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Image Captioning Project on Medical Images (X-Rays)

Submitted by

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ABSTRACT

This project explores the development of an automatic image captioning system that combines natural language processing (NLP) and deep learning techniques. The goal is to generate descriptive captions for a diverse set of images. The dataset includes image caption pairs, and preprocessing involved standardizing text to lowercase, removing URLs and special characters, and applying stemming and lemmatization. For images, preprocessing included resizing and converting to tensors.

The data was divided into training, validation, and test sets to enable thorough evaluation and tuning. The image captioning model integrates Convolutional Neural Networks (CNNs) for extracting image features with Recurrent Neural Networks (RNNs) for processing text sequences. Specifically, a pretrained InceptionV3 model was used for feature extraction from images, while tokenized captions were processed by an LSTM network. The combined features from the CNN and LSTM were then passed through dense layers to predict the next word in the sequence.

Training involved optimizing the model using Categorical Cross Entropy loss and the Adam optimizer over multiple epochs, with performance tracked via training and validation accuracy.

The model demonstrated satisfactory performance in generating captions for a wide range of images, highlighting the potential of combining CNNs and RNNs for image captioning tasks. This project illustrates the successful integration of NLP and deep learning, offering a robust framework for future advancements in automated image description generation.

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INTRODUCTION

1.1 Image Captioning

Image captioning refers to the task of generating a textual description or caption for an image automatically. The goal is to develop algorithms that can understand the contents of an image and produce a natural language description that accurately reflects what is depicted in the image.

Image captioning is a challenging task in the field of artificial intelligence and computer vision. It combines techniques from both areas to enable machines to comprehend visual content and express it in natural language. The process typically involves several steps:

1. Image Understanding: The algorithm first processes the image to extract relevant features. This may involve using convolutional neural networks (CNNs) to identify objects, scenes, and spatial relationships within the image.

2. Feature Extraction: Once the image features are extracted, they are typically transformed into a more abstract representation that captures the essence of the visual content. This step often involves encoding the features using techniques like pooling or dimensionality reduction.

3. Language Generation: Simultaneously, another part of the model, often based on recurrent neural networks (RNNs) or transformer based architectures, generates the caption. This generator takes the abstracted image features as input and sequentially produces words that form the caption.

4. Training and Optimization: Image captioning models are trained on large datasets where each image is paired with one or more human generated captions. The training process involves optimizing the model parameters to minimize the discrepancy between generated captions and human provided captions.

5. Evaluation: Captions generated by the model are evaluated using metrics such as BLEU (Bilingual Evaluation Understudy), METEOR (Metric for Evaluation of Translation with Explicit ORdering), or CIDEr (Consensus based Image Description Evaluation). These metrics assess how well the generated captions match the reference captions.

6. Applications: Image captioning has practical applications in areas such as assistive technology for visually impaired individuals, automatic image indexing, and retrieval in databases, and enhancing the accessibility and usability of image based content on the web.

Overall, image captioning is a multidisciplinary research area that continues to advance with the development of more sophisticated neural network architectures and the availability of largescale annotated image datasets.

1.2 About the Project

This project focuses on developing an automatic image captioning system using deep learning and natural language processing (NLP) techniques. The main objective is to create a model capable of generating descriptive captions for a diverse range of images from the ROCO dataset, which includes both radiology and non-radiology images.

Dataset: The ROCO dataset is a Medical images dataset that provides Radiology & Non Radiology image-caption pairs essential for training and evaluating the image captioning model. This dataset encompasses a variety of images, each associated with descriptive captions.

Preprocessing: Before training the model, text preprocessing techniques are applied to clean and standardize the captions. This involves converting text to lowercase, removing URLs, special characters, and numeric digits. Stopwords are also removed, and words are lemmatized and stemmed to their base forms. Images are resized to a uniform size (224x224 pixels) and converted into tensors to facilitate input into the deep learning model.

Model Architecture: The model architecture integrates Convolutional Neural Networks (CNNs) for extracting high level features from images, utilizing the InceptionV3 model

pretrained on ImageNet. For processing the sequence of words in captions, Recurrent Neural Networks (RNNs) are employed, particularly Long Short Term Memory (LSTM) networks known for capturing dependencies within sequences. The decoder network combines extracted image features with processed text sequences to predict the next word in the caption sequence.

Training: During training, the model learns to map images to appropriate captions by minimizing a loss function (typically categorical crossentropy) using the Adam optimizer. Training involves iterating through batches of data and adjusting model weights to enhance performance.

