebMIIA-7B | .0611 | .0973 | .1041 | .0453 | .0770 |
| | instruct | Minerva-7B | .0419 | .0498 | .0520 | .0260 | .0424 |
| | | EuroLLM-9B | .0238 | .1143 | .1233 | .0260 | .0719 |
| | | Velvet-14B | .0294 | .0317 | .0317 | .0272 | .0300 |
| | | FastwebMIIA-7B | .0396 | .0848 | .0815 | .0441 | .0625 |
| | | LLaVA-NeXT 8B | .0022 | **.1810** | **.1810** | **.1176** | **.1205** |
| EXAMS-V-IT | base | Minerva-7B | .1655 | .2117 | .0000 | .0658 | .1108 |
| | | EuroLLM-9B | .2420 | .2402 | .2367 | .2331 | .2380 |
| | | FastwebMIIA-7B | .2438 | **.2580** | .2402 | **.2456** | **.2469** |
| | instruct | Minerva-7B | **.2456** | .2456 | .0000 | .0260 | .1293 |
| | | EuroLLM-9B | .2420 | .2402 | .2402 | .2384 | .2402 |
| | | Velvet-14B | .1833 | .1744 | .1673 | .2420 | .1918 |
| | | FastwebMIIA-7B | 2438 | .2438 | **.2438** | .2438 | .2438 |
| | | LLaVA-NeXT 8B | .0000 | .2171 | .1299 | .0160 | .0908 |

nodes. The software stack was based on open-source libraries, including Transformers from Hugging Face [19], which provides seamless integration with PyTorch [20] and DeepSpeed [21]. This software stack has been instrumental in efficiently handling large data sets and complex models.

This hardware-software configuration ensured reproducibility, scalability and efficiency, which are crucial for the comparative analysis of multiple model architectures and for training large-scale models on Italian-language data. It also reflects a broader national effort towards a sovereign AI infrastructure, ensuring data localisation, transparency and regulatory compliance.

For training the models, we use 2 GPUs. The whole training procedure takes about 24 hours for each model.

# 4. Experiments

## 4.1. Experimental Setting

To evaluate the vision-language ability of these models, we use three datasets: GQA-IT [22, 23], MTVQA [24], EXAMS-V [25]. GQA-IT is a visual question answering dataset on natural scenes. We consider its manually translated split to Italian, consisting of 3,000 instances. MTVQA is a manually annotated text-centric image dataset. The dataset provides splits for several languages, in this work we focus on the Italian split, which consists of 884 question-answer pairs. We refer to it as MTVQA-IT. EXAMS-V is a collection of multiple-choice school exam questions in multiple languages. In this case,

**Table 3**
We report results for GQA-IT and MTVQA-IT for the approximate match setting. Specifically, we report the formatting where the models performed **worst** in the original setting and compare the two results (exact and approximate).

| Dataset | Type | Model | Formatting | Exact Match | Approximate Match |
|---|---|---|---|---|---|
| GQA-IT | base | Minerva-7B | Post-Swap | .2023 | .4133 |
| | | EuroLLM-9B | Post-Swap | .0973 | .4807 |
| | | FastwebMIIA-7B | Post-Swap | .0297 | .4853 |
| | instruct | Minerva-7B | Post-Swap | .0533 | .4610 |
| | | EuroLLM-9B | Pre | .0370 | .4977 |
| | | Velvet-14B | Post-Swap | .2843 | .2967 |
| | | FastwebMIIA-7B | Post-Swap | .0790 | .4846 |
| | | LLaVA-NeXT 8B | Pre | .0009 | .4709 |
| MTVQA-IT | base | Minerva-7B | Post-Swap | .0373 | .0656 |
| | | EuroLLM-9B | Post-Swap | .0792 | .1358 |
| | | FastwebMIIA-7B | Post-Swap | .0453 | .1301 |
| | instruct | Minerva-7B | Post-Swap | .0260 | .0724 |
| | | EuroLLM-9B | Pre | .0238 | .1652 |
| | | Velvet-14B | Post-Swap | .0272 | .0305 |
| | | FastwebMIIA-7B | Pre | .0396 | .1244 |
| | | LLaVA-NeXT 8B | Pre | .0022 | .2398 |

we focus on the Italian split as well, which consists of 1,645 question-answer pairs. We refer to it as EXAMS-V-IT

