IMAGE ANNOTATION

By Team CODELL

Members:
Chetan Pediredla
Harshit Singh
Khushi Sahoo
Saswat Samal
Saumya Panda

The problem

Aimed towards

Visually impaired people do not have the privilege to view images.

Describing the content of the images in words will help them to understand and appreciate the images.

Context

Describing an image, also known as image annotation is a processing converting an image to text.

Problem statement

We are expecting the team to build a model that can analyze an image, understand it contents and translate it into a human readable text format.

Challenges deep-dive

Challenge 1

Object classification

Take simple images to start which contain objects like ball, hat, human etc.

Challenge 2

Caption generation

Should be extensible to translate complex image.

Challenge 3

Providing free end-to-end solution

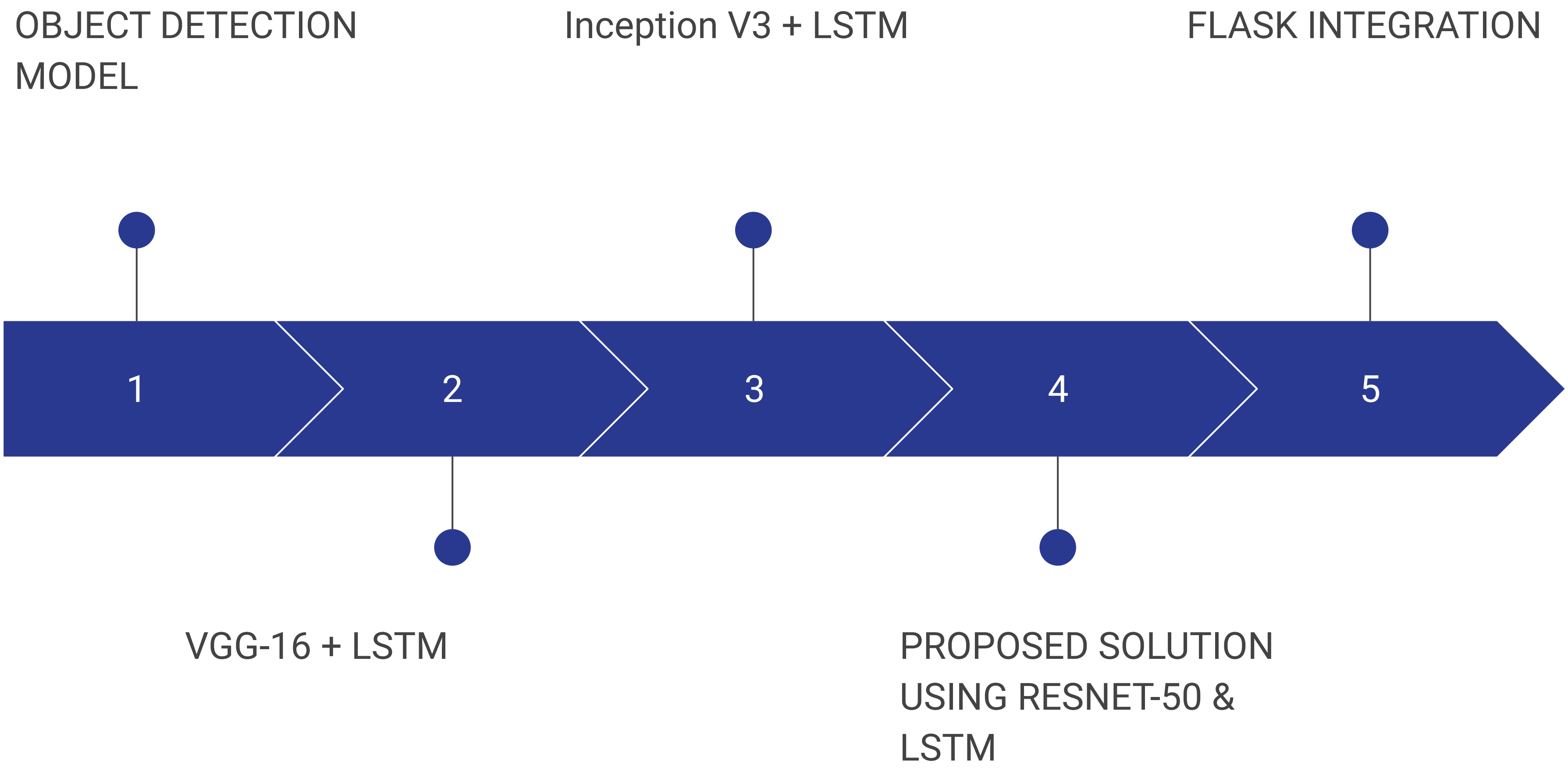
Product creation

Solution

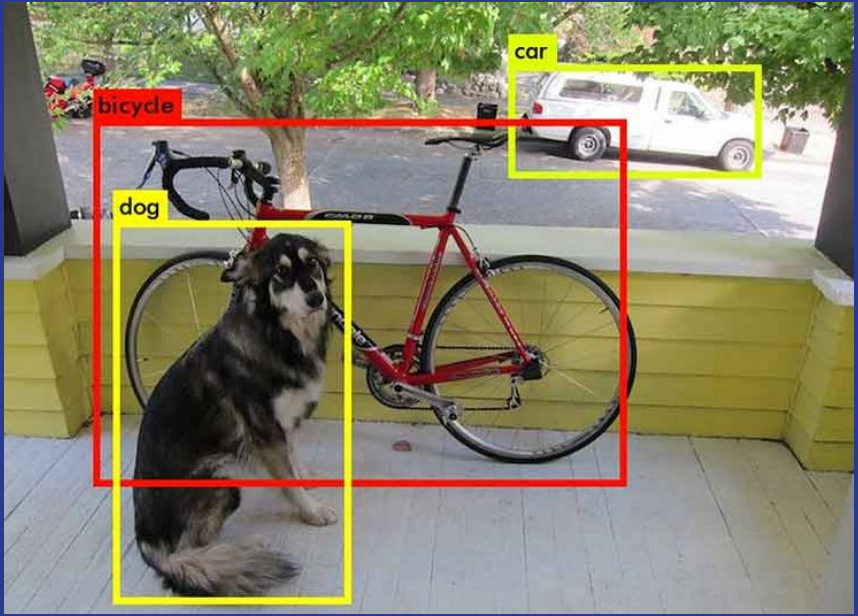
WEB APPLICATION

The solution involves creation of a functional, deployable web app that automatically generates captions for uploaded images.

