Image Captioning

Image captioning is a process that involves generating descriptive textual explanations or captions for images. It typically combines techniques from computer vision and natural language processing to analyze the content of an image and produce a relevant and coherent description.

Import Libraries

In [1]:
```
import numpy as np
import pandas as pd
import os
import tensorflow as tf
from tqdm import tqdm
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import Sequence
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D, Activation, Dropout, Flatten, Dense, Input, Layer
from tensorflow.keras.layers import Embedding, LSTM, add, Concatenate, Reshape, concatenate, Bidirectional
from tensorflow.keras.applications import VGG16, ResNet50, DenseNet201
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
from textwrap import wrap

plt.rcParams['font.size'] = 12
sns.set_style("dark")
warnings.filterwarnings('ignore')
```

In [2]:
```
image_path = '../input/flickr8k/Images'
```

In [3]:
```
data = pd.read_csv("../input/flickr8k/captions.txt")
data.head()
```

Out[3]:

	image	caption
0	1000268201_693b08cb0e.jpg	A child in a pink dress is climbing up a set o...
1	1000268201_693b08cb0e.jpg	A girl going into a wooden building .
2	1000268201_693b08cb0e.jpg	A little girl climbing into a wooden playhouse .
3	1000268201_693b08cb0e.jpg	A little girl climbing the stairs to her playh...
4	1000268201_693b08cb0e.jpg	A little girl in a pink dress going into a woo...

In [4]:
```
def readImage(path,img_size=224):
    img = load_img(path,color_mode='rgb',target_size=(img_size,img_size))
    img = img_to_array(img)
    img = img/255.
```

```
    return img

def display_images(temp_df):
    temp_df = temp_df.reset_index(drop=True)
    plt.figure(figsize = (20 , 20))
    n = 0
    for i in range(15):
        n+=1
        plt.subplot(5 , 5, n)
        plt.subplots_adjust(hspace = 0.7, wspace = 0.3)
        image = readImage(f"../input/flickr8k/Images/{temp_df.image[i]}")
        plt.imshow(image)
        plt.title("\n".join(wrap(temp_df.caption[i], 20)))
        plt.axis("off")
```

Visualization

- Images and their corresponding captions

In [5]:
```
display_images(data.sample(15))
```

A woman drinking from a mug and reading the paper .

People stand on a sidewalk outside of retail stores .

A young woman dressed in black and another with purple hair hold up signs offering free hugs .

A woman in a green jacket is waiting to cross the street at a light .

Four white dogs are running and jumping with masks over their mouth .

a man wearing a grey shirt waving in the middle of a plant nursery

This man is wearing a Barack Obama T-shirt and carrying a drink .

Two people stand on the edge of a recently snowed on cliff .

Family purchasing standing at a vending machine .

A man in a black jacket walks thorugh an Asian market .

A black dog holds a beat up soccer ball in his mouth on the grass in front of a home .

Two boys pulling a wagon .

A person in a red vest is touching the blue ice skates on another person .

Kids jump their bikes off of dirt ramps near a waterfront .

A dog catching an orange ball , in the snow .

Caption Text Preprocessing Steps

- Convert sentences into lowercase
- Remove special characters and numbers present in the text
- Remove extra spaces
- Remove single characters
- Add a starting and an ending tag to the sentences to indicate the beginning and the ending of a sentence

In [6]:
```
def text_preprocessing(data):
    data['caption'] = data['caption'].apply(lambda x: x.lower())
    data['caption'] = data['caption'].apply(lambda x: x.replace("[^A-Za-z]",""))
    data['caption'] = data['caption'].apply(lambda x: x.replace("\s+"," "))
```

```
    data['caption'] = data['caption'].apply(lambda x: " ".join([word for word in x.split() if len(word)>1]))
    data['caption'] = "startseq "+data['caption']+" endseq"
    return data
```