To take into account the effect of using different prompts for the same model, we test all models and all datasets using four different styles of formatting. Specifically, to evaluate these models, an additional string is added to the prompt to limit the generated output. In English, this string that is used depends on the model and the formatting of its training mixture, however the original LLᴀVA, and most other models following its setup, used "Answer the question using a single word or phrase." for open-ended tasks and "Answer with the option's letter from the given choices directly." for closed-ended ones. Thanks to this, it is possible to use *exact match* as metric, where the generated output is compared directly to the ground truth (i.e. hard syntactic match), since the model is instructed to generate only the text that is relevant w.r.t. the label. Due to this, we want to understand if and how the model performance is affected by this string. If we change this string to one with a similar meaning, does the model generate outputs consistently? Does the position of the string matter? To answer these questions, we apply four different formattings to the datasets:

- **Pre**: "Rispondi in modo breve e diretto.\s" (or "Rispondi con la lettera.\s" for closed-ended tasks) appended to the **beginning** of the instruction

- **Post**: "\nRispondi utilizzando una sola parola o frase." (or "\nRispondi utilizzando direttamente la lettera dell'opzione corretta tra quelle date." for closed-ended tasks) appended to the **end** of the instruction

- **Pre-Swap**: "Rispondi utilizzando una sola parola o frase.\n" (or "Rispondi utilizzando direttamente la lettera dell'opzione corretta tra quelle date.\n" for closed-ended tasks) appended to the **beginning** of the instruction

- **Post-Swap**: "\sRispondi in modo breve e diretto." (or "\sRispondi con la lettera." for closed-ended tasks) appended to the **end** of the instruction

A model that performs well for all four formattings can be considered to be a consistent model, capable of answering user queries despite the syntax used in the request. Finally, all results are obtained using greedy decoding as sampling strategy at inference time, which removes randomness in generation and guarantees improved reproducibility of the obtained results. For all tasks, we use the question and answer pairs provided by the task itself. The only exception is EXAMS-V-IT where, since the question and choices are embedded within the image itself, we use the following string as question: "Fornisci una risposta alla domanda presente nell'immagine." ("Provide an answer to the question in the image" in English). All

**Table 4**

We report results for GQA-IT and MTVQA-IT for the approximate match setting. Specifically, we report the formatting where the models performed **best** in the original setting and compare the two results (exact and approximate).

| Dataset | Type | Model | Formatting | Exact Match | Approximate Match |
|---|---|---|---|---|---|
| GQA-IT | base | Minerva-7B | Post | .3523 | .3723 |
| | | EuroLLM-9B | Pre-Swap | .4157 | .4497 |
| | | FastwebMIIA-7B | Post | .4147 | .4313 |
| | instruct | Minerva-7B | Post | .3520 | .3640 |
| | | EuroLLM-9B | Pre-Swap | .4187 | .4283 |
| | | Velvet-14B | Pre-Swap | .3107 | .3147 |
| | | FastwebMIIA-7B | Post | .3233 | .3543 |
| | | LLaVA-NeXT 8B | Pre-Swap | .3454 | .3520 |
| MTVQA-IT | base | Minerva-7B | Post | .0577 | .0634 |
| | | EuroLLM-9B | Pre-Swap | .1143 | .1290 |
| | | FastwebMIIA-7B | Pre-Swap | .1041 | .1165 |
| | instruct | Minerva-7B | Pre-Swap | .0520 | .0656 |
| | | EuroLLM-9B | Pre-Swap | .1233 | .1324 |
| | | Velvet-14B | Post | .0317 | .0362 |
| | | FastwebMIIA-7B | Post | .0848 | .0928 |
| | | LLaVA-NeXT 8B | Pre-Swap | .1810 | .1991 |

models are evaluated using the *lmms-eval*[7] framework, loaded in float16 as dtype and inference is performed with a batch size of 1, ensuring reproducibility of the results. Finally, we lowercase text and ground truth and ignore whitespaces when evaluating using *exact match*.

### 4.2. Results Discussion

We report the results of the experiments in Table 2. For the sake of comparison against already existing models, we also report the results of LLaVA-NeXT 8B [26], a LLaVA-NeXT model trained from the LLaMA 3 Instruct 8B checkpoint, on these benchmarks. Overall, models trained on Italian perform well w.r.t. LLaVA-NeXT 8B. Remarkably, the base version of EuroLLM has the best average performance in GQA, while the base version of FastwebMIIA has the best average performance in EXAMS-V-IT. In MTVQA-IT, Italian models tend to perform poorly w.r.t. LLaVA-NeXT 8B. We believe this is due to the low quantity of text-centric vision-language instances in the training mixture, since MultiInstruct tasks focus more on natural scenes and everyday images. We can reasonably expect an improvement in performance for text-centric tasks when integrating this type of tasks in the training mixture.

