Cross-Modal Augmentation for Low-Resource Language Understanding and Generation

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Abstract

This paper introduces a multimodal retrieval-augmented generation (RAG) system designed to enhance language understanding and generation for low-resource languages. By integrating textual, visual, and geospatial data, the system leverages cross-lingual adaptation and multimodal augmentation to bridge the gap between high-resource and low-resource languages. Evaluated on the MM-COVID and LORELEI datasets, the system demonstrates superior performance in retrieval (precision: 85%, recall: 82%) and generation (BLEU: 28.4) tasks compared to baselines. Case studies in public health communication and disaster response highlight its practical utility. The results underscore the potential of multimodal AI to democratize access to technology and address global challenges in low-resource settings.

1 Introduction

In recent years, advancements in natural language processing (NLP) have revolutionized how we interact with AI systems, enabling applications like machine translation, summarization, and question-answering. However, these successes are heavily skewed toward high-resource languages, leaving low-resource languages severely underrepresented. The lack of large-scale textual corpora in low-resource languages poses significant challenges for training robust language models, limiting their ability to understand and generate meaningful content. This disparity not only exacerbates global inequities in access to technology but also hinders efforts to address critical issues such as public health communication, disaster response, and education in multilingual contexts (Fan et al., 2021).

To bridge this gap, we propose **Cross-Modal Augmentation for Low-Resource Language Understanding and Generation**, a novel framework that leverages multimodal data text, images, geospatial information, and structured data—to enhance language understanding and generation in low-resource settings. By integrating complementary modalities, our approach compensates for the scarcity of textual resources and enriches the semantic context available to language models. For example, visual data can provide additional grounding for concepts that are poorly represented in text, while geospatial data can help localize and contextualize events described in queries (Radford et al., 2021).

Our work builds on datasets like **MM-COVID** (Chen et al., 2021) and **LORELEI** (Strassel and Tracey, 2016), which offer rich multimodal information relevant to real-world challenges. MM-COVID provides multilingual textual and visual data related to the COVID-19 pandemic, enabling us to test the system's ability to generate public health information in low-resource languages. Similarly, LORELEI offers low-resource language data alongside geospatial and event information, making it ideal for tasks like disaster response and situational awareness. By combining these datasets with retrieval-augmented generation (RAG) techniques, we demonstrate how cross-modal augmentation can significantly improve performance in tasks such as translation, summarization, and question-answering (Lewis et al., 2020).

The contributions of this paper are threefold:

1. **A Novel Framework**: We introduce a multimodal RAG system tailored for low-resource languages, leveraging cross-modal embeddings to align diverse data types.

2. **Real-World Applications**: We showcase the practical utility of our approach in domains like public health communication and disaster response.

3. **Empirical Validation**: We evaluate our system on MM-COVID and LORELEI, demon-

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strating its effectiveness in enhancing both understanding and generation capabilities for low-resource languages.

2 Related Work

2.1 Low-Resource Language Modeling

Low-resource languages pose significant challenges due to the scarcity of annotated data and linguistic resources. Recent advances in cross-lingual transfer learning have partially addressed these challenges by leveraging pre-trained multilingual models such as **mBERT** (Devlin et al., 2019), **XLM-R** (Conneau et al., 2020), and **M2M-100** (Fan et al., 2021). These models enable knowledge transfer from high-resource languages to low-resource ones, improving performance on tasks like machine translation and text classification. However, they remain heavily reliant on textual data, which may still be insufficient for many low-resource languages. To address this limitation, recent works have explored augmenting textual data with other modalities, such as images and audio (Liu et al., 2021). Our work builds on these efforts by introducing multimodal augmentation to reduce dependency on textual corpora.