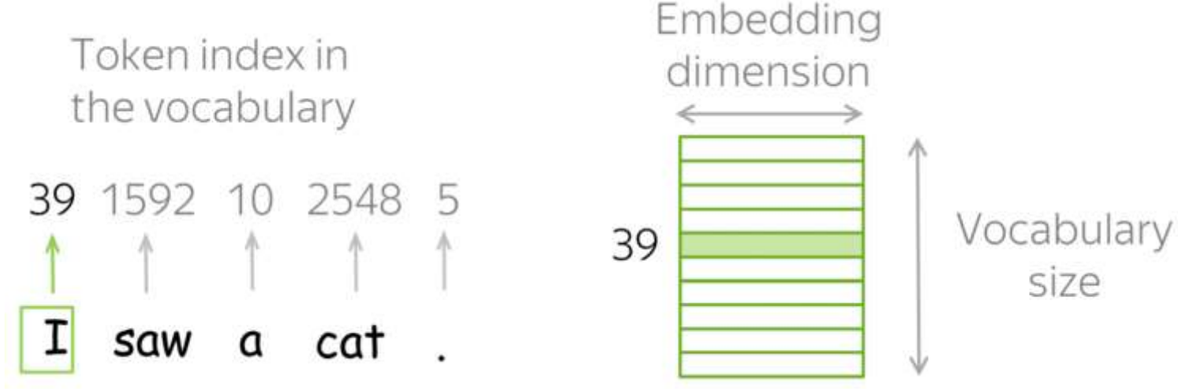
Preprocessed Text

In [7]:
```
data = text_preprocessing(data)
captions = data['caption'].tolist()
captions[:10]
```

Out[7]:
```
['startseq child in pink dress is climbing up set of stairs in an entry way endseq',
 'startseq girl going into wooden building endseq',
 'startseq little girl climbing into wooden playhouse endseq',
 'startseq little girl climbing the stairs to her playhouse endseq',
 'startseq little girl in pink dress going into wooden cabin endseq',
 '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']
```

Tokenization and Encoded Representation

- The words in a sentence are separated/tokenized and encoded in a one hot representation
- These encodings are then passed to the embeddings layer to generate word embeddings



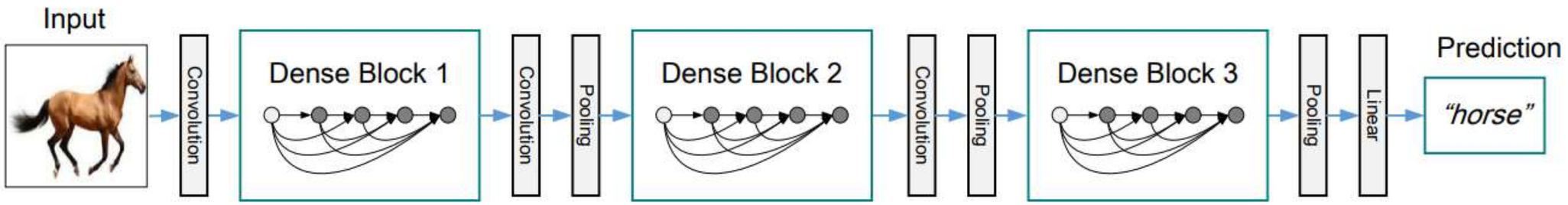
In [8]:
```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(captions)
vocab_size = len(tokenizer.word_index) + 1
max_length = max(len(caption.split()) for caption in captions)

images = data['image'].unique().tolist()
nimages = len(images)

split_index = round(0.85*nimages)
train_images = images[:split_index]
val_images = images[split_index:]

train = data[data['image'].isin(train_images)]
```

```
test = data[data['image'].isin(val_images)]

train.reset_index(inplace=True,drop=True)
test.reset_index(inplace=True,drop=True)

tokenizer.texts_to_sequences([captions[1]])[0]
```

