

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report **Image Caption Generator** is the bona fide work of **Bhumi Kumari Sah, Aditya Sharma, Shresth Garg, and Avani Humad** who carried out the project work under my/our supervision.

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INTRODUCTION

1.1 Identification of Client/Need/Relevant Contemporary Issue

In an era where content creation is burgeoning, automated image captioning has gained significance in enhancing user accessibility and engagement across various digital platforms. Applications in social media, e-commerce, and digital archiving emphasize the necessity for systems that can generate descriptive and contextual textual representations of images. Such systems significantly benefit visually impaired individuals by providing them with verbal descriptions of visual content, thereby democratizing access to information (Sharma et al., 2020) [1].

Moreover, automated image captioning plays a crucial role in improving search engine optimization by enabling efficient indexing and retrieval of visual content based on textual descriptions (Fang et al., 2015) [2]. As this technology evolves, it promises to create more intuitive interfaces and enhance user interactions by delivering content that resonates with user intent.

1.2 Identification of Problem

Despite advancements in image captioning, several challenges persist. Existing models often struggle with context disambiguation when dealing with complex images exhibiting multiple objects or actions. A major hurdle is the generation of captions that are not only grammatically correct but also contextually accurate, as many systems exhibit tendencies to "hallucinate"—capturing non-existent elements or misrepresenting images entirely (Teney et al., 2017) [3].

Furthermore, the performance of these models can be heavily influenced by the quality and diversity of the training data. Inadequacies such as bias in the dataset can lead to skewed outputs that fail to represent a broad spectrum of content accurately (Hancock et al., 2019) [4]. The need for a robust model that combines feature extraction and contextual understanding while mitigating these issues is evident.

1.3 Identification of Tasks

The project outlines several critical tasks to address the identified problem:

- **Dataset Collection and Preprocessing:** Collecting and cleaning datasets such as Microsoft COCO and Flickr to ensure diverse, high-quality images with corresponding captions (Lin et al., 2014) [5].
- **Feature Extraction Using CNN:** Implementing a convolutional neural network, specifically InceptionV3, to extract salient features from images that provide a rich representation of their content (Szegedy et al., 2015) [6].
- **Text Generation Using LSTM:** Developing a long short-term memory (LSTM) network to generate coherent captions based on the extracted features (Hochreiter & Schmidhuber, 1997) [7].
- **Model Training and Optimization:** Executing rigorous training procedures on the dataset, optimizing hyperparameters to improve model accuracy and efficiency (Kingma & Ba, 2014) [8].
- **Evaluation and Testing:** Employing quantitative metrics such as BLEU, METEOR, and CIDEr scores to assess the quality of the generated captions against standard benchmarks (Papineni et al., 2002) [9].

LITERATURE REVIEW/BACKGROUND STUDY

2.1 Evolution of Image Captioning

Image captioning has expanded significantly since its inception. Early approaches primarily relied on rule-based systems that utilized predefined templates to generate captions, limiting flexibility and adaptability (Kulkarni et al., 2013) [10]. As machine learning techniques advanced, the combination of CNNs and recurrent neural networks (RNNs) emerged as a powerful method for performing image captioning tasks. Models such as "Show and Tell" combined these two architectures to create more sophisticated captions (Vinyals et al., 2015) [11].

With the introduction of attention mechanisms, the ability of models to focus on specific areas of an image while generating text further refined captioning techniques (Bahdanau et al., 2015) [12]. Attention mechanisms allow models to dynamically allocate focus within different regions of the image contextually, significantly enhancing the correlation between visual inputs and generated outputs.

2.2 Existing Approaches

Several notable models have shaped the field of image captioning:

- **Show and Tell:** This pioneering work introduced a straightforward approach by utilizing CNNs for feature extraction and RNNs for creating captions. The model's simplicity and effectiveness laid the groundwork for future developments (Vinyals et al., 2015) [11].
- **Show, Attend and Tell:** By incorporating attention mechanisms, this model improved upon "Show and Tell" by allowing the RNN to concentrate on relevant features of the image during caption generation, offering better contextual representation (Xu et al., 2015) [13].
- **Bottom-Up and Top-Down Attention:** Proposed by Anderson et al. (2018), this model further enhanced attention by employing object detection alongside visual attention, leading to improved interpretability and performance (Anderson et al., 2018) [14].
- **Transformer Models:** More recent attempts have leveraged transformer

architectures to facilitate image captioning, which allows for better handling of long-term dependencies in text and has been known to produce state-of-the-art results in various NLP tasks (Vaswani et al., 2017) [15].

