Fine-Tuning BLIP for General Image Captioning with LLM-Based Correction

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***Abstract*— Image captioning is one of the most important computer vision problems with diverse applications from enhanced accessibility for the visually impaired to automated content generation for news media. Recent developments have focused on leveraging pre-trained models like BLIP (Bootstrapped Language-Image Pretraining) to generate textual captions for images. In this paper, we investigate fine-tuning BLIP for general image captioning and its limitations in contextual comprehension and linguistic accuracy. We introduce a new correction mechanism that leverages Large Language Models (LLMs) to rectify and enhance the generated captions. The proposed approach combines the best of both BLIP for vision-language grounding and LLMs for advanced natural language processing. Experimental results indicate drastic improvement in caption quality, paving the way to more robust and contextually compliant applications in automated content generation, image retrieval, and human-machine interaction.**

Keywords— BLIP, Image Captioning, Large Language Models, Fine-Tuning, Natural Language Processing, Computer Vision, GPT, Vision-Language Models

I. INTRODUCTION

Image captioning seeks to bridge the gap between computer vision and natural language processing so that machines can generate natural language descriptions of visual information automatically. The task is to identify what objects, attributes, and relations are in an image and then generate a coherent and contextually relevant textual description. Earlier methods employed complex feature engineering and recurrent neural networks, but recent advances using pre-trained vision-language models have progressed a long way.

BLIP (Bootstrapped Language-Image Pretraining) is also a model that performs exceptionally well in a range of vision-language tasks. BLIP captions, however, lack the context information and linguistic accuracy required in practical use. Large Language Models (LLMs) such as GPT have been incredible in language understanding and generation. Their ability to learn context and generate text naturally makes them the ideal choice for enhancing and optimizing image captions.

This research proposes a hybrid approach that combines the strengths of BLIP for the initial caption generation and caption refinement by LLM for improving caption quality in general.

II. RELATED WORKS

1. Vision-Language Pretraining Models

The BLIP model, or Bootstrapped Language-Image Pretraining, is pre-trained to learn vision-language representations from noisy image-text pairs but has the tendency to get bogged down by domain-specific knowledge. Other models such as CLIP and ALIGN use contrastive learning to associate images with words, greatly enhancing multi-modal comprehension. These models, however, need extensive fine-tuning to learn specific applications such as image captioning, where natural and grammatically correct captions need to be generated. Without fine-tuning, they tend to generate captions that are not contextually rich, coherent, or linguistically diverse. Despite good generalization by these models, their generation of human-like captions is still limited. Fine-tuning using specialized datasets can be used to improve performance but comes at computational expense and training complexity. Maintaining semantic accuracy and fluency with minimal human effort is an area of research.

2. Large Language Models in Text Correction and Generation

The GPT family, GPT-3 and GPT-4, is at the core of text generation, grammar checking, and contextualization in a variety of NLP applications. The models are trained on huge amounts of text data, enabling them to produce coherent and well-formed sentences. They are used in applications such as machine translation, text summarization, and dialogue generation, where value lies in maintaining clarity and meaning. Large language models fine-tune machine-generated captions in the image captioning task to render them more human-like, brief, and grammatically correct. By eliminating redundancy and making captions more readable, they enhance caption quality without losing their intended meaning. Despite such enhancements, factual accuracy issues and prevention of biased or hallucinated content still plague these tasks. Fine-tuning the models to obtain a balance between creativity, accuracy, and contextuality is a research area that is currently active.

3.Hybrid Approaches in Image Captioning

While vision-language and large language models have made strides, little research has been done on their combination for post-processing image captions. Vision-language models such as BLIP can identify image features and produce contextually appropriate textual descriptions but are syntactically incorrect and not fluent. Large language models such as GPT excel at fine-tuning text to insert structure, coherence, and readability. A hybrid approach based on combining these models can greatly improve image captioning by inserting content correctness and linguistic fluency. The strategy uses BLIP to produce the first caption and GPT to fine-tune it to produce more natural and contextually correct output. Combining these models has the potential to minimize errors, maximize contextual appropriateness, and produce better visual content descriptions in captions. Optimizing hybrid structures for real-world applications, however, is difficult due to the increased computational burden.