Out[8]:
```
[1, 18, 315, 63, 195, 116, 2]
```

Image Feature Extraction

- DenseNet 201 Architecture is used to extract the features from the images
- Any other pretrained architecture can also be used for extracting features from these images
- Since the Global Average Pooling layer is selected as the final layer of the DenseNet201 model for our feature extraction, our image embeddings will be a vector of size 1920



In [9]:
```
model = DenseNet201()
fe = Model(inputs=model.input, outputs=model.layers[-2].output)

img_size = 224
features = {}
for image in tqdm(data['image'].unique().tolist()):
    img = load_img(os.path.join(image_path,image),target_size=(img_size,img_size))
    img = img_to_array(img)
    img = img/255.
    img = np.expand_dims(img,axis=0)
    feature = fe.predict(img, verbose=0)
    features[image] = feature
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet201_weights_tf_dim_ordering_tf_kernels.h5
82526208/82524592 [==============================] - 1s 0us/step
82534400/82524592 [==============================] - 1s 0us/step
100%|████████| 8091/8091 [10:51<00:00, 12.41it/s]
```

Data Generation

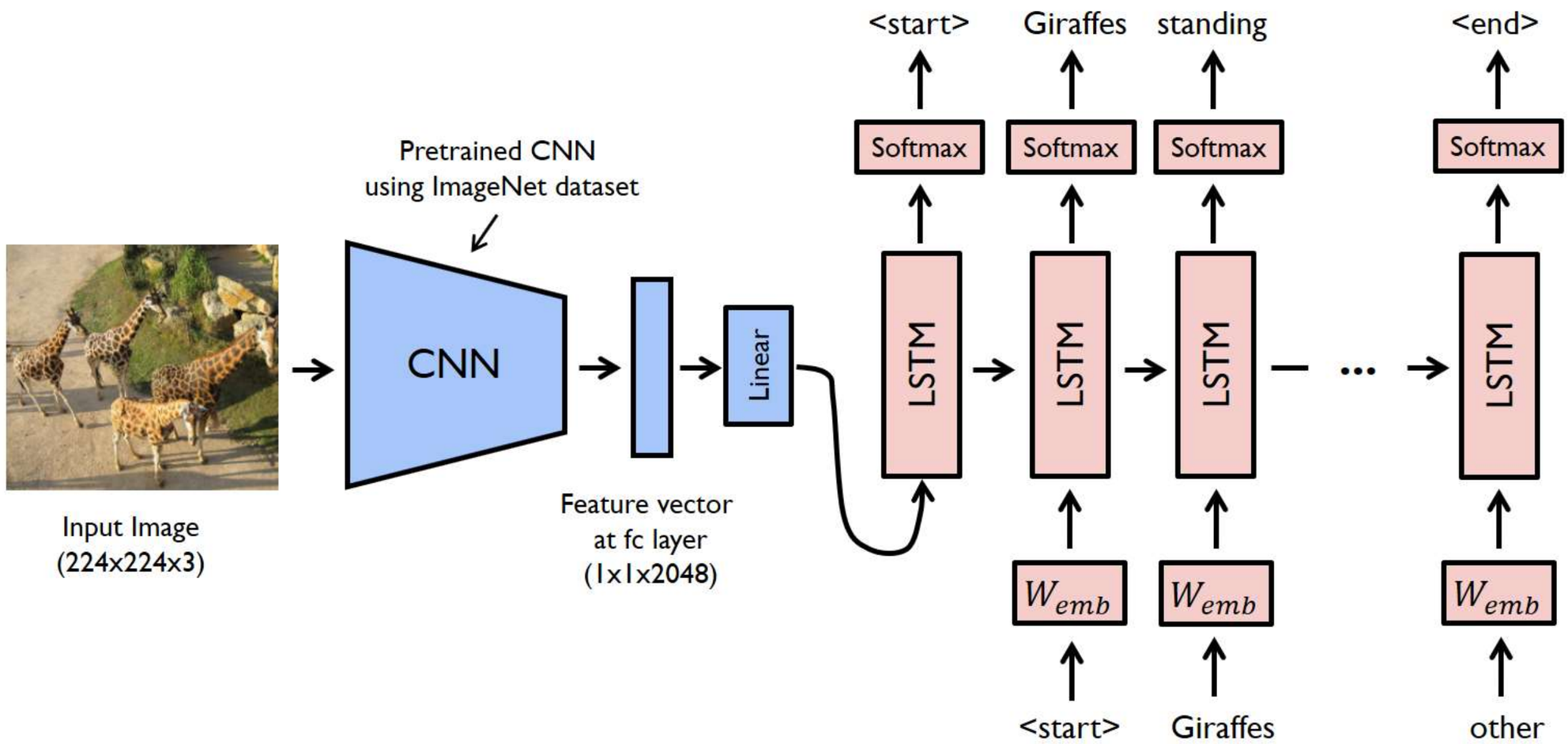
- Since training an Image Caption model, like any other neural network training, is a highly resource-intensive process, we cannot load all the data into the main memory at once. Therefore, we need to generate the data in the required format batch-wise.
- The inputs will be the image embeddings and their corresonding caption text embeddings for the training process
- The text embeddings are passed word by word for the caption generation during inference time