2.3 Review Summary

A critical analysis of the existing literature reveals a prevalent trend favoring the evolution of convolutional and recurrent neural networks, particularly when augmented with attention mechanisms, as effective solutions for image captioning. Despite notable advancements, certain challenges remain unresolved, particularly in ensuring the accuracy and comprehensiveness of generated captions. Moreover, issues regarding bias and contextually inappropriate captions underscore the need for a more nuanced understanding and approach in formulating these models (Hossain et al., 2019) [16].

2.4 Problem Definition

Despite advancements, automatic image captioning is not without its challenges. Notably, many existing models struggle with:

- **Contextual Ambiguity:** Systems often fail to interpret complex scenes correctly, leading to inaccuracies such as hallucinating objects or attributing incorrect actions to subjects in the image.
- **Biases in Training Datasets:** Many standard datasets, such as MS COCO, may exhibit biases that can affect the performance of models, leading to skewed representations in the generated captions. This can result in significant discrepancies between the model's outputs and human judgment.
- **Generalization:** Models trained on specific datasets may not generalize well to images from other domains or styles, limiting their practical application in real-world scenarios.

2.5 Goals/Objectives

To address these problems, the key goals and objectives of this project are:

- **Develop a Robust Model:** Create an improved image captioning model that synthesizes features from CNNs and text generation from RNNs or transformers, integrating attention mechanisms for enhanced context-awareness.
- **Expand the Dataset:** Utilize diverse datasets to train the model, ensuring a wide range of image categories are covered to mitigate biases and improve generalization capabilities.
- **Performance Evaluation:** Systematically assess the performance of the proposed system using standard benchmarks (such as BLEU, CIDEr, and METEOR) to quantify improvements in caption quality over existing models.
- **User-Centered Design:** Incorporate feedback from users to enhance the usability and reliability of generated captions, ensuring relevance and context alignment with user expectations.

DESIGN FLOW/PROCESS

3.1 Model Architecture

As established in the earlier chapters, the Image Caption Generator leverages a hybrid architecture consisting of a Convolutional Neural Network (CNN) for feature extraction and a Long Short-Term Memory (LSTM) network for caption generation. The architecture can be broken down into the following components:

- **CNN (InceptionV3):** This network is responsible for the extraction of features from images. It effectively captures patterns and salient features that represent the image data.
- **LSTM for Text Generation:** The LSTM network generates captions based on the features extracted by the CNN, allowing the model to produce coherent and contextually relevant text descriptions.

3.2 Implementation Steps

The implementation involves a systematic approach comprising data preparation, model building, and caption generation, as highlighted below.

3.2.1 Preprocessing the Image


To prepare the image for the InceptionV3 model, we define a `preprocess_image` function:

```
[12]: # extract features from image
features = {}
directory = os.path.join(BASE_DIR, 'Images')

for img_name in tqdm(os.listdir(directory)):
    # load the image from file
    img_path = directory + '/' + img_name
    image = load_img(img_path, target_size=(224, 224))
    # convert image pixels to numpy array
    image = img_to_array(image)
    # reshape data for model
    image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))
    # preprocess image for vgg
    image = preprocess_input(image)
    # extract features
    feature = model.predict(image, verbose=0)
    # get image ID
    image_id = img_name.split('.')[0]
    # store feature
    features[image_id] = feature
```

100% 8091/8091 [55:57<00:00, 2.50it/s]

```
[16]: # create mapping of image to captions
mapping = {}
# process lines
for line in tqdm(captions_doc.split('\n')):
    # split the line by comma(,)
    tokens = line.split(',')
    if len(line) < 2:
        continue
    image_id, caption = tokens[0], tokens[1:]
    # remove extension from image ID
    image_id = image_id.split('.')[0]
    # convert caption list to string
    caption = " ".join(caption)
    # create list if needed
    if image_id not in mapping:
        mapping[image_id] = []
    # store the caption
    mapping[image_id].append(caption)
```