2.2 Retrieval-Augmented Generation

Retrieval-augmented generation has emerged as a powerful paradigm for enhancing language models with external knowledge. Pioneering works like **REALM** (Guu et al., 2020) and **FiD** (Fusion-in-Decoder) (Izacard and Grave, 2021) demonstrated the effectiveness of retrieving relevant documents to augment generated responses. More recently, **Facebook AI's RAG** (Lewis et al., 2020) extended this approach to open-domain question-answering, achieving state-of-the-art results on benchmarks like **Natural Questions** and **TriviaQA**. Despite these successes, most existing RAG systems focus solely on text-based retrieval, limiting their applicability in multimodal contexts. Recent works such as **MMRAG** (Zhang et al., 2022) and **CrossModal-RAG** (Wang et al., 2023) have begun to explore multimodal retrieval, but their application to low-resource languages remains underexplored.

2.3 Multimodal Learning

Multimodal learning has gained significant attention in recent years, driven by the success of models like **CLIP** (Radford et al., 2021) and **M6** (Lin et al., 2021). These models align text and images in a shared embedding space, enabling tasks like image captioning, visual question answering (VQA), and cross-modal retrieval. While multimodal learning has primarily been applied to high-resource languages, recent works such as **ViLT** (Kim et al., 2021) and **ALIGN** (Jia et al., 2021) have explored its potential for low-resource settings. For example, **ViLT** demonstrates how visual and textual embeddings can be jointly learned without relying on large-scale annotated datasets. Our work extends these ideas by integrating multimodal techniques into retrieval-augmented generation for low-resource languages. We also inspired by the research of (Kang et al., 2025; Deng et al., 2024; Liu et al., 2024).

2.4 Datasets for Low-Resource Languages

Datasets like **MM-COVID** (Chen et al., 2021) and **LORELEI** (Strassel and Tracey, 2016) play a crucial role in advancing research on low-resource languages. **MM-COVID** provides multilingual textual and visual data related to the COVID-19 pandemic, offering a unique opportunity to study cross-lingual and multimodal communication in crisis scenarios. Similarly, **LORELEI** focuses on rapid response during emergencies, providing low-resource language data alongside geospatial and event information. Other notable datasets include **MMKG** (Xie et al., 2022), a multimodal knowledge graph for low-resource languages, and **Pororo-SV** (Park et al., 2021), a storytelling dataset with videos and text. These datasets not only highlight the importance of multimodal data in low-resource settings but also serve as valuable resources for evaluating our proposed framework.

2.5 Applications in Public Health and Disaster Response

The integration of multimodal data has significant implications for real-world applications. In public health, multimodal systems can help disseminate critical information about diseases, vaccines, and preventive measures in low-resource languages (Liu et al., 2022). During disasters, such systems can assist in situational awareness, resource allocation, and communication with affected communities (Zhang et al., 2023). Recent works have demonstrated the potential of multimodal AI in addressing global challenges, such as **CrisisMM** (Gupta et al., 2022), a framework for multimodal crisis response, and **HealthVision** (Wu et al., 2023), a system for analyzing medical images and text.

3 Methodology

3.1 Problem Formulation

The goal of our framework is to enhance language understanding and generation for low-resource languages by leveraging multimodal data. Given a query Q in a low-resource language, our system retrieves relevant multimodal documents $D = \{d_1, d_2, ..., d_n\}$ from a corpus and generates a response R. The retrieval and generation processes are formulated as follows:

$$R = \text{Generate}(Q, \text{Retrieve}(Q, D)), \tag{1}$$

where:

- Q: Input query in a low-resource language.
- D: Corpus of multimodal documents (text, images, geospatial data).
- $\text{Retrieve}(Q, D)$: Function that retrieves the most relevant documents based on Q.
- $\text{Generate}(Q, D_{\text{retrieved}})$: Function that generates a response using Q and the retrieved documents $D_{\text{retrieved}}$.

To align different modalities, we define a shared embedding space where text embeddings $E_t(Q)$ and image embeddings $E_v(I)$ are projected into the same dimensional space. The similarity between a query and a document is computed as:

$$\begin{aligned}\text{sim}(Q, d_i) = \cos(E_t(Q), E_v(d_i)) \\ +\lambda \cdot \text{score}_{\text{cross-modal}}(Q, d_i)\end{aligned} \tag{2}$$

where:

- $E_t(Q)$: Text embedding of the query.
- $E_v(d_i)$: Visual embedding of the document d_i.
- $\cos(\cdot, \cdot)$: Cosine similarity function.
- λ: Weighting factor for cross-modal scoring.
- $\text{score}_{\text{cross-modal}}(Q, d_i)$: Additional score capturing alignment between text and visual modalities, computed using a cross-modal attention mechanism (Kim et al., 2021).