In [10]:
```
class CustomDataGenerator(Sequence):

    def __init__(self, df, X_col, y_col, batch_size, directory, tokenizer,
                 vocab_size, max_length, features,shuffle=True):

        self.df = df.copy()
        self.X_col = X_col
        self.y_col = y_col
        self.directory = directory
        self.batch_size = batch_size
        self.tokenizer = tokenizer
        self.vocab_size = vocab_size
        self.max_length = max_length
        self.features = features
        self.shuffle = shuffle
        self.n = len(self.df)

    def on_epoch_end(self):
        if self.shuffle:
            self.df = self.df.sample(frac=1).reset_index(drop=True)

    def __len__(self):
        return self.n // self.batch_size

    def __getitem__(self,index):

        batch = self.df.iloc[index * self.batch_size:(index + 1) * self.batch_size,:]
        X1, X2, y = self.__get_data(batch)
        return (X1, X2), y

    def __get_data(self,batch):

        X1, X2, y = list(), list(), list()

        images = batch[self.X_col].tolist()

        for image in images:
            feature = self.features[image][0]

            captions = batch.loc[batch[self.X_col]==image, self.y_col].tolist()
            for caption in captions:
                seq = self.tokenizer.texts_to_sequences([caption])[0]

                for i in range(1,len(seq)):
                    in_seq, out_seq = seq[:i], seq[i]
                    in_seq = pad_sequences([in_seq], maxlen=self.max_length)[0]
                    out_seq = to_categorical([out_seq], num_classes=self.vocab_size)[0]
                    X1.append(feature)
                    X2.append(in_seq)
                    y.append(out_seq)

        X1, X2, y = np.array(X1), np.array(X2), np.array(y)

        return X1, X2, y
```

Modelling

- The image embedding representations are concatenated with the first word of sentence ie. starseq and passed to the LSTM network

- The LSTM network starts generating words after each input thus forming a sentence at the end



In [11]:
```
input1 = Input(shape=(1920,))
input2 = Input(shape=(max_length,))

img_features = Dense(256, activation='relu')(input1)
img_features_reshaped = Reshape((1, 256), input_shape=(256,))(img_features)

sentence_features = Embedding(vocab_size, 256, mask_zero=False)(input2)
merged = concatenate([img_features_reshaped,sentence_features],axis=1)
sentence_features = LSTM(256)(merged)
x = Dropout(0.5)(sentence_features)
x = add([x, img_features])
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(vocab_size, activation='softmax')(x)
```

```
caption_model = Model(inputs=[input1,input2], outputs=output)
caption_model.compile(loss='categorical_crossentropy',optimizer='adam')
```

