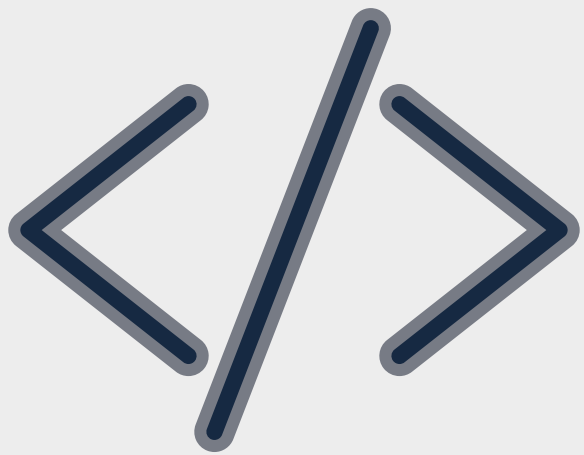


Caption Generation Using Deep Learning



Subject: Deep Learning A

Submitted to: Dr. Dinesh K Vishwakarma



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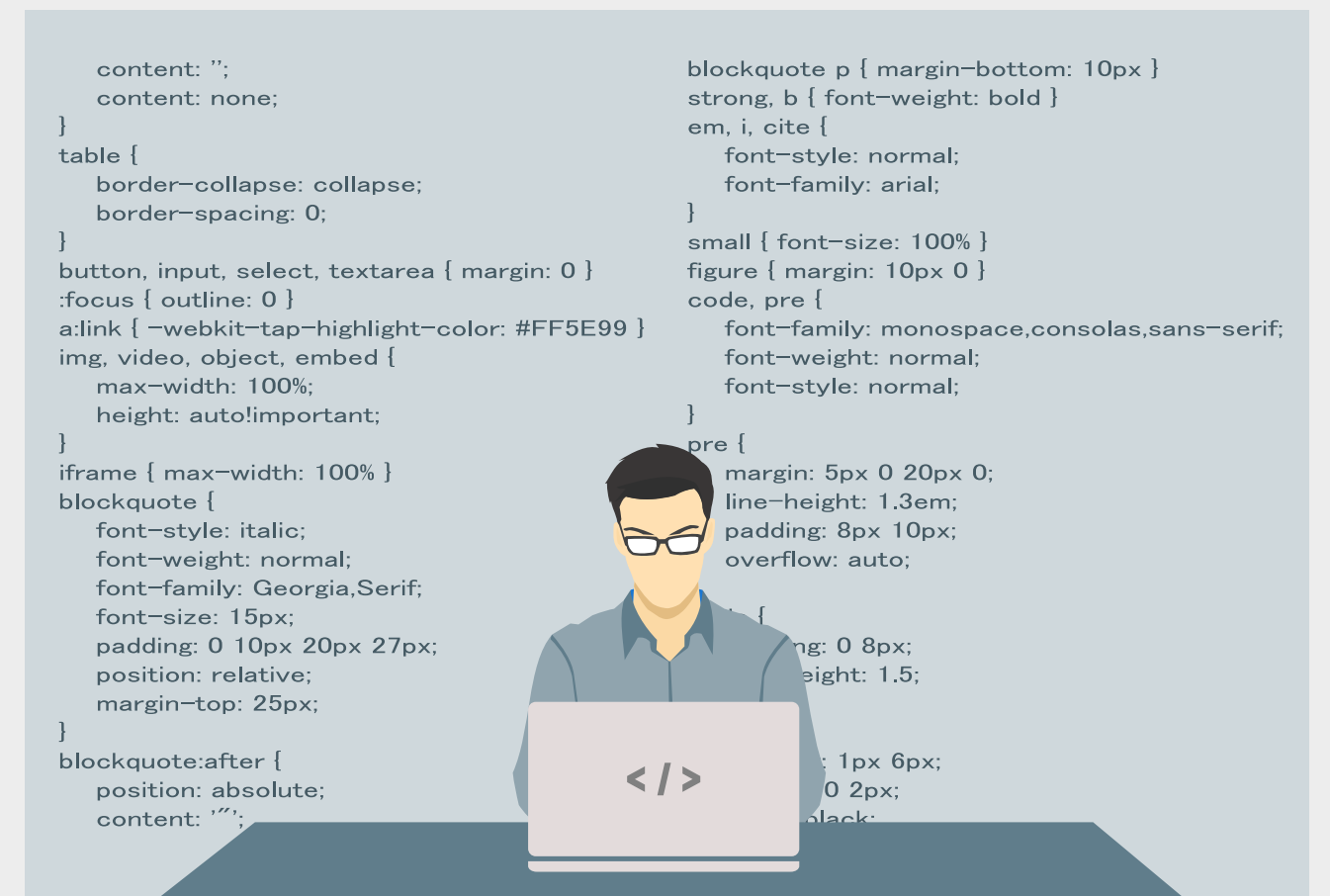
Results



