NOTEBOOK TO DEVELOP AN IMAGE CAPTIONING MODEL

This notebook is intented to develop a model which will take in as input an image and output the captions from it, that is to say, it will describe the differnet objects present in the image.

MOUNTING GDRIVE ONTO THE NOTEBOOK

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
COLAB = True

     Mounted at /content/drive
```

IMPORTING NECCESSARY LIBRARIES

```
import os
import string
import glob
from tensorflow.keras.applications import MobileNet
import tensorflow.keras.applications.mobilenet

from tensorflow.keras.applications.inception_v3 import InceptionV3
import tensorflow.keras.applications.inception_v3


from tqdm import tqdm
import tensorflow.keras.preprocessing.image
import pickle
from time import time
import numpy as np
from PIL import Image
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import (LSTM, Embedding,
    TimeDistributed, Dense, RepeatVector,
    Activation, Flatten, Reshape, concatenate,
    Dropout, BatchNormalization)
from tensorflow.keras.optimizers import Adam, RMSprop
from tensorflow.keras import Input, layers
from tensorflow.keras import optimizers

from tensorflow.keras.models import Model

from tensorflow.keras.layers import add
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

START = "startseq"
STOP = "endseq"
```

```
EPOCHS = 10
USE_INCEPTION = True


# Nicely formatted time string
def hms_string(sec_elapsed):
    h = int(sec_elapsed / (60 * 60))
    m = int((sec_elapsed % (60 * 60)) / 60)
    s = sec_elapsed % 60
    return f"{h}:{m:>02}:{s:>05.2f}"
```

ROOT_CAPTIONING WILL HOLD THE ROOT ADDRESS OF ALL THE FILES AND FOLDERS BEING USED IN THIS NOTEBOOK

DATASETS NEEDED

For the development of this project the Flickr8k dataset has been used to trai the images against captions.It is an open-source dataset containing 8k images each with at least one object. Corresponding to each image we have a captions that accurately describes the image. The captions are stores in the Folder Flickr8k_text->Flickr8k.token.txt.This tokens data contains upto 5 captions for each image [resent in the Fliker8k_image dataset.

Along with flickr8k datset we also used the glove.6B dataset which stores the vector representation of common words we encounter in our day-to-day life.

```
root_captioning="/content/drive/MyDrive/Colab Notebooks/CAPTIONING"
```

PREPARING THE DATASET

Each image in the dataset contains upto 5 captions associated with it.these captions are strings which may have uneccessary punctuations and/or spaces in between. We must clean these irregularities. We also prepare a dictionary,lookup, where each entry contains the list of all the image caption captions for a particular image index. The lex set contains all the unique words present in the tokens dataset.

```
null_punct = str.maketrans('', '', string.punctuation)
lookup = dict()

with open( os.path.join(root_captioning,'Flickr8k_text','Flickr8k.token.txt'), 'r') as fp:

  max_length = 0
  for line in fp.read().split('\n'):
    tok = line.split()
    if len(line) >= 2:
      id = tok[0].split('.')[0]
      desc = tok[1:]
      # Cleanup description
      desc = [word.lower() for word in desc]
      desc = [w.translate(null_punct) for w in desc]
      desc = [word for word in desc if len(word)>1]
      desc = [word for word in desc if word.isalpha()]
      max_length = max(max_length,len(desc))

      if id not in lookup:
        lookup[id] = list()
      lookup[id].append(' '.join(desc))

lex = set()
for key in lookup:
  [lex.update(d.split()) for d in lookup[key]]


print(len(lookup)) # The length of the dictionary
print(len(lex)) # How many unique words
print(max_length) # Maximum length of a caption (in words)
```

```
8092
8763
32
```

FINDING PATH TO THE IMAGES

the glob module defined below is ued to find path to all the images present in the Flicker8k_Datset

```
img = glob.glob(os.path.join(root_captioning,'Flicker8k_Dataset', '*.jpg'))


print(len(img))
img[0:5]#printing the addresses of the first 5 images
```

```
8166
['/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/3282634762_2656
 '/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/3273403495_fcd6
 '/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/2483993772_f64e
 '/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/3563461991_de05
 '/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/1020651753_0607
```