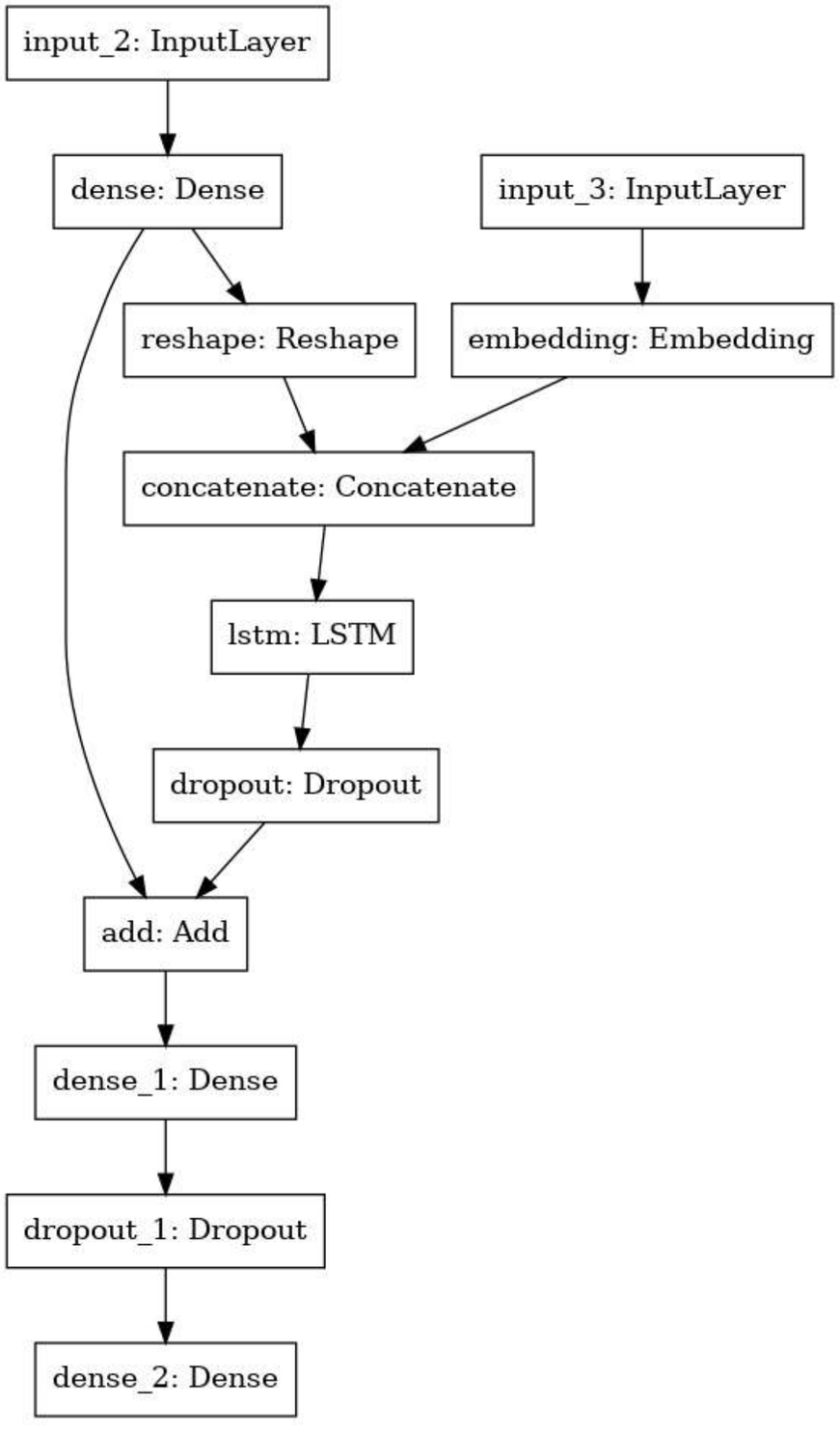
In [12]:
```
from tensorflow.keras.utils import plot_model
```