References

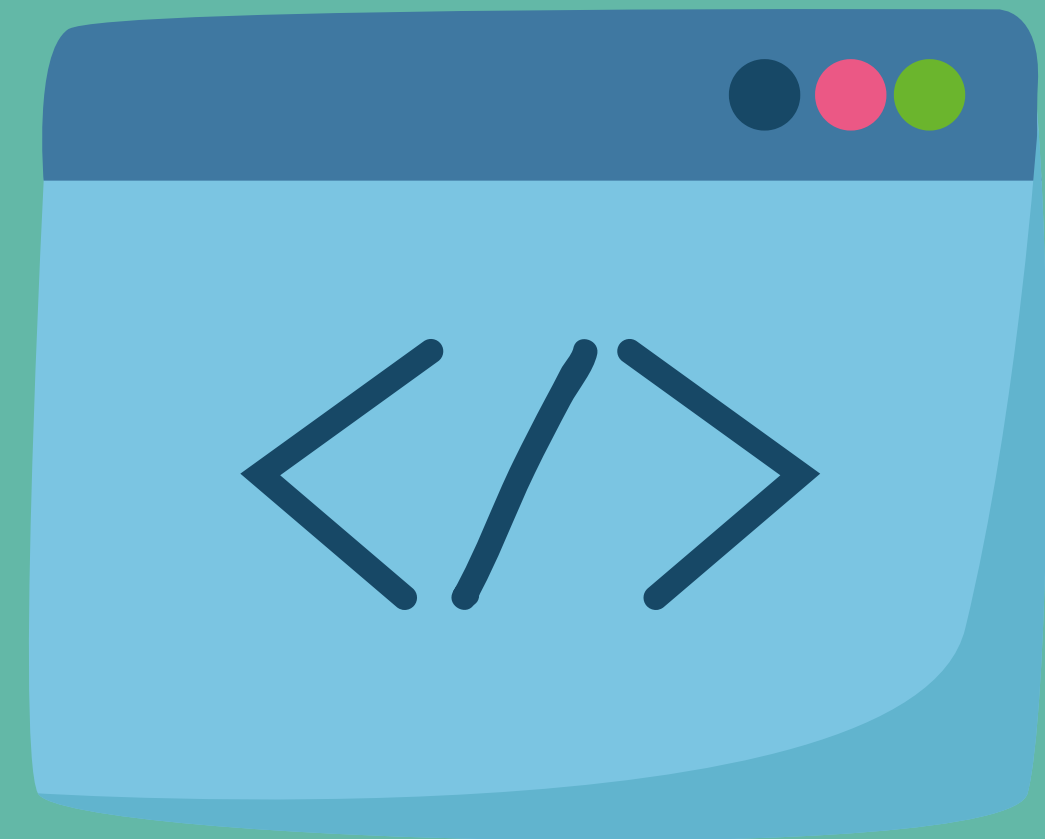
IMAGE CAPTION GENERATOR USING DEEP LEARNING

Presentation Structure



OBJECTIVES

- Preprocessing of the image and text data to train the Deep Neural Network. The dataset will be divided into Train, Development and test sets.
- Build a merged deep learning neural network using CNN and RNN and train it on the preprocessed dataset. The model will be trained to predict the caption(sequence of words), given an image.
- Evaluate the trained caption generator model on the Test set using BLEU Score.



Introduction

- Caption generation is an artificial intelligence problem where a textual description is generated for a given photograph.
- It requires both methods from computer vision to understand the content of the image and a language model from the field of natural language processing to turn the understanding of the image into words in the right order.
- A Convolutional Neural Network (CNN) was used to extract the features from the image.
- A Recurrent Neural Network (RNN), is a sequence model that was used to represent linguistic features of the Text Data.