```
train_images_path = os.path.join(root_captioning,'Flickr8k_text','Flickr_8k.trainImages.tx
train_images = set(open(train_images_path, 'r').read().strip().split('\n'))#STORES THE ADD
test_images_path = os.path.join(root_captioning,'Flickr8k_text','Flickr_8k.testImages.txt'
test_images = set(open(test_images_path, 'r').read().strip().split('\n')) #STORES THE ADDR

train_img = [] #stores the train addresses in a list
test_img = [] #stores the test addresses in a lis

for i in img:
  f = os.path.split(i)[-1]
  if f in train_images:
    train_img.append(f)
  elif f in test_images:
    test_img.append(f)
```

```
print(len(train_images))#stores the addresses of all the train images
print(len(test_images))#stores the addresses of all the test images
```

```
6000
1000
```

BUILDING A DICTIONARY FOR STORING THE TRAIN IMAGES ALONG WITH ITS CAPTIONS. WE ALSO ADD A SPECIAL START AND END TOKEN IN THE BEGINNING/END SO AS TO KNOW WHEN TO START A CAPTION AND WHEN TO FINISH IT

```
train_descriptions = {k:v for k,v in lookup.items() if f'{k}.jpg' in train_images}
for n,v in train_descriptions.items():
  for d in range(len(v)):
    v[d] = f'{START} {v[d]} {STOP}'
```

```
print(len(train_descriptions))
```

```
6000
```

EXTRACTING FEATURES FROM IMAGES

THE IMAGES TO BE PASSED TO THE CAPTIONING MODEL CANNOT BE RAW IMAGES, WE HAVE TO EXTRACT THE FEATURES FROM EACH OF THESE IMAGES AN THEN PASS IT ONTO THE CAPTIONING MODEL.FOR DOING THIS WE USE THE PRE-TRAINED INCEPTIONV3 CNN MODEL. THIS FORMS OUR ENCODING MODEL.WITHOUT THE USE OF SUCH PRE-BUILD MODELS THE IMAGES WILL TAKE IN SIGNIFICANTLY MORE TRAINING.

```
encode_model = InceptionV3(weights='imagenet')
encode_model = Model(encode_model.input, encode_model.layers[-2].output)
WIDTH = 299
HEIGHT = 299
OUTPUT_DIM = 2048
preprocess_input = tensorflow.keras.applications.inception_v3.preprocess_input
```

```
encode_model.summary()
```

```
__________________________________________________________________________________________________
activation_278 (Activation)     (None, 8, 8, 384)    0           batch_normalizati
__________________________________________________________________________________________________
conv2d_275 (Conv2D)             (None, 8, 8, 384)    442368      activation_274[0]
__________________________________________________________________________________________________
conv2d_276 (Conv2D)             (None, 8, 8, 384)    442368      activation_274[0]
__________________________________________________________________________________________________
```