Our Evaluation


OBJECT DETECTION MODEL
Inception V3 + LSTM
FLASK INTEGRATION
1
2
3
4
5
VGG-16 + LSTM
PROPOSED SOLUTION USING RESNET-50 & LSTM

OBJECT DETECTION



DATASET COLLECTION

There are many open source datasets:

- Flickr 8K
- Flickr 30K
- MS COCO with 180K images

  And many more

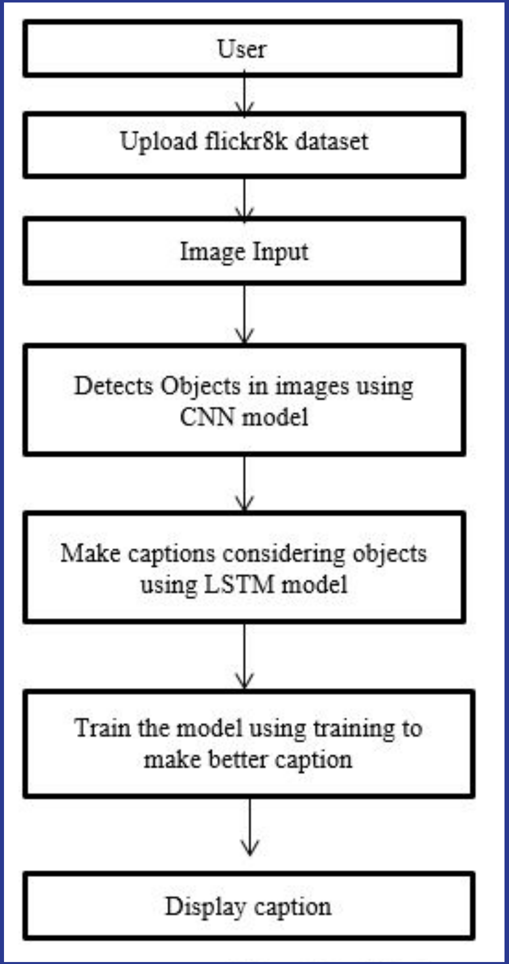
The Flickr 8K dataset contains 8000 images and each image contains 5 different captions.

69189650_6687da7280.jpg, A brown dog is running through a brown field .
69189650_6687da7280.jpg, A brown dog is running through the field .
69189650_6687da7280.jpg, A brown dog with a collar runs in the dead grass with his tongue hanging out to the side .
69189650_6687da7280.jpg, a brown dog with his tongue wagging as he runs through a field
69189650_6687da7280.jpg, A dog running in the grass .