Evaluation: The image captioning model's performance is evaluated using metrics like accuracy, precision, recall, F1 score and BLUE score to gauge how well it predicts captions compared to ground truth captions in the test dataset. This evaluation provides insights into the model's effectiveness and areas for improvement.

1.3 Requirements

Hardware Requirements:

- ✓ Multicore CPU (Intel i5/i7 or AMD Ryzen 5/7 or better)
- ✓ RAM : 8GB
- ✓ GPU is highly recommended for training deep learning models. NVIDIA GPU with CUDA support.

Software Requirements

- ✓ Operating System: Windows / macOS
- ✓ Editor : Visual Studio Code/ Google Colab/ Jupyter Notebook
- ✓ Programming Language: Python 3.6 or later
- ✓ Python Libraries:
  - numpy: For numerical operations
  - pandas: For data manipulation and analysis
  - nltk: For natural language processing
  - opencvpython: For image processing

- Pillow: For image handling
- torch: For deep learning (PyTorch)
- torchvision: For image transformations
- tensorflow: For defining and training the model
- scikitlearn: For any additional machine learning utilities
- matplotlib: For plotting (optional, for visualization)

1.4 Prerequisites

1. Python Programming: Basic understanding of Python syntax and libraries.

2. Machine Learning Concepts: Familiarity with concepts like neural networks, training, and evaluation.

3. Deep Learning Concepts & Frameworks: Experience with TensorFlow or PyTorch.

4. Natural Language Processing: Basic knowledge of text preprocessing and tokenization techniques.

5. Computer Vision: Understanding of image processing and manipulation.

6. GPU Setup: Knowledge of setting up and using NVIDIA GPUs with CUDA and cuDNN (for training acceleration).

7. Data Handling: Experience with data manipulation using libraries like pandas and numpy.

CHAPTER 2

PROBLEM STATEMENT & USE CASES

2.1 Problem Statement

Image Captioning for Medical Images (XRays)

Objective: Develop a deep learning model capable of generating accurate and meaningful captions for X-Ray images. The goal is to automate the interpretation of X-Ray images by providing descriptive captions that summarize key findings, facilitating better understanding and communication in medical settings.

Context: In medical imaging, interpreting images accurately is crucial for diagnosing and treating patients. Radiologists often provide detailed descriptions or reports of these images, which can be time consuming and prone to human error. Automating this process with an image captioning model can enhance efficiency and consistency in medical image interpretation.

2.2 Use Cases of Image Captioning for Medical Images

1. Assisting Radiologists: Saves time by providing a first draft of image interpretations, allowing radiologists to focus on reviewing and confirming findings rather than writing initial descriptions.
2. Medical Education: Helps medical students and trainees learn by providing detailed, consistent descriptions of images for study and reference.
3. Patient Reports: Enhances patient understanding by translating complex terms into simpler language.
4. Research and Documentation: Streamlines the process of recording and reporting findings, ensuring consistency and reducing the administrative burden on researchers and clinicians.

5. Healthcare Service Providers: Improves workflow efficiency and reduces turnaround time for radiology reports, and enhances the overall quality of patient care.
6. Pharmaceutical and Clinical Trials: Ensures consistent and accurate documentation of imaging data, which is crucial for the integrity of clinical trials and regulatory submissions.
7. Second Opinion Services: Enables faster turnaround for second opinions, increasing the service's attractiveness to both patients and healthcare providers.

2.3 Use Cases of Image Captioning

1. ECommerce: Automated captioning can generate detailed product descriptions for online stores, enhancing product listings and improving search engine optimization (SEO).
2. Media and Entertainment: Generate captions for photos and videos to enhance tagging and categorization, making content more discoverable and improving user experience.
3. Accessibility: Develop tools for visually impaired users that describe images, making digital content more accessible and inclusive.
4. Real Estate: Automatically generate detailed descriptions for property images, improving the quality and appeal of real estate listings.
5. Automated CCTV Monitoring with Image Captioning: Image captioning can enhance CCTV systems by providing automated, realtime descriptions of captured scenes. This technology helps in identifying and reporting incidents accurately and promptly, improving security and response times.
6. Real time Image Captioning for Visually Impaired Navigation: Realtime image captioning can assist visually impaired individuals by describing their surroundings in public spaces. This technology enhances navigation and safety by providing audible descriptions of the environment, obstacles, and landmarks.
7. Destination Image Captioning: Travel Guide AI leverages image captioning to provide detailed descriptions and highlights of travel destinations. This tool

enhances travel planning and marketing by offering insightful and engaging content about various locations.