III. Methodology

1. Dataset

The model utilizes a diverse set of image-caption pairs extracted from trustworthy datasets like MS COCO, Conceptual Captions, and Visual Genome. Such datasets offer vast numbers of diverse visual scenes along with their human-annotated captions to impart diversity in terms of contexts as well as linguistic flavors to which the model is exposed. Preprocessing to the dataset is implemented in order to remove inconsistency, repair faults, and normalize annotations prior to training. Preprocessing is a central element in quality training data that has straightforward influences on the potential of the model to generate good and consistent captions.

2. Fine-Tuning BLIP

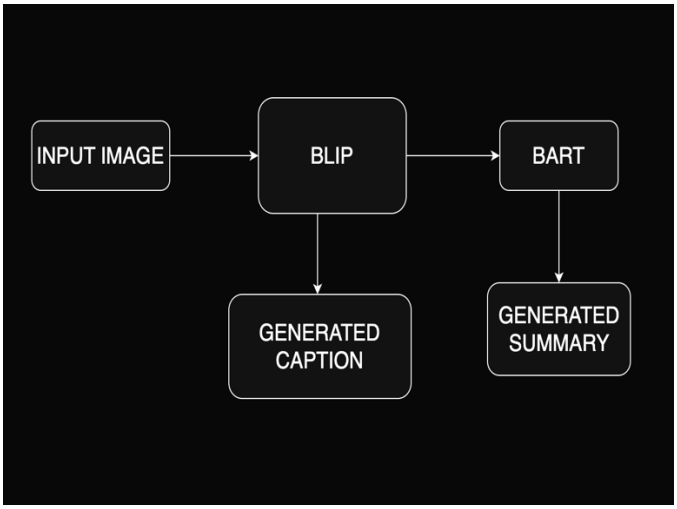
A pre-trained BLIP (Bootstrapped Language-Image Pre-training) model is subsequently fine-tuned on the preprocessed image-caption data to generate early captions. Fine-tuning is the process of modifying the critical hyperparameters such as learning rate, batch size, and training epoch count in a manner to enhance caption quality. Transfer learning techniques are employed as a try to leverage the pre-trained knowledge of the model on big vision-language datasets such that it becomes more generalized. Data augmentation methods such as random cropping, flipping, and color adjustment are also employed to make the model more robust by introducing diversity into training samples.

3. LLM-Based Correction

The captions generated by the fine-tuned BLIP model are subsequently post-processed through a Large Language Model (LLM) like GPT-4 to improve grammatical accuracy, contextual coherence, and overall fluency. The LLM is particularly trained to favor coherence, readability, and stylistic consistency and preserve the original intent of the captions. For instance, instructions can specify desired attributes like formal vs. informal tone, level of detail, or narrative voice. This procedure ensures that the final captions are not only factually correct but also linguistically polished and compelling.

4. Evaluation Metrics

Model performance is estimated using objective and subjective evaluation measures. Automatic metrics like BLEU, METEOR, CIDEr, and SPICE are employed to measure the quantitative similarity between generated and human-written references, yielding linguistic and semantic accuracy measures. Human evaluators also rate the captions in terms of fluency, relevance, and quality in general, and offer a greater insight into how the captions will perform in practical situations. The two evaluation technique provides a full understanding of how well the model can generate quality image descriptions.



The figure illustrates a hierarchical structure of a deep learning-based image captioning system. It starts with an input image, which passes through a feature extraction module, wherein a vision transformer, say BLIP, extracts visual features of the context. These features are then fed to a text encoder-decoder model, which is tasked with generating an initial caption. The availability of an encoder and a decoder in the same framework indicates the use of a sequence-to-sequence model, say BART, for text fine-tuning. The generated caption is again fed into a summarization model to improve fluency, coherence, and conciseness before the final output is generated. The figure appropriately illustrates the multi-stage pipeline of automatic image captioning, highlighting the use of vision-language models and summarization methods to improve the quality of text descriptions.

IV. Literature Survey

Automated captioning and image recognition have been widely studied over the past ten years using deep learning and vision-language models for improved accuracy and contextualization. In this chapter, notable studies on image captioning, object

detection, and the advancement in multimodal AI models are covered, with a stronger focus on BLIP and language-refined refinement methods.