Additionally, we showcase that the models are very sensitive to the formatting of the prompt. For example, while the base version of EuroLLM achieves the best average performance on GQA-IT, it performs well on only two out of the four formattings. This pattern can also be seen in other models in our evaluation, in most cases, the models tend to perform better in a limited subset of formattings. After manually analyzing the generated outputs, we find that there are cases where the models generated the correct answer, but with additional contextual text. For example, for the question "È nuvoloso?" ("Is it cloudy" in English) with label "Sì" ("Yes" in English), MINERVA instruct answered "Sì" in the Post formatting, while it answered with "Sì, è nuvoloso nell'immagine." ("Yes, it is cloudy in the image" in English) in the Post-Swap formatting. In both cases, the answer is correct, but the *exact match* metric fails to consider the second case as correct, since there is no hard syntactic match between the generated output and the label. In light of this, we propose further evaluation to study the relationship between performance and the length of the generated response.

### 4.3. Evaluating for Response Length

To further understand if the models provide outputs that are relevant, we evaluate them by performing an approx-

**Figure 1:** Visualization of some examples from GQA-IT and MTVQA-IT for the problem of evaluating using *exact match* as metric. For both formattings (Pre and Post in this example) the model correctly generates the output response, however the *exact match* metric fails to capture the correctness of the response for the Pre formatting. Beneath each Italian text we provide its corresponding English translation.

imate match between the label and the generated output. That is, we check that the label is a substring of the generated output. This allows us to cover cases where the model keeps generating contextual text together with the task answer. For example, for the question "C'è una palla da calcio nell'immagine?" ("Is there a football ball in the image?" in English) with label "Sì" ("Yes" in English), the model may generate "Sì, c'è una palla da calcio nell'immagine.". This case is considered incorrect in the *exact match* metric, since the generated output is not the same as the ground truth label. However, the answer is correct, and the ground truth label is in the generated string itself. Our approach allows to cover these corner cases, however, note that this strategy suffers from false positives. For example, for the question "C'è una mano nell'immagine?" ("Is there a hand in the image?" In English) with label "No", the model may generate "Sì, c'è una mano nell'immagine" ("Yes, there is a hand in the image" in English), and it would be considered a correct answer since "no" is a substring of "mano". We showcase some examples in Figure 1 To assess the performance of the models regardless of the response length, we consider the formatting where each model has performed the worst. We retrieve the generated outputs and corresponding ground truth labels and evaluate them using an approximate match. We expect an improvement in performance w.r.t. *exact match*. Note that we do not perform this evaluation for EXAMS-V, since the task is closed-ended, the answers are the identifiers of the options (e.g. "A", "B"), making it impossible to evaluate the

task using this strategy. Results for evaluation performed using this approach are reported in Table 3. As expected, we can appreciate a great improvement in performance for most models. For example, for the base version of EuroLLM-9B, performance rises from .0973 to .4807, and a similar trend can be seen in the instruct version of the model. For most models, we can observe an increase in performance in approximate match, except for Velvet, where the performance remains the same. To further validate this finding, we also evaluate under the same setting the formatting where the models performed best, Results for approximate match evaluation of the best formatting are reported in Table 4. Overall, the results are a lot more stable, and the degree of improvement is less with respect to worse formatting using approximate match. This highlights that the models in their best formatting performed well because they were able to generate the expected output directly and consistently, without adding additional contextual text to the answer. However, we emphasize that the worst formatting evaluated with approximate match actually showcases better performance w.r.t. best formatting evaluated with approximate match. For example, the base version of EuroLLM achieves an approximate match of .4807 on GQA-IT for its worst formatting, while it achieves an approximate match of .4497 for its best one. This pattern can be seen for all models, including LLaVA NeXT, the only exception being Velvet, where performance is consistent for both formattings. This finding highlights that LLMs tend to provide better answers when they are able to provide a

**Table 5**

We report zero-shot results for Global-MMLU-Lite on the Italian language for each subset. For each model and each category of the dataset, we underline the best result between the multimodal model (LVLM) and its original checkpoint (LLM).