MODELS USED

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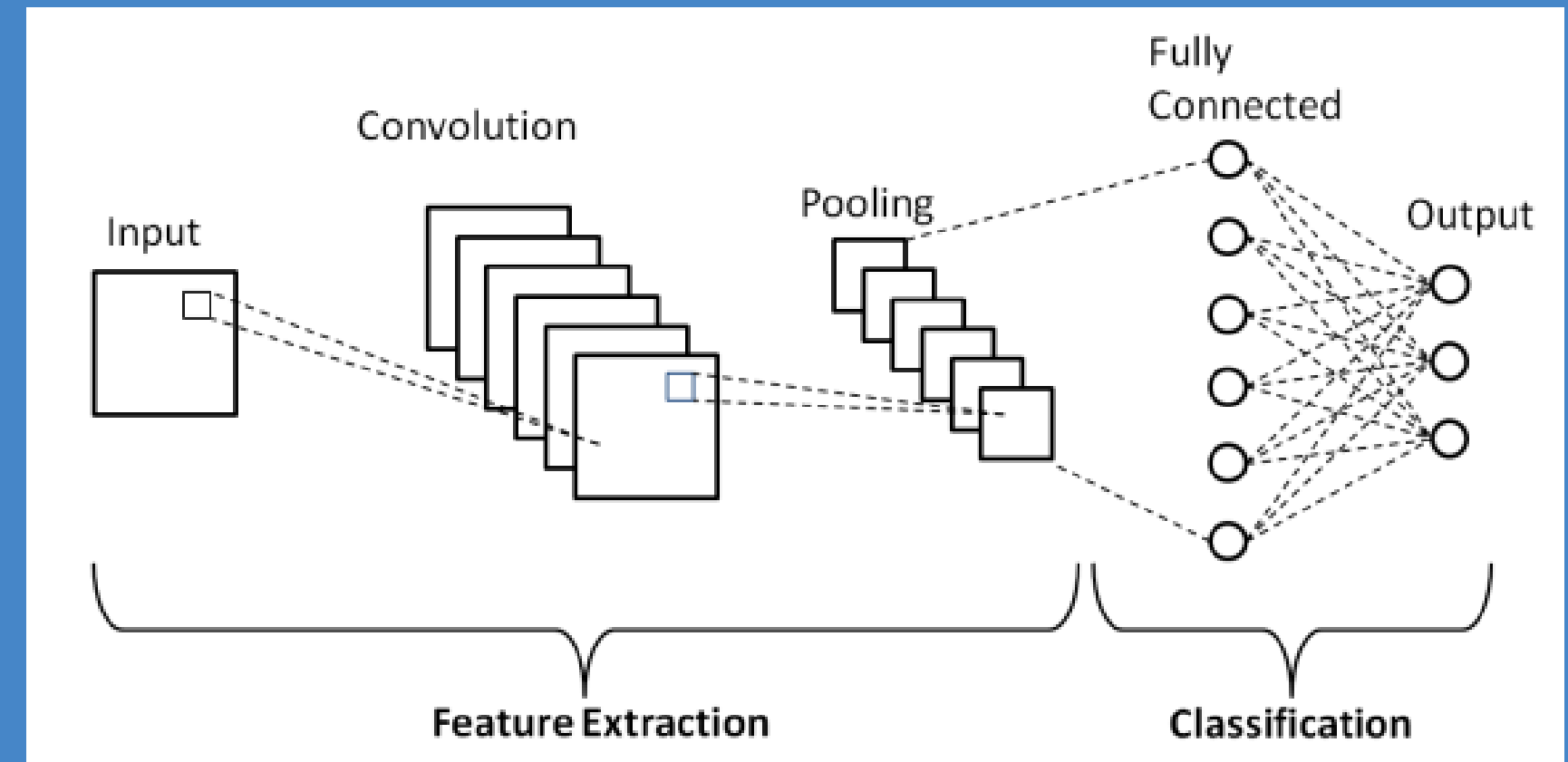
Deep Convolutional Neural Network: VGG-16

CNN is a class of deep, feed-forward artificial neural systems, extracting features from the Image Data.

CNN collect valuable features from an image by passing it through a series of convolution layers, non-linear activation functions, pooling (down-sampling), and fully connected dense layers.

We used a pre-trained Deep Convolutional Neural Network called VGG-16 imported from keras.applications.