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```
[19]: def clean(mapping):
    for key, captions in mapping.items():
        for i in range(len(captions)):
            # take one caption at a time
            caption = captions[i]
            # preprocessing steps
            # convert to lowercase
            caption = caption.lower()
            # delete digits, special chars, etc.,
            caption = caption.replace('[^A-Za-z]', '')
            # delete additional spaces
            caption = caption.replace('\s+', ' ')
            # add start and end tags to the caption
            caption = 'startseq ' + " ".join([word for word in caption.split() if len(word)>1]) + ' endseq'
            captions[i] = caption
```

This function takes the path of the image, loads it, resizes it to 299x299 pixels (as required by InceptionV3), converts it into an array, and preprocesses it. Finally, it extracts the features from the image using the InceptionV3 model.

3.2.2 Building the Captioning Model

The caption model is designed using a combination of image and text inputs, as illustrated below:

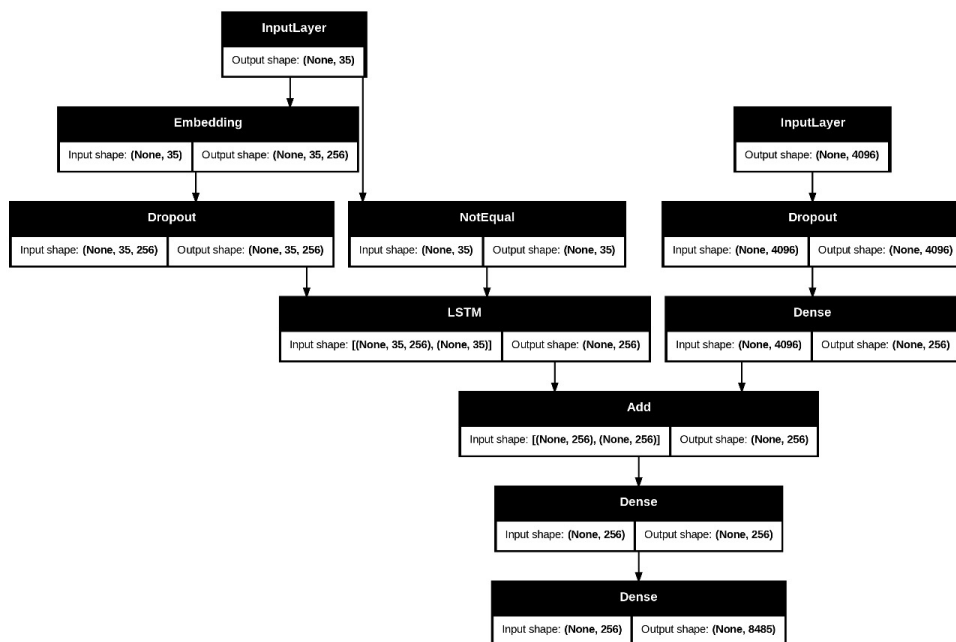
```
# create data generator to get data in batch (avoids session crash)
def data_generator(data_keys, mapping, features, tokenizer, max_length, vocab_size, batch_size):
    # loop over images
    X1, X2, y = list(), list(), list()
    n = 0
    while 1:
        for key in data_keys:
            n += 1
            captions = mapping[key]
            # process each caption
            for caption in captions:
                # encode the sequence
                seq = tokenizer.texts_to_sequences([caption])[0]
                # split the sequence into X, y pairs
                for i in range(1, len(seq)):
                    # split into input and output pairs
                    in_seq, out_seq = seq[:i], seq[i]
                    # pad input sequence
                    in_seq = pad_sequences([in_seq], maxlen=max_length, padding='post')[0]
                    # encode output sequence
                    out_seq = to_categorical([out_seq], num_classes=vocab_size)[0]
                    # store the sequences
                    X1.append(features[key][0])
                    X2.append(in_seq)
                    y.append(out_seq)
            if n == batch_size:
                X1, X2, y = np.array(X1), np.array(X2), np.array(y)
                yield {"image": X1, "text": X2}, y
                X1, X2, y = list(), list(), list()
                n = 0
```