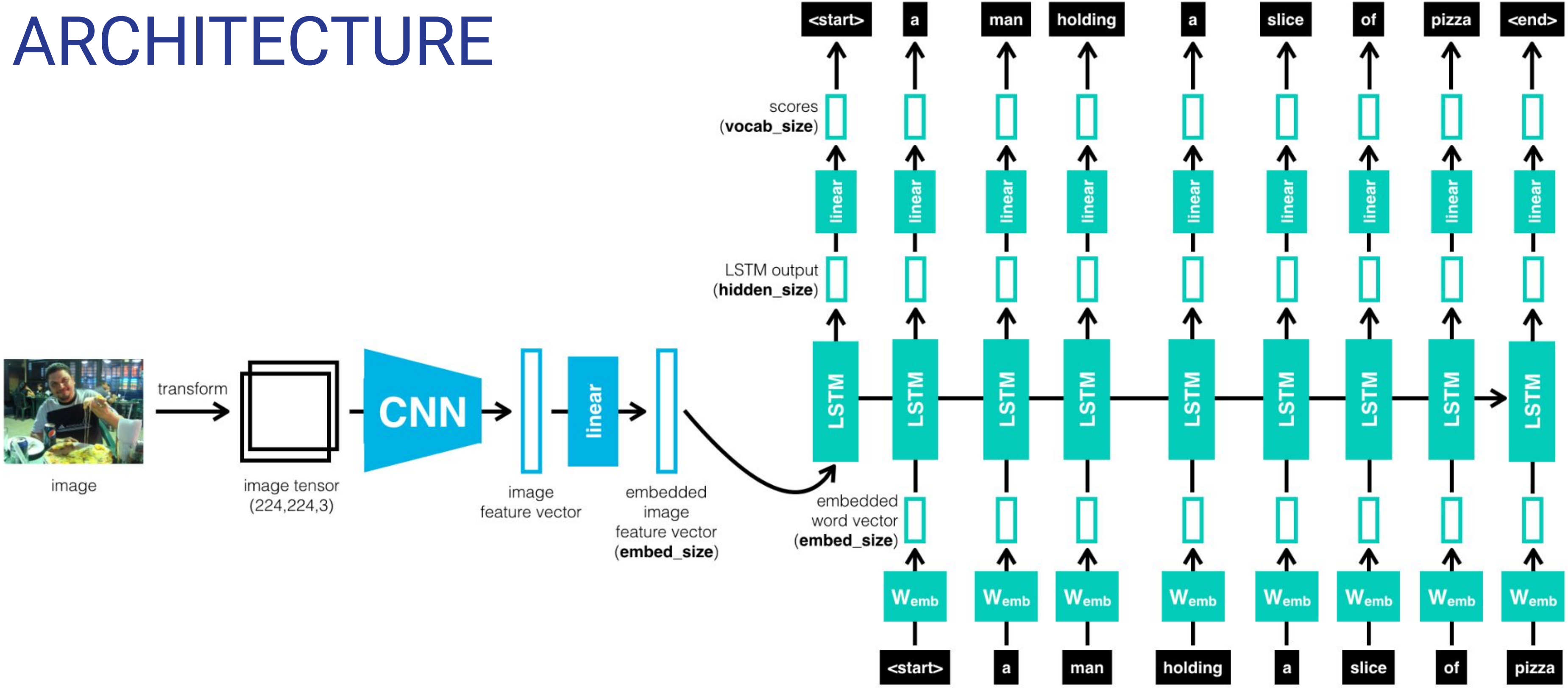
FLOW CHART

Caption

Image

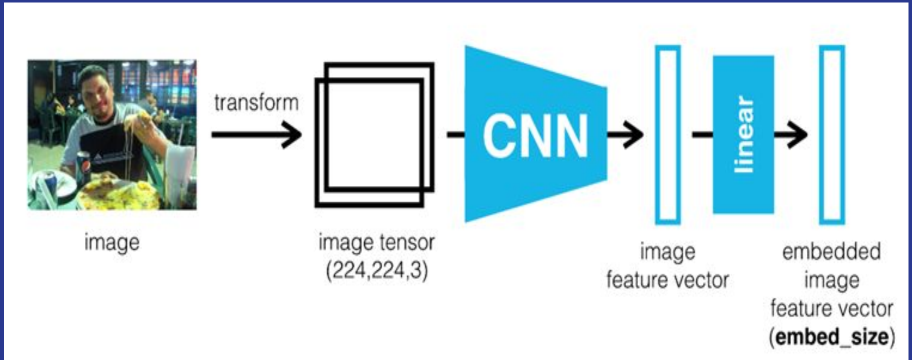


PROPOSED ARCHITECTURE



Encoder:

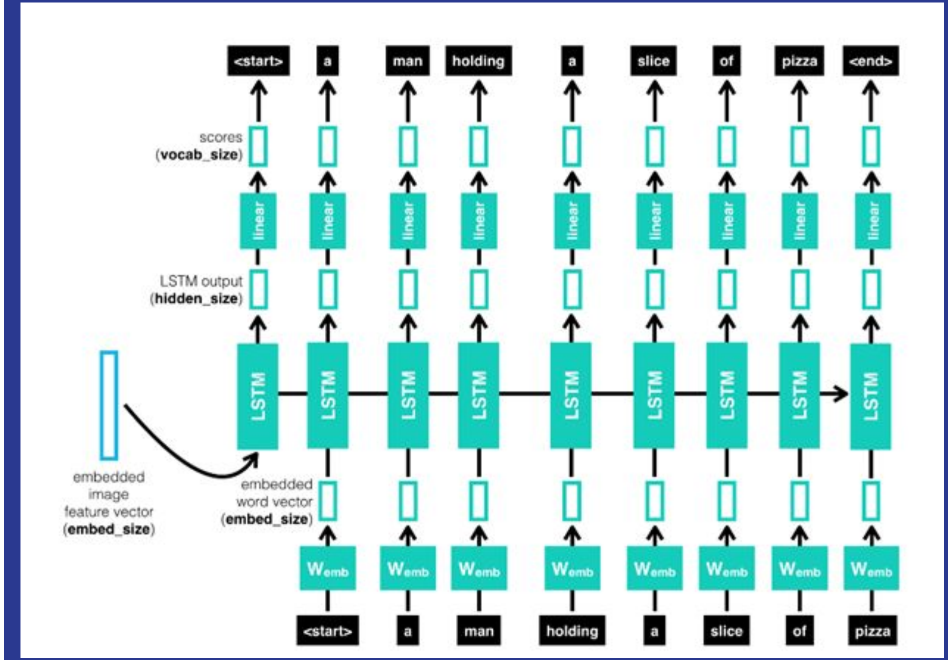
- The encoder is based on a Convolutional Neural Network that encodes an image into a featurized compact representation (in the form of an embedding).



Decoder:

- The feature vector is fed into the "Decoder RNN". Each word appearing as output at the top is fed back to the network as input (at the bottom) in a subsequent time step, until the entire caption is generated.

- The arrow pointing to the right that connects the LSTM boxes together represents hidden state information, which represents the network's "memory", also fed back to the LSTM at each time step.



Training:

The output from the last hidden state of the CNN(Encoder) is given to the first time step of the decoder. We set x_1 =*<START>* vector and the desired label y_1 = *first word in the sequence*. Analogously, we set x_2 =*word vector of the first word* and expect the network to predict the *second word*. Finally, on the last step, x_T = *last word*, the target label y_T =*<END>* token.

During training, the correct input is given to the decoder at every time-step, even if the decoder made a mistake before.

