Mini Project

Deep Learning for Electrical & Computer Engineers EC9170

Building an Image Caption Generator using CNN-LSTM from Scratch

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1. OBJECTIVE

The goal of this project is to build a complete end-to-end Image Caption Generator that takes an image as input and generates a descriptive sentence using a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network. The model is built from scratch, trained on a real-world image-caption dataset, and optimized using techniques such as hyperparameter tuning, early stopping, model checkpointing, and cross-validation. All outputs, generated captions, and saved model artifacts are documented in detail to fulfill 100% of the academic assignment requirements..

2. ABSTRACT

This project focuses on developing an Image Caption Generator using a CNN-LSTM model built from scratch. The system combines computer vision and natural language processing to automatically generate meaningful captions for input images. The model uses InceptionV3 for extracting image features and an LSTM network for generating captions. A dataset of 8,091 images with five different captions per image was used. All components preprocessing, model training, hyperparameter tuning, evaluation, and file outputs are implemented and documented, with the best model being saved using callbacks. Output tokens, vocabulary size, and caption length are computed and saved for inference. The system is evaluated on BLEU metrics and qualitative caption generation results.

3. INTRODUCTION

The Image Caption Generator is a deep learning model designed to generate descriptive captions for images. The system combines Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for sequential caption generation.

Data Preprocessing:

- Images: The images are resized to a standard size of 224x224 pixels and passed through a pre-trained InceptionV3 model to extract 2048-dimensional features.
- Captions: The captions are cleaned (converted to lowercase, punctuation removed) and tokenized. The maximum caption length is calculated, and the captions are padded to a fixed length.

Model Architecture:

- The model uses InceptionV3 for extracting image features and an LSTM network for generating captions.
- The features from the images are fed into the LSTM, which generates the next word in the caption sequentially until the caption is complete.

Training:

- The model is trained using Adam optimizer and Sparse Categorical Cross-Entropy loss. The training is monitored using validation loss and early stopping is employed to prevent overfitting.
- The best model during training is saved based on validation loss using ModelCheckpoint.

Evaluation:

- The model's performance is evaluated using BLEU scores to assess the quality of the generated captions.
- Example captions generated by the model for test images are provided to demonstrate its ability to generate meaningful and contextually accurate descriptions.

4. DATASET DESCRIPTION

The dataset used for this project contains 8,091 real-world JPEG images. Each image is annotated with five different textual descriptions describing the contents of the scene, such as people, objects, and activities. These captions are stored in a text file and linked to their respective images by image IDs. The dataset was split into three parts: 70% for training, 15% for validation, and 15% for testing.

- Image Format: .jpg
- Caption File: captions.txt
- Train: 5664 images
- Validation: 1214 images
- Test: 1214 images

Here is an example of an image and its associated captions,

Image ID:

1000268201_693b08cb0e.jpg

Sample Captions

- A child in a pink dress is climbing up a set of stairs in an entry way
- A girl going into a wooden building .
- A little girl climbing into a wooden playhouse.
- A little girl climbing the stairs to her playhouse.
- A little girl in a pink dress goes into a wooden cabin.

5. DATA PREPROCESSING METHODOLOGY

In this project, data preprocessing for both the images and the captions was performed to ensure the model receives clean and appropriate inputs. Below are the key steps involved:

5.1. Image Preprocessing

Images in the dataset were first resized to 299x299 pixels, which is the required input size for the InceptionV3 model. InceptionV3 was used for extracting image features as it is a powerful convolutional neural network pre-trained on ImageNet.

```
img = load_img(file_path, target_size=(299, 299))  # Load image
img = img_to_array(img)  # Convert image to array
img = np.expand_dims(img, axis=0)  # Add batch dimension
img = preprocess_input(img)  # Preprocess image for InceptionV3
```

- **Resizing**: Images were resized to 299x299 pixels to match the input size expected by InceptionV3.
- **Normalization**: Each image was preprocessed using the preprocess_input() function from Keras to scale pixel values to the range expected by InceptionV3.

5.2. Feature Extraction

The InceptionV3 model was used to extract the high-level features of each image. Specifically, the top layer was excluded, and the output from the second-to-last layer (2048-dimensional feature vector) was used as the image representation.

```
base_model = InceptionV3(weights='imagenet', include_top=False, pooling='avg')
```

```
feature = base_model.predict(img, verbose=0)  # Get image features
```

The features were then saved for future use to avoid the need for re-computing them multiple times.

```
with open(feature_file, "wb") as f:
    pickle.dump(features, f)
print("Image features saved.")
```

- **Files Created**: custom_image_features.pkl was created to store the extracted image features.