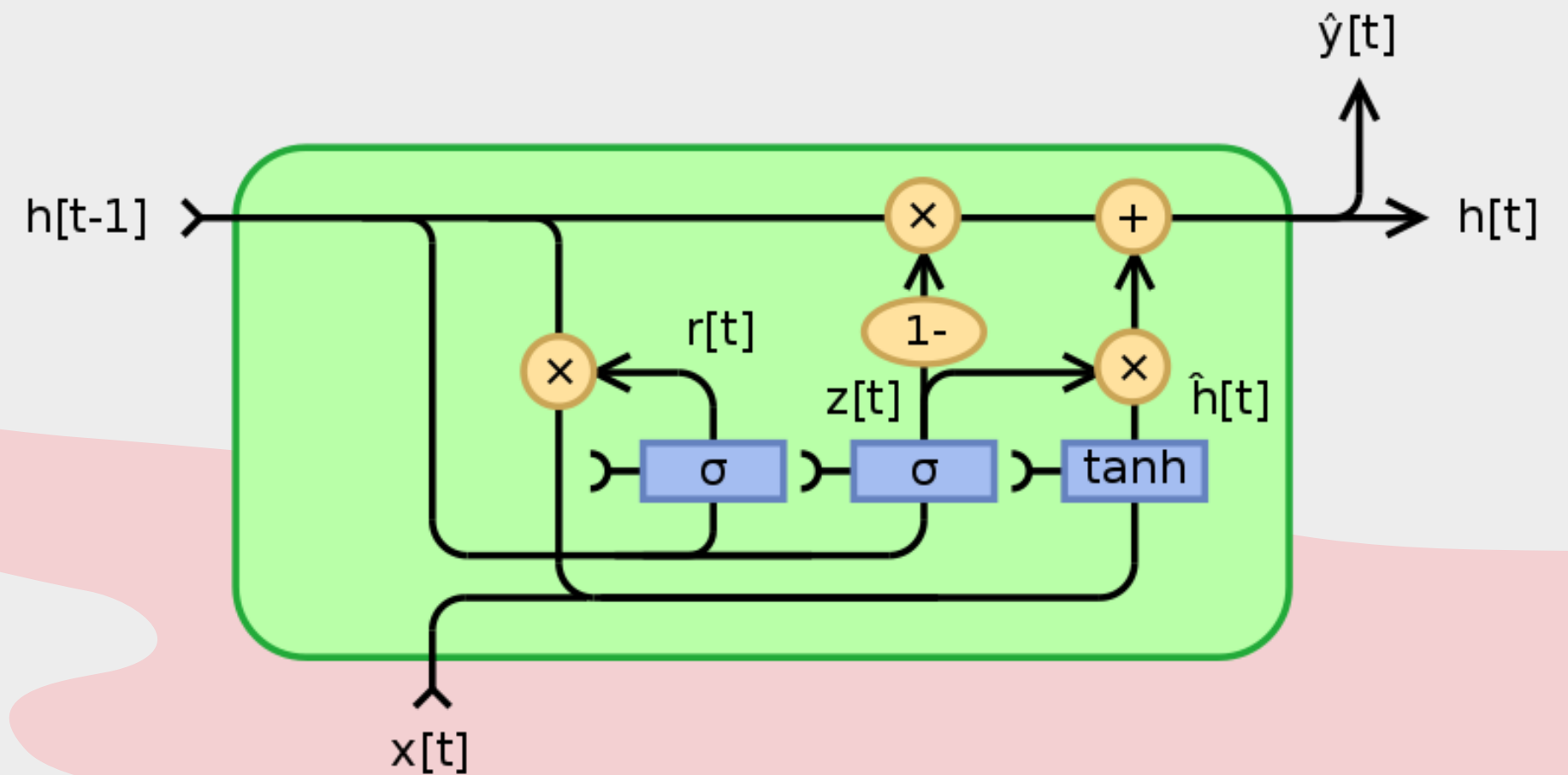
VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman (2014.) having 13 Convolutional layers, 5 Max-Pooling Layers and 3 Fully connected Dense Layers. (First 2 having 4096 Nodes.)



2. GRU

- GRU is a Recurrent Neural Networks (RNNs) / Sequence Model.
- GRU are a variant of Long Short Term Memory (LSTM) but with fewer training parameters. They were introduced in 2014 by Kyunghyun Cho et al.
- It uses two Gates: Update Gate and Reset Gate to decide the flow of information onto next time steps..
- The memory unit present in GRUs solves the problem of vanishing gradient descent for longer sequences.
- It is used in Natural Language Processing tasks to encode linguistic features and Generate word sequences (Captions in this Case).