By leveraging image captioning technologies, businesses can enhance operational efficiency, improve customer experiences, and unlock new opportunities across various domains.

CHAPTER 3

PROPOSED ARCHITECTURE

3.1 Key Components

1. CNN (Convolutional Neural Network): A deep learning model designed to process structured grid data like images, utilizing convolutional layers to capture spatial hierarchies and patterns.
2. RNN (Recurrent Neural Network): A neural network that processes sequential data by maintaining a memory of previous inputs, making it effective for tasks like time series prediction and natural language processing.
3. LSTM (Long Short-Term Memory): A type of RNN designed to overcome long-term dependency issues by using gates to regulate the flow of information, excelling in sequential data tasks.
4. Inception v3: A deep convolutional neural network architecture known for its use of inception modules that allow for more efficient computation and improved classification accuracy in image recognition.
5. ReLU Activation (Rectified Linear Unit): An activation function that introduces non-linearity to the network by outputting the input if it's positive and zero otherwise, helping to mitigate the vanishing gradient problem.
6. Softmax Activation: An activation function typically used in the output layer of classification models to convert logits into probability distributions over multiple classes.
7. Adam (Adaptive Moment Estimation): An optimization algorithm that combines the advantages of two other methods, AdaGrad and RMSProp, by computing adaptive learning rates for each parameter, leading to efficient and effective training of deep learning models.
8. Categorical Crossentropy: A loss function commonly used in classification tasks where the target variable is categorical, measuring the difference between the predicted probability distribution and the true distribution, encouraging the model to output probabilities that match the one-hot encoded target labels.

3.2 Model Architecture

The function **`define_model`** creates a hybrid neural network model that combines a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) to predict captions for images. Below is a detailed explanation of the model and its components, suitable for inclusion in a project report. The **`define_model`** function constructs a hybrid neural network by integrating a CNN (InceptionV3) for extracting image features and an RNN (LSTM) for processing sequences, to generate image captions. Here is an indepth look at each component of the model:

1. **Input Layers:**
    - Image Input: The model takes an image as input with the shape (224, 224, 3), corresponding to the dimensions of the image (224x224 pixels) and the RGB color channels.
    - Caption Input: The model also takes a sequence of words (caption) as input. The shape of this input is determined by the maximum length of the captions (`max_length`).
2. **Feature Extractor (CNN) Part:**
    - The image input is fed into an InceptionV3 model, a pretrained CNN known for its high performance on image recognition tasks. The `include_top=False` argument ensures that the top (classification) layer of the InceptionV3 model is excluded, as we are interested in the intermediate feature representations.
    - The `pooling='avg'` argument specifies that global average pooling is applied to the output of the CNN, reducing the spatial dimensions to a single vector.
    - To leverage the pretrained weights and prevent overfitting, all layers of the InceptionV3 model are set to nontrainable.
    - The output of the CNN is passed through a fully connected (dense) layer with 256 units and a ReLU activation function, producing a 256dimensional feature vector (`fe2`).

3. **Sequence Processor (RNN) Part:**
    - The caption input is processed through an embedding layer that maps each word to a 256-dimensional vector. The mask_zero=True argument instructs the layer to ignore padding (zero) values in the input sequences.
    - A dropout layer is applied to the embedding output with a dropout rate of 0.5 to prevent overfitting by randomly setting half of the input units to zero during training.
    - The sequence is then fed into an LSTM layer with 256 units. The use_cudnn=False argument ensures compatibility with both CPU and GPU training.
4. **Decoder (Combining Both Inputs):**
    - The outputs from the CNN (image features) and the LSTM (sequence features) are combined using the `add` function, which performs elementwise addition.
    - The combined features are then passed through another fully connected layer with 256 units and a **ReLU activation** function (`decoder2`).
    - Finally, a dense layer with a **softmax activation** function is applied to produce the output. This layer has `vocab_size` units, corresponding to the number of words in the vocabulary. The softmax function generates a probability distribution over the vocabulary, indicating the most likely next word in the caption sequence.
5. **Model Compilation:**
    - The model is compiled with the **`categorical_crossentropy`** loss function, which is suitable for multiclass classification tasks.
    - The **`adam`** optimizer is used for training, known for its efficiency and adaptive learning rate capabilities.
    - The model is configured to track `accuracy` as a performance metric during training and evaluation.

