

VIETNAMESE IMAGE CAPTIONING USING CLIP PREFIX AND GPT-2 LANGUAGE MODEL

Vu Nguyen Ha Anh¹

¹University of Information Technology – UIT, Ho Chi Minh City, Vietnam

W
H
Y
?

- Language Gap:** Lack of SOTA captioning solutions for Vietnamese (low-resource language).
- Resource Efficiency:** Avoids high data and compute costs of training from scratch.

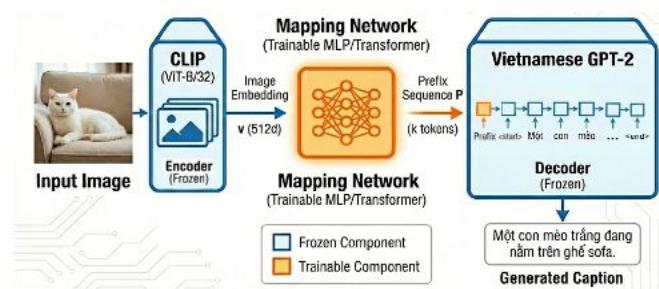


W
H
A
T
?

- ViClipCap** introduced as a **lightweight framework** for Vietnamese Image Captioning based on **Prefix Tuning**. We have:
- Architecture:** Bridges frozen CLIP and VN GPT-2 via a lightweight **Mapping Network**.
 - Method:** Projects visual features into semantic prefixes for generation.
 - Impact:** Parameter-efficient transfer learning for low-resource languages.

O
V
E
R
V
I
E
W

Mechanism: A semantic translator bridging frozen CLIP and GPT-2. Lightweight Mapping Network converts visual insights into language prompts without retraining backbones.



M
E
T
R
I
C
S

- BLEU-4:** Measures precision of 4-gram overlaps.
- ROUGE-L:** Focuses on recall via Longest Common Subsequence.
- METEOR:** Aligns tokens using synonyms and stemming.
- CIDEr:** Uses TF-IDF to weight consensus (caption-specific).
- SPICE:** Evaluates semantic accuracy via Scene Graphs.

D
A
T
A
S
E
T

- Selection:** Prioritized KTVIC (Life Domain) over UIT-ViIC (Sports) to capture diverse daily activities.
- Focuses:** Life Domain, daily activities for Vietnamese context.
- Scale:** 4,327 images annotated with 21,635 captions (~5 captions/image).
- Goal:** Addresses low-resource challenges in Vietnamese Vision-Language research.

DESCRIPTION

1. Frozen Visual Encoder (CLIP)

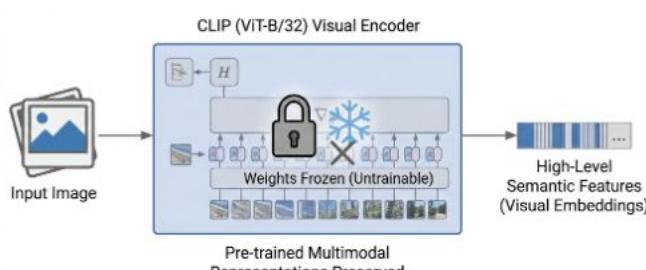


Figure 1: Frozen Visual Encoder (CLIP). ViT-B/32 backbone extracts features with locked weights, preserving pre-trained knowledge and reducing compute.

- Backbone:** CLIP (ViT-B/32) extracts high-level semantic features.
- Mechanism:** **Frozen weights** preserve pre-trained knowledge and significantly reduce compute.

3. Frozen Text Decoder (Vietnamese GPT-2)

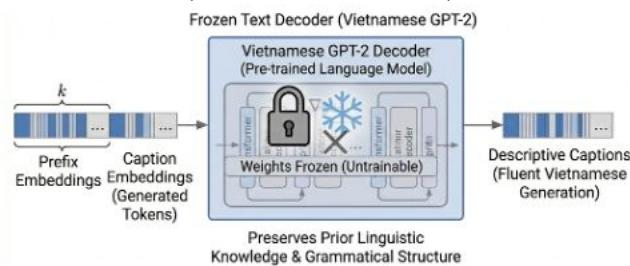


Figure 3: Frozen Text Decoder (Vietnamese GPT-2). Generates fluent captions from prefix inputs while keeping weights fixed.

- Decoder:** Pre-trained Vietnamese GPT-2 (Frozen).
- Input:** Concatenated sequence: **[Prefix Embeddings, Caption Embeddings]**
- Benefit:** Preserves linguistic knowledge for **fluent Vietnamese generation**.

2. Trainable Mapping Network

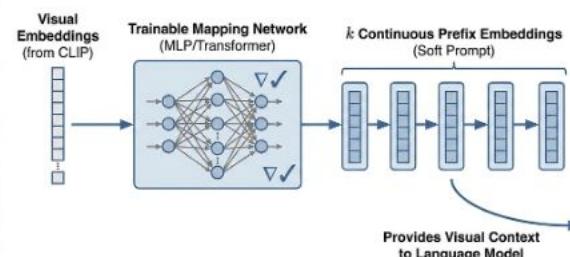


Figure 2: Trainable Mapping Network. Projects visual features into continuous prefix embeddings (soft prompts).

- Bridge:** Links CLIP & GPT-2 via a lightweight Mapping Network.
- Function:** Projects features into **Prefix Embeddings** ("soft prompts") to guide the **frozen LM**.

4. Training Objective & Optimization

- Objective:** Minimize **Cross-Entropy Loss**:

$$\mathcal{L} = - \sum_{t=1}^T \log P_{\theta}(y_t | y_{<t}, \mathbf{p})$$

- Optimization:** AdamW with **Linear Warmup**.

- Efficiency:** Updates *only* Mapping Network, preventing catastrophic forgetting.

5. Experimental Results

Metric	CNN+LSTM	ViClipCap
BLEU-4	0.2572	0.3431
ROUGE-L	0.4895	0.5204
CIDEr	0.6282	0.8127
METEOR	0.2995	0.3194
SPICE	0.0782	0.0829

- ViClipCap outperforms the CNN+LSTM across **all metrics** on the KTVIC dataset.
- Demonstrates that high quality can be achieved with minimal trainable parameters via **Prefix Tuning**.

CONCLUSION

- Adaptation:** Optimized CLIP & GPT-2 for Vietnamese Life Domain (KTVIC).
- Performance:** Fluent, efficient generation via Prefix Tuning without catastrophic forgetting.
- Future:** Scaling to larger backbones and multilingual expansion.

R
E
F
S

- [1] Ron Mokady, Amir Hertz, Amit H. Bermano: [ClipCap: CLIP Prefix for Image Captioning](#).
- [2] Matteo Stefanini, Marcella Cornia, Lorenzo Baraldi, Silvia Cascianelli, Giuseppe Fiameni, Rita Cucchiara: [From Show to Tell: A Survey on Deep Learning-Based Image Captioning](#).