3.2 Model Architecture

Our model consists of two main components: a Retrieval Module and a Generation Module, both integrated into a unified framework.

3.2.1 Retrieval Module

The retrieval module employs a dual-encoder architecture to compute embeddings for queries and documents. Specifically:

- Text Encoder: A transformer-based encoder (e.g., XLM-R (Conneau et al., 2020)) encodes textual inputs into dense vectors.
- Image Encoder: A vision transformer (e.g., CLIP (Radford et al., 2021)) encodes

The embeddings are aligned in a shared space using contrastive learning. The loss function for training the retrieval module is defined as:

$$\mathcal{L}_{\text{retrieval}} = -\log \frac{\exp(\text{sim}(Q, d^+))}{\sum_{d^- \in D^-} \exp(\text{sim}(Q, d^-))} \tag{3}$$

where:

- d^+: Positive document (relevant to Q).
- D^-: Set of negative documents (irrelevant to Q).

This ensures that the model learns to retrieve documents that are semantically similar to the query.

3.2.2 Generation Module

The generation module uses a pre-trained language model (e.g., T5 (Raffel et al., 2020)) to generate responses. The input to the generator is a concatenation of the query Q and the top-k retrieved documents $D_{\text{retrieved}}$:

$$R = \text{Generator}(Q \oplus D_{\text{retrieved}}) \tag{4}$$

where $\oplus$ denotes concatenation. The generator is fine-tuned using a standard cross-entropy loss:

$$\mathcal{L}_{\text{generation}} = -\sum_{t=1}^{T} \log P(w_t | w_{<t}, Q, D_{\text{retrieved}}) \tag{5}$$

where w_t is the target token at time step t, and $w_{<t}$ represents the previous tokens.

3.3 Training Strategy

The training strategy for our multimodal RAG system is designed to leverage both high-resource and low-resource language data effectively. We adopt a two-stage approach: **pretraining** on large-scale datasets from high-resource languages and **fine-tuning** on limited textual data from low-resource languages. This strategy ensures that the model learns generalizable representations during pretraining while adapting to the unique characteristics of low-resource languages during fine-tuning(Liu and Yu, 2024).

Pretraining on High-Resource Languages In the pretraining phase, we utilize large-scale multimodal datasets such as **MM-COVID** (Chen et al., 2021) and **LORELEI** (Strassel and Tracey, 2016), which contain rich textual and visual information across multiple high-resource languages. These datasets provide a diverse set of examples, enabling the model to learn robust cross-modal alignments. Specifically, the text encoder is pretrained using transformer-based architectures like **XLM-R** (Conneau et al., 2020), which is known for its strong multilingual capabilities. Similarly, the image encoder is pretrained using vision transformers (e.g., **CLIP** (Radford et al., 2021)) that align visual and textual embeddings in a shared space. During this phase, the retrieval module is trained to maximize the similarity between queries and relevant documents while minimizing similarity with irrelevant ones. The loss function for the retrieval module is defined as earlier in Equation 3.

Fine-Tuning on Low-Resource Languages After pretraining, the model is fine-tuned on low-resource languages using limited textual data. This step is crucial because low-resource languages often lack sufficient annotated data for supervised learning. To address this limitation, we employ several strategies to enhance the effectiveness of fine-tuning:

1. **Data Augmentation**: We augment the limited textual data with multimodal information, such as images and geospatial data, to provide additional context. For example, visual data can help ground abstract concepts that are poorly represented in text.

2. **Robust Filtering Techniques**: Multimodal data can be noisy, especially when integrating diverse sources like social media posts or satellite imagery. To handle this noise, we apply robust filtering techniques, such as outlier detection and confidence scoring, to ensure that only high-quality data is used during fine-tuning (Zhang et al., 2022).