Model Modification

- A slight change has been made in the original model architecture to push the performance. The image feature embeddings are added to the output of the LSTMs and then passed on to the fully connected layers

In [13]:
```
plot_model(caption_model)
```

Out[13]:


input_2: InputLayer
dense: Dense
input_3: InputLayer
reshape: Reshape
embedding: Embedding
concatenate: Concatenate
lstm: LSTM
dropout: Dropout
add: Add
dense_1: Dense
dropout_1: Dropout
dense_2: Dense

Train the model

In [14]:
```
caption_model.summary()
```

```
Model: "model_1"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_2 (InputLayer)            [(None, 1920)]       0
__________________________________________________________________________________________________
dense (Dense)                   (None, 256)          491776      input_2[0][0]
__________________________________________________________________________________________________
input_3 (InputLayer)            [(None, 34)]         0
__________________________________________________________________________________________________
reshape (Reshape)               (None, 1, 256)       0           dense[0][0]
__________________________________________________________________________________________________
embedding (Embedding)           (None, 34, 256)      2172160     input_3[0][0]
__________________________________________________________________________________________________
concatenate (Concatenate)       (None, 35, 256)      0           reshape[0][0]
                                                                 embedding[0][0]
__________________________________________________________________________________________________
lstm (LSTM)                     (None, 256)          525312      concatenate[0][0]
__________________________________________________________________________________________________
dropout (Dropout)               (None, 256)          0           lstm[0][0]
__________________________________________________________________________________________________
add (Add)                       (None, 256)          0           dropout[0][0]
                                                                 dense[0][0]
__________________________________________________________________________________________________
dense_1 (Dense)                 (None, 128)          32896       add[0][0]
__________________________________________________________________________________________________
dropout_1 (Dropout)             (None, 128)          0           dense_1[0][0]
__________________________________________________________________________________________________
dense_2 (Dense)                 (None, 8485)         1094565     dropout_1[0][0]
==================================================================================================
Total params: 4,316,709
Trainable params: 4,316,709
Non-trainable params: 0
__________________________________________________________________________________________________
```

In [15]:
```
train_generator = CustomDataGenerator(df=train,X_col='image',y_col='caption',batch_size=64,directory=image_path,
                                      tokenizer=tokenizer,vocab_size=vocab_size,max_length=max_length,features=features)

validation_generator = CustomDataGenerator(df=test,X_col='image',y_col='caption',batch_size=64,directory=image_path,
                                      tokenizer=tokenizer,vocab_size=vocab_size,max_length=max_length,features=features)
```

In [16]:
```
model_name = "model.h5"
checkpoint = ModelCheckpoint(model_name,
                             monitor="val_loss",
                             mode="min",
                             save_best_only = True,
                             verbose=1)

earlystopping = EarlyStopping(monitor='val_loss',min_delta = 0, patience = 5, verbose = 1, restore_best_weights=True)

learning_rate_reduction = ReduceLROnPlateau(monitor='val_loss',
                                            patience=3,
                                            verbose=1,
```

```
                                            factor=0.2,
                                            min_lr=0.00000001)
```