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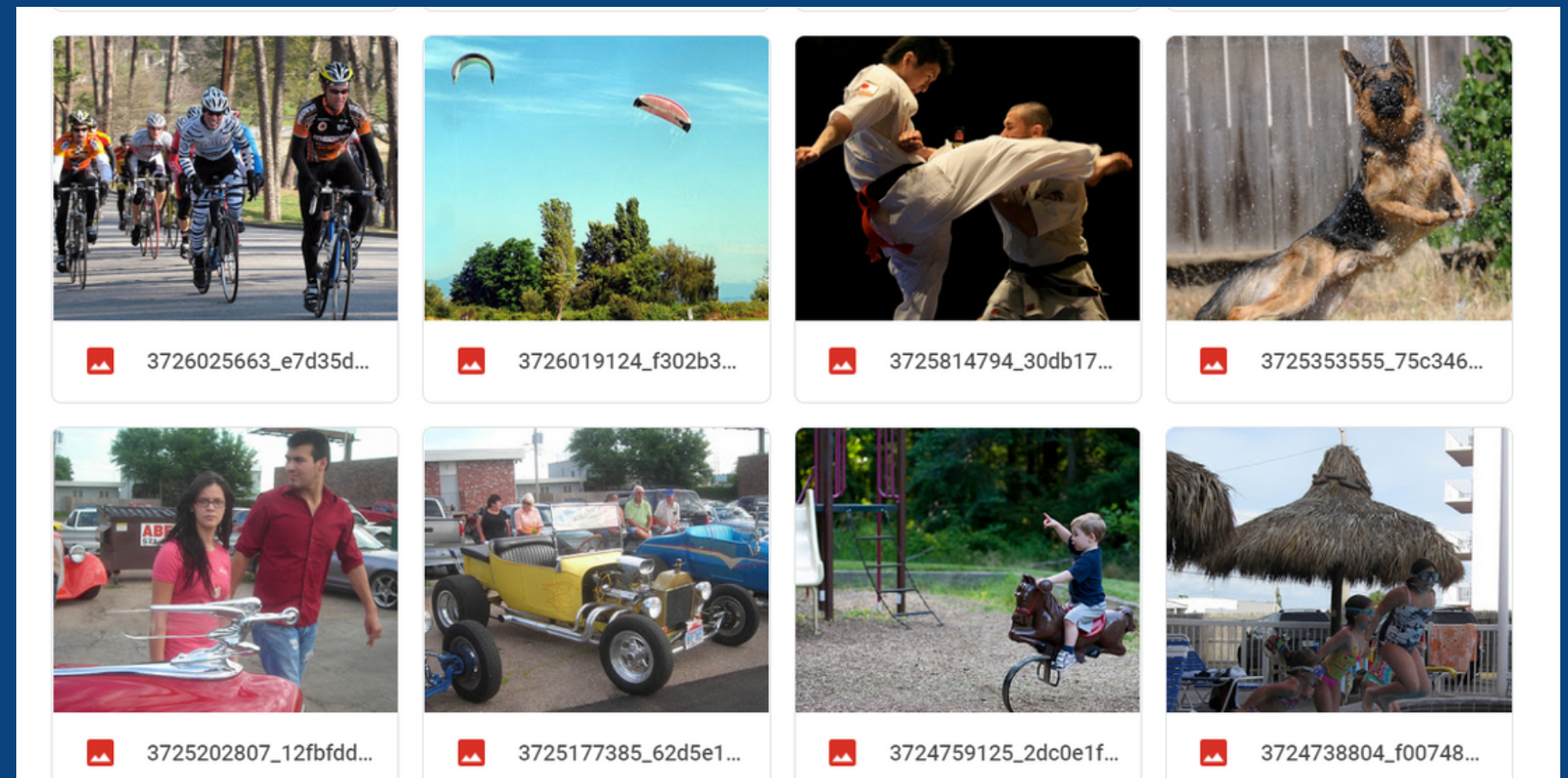


$$\begin{aligned} z &= \sigma(W_z \cdot x_t + U_z \cdot h_{(t-1)} + b_z) \\ r &= \sigma(W_r \cdot x_t + U_r \cdot h_{(t-1)} + b_r) \\ \tilde{h} &= \tanh(W_h \cdot x_t + r * U_h \cdot h_{(t-1)} + b_z) \\ h &= z * h_{(t-1)} + (1 - z) * \tilde{h} \end{aligned}$$

DATASET

- We used Flickr8k Dataset containing 8000 images in JPEG Format, and multiple text descriptions corresponding to each photograph.
- These models will be trained and deployed using Python along with the Deep Learning API TensorFlow-Keras.
- The dataset will be divided into training dataset (6,000 images), development dataset (1,000 images), and test dataset (1,000 images).
- We will use the BLEU score (Bilingual Evaluation Understudy) to evaluate the Captions predicted from the Model.