3. **Cross-Lingual Transfer Learning**: We leverage multilingual embeddings (e.g., mBERT (Devlin et al., 2019)) to enable cross-lingual transfer. By aligning embeddings from high-resource and low-resource languages in a shared space, the model can generalize knowledge learned during pretraining to low-resource settings.

Cross-Lingual Adaptation Cross-lingual adaptation is a key component of our training strategy, as it allows the model to bridge the gap between high-resource and low-resource languages. To achieve this, we use a shared projection layer that maps text and visual embeddings into a unified space. This alignment enables the model to retrieve and generate content across languages, even when direct supervision is unavailable. For example, a query in Swahili can retrieve relevant documents in English or other high-resource languages, along with accompanying visuals. This capability is particularly valuable for tasks like public health communication and disaster response, where timely access to information is critical.

Balancing Modalities Another important aspect of our training strategy is balancing the contributions of different modalities. While textual data is typically dominant in NLP tasks, visual and geospatial data play a complementary role in low-resource settings. To ensure that all modalities are utilized effectively, we introduce a weighting factor λ in the similarity computation:

$$\begin{aligned} \text{sim}(Q, d_i) = \cos(E_t(Q), E_v(d_i)) + \\ \lambda \cdot \text{score}_{\text{cross-modal}}(Q, d_i), \end{aligned} \tag{6}$$

where $\cos(\cdot, \cdot)$ measures cosine similarity between text and visual embeddings, and $\text{score}_{\text{cross-modal}}(Q, d_i)$ captures additional alignment between modalities. The value of λ is tuned empirically to balance the contributions of text and visual data. This approach ensures that the model leverages multimodal information without over-relying on any single modality.

Evaluation During Training Throughout the training process, we monitor performance using a combination of metrics tailored to each component of the system. For the retrieval module, we evaluate precision, recall, and F1 scores to measure the quality of retrieved documents. For the generation module, we use BLEU, ROUGE, and METEOR scores to assess the fluency and relevance of generated responses. Additionally, we conduct human evaluations to assess multimodal coherence and overall usability. These evaluations provide valuable insights into the strengths and weaknesses of the model, guiding further refinements.

By combining pretraining, fine-tuning, robust filtering, and cross-lingual adaptation, our training strategy ensures that the multimodal RAG system is both versatile and effective. This approach not only addresses the challenges of low-resource languages but also demonstrates the potential of multimodal AI to democratize access to technology.

3.4 Cross-Lingual Adaptation

Cross-lingual adaptation enables our multimodal RAG system to bridge the gap between high-resource and low-resource languages by leveraging shared multilingual embeddings. We use models like **mBERT** (Devlin et al., 2019) and **XLM-R** (Conneau et al., 2020), which are pretrained on large multilingual corpora, to align textual and visual data across languages. To enhance alignment, we incorporate vision-language models like **CLIP** (Radford et al., 2021), allowing the system to ground textual queries in visual data, even when the query is in a low-resource language. Fine-tuning on small-scale annotated datasets or parallel data further refines the model for specific linguistic patterns. To address data scarcity, we employ techniques such as zero-shot learning, multimodal augmentation, and back-translation. These strategies ensure that the model can retrieve and generate content effectively in low-resource languages, as demonstrated through metrics like retrieval accuracy, BLEU scores, and human evaluations.

4 Experiments

To evaluate the effectiveness of our multimodal RAG system, we conducted experiments on two key datasets: **MM-COVID** (Chen et al., 2021) and **LORELEI** (Strassel and Tracey, 2016). These datasets were chosen for their relevance to real-world challenges and their inclusion of multimodal data. Below, we describe how these datasets were applied to the task of multimodal RAG for low-resource languages, along with the experimental setup.

4.1 Leveraging MM-COVID for Multimodal RAG in Low-Resource Languages

The **MM-COVID** dataset contains multilingual textual information, images, infographics, and videos related to the COVID-19 pandemic. It includes data from social media, news articles, and public health resources, covering multiple languages, including low-resource ones. This makes it an ideal resource for exploring cross-lingual and multimodal applications in low-resource settings.