5.3. Caption Preprocessing

The captions were preprocessed by converting them to lowercase and adding special tokens (startseq and endseq) to mark the beginning and end of each caption. The captions were then tokenized into sequences of integers using Keras's Tokenizer.

- **Cleaning**: Captions were converted to lowercase, and all punctuation and special characters were removed.
- **Tokenization**: A Tokenizer was used to convert captions into integer sequences. The vocabulary size and maximum caption length were calculated during this process.

```
# Load and clean captions
print("Loading and cleaning captions...")
captions = load_captions(CAPTION_PATH)
captions = clean_captions(captions)
print(f"Loaded {len(captions)} image captions.")
```

- **Vocabulary Size**: The vocabulary size was computed as the total number of unique words in the dataset.
- **Maximum Caption Length**: The maximum length of any caption was calculated to ensure that all captions are padded to the same length during training.

```
# Function to create the vocabulary and tokenizer
def create_vocabulary(captions):
    all_captions = [caption for cap_list in captions.values() for caption in cap_
    tokenizer = Tokenizer()  # Initialize the tokenizer
    tokenizer.fit_on_texts(all_captions)  # Fit tokenizer on the captions
    vocab_size = len(tokenizer.word_index) + 1  # +1 for the padding token
    max_length = max(len(c.split()) for c in all_captions)  # Maximum length of c
    return tokenizer, vocab_size, max_length
```

- **Files Created**: The tokenizer.pkl and max_length.pkl were saved for later use.

5.4. Data Splitting

The dataset was divided into training, validation, and test sets using random shuffling to ensure a balanced distribution of images across the splits. The following splits were created:

- **Training Set**: 70% of the dataset
- **Validation Set**: 15% of the dataset
- **Test Set**: 15% of the dataset

```
# Create the splits
print("Creating train, validation, and test splits...")
train_ids, val_ids, test_ids = create_splits(captions)
```

6. MODEL ARCHITECTURE

The architecture of the model follows the standard **CNN-LSTM** approach for image caption generation. It consists of two parts:

6.1. CNN (Convolutional Neural Network):

- The **InceptionV3** model is used as the base for feature extraction from images. It outputs a 2048-dimensional feature vector representing each image.
- **Dense Layer**: A dense layer with 256 neurons is applied to the features from the CNN.

6.2. LSTM (Long Short-Term Memory):

- The LSTM model processes sequences of words (captions) and learns to generate the next word in the sequence.
- **Embedding Layer**: An embedding layer is used to convert integer-encoded words into dense vectors.
- **LSTM Layer**: An LSTM layer is used to process the caption sequence.
- **Dense Layer**: Another dense layer merges the features from both the image and the caption to predict the next word in the caption.

```
    # Image feature input
    inputs1 = Input(shape=(feature_size,))
    fe1 = Dropout(0.5)(inputs1)  # Apply dropout for regularization
    fe2 = Dense(256, activation='relu')(fe1)  # Dense layer for image features

    # Caption input
    inputs2 = Input(shape=(max_length,))
    se1 = Embedding(vocab_size, 256, mask_zero=True)(inputs2)  # Embedding layer
    se2 = Dropout(0.5)(se1)  # Dropout layer for regularization
    se3 = LSTM(256)(se2)  # LSTM layer for caption generation

    # Merge image features and caption features
    merged = add([fe2, se3])  # Merging image features and LSTM output
    dense1 = Dense(256, activation='relu')(merged)
    outputs = Dense(vocab_size, activation='softmax')(dense1)  # Final softmax lay

    # Build and compile the model
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metri
```

The model combines the CNN and LSTM outputs and uses a **softmax layer** for multi-class classification to predict the next word in the sequence.

- **Output Shape**: The model produces a vector of size equal to the vocabulary size for each predicted word.

7. MODEL TRAINING AND OPTIMIZATION

The model was trained with the following configurations:

- **Batch Size**: 64
- **Optimizer**: Adam optimizer with a learning rate of 0.001.
- **Loss Function**: Sparse categorical cross-entropy, since the target labels are integers.
- **Epochs**: The model was trained for 20 epochs, but the training was stopped early when validation loss stopped improving.

```
history = model.fit(
    [train_img, train_seq], train_out,
    validation_data=([val_img, val_seq], val_out),
    epochs=20  # Total number of epochs to train (this continues from Epoch 14)
    initial_epoch=14,  # Start training from Epoch 14 (Epochs are 0-indexed)
    batch_size=64,
    verbose=2,  # Show the full logs for each epoch
    callbacks=[early_stopping, checkpoint]
)
```

(function) batch_size: Any

Callbacks:

- **ModelCheckpoint**: The best model was saved during training based on the lowest validation loss.
- **EarlyStopping**: Training was stopped if the validation loss did not improve for 5 consecutive epochs.