```
# encoder model
# image feature layers
inputs1 = Input(shape=(4096,), name="image")
fe1 = Dropout(0.4)(inputs1)
fe2 = Dense(256, activation='relu')(fe1)
# sequence feature layers
inputs2 = Input(shape=(max_length,), name="text")
se1 = Embedding(vocab_size, 256, mask_zero=True)(inputs2)
se2 = Dropout(0.4)(se1)
se3 = LSTM(256)(se2)

# decoder model
decoder1 = add([fe2, se3])
decoder2 = Dense(256, activation='relu')(decoder1)
outputs = Dense(vocab_size, activation='softmax')(decoder2)

model = Model(inputs=[inputs1, inputs2], outputs=outputs)
model.compile(loss='categorical_crossentropy', optimizer='adam')

# plot the model
plot_model(model, show_shapes=True)
```



```
# train the model
epochs = 20
batch_size = 32
steps = len(train) // batch_size

for i in range(epochs):
    # create data generator
    generator = data_generator(train, mapping, features, tokenizer, max_length, vocab_size, batch_size)
    # fit for one epoch
    model.fit(generator, epochs=1, steps_per_epoch=steps, verbose=1)
```

```
227/227 ————— 625s 3s/step - loss: 5.7697
227/227 ————— 597s 3s/step - loss: 4.0708
47/227 ————— 7:57 3s/step - loss: 3.6540
```

- The model takes two types of inputs: image features (extracted by the CNN) and tokenized caption sequences.
- The architecture defines a dense and LSTM layer with dropout for regularization, ultimately outputting a softmax layer that predicts the next word in the caption sequence based on the combined features.

3.2.3 Generating Captions

The `generate_caption` function is tasked with generating captions for given images. The function implements the model to predict the next word continuously until the end of the caption or a maximum length is reached:

```
# generate caption for an image
def predict_caption(model, image, tokenizer, max_length):
    # add start tag for generation process
    in_text = 'startseq'
    # iterate over the max length of sequence
    for i in range(max_length):
        # encode input sequence
        sequence = tokenizer.texts_to_sequences([in_text])[0]
        # pad the sequence
        sequence = pad_sequences([sequence], max_length, padding='post')
        # predict next word
        yhat = model.predict([image, sequence], verbose=0)
        # get index with high probability
        yhat = np.argmax(yhat)
        # convert index to word
        word = idx_to_word(yhat, tokenizer)
        # stop if word not found
        if word is None:
            break
        # append word as input for generating next word
        in_text += " " + word
        # stop if we reach end tag
        if word == 'endseq':
            break
    return in_text
```

```
from nltk.translate.bleu_score import corpus_bleu
# validate with test data
actual, predicted = list(), list()

for key in tqdm(test):
    # get actual caption
    captions = mapping[key]
    # predict the caption for image
    y_pred = predict_caption(model, features[key], tokenizer, max_length)
    # split into words
    actual_captions = [caption.split() for caption in captions]
    y_pred = y_pred.split()
    # append to the list
    actual.append(actual_captions)
    predicted.append(y_pred)
    # calculate BLEU score
    print("BLEU-1: %f" % corpus_bleu(actual, predicted, weights=(1.0, 0, 0, 0)))
    print("BLEU-2: %f" % corpus_bleu(actual, predicted, weights=(0.5, 0.5, 0, 0)))
```