```
conv2d_279 (Conv2D)             (None, 8, 8, 384)    442368      activation_278[0]
________________________________________________________________________________
conv2d_280 (Conv2D)             (None, 8, 8, 384)    442368      activation_278[0]
________________________________________________________________________________
average_pooling2d_26 (AveragePo (None, 8, 8, 2048)   0           mixed9[0][0]
________________________________________________________________________________
conv2d_273 (Conv2D)             (None, 8, 8, 320)    655360      mixed9[0][0]
________________________________________________________________________________
batch_normalization_275 (BatchN (None, 8, 8, 384)    1152        conv2d_275[0][0]
________________________________________________________________________________
batch_normalization_276 (BatchN (None, 8, 8, 384)    1152        conv2d_276[0][0]
________________________________________________________________________________
batch_normalization_279 (BatchN (None, 8, 8, 384)    1152        conv2d_279[0][0]
________________________________________________________________________________
batch_normalization_280 (BatchN (None, 8, 8, 384)    1152        conv2d_280[0][0]
________________________________________________________________________________
conv2d_281 (Conv2D)             (None, 8, 8, 192)    393216      average_pooling2d
________________________________________________________________________________
batch_normalization_273 (BatchN (None, 8, 8, 320)    960         conv2d_273[0][0]
________________________________________________________________________________
activation_275 (Activation)     (None, 8, 8, 384)    0           batch_normalizati
________________________________________________________________________________
activation_276 (Activation)     (None, 8, 8, 384)    0           batch_normalizati
________________________________________________________________________________
activation_279 (Activation)     (None, 8, 8, 384)    0           batch_normalizati
________________________________________________________________________________
activation_280 (Activation)     (None, 8, 8, 384)    0           batch_normalizati
________________________________________________________________________________
batch_normalization_281 (BatchN (None, 8, 8, 192)    576         conv2d_281[0][0]
________________________________________________________________________________
activation_273 (Activation)     (None, 8, 8, 320)    0           batch_normalizati
________________________________________________________________________________
mixed9_1 (Concatenate)          (None, 8, 8, 768)    0           activation_275[0]
                                                                 activation_276[0]
________________________________________________________________________________
concatenate_5 (Concatenate)     (None, 8, 8, 768)    0           activation_279[0]
                                                                 activation_280[0]
________________________________________________________________________________
activation_281 (Activation)     (None, 8, 8, 192)    0           batch_normalizati
________________________________________________________________________________
mixed10 (Concatenate)           (None, 8, 8, 2048)   0           activation_273[0]
                                                                 mixed9_1[0][0]
                                                                 concatenate_5[0][
                                                                 activation_281[0]
________________________________________________________________________________
avg_pool (GlobalAveragePooling2 (None, 2048)         0           mixed10[0][0]
================================================================================
Total params: 21,802,784
Trainable params: 21,768,352
Non-trainable params: 34,432
________________________________________________________________________________
```

THIS FUNCTION TAKES IN A RAW IMAGE AND OUTPUTS THE FEATURES EXTRACTED FROM THEM, SO AS TO BE USED FOR LATER MODELS

```
def encodeImage(img):
  img = img.resize((WIDTH, HEIGHT), Image.ANTIALIAS)
  x = tensorflow.keras.preprocessing.image.img_to_array(img)
  x = np.expand_dims(x, axis=0)
  x = preprocess_input(x)
  x = encode_model.predict(x)
  x = np.reshape(x, OUTPUT_DIM )
  return x
```

STORING THE FEATURES FOR THE TRAIN IMAGES

WE USE THE PICKLE LIBRARY TO STORE THE TRAINING IMAGES ID ALONG WITH ITS EXTRACTED FEATURES IN THE FORM OF A DICTIONARY. DOING THIS WILL SAVE US A LOT OF TIME LATER AND ALSO PREVENT US FROM RE-EXTRACTTING THE SAME FEATURES IF A SITUATION OF RE-TRAINING OCCURS

```
train_path = os.path.join(root_captioning,"data",f'train{OUTPUT_DIM}.pkl')
if not os.path.exists(train_path):
  start = time()
  encoding_train = {}
  for id in tqdm(train_img): #iterating the traing images by using the tqdm function so th
    image_path = os.path.join(root_captioning,'Flicker8k_Dataset', id)
    img = tensorflow.keras.preprocessing.image.load_img(image_path,target_size=(HEIGHT, WI
    encoding_train[id] = encodeImage(img)
  with open(train_path, "wb") as fp:
    pickle.dump(encoding_train, fp)
  print(f"\nGenerating training set took: {hms_string(time()-start)}")
else:
  with open(train_path, "rb") as fp:
    encoding_train = pickle.load(fp)
```

STORING FEATURES FOR TEST IMAGES

SAME AS WE DID FOR THE TRAIN IMAGES, WE ALSO STORE THE FEATURES FOR THE TEST IMAGES INTO PICKLE FILE FOR LATER USE

```
test_path = os.path.join(root_captioning,"data",f'test{OUTPUT_DIM}.pkl')
if not os.path.exists(test_path):
  start = time()
  encoding_test = {}
  for id in tqdm(test_img):
    image_path = os.path.join(root_captioning,'Flicker8k_Dataset', id)
    img = tensorflow.keras.preprocessing.image.load_img(image_path,target_size=(HEIGHT, WI
    encoding_test[id] = encodeImage(img)
  with open(test_path, "wb") as fp:
    pickle.dump(encoding_test, fp)
  print(f"\nGenerating testing set took: {hms_string(time()-start)}")
else:
  with open(test_path, "rb") as fp:
    encoding_test = pickle.load(fp)
```

WE SEPRATE CAPTIONS FROM THE IMAGES, THERE ARE TWO SIDE OF TRAINING THE MODEL,ONE ON IMAGES AND THE OTHER ON CAPTIONS