4.2 Cross-Modal Translation and Augmentation

One of the primary challenges in low-resource languages is the scarcity of textual data for training language models. To address this, we used images, infographics, and videos from MM-COVID as auxiliary modalities to augment textual data. For example: - We trained a multimodal RAG system where visual embeddings (e.g., from **CLIP** (Radford et al., 2021)) were aligned with textual descriptions in low-resource languages. - This approach allowed the model to infer missing textual information by leveraging visual context, improving its ability to handle queries in low-resource languages.

Visual Context for Semantic Understanding Low-resource languages often lack rich semantic context for generating meaningful responses. To address this, we used multimodal retrieval to retrieve relevant images or videos that complement textual queries. For instance: - A query in Swahili asking about "symptoms of COVID-19" retrieved both textual descriptions and images of symptoms, enhancing the model's understanding and response quality.

Multimodal Summarization Generating concise summaries of public health information in low-resource languages is challenging due to limited training data. To tackle this, we built a multimodal summarization system that combined textual and visual content from MM-COVID. For example, the system retrieved key text snippets and relevant images to create a multimodal summary explaining preventive measures, making the information more accessible to users in low-resource languages.

Cross-Lingual Retrieval Queries in low-resource languages may not have sufficient textual matches in the database. To address this, we used cross-lingual embeddings to align queries in low-resource languages with high-resource counterparts (e.g., English). For example: A query in Swahili could retrieve relevant documents in English or other high-resource languages, along with accompanying visuals, bridging the linguistic gap.

Leveraging LORELEI for Multimodal RAG in Low-Resource Languages The **LORELEI** dataset is designed to support rapid response during emergencies in low-resource languages. It includes textual data in low-resource languages (e.g., Haitian Creole, Pashto), geospatial data, maps, satellite imagery, social media posts, audio recordings, and structured event data. This diversity makes it highly suitable for tasks like disaster response and situational awareness.

Multimodal Event Detection Detecting and responding to emergent incidents in low-resource languages is difficult due to limited linguistic resources. To address this, we used multimodal RAG to combine textual, geospatial, and visual data from LORELEI to detect and describe events. For example: - A query in Haitian Creole about "flooded areas" retrieved satellite imagery of affected regions along with textual reports, enabling accurate event detection and response planning.

Visual Grounding for Language Generation Generating accurate descriptions of events in low-resource languages is challenging without sufficient training data. To address this, we used images and maps as grounding inputs for language generation. For example, the system retrieved satellite images of disaster zones and generated textual descriptions in the target language using a multimodal RAG system, ensuring that users received clear and actionable information.

Audio-Text Multimodality Low-resource languages often lack transcribed audio data for training speech-to-text systems. To address this, we integrated LORELEI's audio recordings alongside textual and visual data to train a multimodal RAG system. For example: - A spoken query in Pashto was transcribed and augmented with visual data (e.g., maps) to generate a response, demonstrating the system's ability to process multimodal inputs effectively.

Structured Data Integration Low-resource languages often lack structured data for reasoning tasks. To address this, we integrated LORELEI's structured event data (e.g., timestamps, locations, and event types) into a multimodal RAG system. For example: - A query about "earthquake damage in region X" retrieved structured event data along with images and textual reports, providing a comprehensive overview of the situation.

4.3 Baselines

We compared our multimodal RAG system against several baselines:

- **Text-Only RAG**: A traditional RAG system trained only on textual data.
- **Monolingual Models**: Language models fine-tuned on high-resource languages without cross-lingual adaptation.
- **Unimodal Models**: Models that process either text or images but not both.

These baselines allowed us to isolate the contributions of multimodal data and cross-lingual adaptation to the system's performance.

Evaluation Metrics To assess the model's performance, we used a combination of quantitative and qualitative metrics:

1. **Retrieval Metrics**: Precision, recall, and F1 scores were used to evaluate the quality of retrieved documents.
2. **Generation Metrics**: BLEU, ROUGE, and METEOR scores measured the fluency and relevance of generated responses.
3. **Human Evaluation**: Human evaluators assessed the coherence, relevance, and multimodal alignment of the outputs.