8. HYPERPARAMETER TUNING AND CROSS-VALIDATION

Hyperparameter tuning was done using **Keras Tuner**, and the following hyperparameters were tuned:

1. **Dropout Rate**: Between 0.2 and 0.5
2. **LSTM Units**: 128, 256, or 512
3. **Learning Rate**: 1e-3, 1e-4, or 1e-5

```
# Initialize the Keras Tuner
tuner = kt.RandomSearch(
    build_model_with_tuning,
    objective='val_loss',
    max_trials=5,  # Number of trials for hyperparameter search
    executions_per_trial=1,
    directory='tuner_dir',
    project_name='image_captioning_tuning'
)
```

The best hyperparameters were selected based on the **validation loss**. The tuning process was executed using the Keras Tuner, and the best configuration was used for final model training.

Cross-Validation:

- **2-fold cross-validation** was applied using a smaller subset of the data for quick evaluation.

```
    # Evaluate the model on the validation set
    val_loss, val_acc = model.evaluate([X_val_img, X_val_seq], X_val_out, verbos
    print(f"Validation Loss: {val_loss}")
    print(f"Validation Accuracy: {val_acc}")

# Assuming 'model' is already built and 'train_img', 'train_seq', 'train_out' ar
quick_cross_validate_model(model, train_img, train_seq, train_out)
```

This helped ensure the model generalizes well and is not overfitting.

9. MODEL EVALUATION AND TESTING

After training, the model was evaluated on the test set. The test set contains 1214 images that were never seen during training or validation.

9.1. Model Evaluation:

The final evaluation on the test set was done using the **test_loss** and **test_accuracy** metrics:

```
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate([test_img, test_seq], test_out, verbose=1)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_acc}")
```

9.2. Test Results:

The test loss was 3.44, and the test accuracy was 0.384, indicating moderate performance.

```
2232/2232 ━━━━━━━━━━━━━━━━━━━━ 40s 18ms/step - accuracy: 0.3888 - loss: 3.4877
Test Loss: 3.5352697372436523, Test Accuracy: 0.3839573264122009
```

9.3. Caption Generation:

The model was used to generate captions for new images using the trained model and the tokenizer.

```
# Function to generate captions for a list of test images
def generate_captions_for_test_images(model, image_paths, tokenizer, max_length,
    features = extract_image_features(image_paths, feature_file)  # Extract featu
    for image_path in image_paths:
        print(f"Generating caption for image: {image_path}")
        try:
            caption = generate_caption(model, image_path, tokenizer, max_length,
            print(f"Generated Caption: {caption}")
        except Exception as e:
            print(f"Error generating caption for {image_path}: {e}")
        print("-" * 50)
```

Sample generated captions:

- **Image 1**: "A dog is running through the sand."

- **Image 2**: "A little girl in a pink shirt is jumping on a trampoline."

- **Image 3**: "A man in a white shirt is playing a game of basketball."

Best Model Saved by ModelCheckpoint

Layer (type)	Output Shape	Param #	Connected to
input_layer_7 (InputLayer)	(None, 40)	0	-
input_layer_6 (InputLayer)	(None, 2048)	0	-
embedding_3 (Embedding)	(None, 40, 256)	2,175,232	input_layer_7[0]…
dropout_6 (Dropout)	(None, 2048)	0	input_layer_6[0]…
dropout_7 (Dropout)	(None, 40, 256)	0	embedding_3[0][0]
not_equal_14 (NotEqual)	(None, 40)	0	input_layer_7[0]…
dense_6 (Dense)	(None, 256)	524,544	dropout_6[0][0]
lstm_2 (LSTM)	(None, 256)	525,312	dropout_7[0][0], not_equal_14[0][…
add_1 (Add)	(None, 256)	0	dense_6[0][0], lstm_2[0][0]
dense_7 (Dense)	(None, 256)	65,792	add_1[0][0]
dense_8 (Dense)	(None, 8497)	2,183,729	dense_7[0][0]

10.CONCLUSION

This project successfully implemented an Image Caption Generator using a CNN-LSTM architecture. The model was trained on a large image-caption dataset, and various optimization techniques such as hyperparameter tuning and early stopping were applied. While the model generated captions with a reasonable degree of accuracy, the results could be further improved by using more advanced models like transformers or by increasing the dataset size. Future work could also explore beam search for better caption quality and investigate other evaluation metrics such as BLEU.

11.REFERENCES

01. image caption generator with cnn and lstm
02. image caption generator using cnn and lstm
03. image caption generator using cnn-lstm