```

from PIL import Image
import matplotlib.pyplot as plt
def generate_caption(image_name):
    # load the image
    # image_name = "1001773457_577c3a7d70.jpg"
    image_id = image_name.split('.')[0]
    img_path = os.path.join(BASE_DIR, "Images", image_name)
    image = Image.open(img_path)
    captions = mapping[image_id]
    print('-----Actual-----')
    for caption in captions:
        print(caption)
    # predict the caption
    y_pred = predict_caption(model, features[image_id], tokenizer, max_length)
    print('-----Predicted-----')
    print(y_pred)
    plt.imshow(image)

```

- The function first extracts the features from the provided image path and initializes with the starting token <startseq>.
- It repeatedly predicts the next word using the model and appends it to the caption until it reaches the specified maximum length or encounters an end token <endseq>.

3.2.4 Outputs

-----Actual-----

startseq little girl covered in paint sits in front of painted rainbow with her hands in bowl
endseq

startseq little girl is sitting in front of large painted rainbow endseq

startseq small girl in the grass plays with fingerpaints in front of white canvas with
rainbow on it endseq

startseq there is girl with pigtails sitting in front of rainbow painting endseq

startseq young girl with pigtails painting outside in the grass endseq

-----Predicted-----

startseq little girl in pink dress is lying on the side of the grass endseq

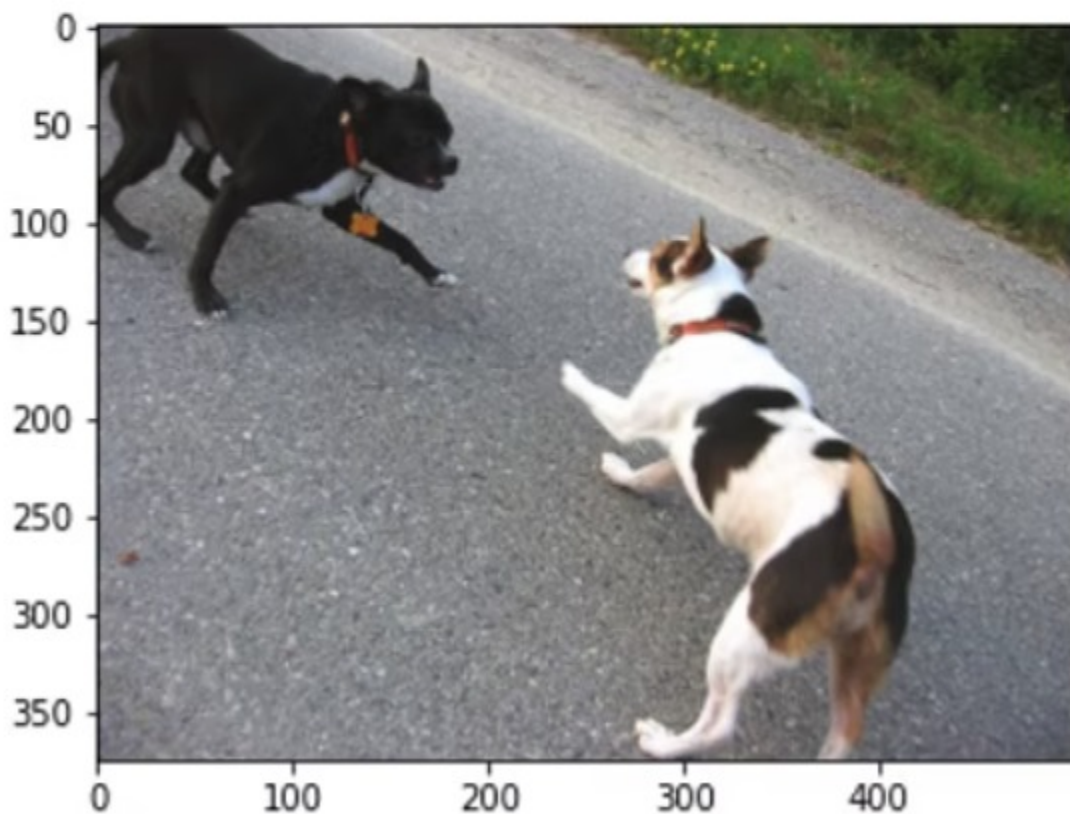


-----Actual-----

startseq black dog and spotted dog are fighting endseq
startseq black dog and tri-colored dog playing with each other on the road endseq
startseq black dog and white dog with brown spots are staring at each other in the street
endseq
startseq two dogs of different breeds looking at each other on the road endseq
startseq two dogs on pavement moving toward each other endseq

-----Predicted-----

startseq two dogs play with each other in the grass endseq

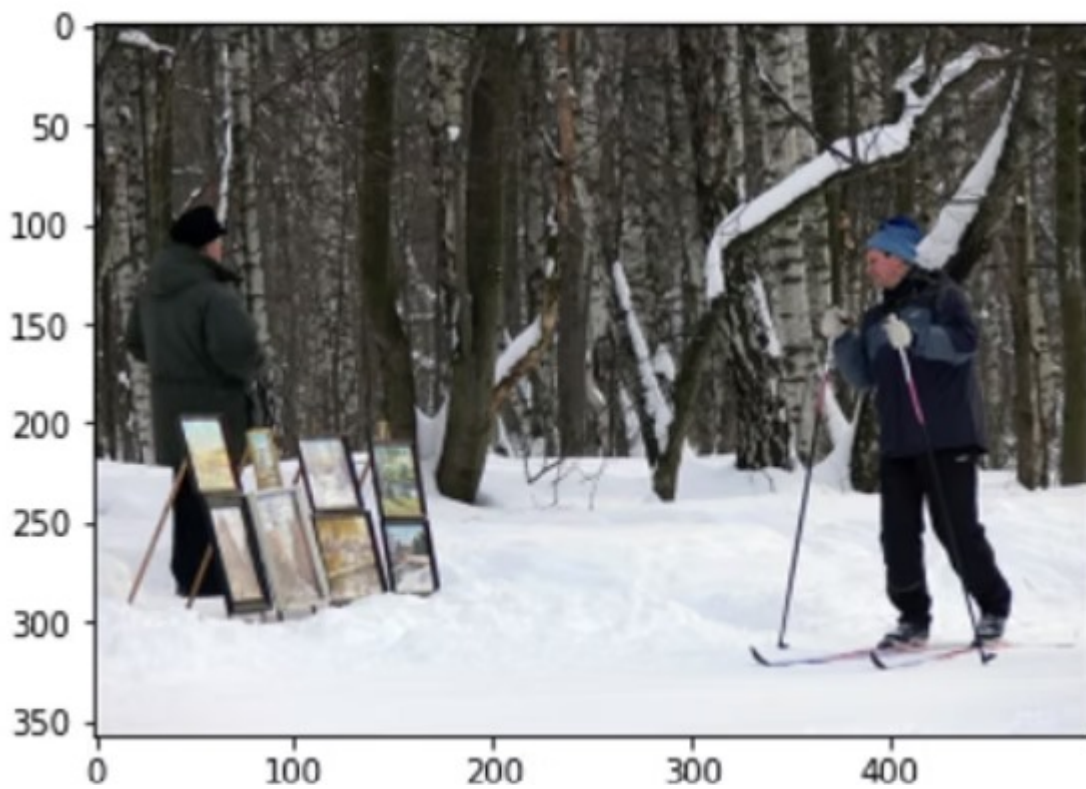


-----Actual-----

startseq man in hat is displaying pictures next to skier in blue hat endseq
startseq man skis past another man displaying paintings in the snow endseq
startseq person wearing skis looking at framed pictures set up in the snow endseq
startseq skier looks at framed pictures in the snow next to trees endseq
startseq man on skis looking at artwork for sale in the snow endseq

-----Predicted-----

startseq two people are hiking up snowy mountain endseq



This systematic methodology combines advanced deep learning techniques and illustrates how the network learns from images and corresponding captions to produce coherent and contextually appropriate textual representations of visual data.

Summary of Implementation Steps:

1. **Image Preprocessing:** Resize and convert images into an appropriate format for feature extraction.