```
all_train_captions = []
for key, val in train_descriptions.items():
    for cap in val:
        all_train_captions.append(cap)
len(all_train_captions)
```

```
30000
```

LESS COMMON WORDS CAN BE BE MISLEADING TO THE NEURAL NETWORK BEING TRAINED, SO WE REMOVE ANY WORD WHICH OCCURS LESS THAN 10 TIMES AND PREPARE A RESULTING VOCABULARY

```
word_count_threshold = 10
word_counts = {} #STORES THE NUMBER OF TIMES EACH WORD HAS OCCURED IN THE CAPTIONS TRAININ
nsents = 0
for sent in all_train_captions:
    nsents += 1
    for w in sent.split(' '):
        word_counts[w] = word_counts.get(w, 0) + 1

vocab = [w for w in word_counts if word_counts[w] >= word_count_threshold]# VOCAB STORES O
print('preprocessed words %d ==> %d' % (len(word_counts), len(vocab)))
```

```
preprocessed words 7578 ==> 1651
```

NOW WE PREPARE TWO DICTIONARIES FOR THE VOCAB, THE IDXTOWORD DICT ASSCOIATES THE INDEX TO CORRESPONDING WORDS PRESENT IN THE VOCAB LIST . TH WORDTOIDX DOES THE OPPOSITE.

```
idxtoword = {}
wordtoidx = {}

ix = 1
for w in vocab:
    wordtoidx[w] = ix
    idxtoword[ix] = w
    ix += 1

vocab_size = len(idxtoword) + 1
vocab_size
```

```
1652
```

STORING THE DICTIONARIES

WE NOW STORE THE IDXTOWORD AND THE WORDTOIDX DICTIONARIES INTO THE GDRIVE IN THE FORM OF PICKLE FILES.THESE WILL BE USED LATER FOR PREDICTING THE RESULTS.

```
idxtoword_path=os.path.join(root_captioning,"data",'idxtoword.pkl')
with open(idxtoword_path, "wb") as fp:
  pickle.dump(idxtoword, fp)
print("data saved")
```

```
     data saved
```

```
wordtoidx_path=os.path.join(root_captioning,"data",'wordtoidx.pkl')
with open(wordtoidx_path, "wb") as fp:
  pickle.dump(wordtoidx,fp)
print("data saved")
```

```
     data saved
```

```
max_length +=2
print(max_length)
```

```
     34
```

USING DATA GENERATORS

Up to this point, we've always generated training data ahead of time and fit the neural network to it. It is not always practical to create all of the training data ahead of time. The memory demands can be considerable. If we generate the training data as the neural network needs it, it is possible to use a Keras generator. The generator will create new data as it is needed. The generator provided here creates the training data for the caption neural network, as it is needed.

```
def data_generator(descriptions, photos, wordtoidx, \
                   max_length, num_photos_per_batch):
  # x1 - Training data for photos
  # x2 - The caption that goes with each photo
  # y - The predicted rest of the caption
  x1, x2, y = [], [], []
  n=0
  while True:
    for key, desc_list in descriptions.items():
      n+=1
      photo = photos[key+'.jpg']
      # Each photo has 5 descriptions
      for desc in desc_list:
        # Convert each caption into a list of sequences.
        seq = [wordtoidx[word] for word in desc.split(' ') if word in wordtoidx]
        # Generate a training case for every possible sequence and outcome
        for i in range(1, len(seq)):
          in_seq, out_seq = seq[:i], seq[i]
          in_seq = pad_sequences([in_seq], maxlen=max_length)[0]
          out_seq = to_categorical([out_seq], num_classes=vocab_size)[0]
          x1.append(photo)
          x2.append(in_seq)
          y.append(out_seq)
      if n==num_photos_per_batch:
        yield ([np.array(x1), np.array(x2)], np.array(y))
        x1, x2, y = [], [], []
        n=0
```

GLOVE IS AN UNSUPERVISED LEARNING ALGORITHM FOR OBTAINING THE VECTOR REPRESENTATION OF THE WORDS. THESE VECTORS ARE GLOBAL IN NATURE AND ARE USED FOR TRAININGS MODELS WHICH TAKE IN WORDS(TEXT) AS INPUT.