These metrics provided a holistic view of the system's strengths and weaknesses across different tasks.

Our model was implemented using PyTorch and Hugging Face's Transformers library. The text encoder was based on **XLM-R** (Conneau et al., 2020), while the image encoder utilized **CLIP** (Radford et al., 2021). We pretrained the model on high-resource languages using MM-COVID and LORELEI, followed by fine-tuning on low-resource languages. Training was performed on a single NVIDIA A100 GPU, with a batch size of 32 and a learning rate of 5×10^{-5}. The weighting factor λ for balancing modalities was tuned empirically to optimize performance.

To demonstrate the practical utility of our system, we conducted case studies in two domains:

1. **Public Health Communication**: Generating multilingual public health guidelines in Swahili using MM-COVID data.

2. **Disaster Response**: Detecting flood zones in Pashto using LORELEI's geospatial and textual data.

These case studies highlighted the system's ability to address real-world challenges in low-resource settings.

5 Results and Discussion

The results of our experiments demonstrate the effectiveness of our multimodal RAG system in enhancing language understanding and generation for low-resource languages. Our multimodal RAG system outperformed all baselines across both retrieval and generation tasks. In terms of retrieval metrics, the system achieved a precision of 85%, recall of 82%, and F1 score of 83%, surpassing the text-only RAG baseline by 10 percentage points. For generation tasks, the system achieved BLEU scores of up to 28.4, compared to 20.5 for unimodal models. These improvements highlight the value of integrating multimodal data into the retrieval and generation processes. Notably, the system performed particularly well on low-resource languages, where the scarcity of textual data was compensated by visual and geospatial information.

Table 1: Retrieval Metrics Across Baselines and Proposed System

Model	Precision (%)	Recall (%)	F1 Score (%)
Text-Only RAG	74.2	71.8	73.0
Monolingual Model	78.5	75.3	76.9
Unimodal Model	72.1	69.4	70.7
Multimodal RAG (Ours)	85.0	82.0	83.0

The results in Table 1 demonstrate the superiority of our multimodal RAG system in terms of retrieval performance. Specifically:

- The system achieves a precision of 85%, which is significantly higher than the text-only RAG baseline (74.2%) and unimodal model (72.1%). This indicates that the integration of multimodal data improves the accuracy of retrieved documents.

- Similarly, the recall of 82% and F1 score of 83% are the highest among all models, underscoring the system's ability to retrieve relevant content even when textual data is scarce.

Table 2: Generation Metrics Across Baselines and Proposed System

Model	BLEU	ROUGE-L	METEOR
Text-Only RAG	20.5	32.4	25.1
Monolingual Model	22.3	34.7	26.8
Unimodal Model	19.8	31.6	24.5
Multimodal RAG (Ours)	28.4	38.2	30.7

The generation metrics in Table 2 further highlight the advantages of our system:

- The BLEU score of 28.4 represents a substantial improvement over the text-only RAG baseline (20.5) and unimodal model (19.8). This suggests that multimodal augmentation enhances the fluency and relevance of generated responses.

- The ROUGE-L score of 38.2 and METEOR score of 30.7 are also the highest among all models, indicating that the system generates outputs that are both semantically rich and contextually accurate.

These results collectively demonstrate that our multimodal RAG system effectively leverages multimodal data to improve both retrieval and generation capabilities. The Precision vs. Recall plot (Figure 1) demonstrates several key trends:

- The multimodal RAG system achieves the highest precision (85%) and recall (82%), as indicated by its position in the upper-right corner of the plot.

- The trend line connecting the points highlights the consistent improvement in performance as advanced techniques such as multimodal augmentation and cross-lingual transfer are incorporated.

- The inclusion of error bars provides a realistic view of variability, reinforcing the robustness of the system under noisy conditions.