IMAGE CAPTION GENERATOR USING DEEP LEARNING

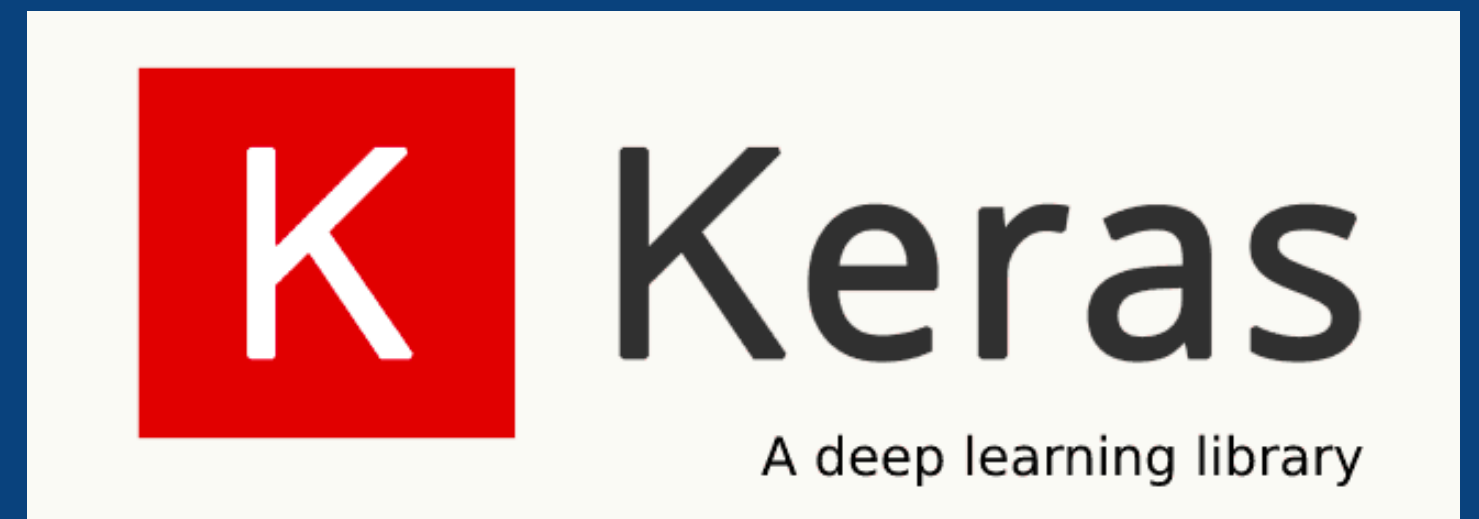


Libraries & Functions



IMAGE CAPTION GENERATOR USING DEEP LEARNING

- Numpy
- Pickle
- OS
- Tensorflow-Keras
- keras.applications.vgg16 -> VGG16, preprocess_input
- keras.preprocessing.image
- keras.utils -> to_categorical, plot_model
- keras.models -> Model
- keras.layers -> Input, GRU, Add, Dense, Embedding, Dropout
- keras.callbacks
- keras.preprocessing.text -> Tokenizer
- keras.preprocessing.sequence -> pad_sequences
- nltk.translate.bleu_score -> corpus_bleu



Model Architecture

VGG-16 model takes a photo input and produces a feature vector of 4,096 elements. These are processed by a FC Dense layer to produce a 256 element representation of the image.

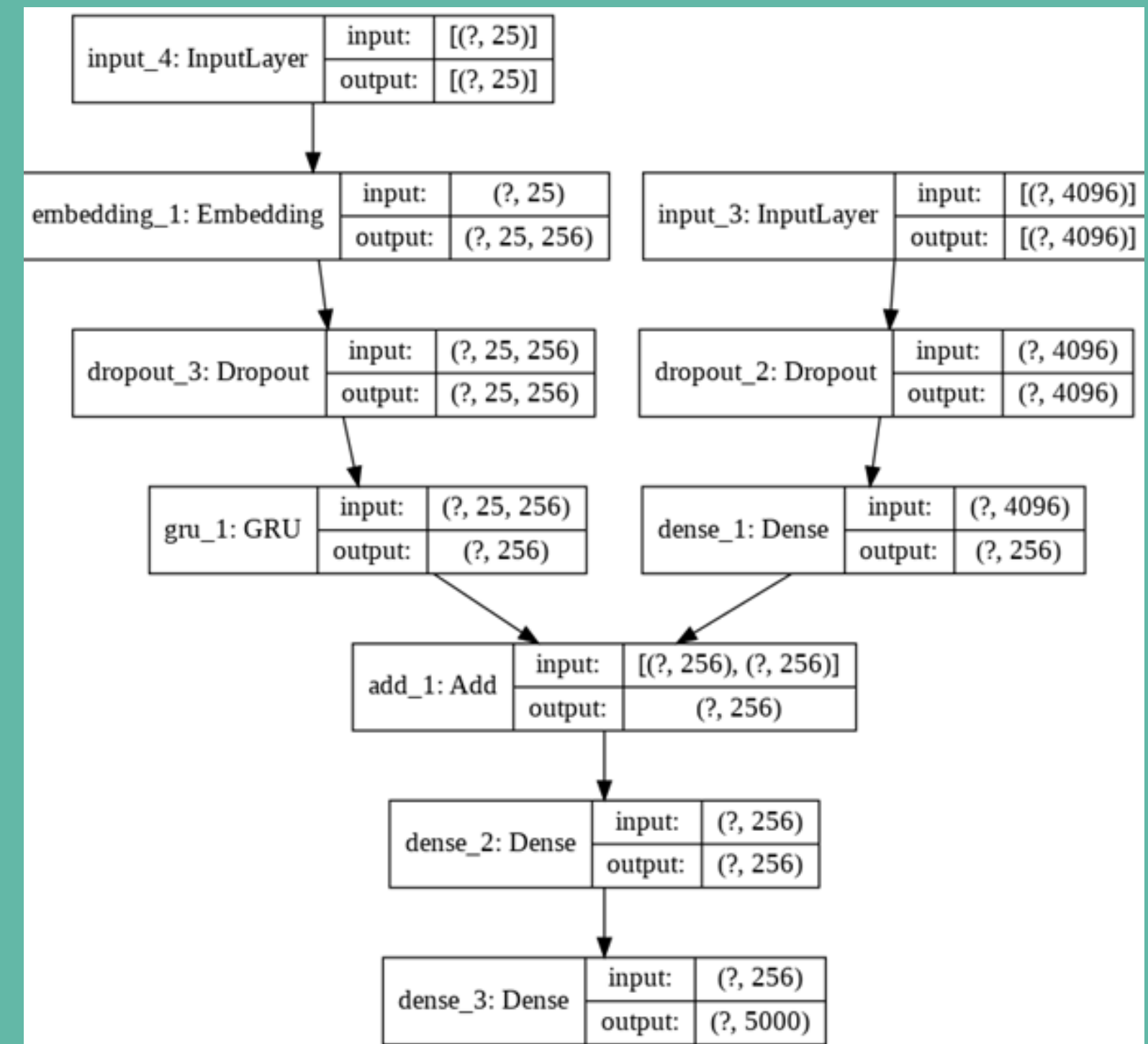
The Sequence model expects input sequences with a length of 25 words which are fed into an Word Embedding layer with 256 Embedding Dimension. It is followed by an GRU layer with 256 memory units.