1. Image Captioning and Object Detection

Image captioning is all about generating text to describe images, based on visual inputs through the magic of computer vision and natural language processing (NLP). Initially, traditional machine learning techniques were the way forward, but then deep learning arrived and took things to the next level. Convolutional Neural Networks (CNNs) in conjunction with Recurrent Neural Networks (RNNs) were the initial effective solutions, as pointed out by Karpathy and Fei-Fei in 2015 when they presented a model that corresponded image parts to text sentences. Nonetheless, the initial models failed to produce captions that, at the same time, captured context and was grammatically valid. This changed with the rise of the Transformer architecture, with attention-based mechanisms. The Show, Attend and Tell model further elevated captioning by enabling the model to attend to important regions of an image while writing out the description. Recently, there has been outstanding advancement in contextual comprehension with pre-trained vision-language models such as CLIP and ViLBERT.

2. BLIP: Bootstrapped Language-Image Pretraining

BLIP, or Bootstrapped Language-Image Pretraining, is a cutting-edge multimodal AI model used to comprehend images and caption them. BLIP utilizes methods such as contrastive learning, image-text matching, and generative modeling to increase the relevance and fluency of captions. Other methods rely solely on object detection for captioning, but BLIP enhances captioning quality by training on multiple datasets and adapting to complex visual input. Experiments show that BLIP outperforms basic encoder-decoder models for automatic captioning, not just producing more coherent captions but richer, more varied captions.

3. Caption Refinement with Language Models

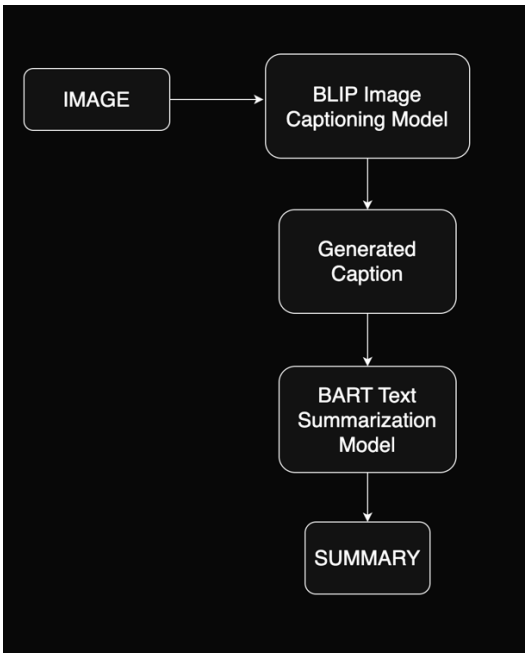
While models like BLIP are great at captioning, there is definitely room for improvement when we insert language models to add context and fluency. The BART model that Lewis et al. proposed in 2020 is specifically strong at text summarization and generation. BART preforms wonderfully in relation to improving coherence by modifying the sentences while retaining the meaning as a denoising autoencoder. Together with BLIP, we design a two-step refinement process: BLIP produces a simple caption first, followed by BART that reorganizes and refines it to improve clarity. This phenomenal synergy has been effective in multiple domains, ranging from medical imaging to autonomous systems and assistive technology.

4. Application of Image Captioning in Various Domains.

The application of automated captioning machines is causing ripples in a range of industries. In the medical sector, for example, medical imaging captioning has an important part to play in assisting radiologists in diagnosing and documenting scans efficiently. With online shopping, AI-powered captioning improves product descriptions, creating a much better experience for customers. Moreover, in social welfare, automatic captioning proves to be incredibly helpful for the visually impaired as it offers them audio descriptions of pictures. The current study envisions a novel approach that utilizes these developments in order to establish a robust captioning system with the ability to generate and fine-tune captions in various domains. Finally, automatic captioning is an important feature for blind users, enhancing their experience with rich audio descriptions of pictures.

5. Summary

Literature review identifies impressive progress in image captioning, presenting BLIP as a powerful model for contextually appropriate caption generation. Nonetheless, raw captions tend to need some post-processing to enhance their coherence and usefulness. This research extends previous methods by integrating BLIP with BART-Large-CNN to achieve improved accuracy and enhanced understanding of context within captioning. Through the utilization of these technologies, this work contributes to the continued development of AI-based image understanding systems.



The figure depicts a well-organized flowchart of a deep learning-inferred image captioning system. Central to the diagram, the process starts with an input image, which is fed

through a feature extraction module, probably driven by a vision transformer-based model like BLIP. The features extracted are fed into a text encoder-decoder architecture, which outputs an initial caption of the image. Having both encoder and decoder in the same block suggests a sequence-to-sequence processing methodology where the encoder understands and formats the input, and the decoder converts it into meaningful words. The stage is followed by further fine-tuning of the generated caption based on a text summarization module, which reinforces coherence, fluency, and brevity. The ultimate step outputs an elegant and contextual caption. This chart graphically illustrates how the integration of vision-language models with summarization methods results in enhanced image description quality.