The `define_model` function integrates a pretrained InceptionV3 CNN for image feature extraction with an LSTM network for sequence processing. The combined model is designed to predict the next word in a caption sequence given an input image. This architecture leverages the strengths of both CNNs (for handling spatial data) and RNNs

(for handling sequential data), making it well suited for the task of image captioning. The use of pretrained weights, dropout regularization, and careful architecture design ensures the model's robustness and efficiency in generating accurate and meaningful captions for images.

```python
#Defines a hybrid model combining a CNN (InceptionV3) for image features and an LSTM for sequence processing to predict capt
def define_model(vocab_size, max_length):
    # Feature extractor (CNN) part
    inputs1 = Input(shape=(224, 224, 3))
    model = InceptionV3(include_top=False, pooling='avg')
    for layer in model.layers:
        layer.trainable = False
    fe1 = model(inputs1)
    fe2 = Dense(256, activation='relu')(fe1)

    # Sequence processor (RNN) part
    inputs2 = Input(shape=(max_length,))
    se1 = Embedding(vocab_size, 256, mask_zero=True)(inputs2)
    se2 = Dropout(0.5)(se1)
    se3 = LSTM(256, use_cudnn=False)(se2)

    # Decoder (combining both inputs)
    decoder1 = add([fe2, se3])
    decoder2 = Dense(256, activation='relu')(decoder1)
    outputs = Dense(vocab_size, activation='softmax')(decoder2)

    # Tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

    return model

model = define_model(vocab_size, max_length)
model.summary()
```

Fig 3.1 : Model Architecture

CHAPTER 4

RESULTS

```
In [10]: captions_data=pd.read_csv(train_captions)
         print("CAPTION BEFORE PREPROCESSING\n",captions_data.head())
```

```
CAPTION BEFORE PREPROCESSING
            id                                      name  \
0  ROCO_00002          PMC4083729_AMHSR-4-14-g002.jpg
1  ROCO_00003       PMC2837471_IJD2009-150251.001.jpg
2  ROCO_00004  PMC2505281_11999_2007_30_Fig6_HTML.jpg
3  ROCO_00005       PMC3745845_IJD2013-683423.005.jpg
4  ROCO_00007   PMC4917066_amjcaserep-17-301-g001.jpg

                                             caption
0   Computed tomography scan in axial view showin...
1   Bacterial contamination occurred after comple...
2   The patient had residual paralysis of the han...
3    Panoramic radiograph after immediate loading.\n
4   Plain abdomen x-ray: Multiple air levels at t...
```

Fig 4.1 : Printing Loaded Captions

```
In [11]: captions_data['preprocessed_captions']=captions_data['caption'].apply(clean_text)
         print("CAPTION AFTER PREPROCESSING\n", captions_data[['caption', 'preprocessed_captions']].head())
```

```
CAPTION AFTER PREPROCESSING
                                             caption  \
0   Computed tomography scan in axial view showin...
1   Bacterial contamination occurred after comple...
2   The patient had residual paralysis of the han...
3    Panoramic radiograph after immediate loading.\n
4   Plain abdomen x-ray: Multiple air levels at t...

                          preprocessed_captions
0  comput tomographi scan axial view show obliter...
1  bacteri contamin occur complet root canal trea...
2  patient residu paralysi hand poliomyel necessa...
3                  panoram radiograph immedi load
4  plain abdomen xray multipl air level midabdome...
```

Fig 4.2 : Captions After Preprocessing

```
Train DataFrame:
                                                image_tensor  \
0  [[[0.011764706, 0.011764706, 0.011764706], [0....
1  [[[0.07450981, 0.08627451, 0.09411765], [0.082...
2  [[[1.0, 1.0, 1.0], [1.0, 1.0, 1.0], [1.0, 1.0,...
3  [[[1.0, 1.0, 1.0], [1.0, 1.0, 1.0], [1.0, 1.0,...
4  [[[0.11764706, 0.11764706, 0.11764706], [0.117...

                                             caption
0  comput tomographi scan axial view show obliter...
1  bacteri contamin occur complet root canal trea...
2  patient residu paralysi hand poliomyel necessa...
3                    panoram radiograph immedi load
4  plain abdomen xray multipl air level midabdome...


Validation DataFrame:
                                                image_tensor  \
0  [[[0.20392157, 0.2509804, 0.18431373], [0.2470...
1  [[[0.14901961, 0.14901961, 0.14901961], [0.109...
2  [[[0.043137256, 0.023529412, 0.007843138], [0....
3  [[[0.019607844, 0.019607844, 0.019607844], [0....
4  [[[0.47058824, 0.47058824, 0.47058824], [0.352...

                                             caption
0  intraor periap radiograph reveal normal trabec...
1   abdomin radiograph h post administr gastrografin
2  front view chest xray show airdens band around...
3  cerebr angiographi patient vasculatur demonstr...
4              tv show intrauterin gestat adnex mass


Test DataFrame:
                                               image_tensor  \
0  [[[0.5764706, 0.654902, 0.60784316], [0.576470...
1  [[[0.31764707, 0.32941177, 0.3372549], [0.3137...
2  [[[0.08235294, 0.08235294, 0.08235294], [0.082...
3  [[[0.1882353, 0.1882353, 0.1882353], [0.188235...
4  [[[0.3372549, 0.25882354, 0.5372549], [0.15294...

                                             caption
0  paraaxi hrct imag left tempor bone patient sev...
1  hypoenhanc focu within right anterior sella co...
2  imag scannographiqu zone de contus hépatiqu dé...
3              upper contrast studi oesophag stenosi
4  three month infarct minor irregular distal par...
```