Both the input models used 50% Dropout Regularization was used to prevent Overfitting, and finally produced a 256 element vector.

Features from both the Input models were merged using an addition layer. This is then fed to another Dense Layer with 256 neurons and then to a final output Dense layer that makes a SoftMax prediction over the entire vocabulary to predict the next word in the sequence.

The model will output a prediction, which will be a probability distribution over all words in the vocabulary. The output data will therefore be a one-hot encoded version of each word, representing an idealized probability distribution with 0 values at all word positions except the actual word position, which has a value of 1.

IMAGE CAPTION GENERATOR USING DEEP LEARNING



```

▶ from os import listdir
  from pickle import dump, load
  from keras.applications.vgg16 import VGG16
  from keras.preprocessing.image import load_img
  from keras.preprocessing.image import img_to_array
  from keras.applications.vgg16 import preprocess_input
  from keras.models import Model

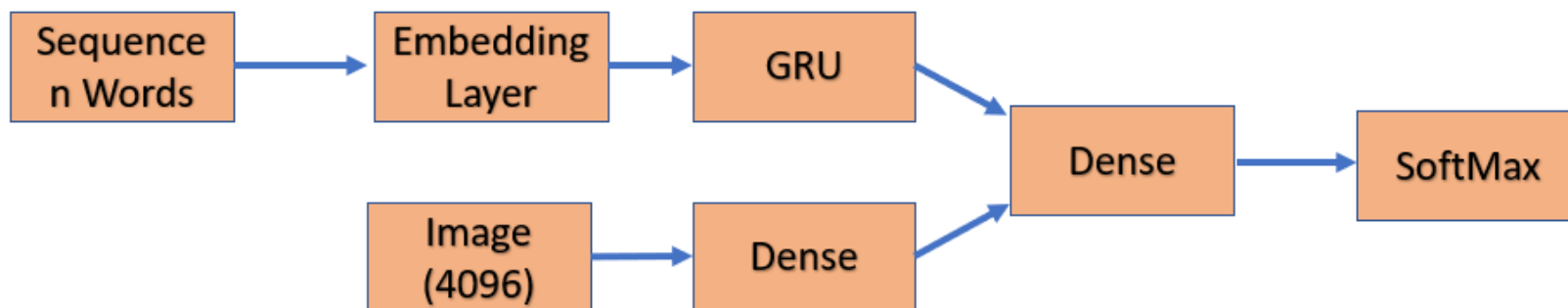
[ ] model = VGG16()
    model = Model(inputs=model.inputs, outputs=model.layers[-2].output)
    print(model.summary())

```

Downloading data from <https://storage.googleapis.com/tensorflow/keras-applications/553467904/553467096> [=====] - 7s 0us/step
 Model: "functional_1"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0

block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
=====		
Total params: 134,260,544		
Trainable params: 134,260,544		
Non-trainable params: 0		



```

# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor model
    inputs1 = Input(shape=(4096,))
    fe1 = Dropout(0.5)(inputs1)
    fe2 = Dense(256, activation='relu')(fe1)
    # sequence model
    inputs2 = Input(shape=(max_length,))
    se1 = Embedding(vocab_size, 256, mask_zero=True)(inputs2)
    se2 = Dropout(0.5)(se1)
    se3 = GRU(256)(se2)
    # decoder model
    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)
    # compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam')
    # summarize model
    model.summary()
    plot_model(model, to_file='model.png', show_shapes=True)
    return model
  