<START>A dog running in the grass **<END>**

Testing:

The image representation is provided to the first time step of the decoder. Set x_1 =*<START>* vector and compute the distribution over the first word y_1. We sample a word from the distribution (or pick the argmax), set its embedding vector as x_2, and repeat this process until the *<END>* token is generated.During Testing, the output of the decoder at time t is fed back and becomes the input of the decoder at time t+1

Creating Dictionaries:

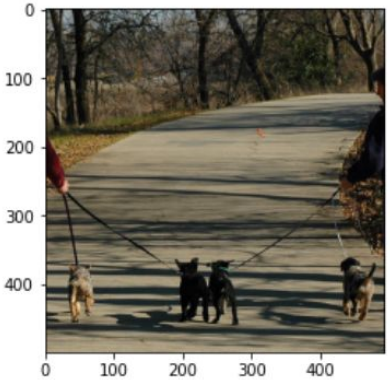
Image_features ={ }
Key : image name
Value : output form model(ResNet/Vgg 16/Inception)

```
images_features = {}
count = 0
for i in images:
    img = cv2.imread(i)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224,224))

    img = img.reshape(1,224,224,3)
    pred = modele.predict(img).reshape(2048,)

    img_name = i.split('/')[-1]

    images_features[img_name] = pred

    count += 1

    if count > 7999:
        break

    elif count % 50 == 0:
        print(count)
```

Captions_dict ={ }
Key : image name
Value : captions

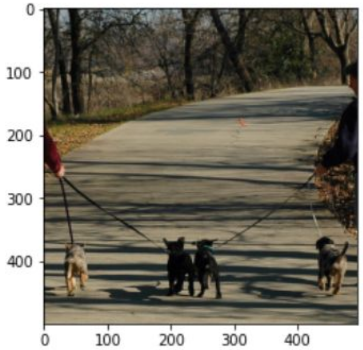
```
captions_dict = {}
for i in captions:
    try:
        img_name = i.split(',')[0]
        caption = i.split(',')[1]
        if img_name in images_features:
            if img_name not in captions_dict:
                captions_dict[img_name] = [caption]

            else:
                captions_dict[img_name].append(caption)

    except:
        pass
```

Create Vocabulary



['Four dogs are being walked by two owners .', 'Four dogs on leashes walk down a sidewalk .', 'Four little dogs on leashes take a walk on a wide path .', 'Four small dogs on leashes walking in a park .', 'Someone is walking their dogs .']

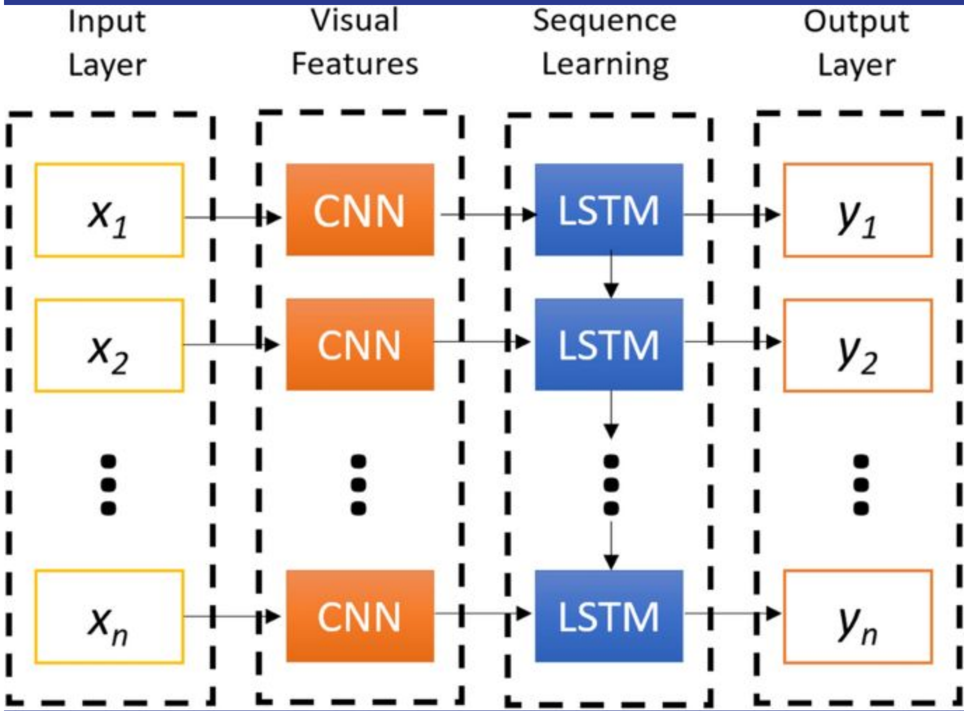
Word Embedding



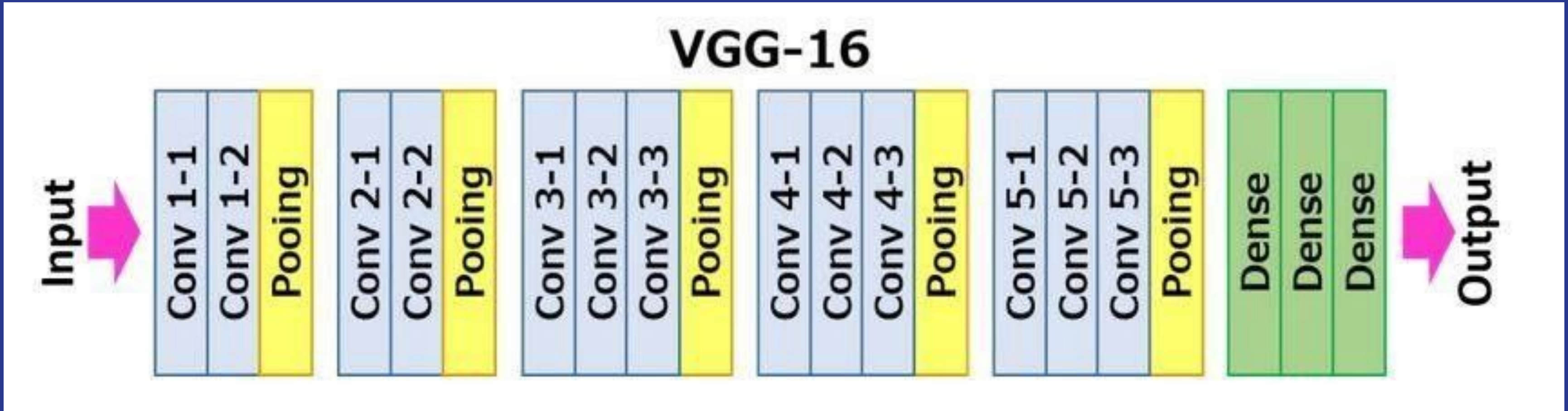
[[1, 367, 84, 131, 644, 2760, 298, 2, 2761, 14, 15], [1, 367, 84, 50, 1791, 256, 101, 6, 471, 14, 15], [1, 367, 137, 84, 50, 1791, 826, 6, 256, 50, 6, 1453, 108, 14, 15], [1, 367, 169, 84, 50, 1791, 174, 39, 6, 86, 14, 15], [1, 1204, 31, 174, 116, 84, 14, 15]]