In [17]:
```
history = caption_model.fit(
        train_generator,
        epochs=50,
        validation_data=validation_generator,
        callbacks=[checkpoint,earlystopping,learning_rate_reduction])
```

```
Epoch 1/50
537/537 [==============================] - 219s 403ms/step - loss: 5.1204 - val_loss: 4.2245

Epoch 00001: val_loss improved from inf to 4.22448, saving model to model.h5
Epoch 2/50
537/537 [==============================] - 45s 84ms/step - loss: 4.1694 - val_loss: 3.8993

Epoch 00002: val_loss improved from 4.22448 to 3.89932, saving model to model.h5
Epoch 3/50
537/537 [==============================] - 45s 84ms/step - loss: 3.9055 - val_loss: 3.7565

Epoch 00003: val_loss improved from 3.89932 to 3.75650, saving model to model.h5
Epoch 4/50
537/537 [==============================] - 46s 86ms/step - loss: 3.7501 - val_loss: 3.6873

Epoch 00004: val_loss improved from 3.75650 to 3.68732, saving model to model.h5
Epoch 5/50
537/537 [==============================] - 46s 85ms/step - loss: 3.6279 - val_loss: 3.6550

Epoch 00005: val_loss improved from 3.68732 to 3.65504, saving model to model.h5
Epoch 6/50
537/537 [==============================] - 46s 85ms/step - loss: 3.5405 - val_loss: 3.6349

Epoch 00006: val_loss improved from 3.65504 to 3.63491, saving model to model.h5
Epoch 7/50
537/537 [==============================] - 46s 85ms/step - loss: 3.4606 - val_loss: 3.6187

Epoch 00007: val_loss improved from 3.63491 to 3.61871, saving model to model.h5
Epoch 8/50
537/537 [==============================] - 45s 84ms/step - loss: 3.3971 - val_loss: 3.6142

Epoch 00008: val_loss improved from 3.61871 to 3.61418, saving model to model.h5
Epoch 9/50
537/537 [==============================] - 45s 84ms/step - loss: 3.3395 - val_loss: 3.6181

Epoch 00009: val_loss did not improve from 3.61418
Epoch 10/50
537/537 [==============================] - 46s 85ms/step - loss: 3.2920 - val_loss: 3.6205

Epoch 00010: val_loss did not improve from 3.61418
Epoch 11/50
537/537 [==============================] - 46s 86ms/step - loss: 3.2456 - val_loss: 3.6371

Epoch 00011: val_loss did not improve from 3.61418

Epoch 00011: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
Epoch 12/50
537/537 [==============================] - 45s 84ms/step - loss: 3.1349 - val_loss: 3.6529

Epoch 00012: val_loss did not improve from 3.61418
Epoch 13/50
537/537 [==============================] - 47s 87ms/step - loss: 3.1051 - val_loss: 3.6641

Epoch 00013: val_loss did not improve from 3.61418
Restoring model weights from the end of the best epoch.
Epoch 00013: early stopping
```