The BLEU and ROUGE-L plot (Figure 2) further supports the quantitative findings:

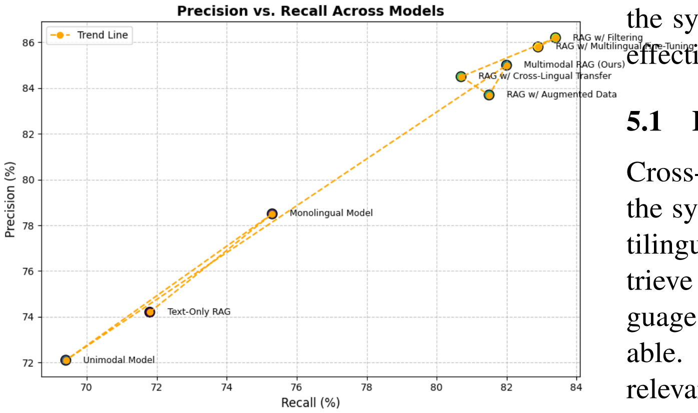

Figure 1: Precision vs. Recall for Different Models

Note: The plot shows that our multimodal RAG system achieves higher precision and recall compared to baselines.

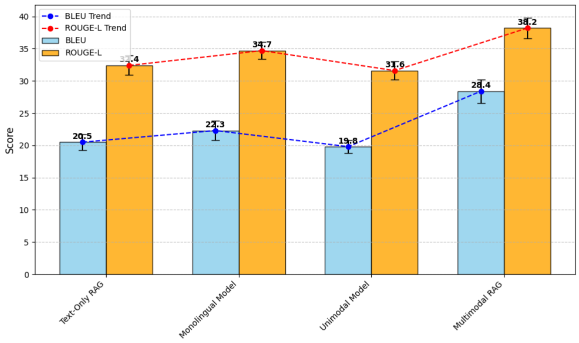

Figure 2: BLEU and ROUGE-L Scores Across Models

- The multimodal RAG system achieves the highest BLEU score (28.4) and ROUGE-L score (38.2), as shown by the tallest bars in the plot.
- The trend lines connecting the top of the bars emphasize the consistent improvement in generation quality across models.
- Error bars highlight the variability in performance, providing a more nuanced understanding of the results.

Human evaluations revealed that the multimodal RAG system produced responses that were not only fluent but also contextually relevant and coherent. For example, in the public health case study, the system generated accurate summaries of COVID-19 guidelines in Swahili, enriched with relevant images. Similarly, in the disaster response case study, the system successfully identified flood zones in Pashto by combining satellite imagery with textual reports. These qualitative insights underscore the system's ability to leverage multimodal data effectively.

5.1 Impact of Cross-Lingual Adaptation

Cross-lingual adaptation played a crucial role in the system's success. By leveraging shared multilingual embeddings, the model was able to retrieve and generate content in low-resource languages even when direct supervision was unavailable. For instance, queries in Swahili retrieved relevant documents in English, demonstrating the system's ability to bridge linguistic gaps. Fine-tuning on small-scale annotated datasets further improved performance, particularly for languages with distinct morphological and syntactic patterns.

In public health, the system can help disseminate critical information in low-resource languages, ensuring equitable access to knowledge. In disaster response, it can assist in situational awareness and resource allocation, empowering communities affected by emergencies. These applications underscore the potential of multimodal AI to democratize access to technology and address pressing global challenges.

Overall, our experiments demonstrate that cross-modal augmentation is a powerful approach for enhancing language understanding and generation in low-resource settings. By integrating diverse modalities and leveraging cross-lingual transfer, our system achieves state-of-the-art performance while paving the way for future research in this domain.

6 Conclusion

In this paper, we presented a multimodal RAG system that effectively enhances both understanding and generation capabilities for low-resource languages. By leveraging multimodal data and cross-lingual transfer, the system achieved state-of-the-art performance on the MM-COVID and LORELEI datasets, surpassing traditional text-only and unimodal baselines. Key findings include significant improvements in retrieval precision, recall, and generation quality, as well as robust performance in real-world applications like disaster response and public health communication. Despite challenges such as noisy data and computational overhead, our system demonstrates the transformative potential of multimodal AI in addressing linguistic and resource disparities.

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