VGG-16

with
LSTM



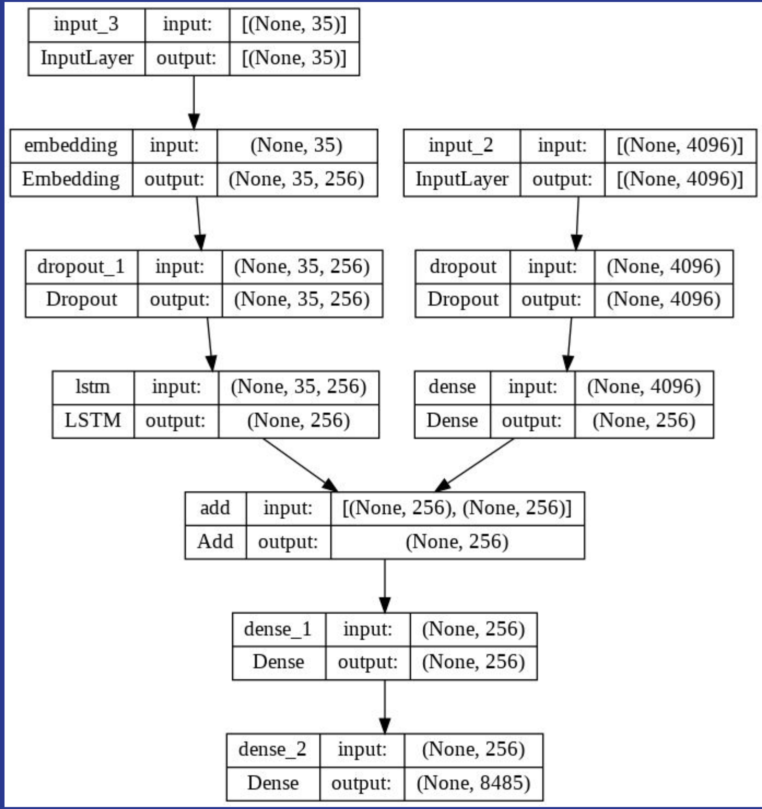
Architecture



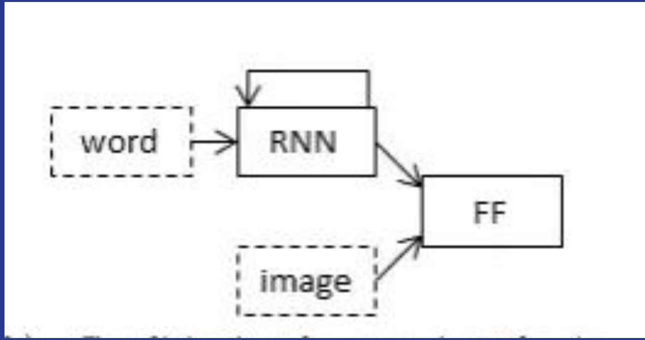
Steps

1. Extract Image Features
2. Load, split and append the captions data with the image
3. Preprocess Text Data
4. Train Test Split
5. Model Creation
6. Train the model

Model



input_3 | input: | [(None, 35)]
InputLayer | output: | [(None, 35)]
embedding | input: | (None, 35)
Embedding | output: | (None, 35, 256)
input_2 | input: | [(None, 4096)]
InputLayer | output: | [(None, 4096)]
dropout_1 | input: | (None, 35, 256)
Dropout | output: | (None, 35, 256)
dropout | input: | (None, 4096)
Dropout | output: | (None, 4096)
lstm | input: | (None, 35, 256)
LSTM | output: | (None, 256)
dense | input: | (None, 4096)
Dense | output: | (None, 256)
add | input: | [(None, 256), (None, 256)]
Add | output: | (None, 256)
dense_1 | input: | (None, 256)
Dense | output: | (None, 256)
dense_2 | input: | (None, 256)
Dense | output: | (None, 8485)



word
RNN
FF
image

Results

	Epochs	Batch Size	Image Data Taken	Accuracy
VGG16	25	32	90%	43%
VGG16	50	32	70%	57%

```
epochs = 50
batch_size = 32
# batch_size = 64
steps = len(train) // batch_size

for i in range(epochs):
    # create data generator
    generator = data_generator(train, mapping, features, tokenizer, max_length, vocab_size, batch_size)
    # fit for one epoch
    model.fit(generator, epochs=1, steps_per_epoch=steps, verbose=1)
```

```
176/176 [==============================] - ETA: 0s - loss: 1.5898 - accuracy: 0.5568WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 44s 251ms/step - loss: 1.5898 - accuracy: 0.5568
176/176 [==============================] - ETA: 0s - loss: 1.5823 - accuracy: 0.5575WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 47s 268ms/step - loss: 1.5823 - accuracy: 0.5575
176/176 [==============================] - ETA: 0s - loss: 1.5716 - accuracy: 0.5604WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 45s 256ms/step - loss: 1.5716 - accuracy: 0.5604
176/176 [==============================] - ETA: 0s - loss: 1.5634 - accuracy: 0.5625WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 44s 252ms/step - loss: 1.5634 - accuracy: 0.5625
176/176 [==============================] - ETA: 0s - loss: 1.5560 - accuracy: 0.5639WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 44s 248ms/step - loss: 1.5560 - accuracy: 0.5639
176/176 [==============================] - ETA: 0s - loss: 1.5472 - accuracy: 0.5658WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 45s 254ms/step - loss: 1.5472 - accuracy: 0.5658
176/176 [==============================] - ETA: 0s - loss: 1.5401 - accuracy: 0.5677WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 47s 268ms/step - loss: 1.5401 - accuracy: 0.5677
176/176 [==============================] - ETA: 0s - loss: 1.5342 - accuracy: 0.5685WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 47s 267ms/step - loss: 1.5342 - accuracy: 0.5685
176/176 [==============================] - ETA: 0s - loss: 1.5262 - accuracy: 0.5696WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which is not available. Available
176/176 [==============================] - 55s 314ms/step - loss: 1.5262 - accuracy: 0.5696
```