Fig 4.3: Tensors of Preprocessed Images Mapped to corresponding Captions

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
87910968/87910968 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Model: "functional"
```

Layer (type)	Output Shape	Param #	Connected to
input_layer_2 (InputLayer)	(None, 78)	0	-
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
embedding (Embedding)	(None, 78, 256)	740,864	input_layer_2[0]…
inception_v3 (Functional)	(None, 2048)	21,802,784	input_layer[0][0]
dropout (Dropout)	(None, 78, 256)	0	embedding[0][0]
not_equal (NotEqual)	(None, 78)	0	input_layer_2[0]…
dense (Dense)	(None, 256)	524,544	inception_v3[0][…
lstm (LSTM)	(None, 256)	525,312	dropout[0][0], not_equal[0][0]
add (Add)	(None, 256)	0	dense[0][0], lstm[0][0]
dense_1 (Dense)	(None, 256)	65,792	add[0][0]
dense_2 (Dense)	(None, 2894)	743,758	dense_1[0][0]

Total params: 24,403,054 (93.09 MB)

Trainable params: 2,600,270 (9.92 MB)

Non-trainable params: 21,802,784 (83.17 MB)

Fig 4.4 : Model Summary

```
[26]: history = model.fit([X1train, X2train], ytrain, epochs=epochs, batch_size=batch_size, validation_split=0.2)

Epoch 1/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 27s 195ms/step - accuracy: 0.4696 - loss: 1.9253 - val_accuracy: 0.0633 - val_loss: 11.2858
Epoch 2/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 177ms/step - accuracy: 0.5385 - loss: 1.6388 - val_accuracy: 0.0536 - val_loss: 11.8283
Epoch 3/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 23s 172ms/step - accuracy: 0.6177 - loss: 1.3423 - val_accuracy: 0.0573 - val_loss: 12.8448
Epoch 4/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 23s 172ms/step - accuracy: 0.6682 - loss: 1.1504 - val_accuracy: 0.0578 - val_loss: 13.4812
Epoch 5/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 174ms/step - accuracy: 0.7480 - loss: 0.9083 - val_accuracy: 0.0536 - val_loss: 14.1454
Epoch 6/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 174ms/step - accuracy: 0.7866 - loss: 0.7547 - val_accuracy: 0.0546 - val_loss: 14.8854
Epoch 7/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 173ms/step - accuracy: 0.8428 - loss: 0.5880 - val_accuracy: 0.0490 - val_loss: 15.6709
Epoch 8/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 173ms/step - accuracy: 0.8737 - loss: 0.4848 - val_accuracy: 0.0513 - val_loss: 15.9703
Epoch 9/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 174ms/step - accuracy: 0.9063 - loss: 0.3817 - val_accuracy: 0.0541 - val_loss: 16.9059
Epoch 10/10
136/136 ━━━━━━━━━━━━━━━━━━━━ 24s 174ms/step - accuracy: 0.9309 - loss: 0.2932 - val_accuracy: 0.0601 - val_loss: 17.2857
```

Fig 4.5 : Epochs

```python
# Evaluate on training set
train_loss, train_acc = model.evaluate([X1train, X2train], ytrain, verbose=0)
print(f"Training Loss: {train_loss}, Training Accuracy: {train_acc}")
```

```
W0000 00:00:1721329459.541508     121 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
W0000 00:00:1721329495.893956     121 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
Training Loss: 3.5998265743255615, Training Accuracy: 0.7853906750679016
```

