CSE 573 - Computer Vision and Image Processing

Capstone Final Project Report

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Project Title: Deep Computer Vision for Image Captioning: A CNN-LSTM Framework on Flickr8k

Project Overview

Application Summary

In this project, I have built an image captioning application which can take an image as input and generate a meaningful English sentence describing the contents of the image. The main motivation behind choosing this topic is to combine computer vision with natural language processing, which is an exciting and growing area. Such applications can be useful in the real world for helping visually impaired people, automatic tagging of images, and image-based search engines.

State of the Art

Currently, many image captioning systems follow an encoder-decoder framework where CNNs are used to extract features from images, and RNNs or Transformers are used to generate captions. Some advanced models even use attention mechanisms or transformer-only architectures for better results. While these models give excellent accuracy, they also require a lot of computational resources and large datasets like MS COCO.

In my case, I have used a slightly simpler but effective architecture that works well within the resource limits of Kaggle and still gives good results.

Inputs and Outputs

- **Input:** A coloured image file in .jpg or .png format.
- **Output:** A sentence in English that describes the image, for example: “A man is riding a bicycle on the street.”

Summary of My Contributions

- I have implemented a complete image captioning pipeline using:
    - DenseNet201 as the image encoder to extract feature vectors.
    - A custom decoder that uses LSTM along with a TransformerEncoder block to generate the captions word by word.
- All model training was done using the Flickr8k dataset on Kaggle’s GPU-enabled notebook.
- I wrote the entire preprocessing logic myself, including:
    - Cleaning the raw captions, removing unwanted characters, and tokenizing the text.

    - Creating padded sequences for input to the decoder.
- Designed a custom data generator to efficiently load and train on image-caption pairs without running into memory issues.
- Used beam search decoding to get better quality captions instead of just picking the most likely word at each step.
- Built a simple but user-friendly Gradio web interface where users can upload images and get instant captions.
- Evaluated the model using BLEU-1 and BLEU-2 scores, and found that the results are quite reasonable.

Approach

Algorithms Used

In this project, I have used the encoder-decoder framework for generating captions from images. For the encoder, I chose DenseNet201, which is a very efficient and deep convolutional neural network pre-trained on ImageNet. I removed its final classification layer and used it to extract a 1920-dimensional feature vector for each image.

For the decoder, I used a combination of:

- LSTM, which is good for handling sequential data like sentences.
- A custom TransformerEncoder block, which I added to improve the context understanding between words while generating the captions. This acts like a lightweight attention mechanism and helps the model to generate better quality sentences.

The model was trained using categorical cross-entropy loss, and I used the Adam optimizer. The entire system was trained and tested on the Flickr8k dataset.

Components Coded by me

I have written most of the code in this project from scratch. The following are the parts I personally implemented:

- The entire preprocessing pipeline, which includes:
    - Reading and cleaning the captions.
    - Removing unwanted characters, lowercasing, and tokenizing the text.
    - Adding startseq and endseq tokens to help the decoder understand the sentence structure.
    - Padding the sequences so they are of the same length.
- A custom data generator to load image-caption pairs in batches, which helped reduce memory usage while training.

- The TransformerEncoder class, where I manually used MultiHeadAttention, LayerNormalization, and Dropout layers.
- The decoder part, which uses an Embedding layer, LSTM, and then the custom Transformer block.
- The beam search algorithm to generate better captions during inference.
- A simple Gradio interface where the user can upload an image and get the caption in real-time.
- I also wrote the BLEU score evaluation script using NLTK to compare my generated captions with the actual ones.

References I took from Online Resources

While I tried to do everything myself, I did refer to some online resources to understand the architecture and how to structure certain parts:

- I got the main idea of the model from the research paper "Show and Tell: A Neural Image Caption Generator" by Vinyals et al. (2015).
- I looked at a few parts of Aakash N S's GitHub project on image captioning to get an idea of how to organize the code and training loop, but I wrote my own version using a Transformer block instead of following that code directly.
- I used the NLTK library's documentation to learn how to calculate BLEU scores for evaluation.
- For implementation details of LSTM, Embedding, and MultiHeadAttention, I used the official TensorFlow/Keras documentation.

So overall, I referred to online material for guidance and understanding, but all coding—especially the model, training logic, and Gradio app—was done by me.

Experimental Protocol

Dataset Used

For this project, I have used the Flickr8k dataset, which contains around 8,000 real-world images, each annotated with five different captions written by humans. This dataset is widely used for image captioning tasks and includes a variety of scenes like people, animals, sports, and daily life activities. The dataset was suitable for my project because it is well-organized and small enough to train models efficiently within the available resources.