```
glove_dir = os.path.join(root_captioning,'glove.6B')
embeddings_index = {}
f = open(os.path.join(glove_dir, 'glove.6B.200d.txt'), encoding="utf-8")

for line in tqdm(f):
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs

f.close()
print(f'Found {len(embeddings_index)} word vectors.')
```

```
     400000it [00:23, 16940.93it/s]Found 400000 word vectors.
```

CREATING EMBEDDING MATRIX

NOW WE USE THE GLOVE EMBEDDINGS TO CREATE A 200 DIM VECTOR FOR EACH WORD PRESENT IN OUR VOCABULARY. WE STORE THESE IN A MATRIX CALLED EMBEDDING MATRIX

```
embedding_dim = 200

# Get 200-dim dense vector for each word in our vocabulary
embedding_matrix = np.zeros((vocab_size, embedding_dim))

for word, i in wordtoidx.items():
    #if i < max_words:
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        # Words not found in the embedding index will be all zeros
        embedding_matrix[i] = embedding_vector
```

```
embedding_matrix.shape
```

```
(1652, 200)
```

CREATING THE CAPTION MODEL

NEXT WE HAVE TO CREATE THE CAPTION MODEL, THIS MODEL TAKES IN AS INPUT AN IMAGE AND OUTPUTS THE PREDICTED CAPTION

```
inputs1 = Input(shape=(OUTPUT_DIM,))
fe1 = Dropout(0.5)(inputs1)
fe2 = Dense(256, activation='relu')(fe1)
inputs2 = Input(shape=(max_length,))
se1 = Embedding(vocab_size, embedding_dim, mask_zero=True)(inputs2)
se2 = Dropout(0.5)(se1)
se3 = LSTM(256)(se2)
decoder1 = add([fe2, se3])
decoder2 = Dense(256, activation='relu')(decoder1)
outputs = Dense(vocab_size, activation='softmax')(decoder2)
caption_model = Model(inputs=[inputs1, inputs2], outputs=outputs)
```

```
embedding_dim
```

```
200
```

```
caption_model.summary()
```

```
Model: "model_4"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_7 (InputLayer)            [(None, 34)]         0
__________________________________________________________________________________________________
input_6 (InputLayer)            [(None, 2048)]       0
__________________________________________________________________________________________________
embedding_1 (Embedding)         (None, 34, 200)      330400      input_7[0][0]
__________________________________________________________________________________________________
dropout_2 (Dropout)             (None, 2048)         0           input_6[0][0]
__________________________________________________________________________________________________
dropout_3 (Dropout)             (None, 34, 200)      0           embedding_1[0][0]
__________________________________________________________________________________________________
dense_3 (Dense)                 (None, 256)          524544      dropout_2[0][0]
__________________________________________________________________________________________________
lstm_1 (LSTM)                   (None, 256)          467968      dropout_3[0][0]
__________________________________________________________________________________________________
add_1 (Add)                     (None, 256)          0           dense_3[0][0]
                                                                 lstm_1[0][0]
__________________________________________________________________________________________________
dense_4 (Dense)                 (None, 256)          65792       add_1[0][0]
__________________________________________________________________________________________________
dense_5 (Dense)                 (None, 1652)         424564      dense_4[0][0]
==================================================================================================
Total params: 1,813,268
```

```
Trainable params: 1,813,268
Non-trainable params: 0
_________________________________________________________________
```

```
caption_model.layers[2].set_weights([embedding_matrix])
caption_model.layers[2].trainable = False
caption_model.compile(loss='categorical_crossentropy', optimizer='adam')
```

```
number_pics_per_bath = 3
steps = len(train_descriptions)//number_pics_per_bath
```

TRAINING THE CAPTION MODEL