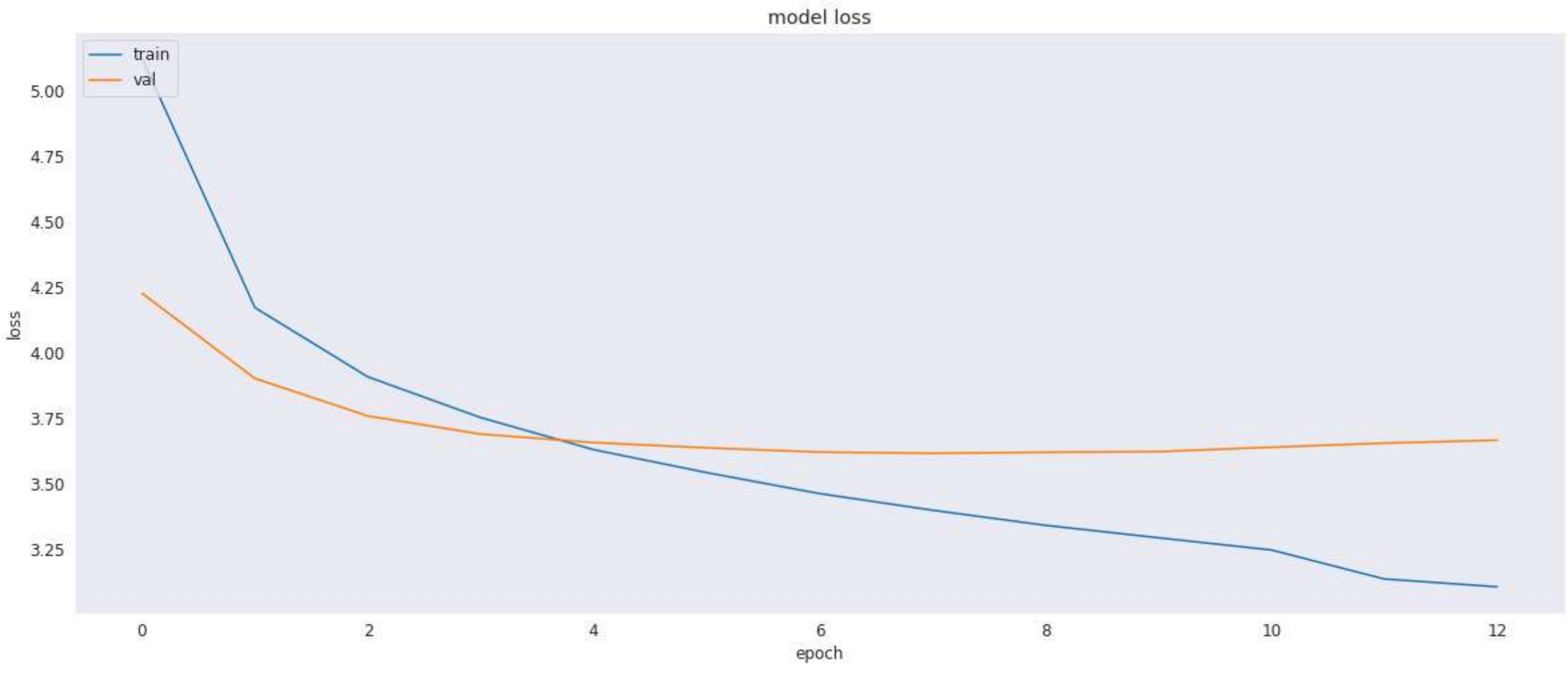
Inference

- Learning Curve (Loss Curve)
- Assessment of Generated Captions (by checking the relevance of the caption with respect to the image, BLEU Score will not be used in this kernel)

Learning Curve

- The model has clearly overfit, possibly due to less amount of data
- We can tackle this problem in two ways
    1. Train the model on a larger dataset Flickr40k
    2. Attention Models

In [18]:
```
plt.figure(figsize=(20,8))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



Caption Generation Utility Functions

- Utility functions to generate the captions of input images at the inference time.
- Here the image embeddings are passed along with the first word, followed by which the text embedding of each new word is passed to generate the next word

In [19]:
```
def idx_to_word(integer,tokenizer):

    for word, index in tokenizer.word_index.items():
        if index==integer:
            return word
    return None
```

In [20]:
```
def predict_caption(model, image, tokenizer, max_length, features):

    feature = features[image]
    in_text = "startseq"
    for i in range(max_length):
        sequence = tokenizer.texts_to_sequences([in_text])[0]
        sequence = pad_sequences([sequence], max_length)

        y_pred = model.predict([feature,sequence])
        y_pred = np.argmax(y_pred)

        word = idx_to_word(y_pred, tokenizer)

        if word is None:
            break

        in_text+= " " + word

        if word == 'endseq':
            break

    return in_text
```

Taking 15 Random Samples for Caption Prediction

In [21]:
```
samples = test.sample(15)
samples.reset_index(drop=True,inplace=True)
```

In [22]:
```
for index,record in samples.iterrows():

    img = load_img(os.path.join(image_path,record['image']),target_size=(224,224))
    img = img_to_array(img)
    img = img/255.

    caption = predict_caption(caption_model, record['image'], tokenizer, max_length, features)
    samples.loc[index,'caption'] = caption
```

Results

- As we can clearly see there is some redundant caption generation e.g. Dog running through the water, overusage of blue shirt for any other coloured cloth
- The model performance can be further improved by training on more data and using attention mechanism so that our model can focus on relevant areas during the text generation
- We can also leverage the interprettability of the attention mechanism to understand which areas of the image leads to the generation of which word

In [23]:
```
display_images(samples)
```

Conclusion:

This may not be the best performing model, but the objective of this kernel is to give a gist of how Image Captioning problems can be approached.