Results

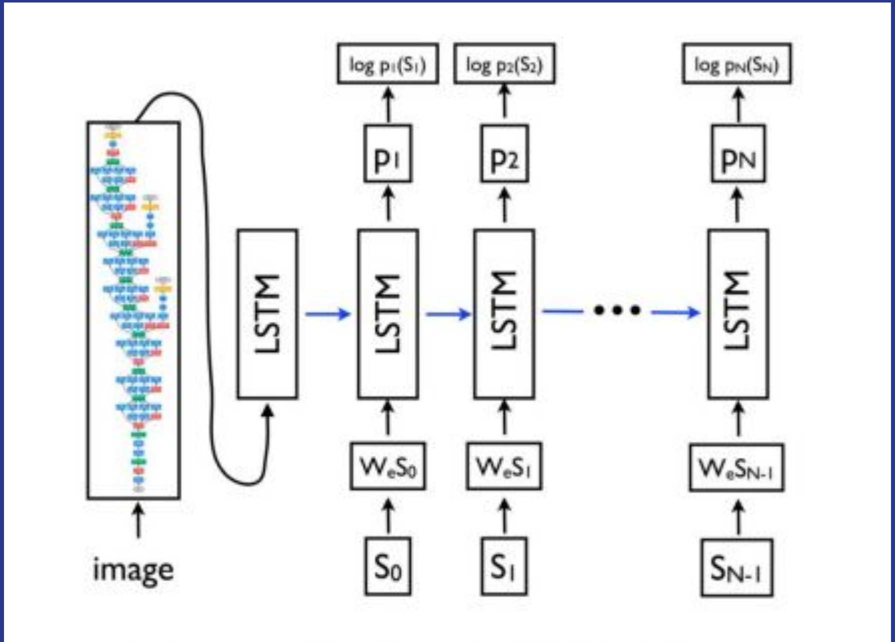
	Epochs	Batch Size	Image Data Taken	Accuracy
VGG19	40	128	70%	41%
VGG19	50	128	50%	46%
VGG19	40	64	50%	49%
VGG19	64	32	50%	65%

```
# train the model
epochs = 70
batch_size = 32
# batch_size = 64
# batch_size = 128
steps = len(train) // batch_size

for i in range(epochs):
    # create data generator
    generator_train = data_generator(train, mapping, features, tokenizer, max_length, vocab_size, batch_size)
    # generator_test = data_generator(test, mapping, features, tokenizer, max_length, vocab_size, batch_size)
    # fit for one epoch
    # model.fit(generator_train, validation_data=generator_test, epochs=1, steps_per_epoch=steps, callbacks =[earlystopping], verbose=1)
    model.fit(generator_train, epochs=1, steps_per_epoch=steps, verbose=1)
```

```
1/75 [..............................] - ETA: 24s - loss: 1.0948 - accuracy: 0.6535
```

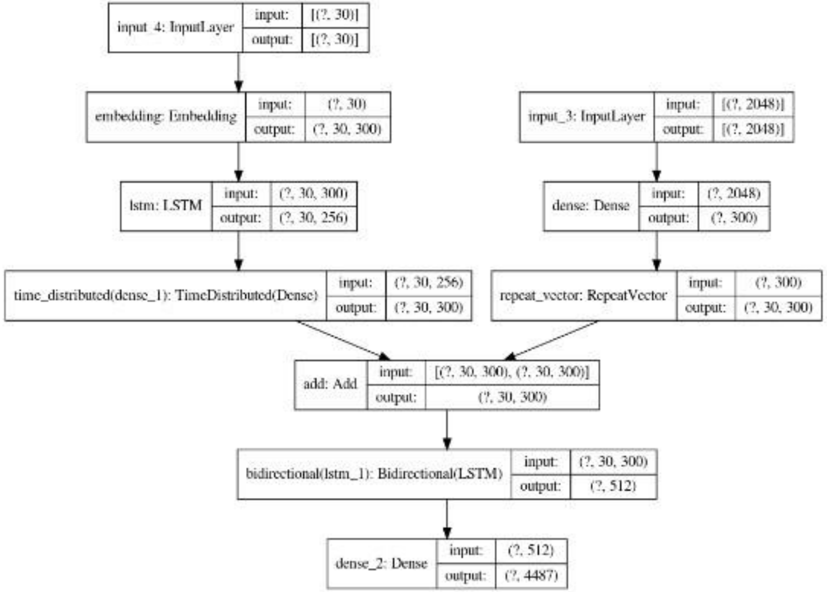
INCEPTION-V3

with
LSTM



Model Generation

In [28]:
```
plot_model(model, to_file='model.png', show_shapes=True)
```
Out[28]:



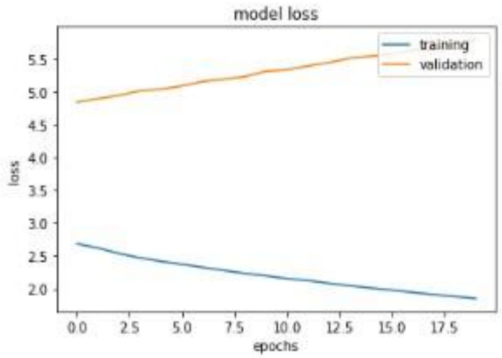

```
# fit model
BATCH_SIZE = 16 * strategy.num_replicas_in_sync

EPOCHS = 20

history = model.fit([train_x1, train_x2],
                    train_y,
                    verbose = 1,
                    epochs = EPOCHS,
                    batch_size = BATCH_SIZE,
                    callbacks = callbacks,
                    validation_data=([validate_x1, validate_x2], validate_y))
```

```
Epoch 9/20
566/566 [==============================] - 12s 21ms/step - loss: 2.2340 - val_loss: 5.2293
Epoch 10/20
566/566 [==============================] - 12s 21ms/step - loss: 2.1978 - val_loss: 5.3119
Epoch 11/20
566/566 [==============================] - 12s 21ms/step - loss: 2.1555 - val_loss: 5.3329
Epoch 12/20
566/566 [==============================] - 12s 21ms/step - loss: 2.1251 - val_loss: 5.3923
Epoch 13/20
566/566 [==============================] - 12s 21ms/step - loss: 2.0832 - val_loss: 5.4425
Epoch 14/20
566/566 [==============================] - 12s 21ms/step - loss: 2.0461 - val_loss: 5.5103
Epoch 15/20
566/566 [==============================] - 13s 23ms/step - loss: 2.0113 - val_loss: 5.5405
Epoch 16/20
566/566 [==============================] - 12s 22ms/step - loss: 1.9801 - val_loss: 5.5701
Epoch 17/20
566/566 [==============================] - 12s 21ms/step - loss: 1.9445 - val_loss: 5.6335
Epoch 18/20
566/566 [==============================] - 12s 21ms/step - loss: 1.9118 - val_loss: 5.6400
Epoch 19/20
566/566 [==============================] - 12s 21ms/step - loss: 1.8824 - val_loss: 5.7397
Epoch 20/20
566/566 [==============================] - 12s 21ms/step - loss: 1.8524 - val_loss: 5.7930
```

Evaluation & Measure

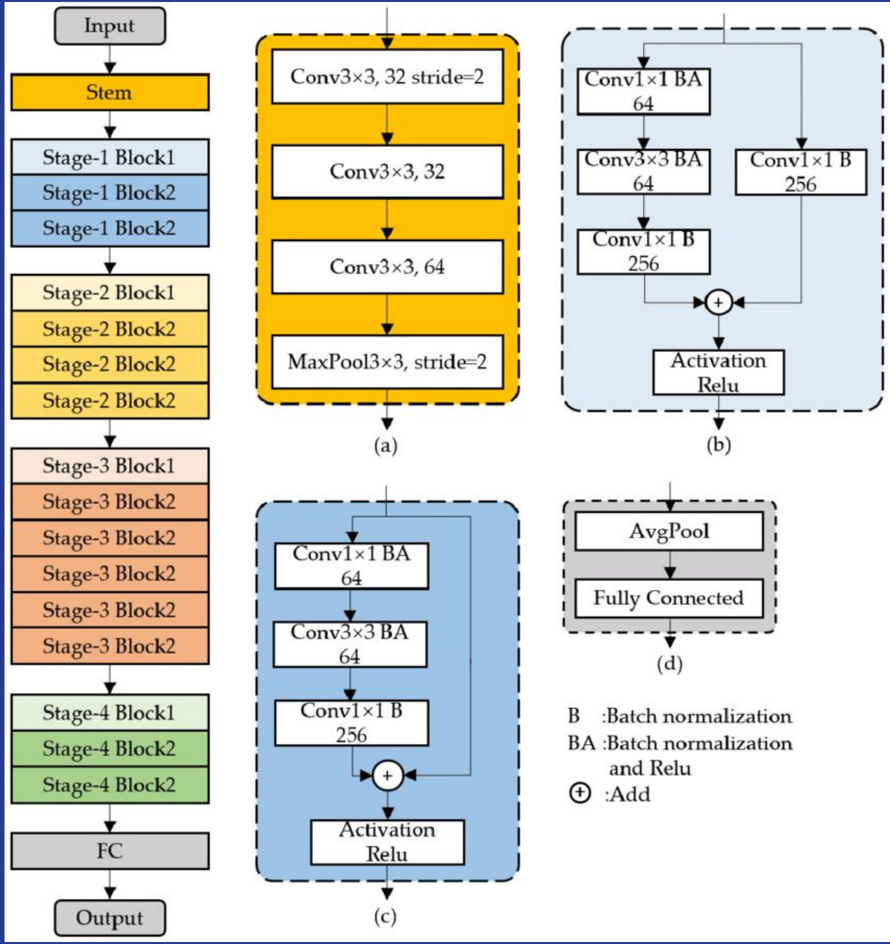
In [44]:

```
# plot training loss and validation loss
import matplotlib.pyplot as plt

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epochs')
plt.legend(['training', 'validation'], loc='upper right')
plt.show()
```



FINAL PROPOSED MODEL

using
RESNET-50 & LSTM



Brief Overview

ON FINAL PROPOSED SOLUTION

Cons of Previous Encoders over ResNet-50

VGG-16

Accuracy of 57% with 50 epochs and Batch size of 32.

VGG-19

Accuracy of 46% with 50 epochs and Batch size of 128.

Inception-V3

Overfitting at an earlier stage.