```
model_path = os.path.join(root_captioning,"data",f'caption-model.hdf5')
if not os.path.exists(model_path):
  for i in tqdm(range(EPOCHS*2)):
      generator = data_generator(train_descriptions, encoding_train,
                    wordtoidx, max_length, number_pics_per_bath)
      caption_model.fit_generator(generator, epochs=1,
                    steps_per_epoch=steps, verbose=1)

  caption_model.optimizer.lr = 1e-4
  number_pics_per_bath = 6
  steps = len(train_descriptions)//number_pics_per_bath

  for i in range(EPOCHS):
      generator = data_generator(train_descriptions, encoding_train,
                    wordtoidx, max_length, number_pics_per_bath)
      caption_model.fit_generator(generator, epochs=1,
                            steps_per_epoch=steps, verbose=1)
  caption_model.save_weights(model_path)
  print(f"\Training took: {hms_string(time()-start)}")
else:
  caption_model.load_weights(model_path)
```

FUNCTION TO OUTPUT THE RESULT

THE GENERATECAPTION FUNCTION IS USED TO TAKE A ENCODED IMAGE AND OUTPUT THE PREDICTED CAPTIONS.

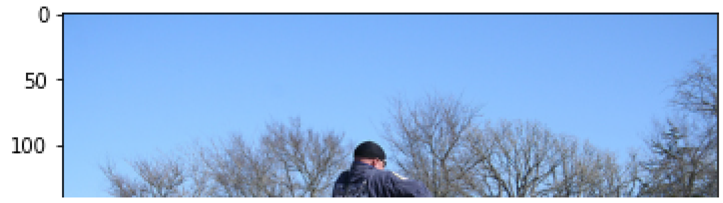
```
def generateCaption(photo):
    in_text = START
    for i in range(max_length):
        sequence = [wordtoidx[w] for w in in_text.split() if w in wordtoidx]
        sequence = pad_sequences([sequence], maxlen=max_length)
        yhat = caption_model.predict([photo,sequence], verbose=0)
        yhat = np.argmax(yhat)
        word = idxtoword[yhat]
        in_text += ' ' + word
        if word == STOP:
            break
    final = in_text.split()
    final = final[1:-1]
    final = ' '.join(final)
    return final
```

TESTING THE DATA

NOW WE TEST THE MODEL AGAINST A FEW OF THE TRAIN IMAGES

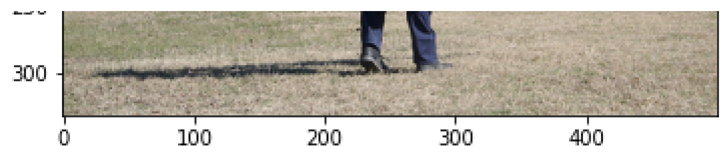
```
for z in range(2): # set higher to see more examples
  pic = list(encoding_test.keys())[z]
  image = encoding_test[pic].reshape((1,OUTPUT_DIM))
  print(os.path.join(root_captioning,'Flicker8k_Dataset', pic))
  x=plt.imread(os.path.join(root_captioning,'Flicker8k_Dataset', pic))
  plt.imshow(x)
  plt.show()
  print("Caption:",generateCaption(image))
  print("_____________________________________")
```

```
/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/3192266178_f9bf5c
```



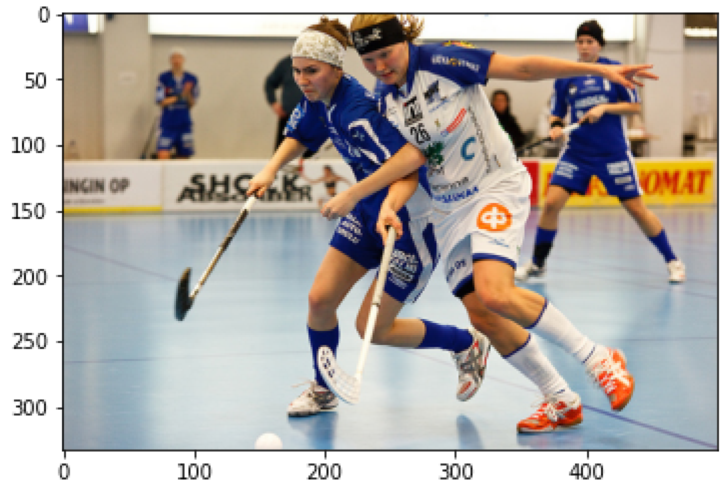
```
encoding_test[pic].shape
```

```
(2048,)
```



```
Caption: man in blue shirt is playing with dog in the grass
```

```
/content/drive/MyDrive/Colab Notebooks/CAPTIONING/Flicker8k_Dataset/3234115903_f4dfc8
```



```
Caption: two men in martial arts match
```

✓ 0s completed at 9:42 PM