| Type | Model | Multimodal | Global MMLU Subset | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | | | Business | Humanities | Medical | Others | Social Sciences | Stem |
| base | Minerva-7B | X | .3103 | .3431 | .4167 | .4107 | <u>.3235</u> | <u>.4130</u> |
| | Minerva-7B | ✓ | <u>.4310</u> | <u>.3725</u> | <u>.4444</u> | <u>.5000</u> | .3137 | .3478 |
| | EuroLLM-9B | X | <u>.6207</u> | <u>.6176</u> | .3889 | <u>.6786</u> | .5392 | .3478 |
| | EuroLLM-9B | ✓ | .5862 | .5980 | <u>.6111</u> | <u>.6786</u> | <u>.6471</u> | <u>.5000</u> |
| | FastwebMIIA-7B | X | .2931 | .3824 | .4444 | .4643 | .3137 | <u>.3261</u> |
| | FastwebMIIA-7B | ✓ | <u>.4655</u> | <u>.4216</u> | <u>.6111</u> | <u>.5357</u> | <u>.4020</u> | .2609 |
| instruct | Minerva-7B | X | .2931 | <u>.3922</u> | .4167 | <u>.4286</u> | <u>.3529</u> | <u>.3478</u> |
| | Minerva-7B | ✓ | <u>.3103</u> | .3725 | <u>.4722</u> | .3393 | .2549 | .2391 |
| | EuroLLM-9B | X | .5862 | <u>.6667</u> | .5556 | <u>.6964</u> | .5784 | .3913 |
| | EuroLLM-9B | ✓ | <u>.6379</u> | .6275 | <u>.6944</u> | .6429 | <u>.5882</u> | <u>.4783</u> |
| | Velvet-14B | X | <u>.5345</u> | <u>.6176</u> | <u>.7222</u> | <u>.6607</u> | <u>.6569</u> | <u>.5870</u> |
| | Velvet-14B | ✓ | .3448 | .3039 | .4167 | .4107 | .3039 | .2609 |
| | FastwebMIIA-7B | X | <u>.5345</u> | <u>.6373</u> | .5833 | .6250 | <u>.6569</u> | <u>.5217</u> |
| | FastwebMIIA-7B | ✓ | .5172 | .5490 | <u>.6111</u> | <u>.6786</u> | .5784 | .4130 |

verbalized response.

## 4.4. Evaluating for Text-only Tasks

Finally, we also test the ability of the LVLMs in solving Italian text-only tasks, rather than vision-language ones. This aims to determine whether the models retain the knowledge they learned during their original text-only training procedure. Since the models didn't see text-only data during vision-language training, we expect their performance to be lower with respect to their original LLM version. Since we only want to have a general estimate of their performance, we consider a relatively small subset of Italian tasks available through the *lm-eval-harness*[8] framework. Namely, we consider *Global-MMLU* [27], specifically its LITE subset. The dataset is a balanced collection of culturally sensitive and culturally agnostic MMLU tasks (a massive multitask test dataset consisting of multiple-choice questions from various branches of knowledge), where only languages with human translation and post-edits are included. Results are reported in Table 5. Surprisingly, there are models which perform better after the visual instruction-tuning step. For example, the base version of Minerva-7B performs better on four out of the six categories of the dataset. Similar behaviour is also showcased by other models, for example, the instruct version of EuroLLM-9B also performs better on four out of the six categories, while the base version of FastwebMIIA performs better on five of them. This showcases that a vision-language training procedure

may also enhance the language-only performance of the model. However, there is an outlier to this pattern, that is Velvet-14B, where the original version of the model performs better on all categories. Furthermore, for the other models, there is no consistent improvement across all categories. This highlights that, while multimodality has helped improve the inherent knowledge of these models, it is not guaranteed, and text-only evaluation is still relevant for multimodal models.

## 5. Conclusions

In this work, we have expanded the current landscape of LVLMs for the Italian language. We have collected a pool of LLMs supporting the Italian language, which only process textual inputs. Then, we have extended them to LVLMs, by employing a state-of-the-art approach, namely LLaVA-NeXT, and a machine-translated corpus of vision-language tasks in Italian. Additionally, we evaluated them using only benchmarks that are natively in Italian and also studied the effect on the length of the generated response in evaluation. Finally, we also benchmarked these models on an Italian text-only benchmark to understand if the performance for text-only tasks was worse after the visual instruction-tuning step. As future work, we plan to further extend the training mixture so that it also considers text-centric tasks in Italian, improving model performance on this type of task that is currently missing in the training mixture. Specifically, we plan to incorporate multimodal document data to enhance these models in document visual question an-

swering. We also plan to further extend the evaluation and to improve the approximate match strategy, which soundness currently suffers from the possibility of false positives.

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## Declaration on Generative AI

During the preparation of this work, the author(s) used Grammarly in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.