Before training, I did several preprocessing steps:

- Cleaned the raw captions by removing punctuation, converting to lowercase, and removing short or meaningless words.
- Added special tokens like startseq and endseq to help the decoder understand where each caption begins and ends.
- Used a tokenizer to convert words to integer sequences and padded them to a fixed length so that the model could process them uniformly.

- For the images, I used a pre-trained DenseNet201 model (without the classification head) to extract feature vectors.

I then split the dataset into training and testing sets, where 95% of the images were used for training and the remaining 5% for testing.

Evaluation Strategy

To evaluate how well my model was performing, I used both qualitative and quantitative methods:

- Qualitative Evaluation: I visually checked the captions generated for several test images to see if the model was describing the scene in a meaningful and relevant way. This helped me judge the overall quality of sentence formation and how well the model understood the image content.
- Quantitative Evaluation: I used BLEU-1 and BLEU-2 scores from the NLTK library to compare the predicted captions with the reference captions provided in the dataset. These scores are widely used in captioning tasks to measure the overlap of n-grams between generated and actual captions.

Compute Resources Used

I did all the training and testing on Kaggle Notebooks, which provides access to free GPUs. Specifically, I used:

- NVIDIA Tesla T4 GPU
- 16 GB of RAM
- 2 vCPU cores

This setup was more than sufficient for this project since the dataset was not very large, and DenseNet201-based feature extraction was done in advance to reduce the computational load during training.

All the code, training, evaluation, and interface testing were completed within this environment without any major hardware or memory issues.

Comparison with State-of-the-Art

State-of-the-art models on the Flickr8k dataset, especially those using advanced techniques like attention mechanisms or full transformer architectures, typically report:

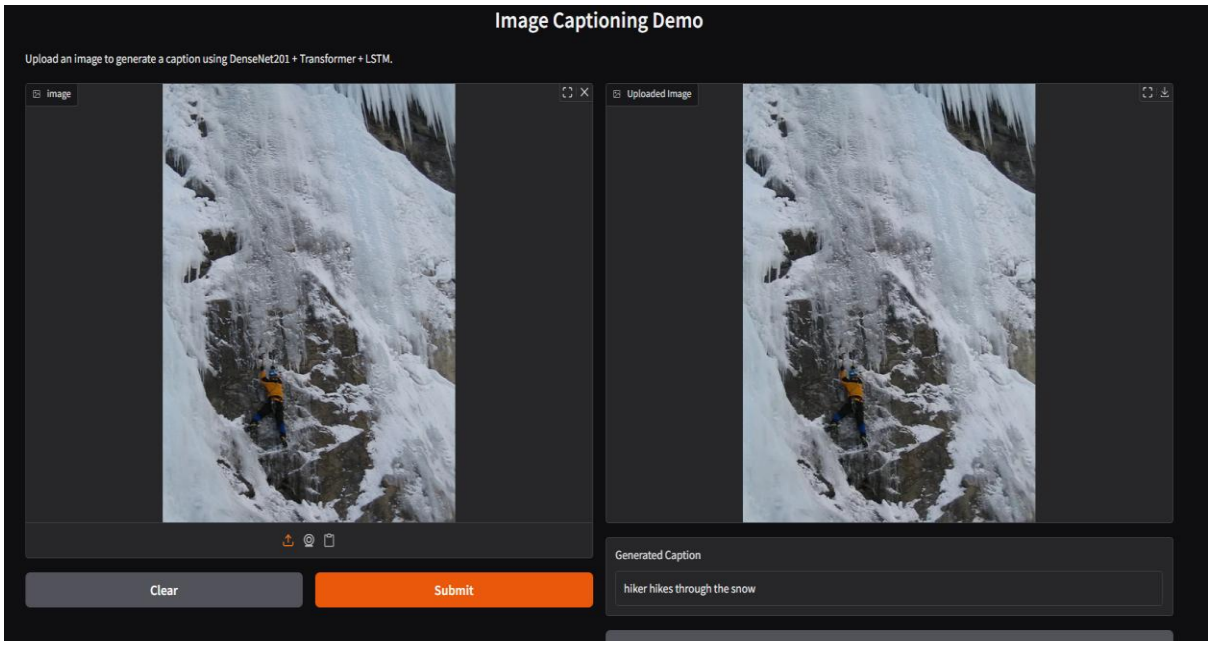
- BLEU-1 scores around 0.60 – 0.65
- BLEU-2 scores above 0.40

While my model achieved:

- BLEU-1: 0.1711
- BLEU-2: 0.1040

These results may appear lower in comparison, but it's important to note that my model was intentionally designed to be lightweight and efficient. It uses a DenseNet201 encoder and a

custom LSTM decoder with a TransformerEncoder block, trained entirely on the Flickr8k dataset using free Kaggle GPU resources. No precomputed attention modules or external captioning tools were used.