```

IMAGE CAPTION GENERATOR USING DEEP LEARNING

Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_2 (InputLayer)	[(None, 25)]	0	
input_1 (InputLayer)	[(None, 4096)]	0	
embedding (Embedding)	(None, 25, 256)	1280000	input_2[0][0]
dropout (Dropout)	(None, 4096)	0	input_1[0][0]
dropout_1 (Dropout)	(None, 25, 256)	0	embedding[0][0]
dense (Dense)	(None, 256)	1048832	dropout[0][0]
gru (GRU)	(None, 256)	394752	dropout_1[0][0]
add (Add)	(None, 256)	0	dense[0][0] gru[0][0]
dense_1 (Dense)	(None, 256)	65792	add[0][0]
dense_2 (Dense)	(None, 5000)	1285000	dense_1[0][0]
=====			
Total params: 4,074,376			
Trainable params: 4,074,376			
Non-trainable params: 0			

Model Evaluation

- We evaluated the model by generating descriptions for all photos in the test dataset and evaluating those predictions using the Bleu Score.
- The model generated a textual description given a trained model, and an image as input.
- The actual and predicted descriptions are collected and evaluated collectively using the BLEU score that summarizes how close the generated text is to the expected text.
- BLEU scores are used in text translation for evaluating translated text against one or more reference translations.
- We then calculate BLEU scores for 1, 2, 3 and 4 cumulative n-grams

```
# evaluate the skill of the model
def evaluate_model(model, descriptions, photos, tokenizer, max_length):
    actual, predicted = list(), list()
    # step over the whole set
    for key, desc_list in descriptions.items():
        # generate description
        yhat = generate_desc(model, tokenizer, photos[key], max_length)
        # store actual and predicted
        references = [d.split() for d in desc_list]
        actual.append(references)
        predicted.append(yhat.split())
    # 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)))
    print('BLEU-3: %f' % corpus_bleu(actual, predicted, weights=(0.3, 0.3, 0.3, 0)))
    print('BLEU-4: %f' % corpus_bleu(actual, predicted, weights=(0.25, 0.25, 0.25, 0.25)))
```

BLEU-1: 0.579114

BLEU-2: 0.344856

BLEU-3: 0.252154

BLEU-4: 0.131446

Scope of Improvement

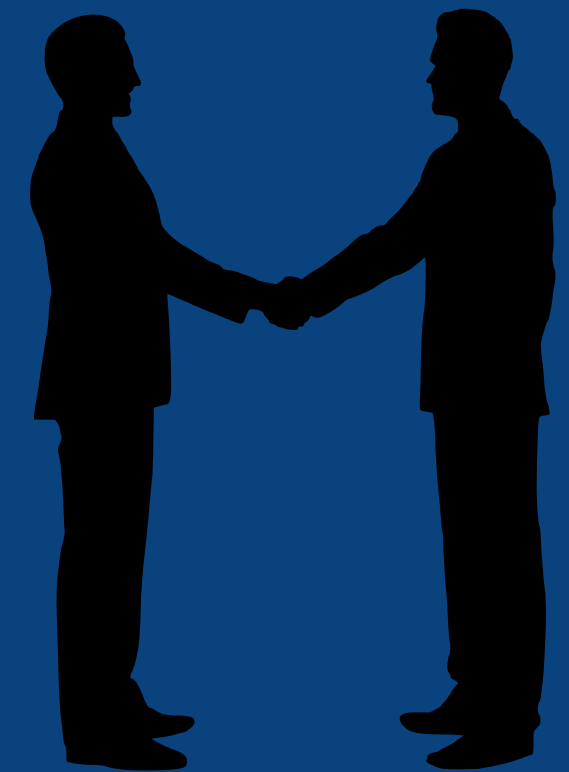
To increase the evaluation metrics for our model we could have used:

- Pre-trained Word2Vec embedding by Google or GloVe Embedding by Pennington (2014) Stanford University, instead of training our own embeddings.
- Other strong language models like using Attention mechanism on the Seq2Seq model.
- We could also have used Transformer models. They aim to solve sequence-to-sequence tasks while handling long-range dependencies with ease.
- Some Popular transformers models are:
 - I. BERT by Google, (Bidirectional Encoder Representations from Transformers)
 - II. RoBERTa A Robustly Optimized BERT Pretraining Approach, by Facebook
 - III. ALBERT A Lite BERT for Self-supervised Learning of Language Representations, by Google
 - IV. StructBERT
 - V. ELMo
 - VI. XLNet by Google



CONCLUSION

- We were able to create a robust machine learning model using a combined architecture of CNN VGG-16 and GRU. The model was evaluated using the Bleu score upon the Flickr8K dataset that contains (8000 images).
- This model provides a dual functionality, first it detects the image and then it further goes onto generate captions for the specific image.





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- Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).
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- <https://keras.io/api/models/>
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- <https://neurohive.io/en/popular-networks/vgg16/>
- <https://towardsdatascience.com/understanding-gru-networks-2ef37df6c9be>
- <https://deepai.org/machine-learning-glossary-and-terms/gated-recurrent-unit>
- <https://towardsdatascience.com/bleu-bilingual-evaluation-understudy-2b4eab9bcfd1>
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