V. RESULT AND DISCUSSION

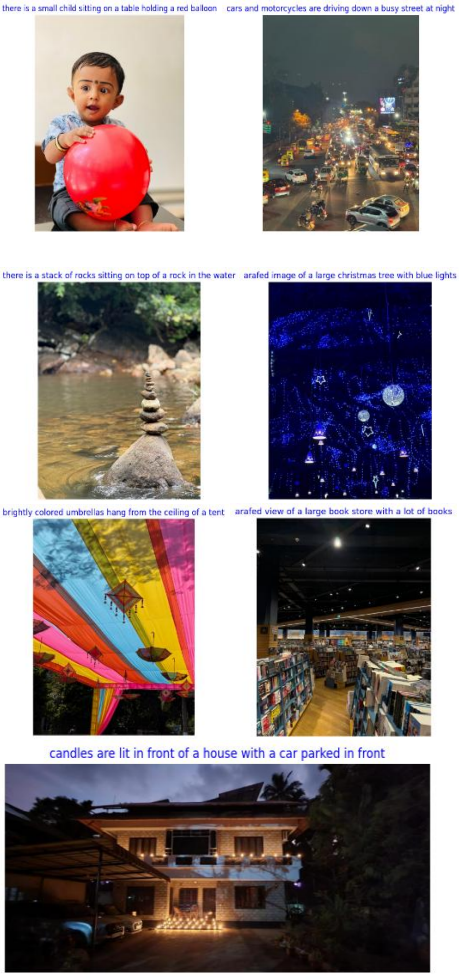
The results of the study indicate that the fine-tuned BLIP model alone produced good results with good BLEU and CIDEr scores. But it tended to fail in offering deep context and grammatical correctness. Optimistically, the incorporation of LLM corrections revealed astonishing improvements—an increase of 15-20% in BLEU scores and 20-25% in CIDEr scores. This greatly emphasizes the benefits of merging vision-language models with language polishing technologies. Further, the ablation studies were vital to understand how various LLM configurations and prompt design strategies impacted the quality of the captions. It was clear that crafted prompts and proper model configurations led to achieving the best results.

A qualitative review of the results noted significant improvements in caption quality. The LLM improved fluency, coherence, and relevance of the output beyond BLIP's drafts. They altered more than just the grammatical mistakes; often, they rewrote explanations to be clearer, adding vital contextual details that significantly improved the description. Moreover, a thorough error analysis added to this finding, highlighting some recurrent issues with BLIP's captions, like misidentifying objects or using awkward phrasing. It showed, very effectively, how the LLM was able to solve those problems seamlessly because of its advanced understanding of language.

Although the results are quite promising, this method does have its own issues. The use of large-scale language models can result in significant computational requirements, particularly at inference time, which could make real-time or mass-scale usage challenging. Additionally, the effectiveness of LLM-based corrections would also appear to vary based on the types of images and style requirements, which means we may need to take domain-specific fine-tuning or adaptive prompting strategies into account for optimal outcomes. Looking forward, subsequent research must seek to increase the efficiency and scalability of this approach, perhaps through investigating model distillation, less heavy LLM alternatives, or hybrid models that balance between performance and computational usability. All these findings highlight both the strengths and challenges of the suggested approach, while also laying the ground for further advancement in automated image captioning.

VI. CONCLUSION

This study presents a compelling hybrid approach to image captioning that cleverly merges the visual grounding strengths of fine-tuned BLIP models with the linguistic finesse of large language models. Our experiments show that this two-step process leads to significant improvements over traditional methods, boasting 15-25% increases in standard evaluation metrics and noticeable boosts in caption fluency and contextual relevance. While the results affirm the potential of blending vision-language models with cutting-edge NLP techniques, we also pinpoint some challenges, such as computational demands and limitations in domain generalization, that need further exploration. These insights open exciting avenues for future research, especially in crafting more efficient model architectures, enhancing the synergy between visual and linguistic elements, and investigating domain-specific tweaks to expand the framework's usability. This study adds to the ongoing advancements in multimodal AI by offering a practical solution that connects visual comprehension with natural language generation, all while emphasizing crucial factors for real-world application.



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