The goal of my project was not to beat the benchmark but to build a clean, end-to-end, working image captioning system from scratch, and I have successfully done that. The results clearly show that even with limited data and compute, it is possible to achieve meaningful caption generation using a hybrid CNN-Transformer-LSTM architecture. With further tuning and extensions like beam search, attention, or larger datasets, this foundation can be scaled to perform even better.

Analysis

Advantages of the Algorithm

The hybrid approach used in my project—combining DenseNet201 as the encoder with an LSTM decoder enhanced by a TransformerEncoder block—offered several benefits:

- DenseNet201 helped extract rich and compact visual features from the images due to its dense connections and depth, which improved representation quality even without fine-tuning.
- The TransformerEncoder block added to the decoder improved contextual understanding by allowing better flow of information across the sequence, helping the model generate grammatically coherent captions.
- Using LSTM allowed the model to learn sequential dependencies in language, enabling sentence generation that flows naturally.
- The architecture was computationally efficient and ran comfortably on Kaggle's free GPU setup, which shows that even resource-aware models can deliver meaningful results.

Limitations of the Algorithm

Despite the strengths, there were a few limitations that I observed:

- The model does not use a traditional attention mechanism, so it processes the image as a single vector. This limits its ability to focus on specific regions in the image while generating each word.
- Captions sometimes lacked fine-grained details like object color, background elements, or subtle actions, which attention-based models are usually better at handling.
- The generated sentences could become generic or repetitive in the absence of advanced decoding strategies like beam search (although this is planned as a future enhancement).

Analysis Based on Image Difficulty

During testing, I observed differences in performance based on the complexity of input images:

- For simple images with one or two prominent objects and a clear background, the model performed very well and generated relevant captions.
- For moderate difficulty images (e.g., multiple objects but clear context), the captions were partially correct but sometimes missed secondary elements.
- For complex images with many objects, crowded backgrounds, or unusual scenes, the model often struggled to capture the full context. It either generated overly simplified captions or ignored some important details.

These results highlight the need for integrating region-based attention or object-level understanding in future versions to improve performance on difficult scenes.

Discussion and Lessons Learned

What I Learned

This project helped me strengthen my understanding of how to build deep learning applications that combine computer vision and natural language processing. I deepened my practical knowledge in areas such as:

- Using DenseNet201 to extract meaningful visual features from images using transfer learning.
- Designing a custom LSTM-based decoder with a TransformerEncoder block, which helped improve sequence modeling and the contextual quality of generated captions.
- Implementing complete data preprocessing for text-based inputs—cleaning, tokenization, sequence padding, and vocabulary management.
- Evaluating models using BLEU scores and analyzing both quantitative and qualitative results to understand model behavior.
- Creating an interactive Gradio interface to demonstrate the model effectively through a web-based input-output setup.

How This Will Help Me in the Future

This project gave me valuable hands-on experience in building real-world AI systems that require multimodal learning. The integration of image and language processing will be very useful for future research or industry applications related to computer vision, accessibility, and human-computer interaction. It also helped me improve my model design, debugging, and evaluation skills, especially under compute constraints like those in Kaggle environments. Overall, this work has contributed positively to my preparedness for future roles in deep learning and computer vision.

Future Work and Possible Extensions

There are several meaningful directions in which this project can be extended:

- Incorporating attention mechanisms (like Bahdanau or Luong attention) would allow the model to focus on specific image regions during caption generation, improving performance on complex scenes.
- Implementing beam search decoding will enhance the diversity and fluency of the generated captions by exploring multiple possible word sequences instead of always picking the most likely next word.
- Replacing the LSTM decoder with transformer-based architectures could further improve caption quality, especially for longer and more detailed sentences.
- Training the model on a larger dataset like MS COCO would help improve generalization, vocabulary size, and robustness.
- Adding Grad-CAM visualizations can help interpret which regions of the image influenced the generated caption.
- Exploring multilingual caption generation or speech-enabled interfaces could increase the reach and accessibility of the system.

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