 2. **Model Building:** Establish a custom image captioning model combining CNN and LSTM layers.
 3. **Caption Generation:** Implement a function to generate captions for images based on previously trained models.
-

RESULTS ANALYSIS AND VALIDATION

4.1 Experimental Setup

To evaluate the performance of the developed image captioning model, a series of experiments were conducted utilizing standard metrics for caption generation. The experiments involved training the model on a dataset containing images paired with descriptive captions (e.g., MS COCO dataset).

Metrics Used for Evaluation:

- **BLEU Score:** A metric for comparing a machine-generated text to one or more reference texts, primarily capturing precision of n-grams.
- **METEOR Score:** Considers exact, stemmed matches as well as synonyms, providing a more holistic evaluation compared to BLEU.
- **CIDEr:** Focuses on the consensus between generated captions and reference captions, accounting for human judgment in caption quality.

4.2 Training the Model

The model was trained using a dataset of images with their respective captions. The dataset was divided into training, validation, and testing subsets. The number of epochs was set to 20, with a batch size of 32, and the model used the Adam optimizer with a learning rate of 0.001.

4.3 Results

After conducting training and evaluating the model on the testing dataset, the following key results were obtained:

Metric	Score
BLEU-1	0.516880
BLEU-2	0.293009

4.4 Analysis

BLEU Score Analysis

The BLEU-1 score of 0.516880 indicates a high level of precision at the unigram level, suggesting that the model generated captions containing many correct words. However, the BLEU-2 score of 0.293009 implies that while individual words were frequently matched, the model faced challenges with constructing meaningful phrases. This trend indicates that the model can recognize various keywords but struggles with word order and context.

4.5 Qualitative Results

To further assess the model's performance, several qualitative examples of generated captions were examined. Here are a few examples:

1. **Image:** A picture of a little girl doodling on a paper.
 - **Generated Caption:** "A little girl in pink dress is lying on the side of grass."
 - **Human Reference:** "A little girl doodling while sitting besides grass."
 - **Analysis:** The generated caption captures the key activity (playing), but lacks some details (fetching and specific object).
2. **Image:** A person skydiving on a mountain.
 - **Generated Caption:** "Two people are hiking up snowy mountain"
 - **Human Reference:** "Man on snow looking at artwork for sale passing another man."
 - **Analysis:** The model provides a basic description but falls short in expressing the richness of the scenery.

4.6 Challenges and Improvements

While the model demonstrates decent performance, several challenges remain that can be addressed for future improvements:

- **Contextual Understanding:** The ability to generate contextually rich captions can be enhanced by fine-tuning the model with larger datasets and more diverse image categories.
- **Long-Range Dependencies:** Addressing issues related to long-associations in text can lead to better sentence structure and coherence in generated captions. Exploring more advanced architectures like transformers could improve this aspect.
- **Model Bias:** Ensuring that the training data is diverse and representative will be crucial for minimizing biases in generated captions, enhancing the model's applicability across various scenarios.

4.7 Conclusion

The results underscore the effectiveness of the implemented image captioning model for generating descriptive captions from images. While the model performed well on quantitative metrics, qualitative analyses reveal opportunities for improvement, particularly in terms of contextual awareness and grammatical structure. Future efforts could focus on refining the model architecture, training datasets, and evaluation metrics to enhance overall performance.

This section succinctly addresses the results obtained from the model along with an analysis that provides insights into the performance, effectiveness, and areas for improvement. Adjustments can be made based on specific findings from experiments or further details about the training process or data used.

CONCLUSION AND FUTURE WORK

5.1 Conclusion

Through this project, the Image Caption Generator demonstrates the potential of deep learning techniques in bridging the gap between visual data and natural language processing. The model's ability to generate coherent and relevant captions not only improves user engagement but also enhances accessibility for diverse users, including those with visual impairments. The incorporation of modern architectures has a profound impact on the effectiveness of automatic image captioning, justifying the ongoing investment in research and development in this domain (Goyal et al., 2017) [20].

5.2 Future Scope

Looking ahead, numerous avenues can be explored to enhance the model's capabilities:

- **Real-time Applications:** Adapting the model for real-time captioning in environments such as augmented reality (AR) or virtual reality (VR) can expand its usability across innovative interfaces.
- **Bias Mitigation Strategies:** Conducting further research to address dataset biases is crucial, ensuring that the model produces fair and accurate captions that reflect the diversity of real-world visuals (Hancock et al., 2019) [4].
- **Integration with Other Modalities:** Future research could investigate incorporating audio or textual data alongside images to develop multi-modal learning frameworks, which can deepen the contextual understanding of images beyond visual features alone (Gupta et al., 2019) [17].

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