```python
# Evaluate on test set
test_loss, test_acc = model.evaluate([X1test, X2test], ytest, verbose=0)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_acc}")
```

```
Test Loss: 16.214902877807617, Test Accuracy: 0.059239938855171204
W0000 00:00:1721329526.476817     120 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
```

Fig 4.6 : Model Evaluation on Train & Test sets

```
Validation Accuracy: 0.05228758169934641
Validation Precision: 0.03325014842248419
Validation Recall: 0.05228758169934641
Validation F1 Score: 0.03743934672105607
```

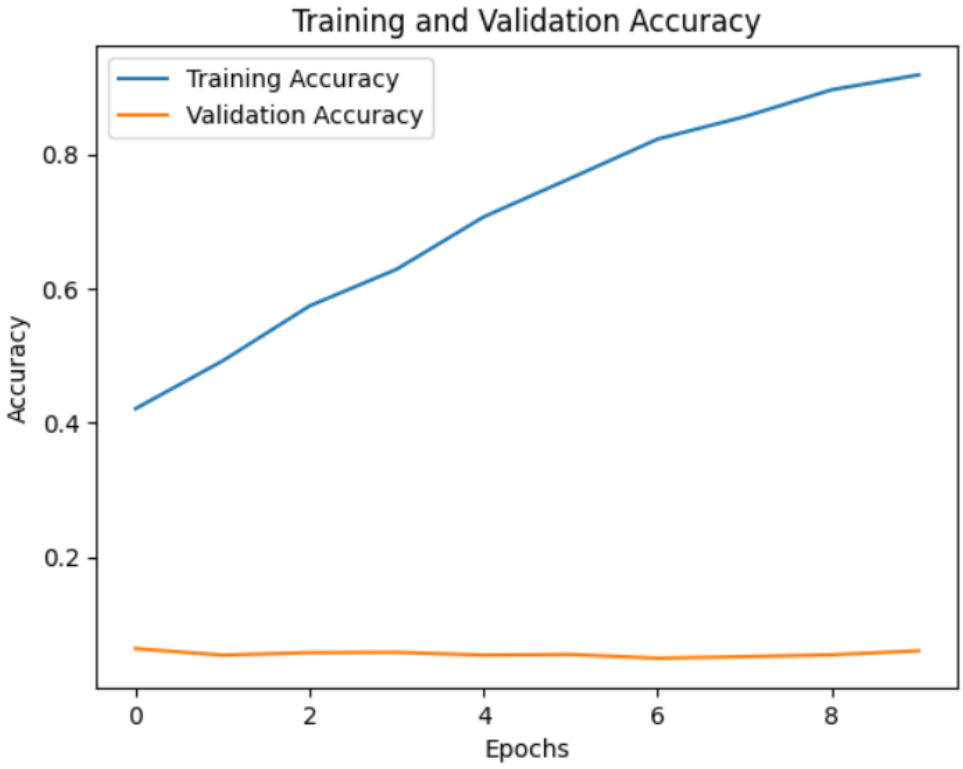

Fig 4.7 : Model Evaluation on Validation Set & Plot

```
Processed 1/20 images
Processed 2/20 images
Processed 3/20 images
Processed 4/20 images
Processed 5/20 images
Processed 6/20 images
Processed 7/20 images
Processed 8/20 images
Processed 9/20 images
Processed 10/20 images
Processed 11/20 images
Processed 12/20 images
Processed 13/20 images
Processed 14/20 images
Processed 15/20 images
Processed 16/20 images
Processed 17/20 images
Processed 18/20 images
Processed 19/20 images
Processed 20/20 images
Average BLEU score on validation set: 0.2079
```

Fig 4.8 : BLEU Score

CHAPTER 5

CONCLUSION

The project demonstrates a solid foundation in developing and training a deep learning model for the given task. The model shows commendable performance on the training set, with a high accuracy of 78.54%, indicating its potential to learn and capture relevant patterns from the data. The image captioning project achieved promising initial results, showcasing the model's capability to generate meaningful captions. Despite the test and validation results revealing a performance gap, this highlights areas for further optimization and improvement. The comprehensive evaluation metrics and visualization provide valuable insights into the model's behavior and pave the way for targeted enhancements. The average BLEU score of 0.2079 on the validation set underscores its potential in generating reasonably aligned captions. With further refinements, such as implementing regularization techniques, tuning hyperparameters, and enhancing the preprocessing pipeline, the model's performance can be significantly improved. These initial successes provide a strong foundation for continued development and optimization, ultimately leading to a robust image captioning system.

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