Model Generation

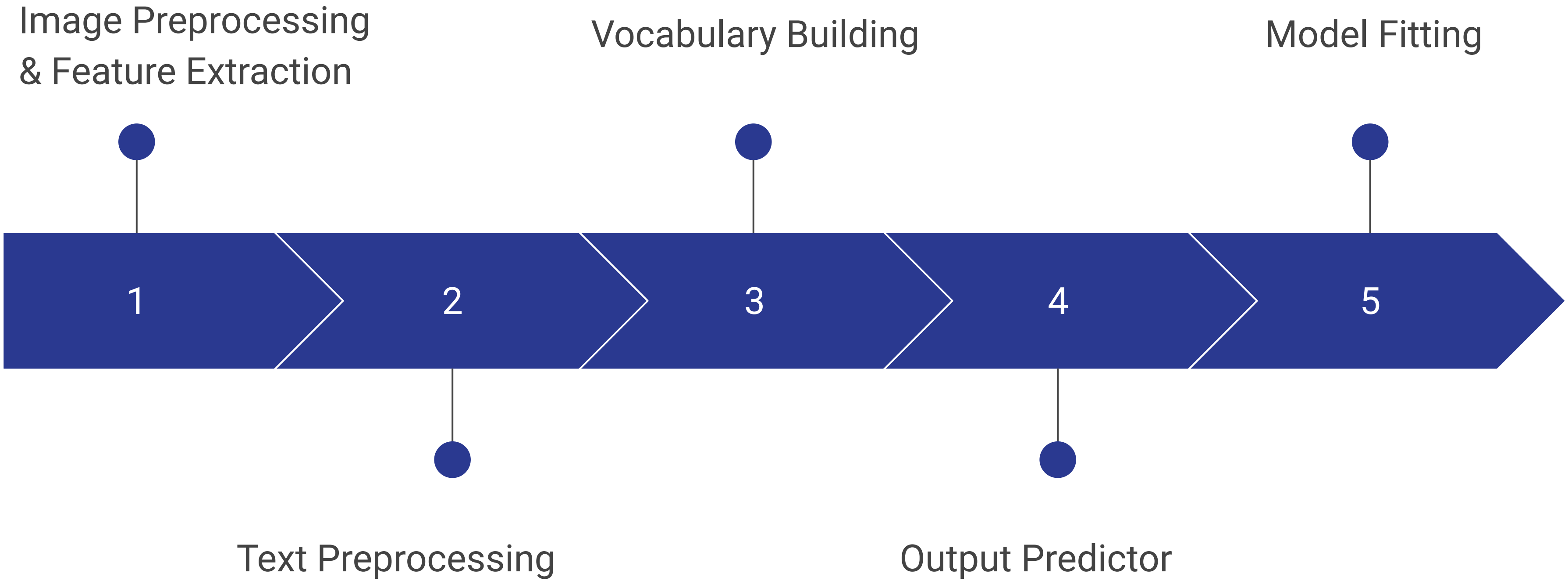


Image Preprocessing & Feature Extraction

Final_Model (ResNet50+LSTM).ipynb

```
from keras.applications import ResNet50
incept_model = ResNet50(include_top=True)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels.h5
102967424/102967424 [==============================] - 5s 0us/step
```

```
from keras.models import Model
last = incept_model.layers[-2].output
modele = Model(inputs = incept_model.input,outputs = last)
```

```
images_features = {}
count = 0
for i in images:
    img = cv2.imread(i)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224,224))

    img = img.reshape(1,224,224,3)
    pred = modele.predict(img).reshape(2048,)
    img_name = i.split('/')[-1]
    images_features[img_name] = pred
    count += 1
    if count > 7999:
        break

    elif count % 50 == 0:
        print(count)
```

```
1/1 [==============================] - 0s 21ms/step
```

Text Preprocessing

Final_Model (ResNet50+LSTM).ipynb

```
def preprocessed(txt):
    modified = txt.lower()
    modified = 'startofseq ' + modified + ' endofseq'
    return modified
```

```
for k,v in captions_dict.items():
    for vv in v:
        captions_dict[k][v.index(vv)] = preprocessed(vv)
```

```
count_words = {}
for k,vv in captions_dict.items():
    for v in vv:
        for word in v.split():
            if word not in count_words:
                count_words[word] = 0
            else:
                count_words[word] += 1
```

```
THRESH = -1
count = 1
new_dict = {}
for k,v in count_words.items():
    if count_words[k] > THRESH:
        new_dict[k] = count
        count += 1
```

```
new_dict[''] = len(new_dict)
```

Vocabulary Building

Final_Model (ResNet50+LSTM).ipynb

```
THRESH = -1
count = 1
new_dict = {}
for k,v in count_words.items():
    if count_words[k] > THRESH:
        new_dict[k] = count
        count += 1
```

```
new_dict[''] = len(new_dict)
```

```
captions_backup = captions_dict.copy()
```

```
captions_dict = captions_backup.copy()
```

```
for k, vv in captions_dict.items():
    for v in vv:
        encoded = []
        for word in v.split():
            if word not in new_dict:
                encoded.append(new_dict[''])
            else:
                encoded.append(new_dict[word])


        captions_dict[k][vv.index(v)] = encoded
```

Output Predictor

Final_Model (ResNet50+LSTM).ipynb

```
embedding_size = 128
max_len = MAX_LEN
vocab_size = len(new_dict)

image_model = Sequential()

image_model.add(Dense(embedding_size, input_shape=(2048,), activation='relu'))
image_model.add(RepeatVector(max_len))

image_model.summary()

language_model = Sequential()

language_model.add(Embedding(input_dim=vocab_size, output_dim=embedding_size, input_length=max_len))
language_model.add(LSTM(256, return_sequences=True))
language_model.add(TimeDistributed(Dense(embedding_size)))

language_model.summary()

conca = Concatenate()([image_model.output, language_model.output])
x = LSTM(128, return_sequences=True)(conca)
x = LSTM(512, return_sequences=False)(x)
x = Dense(vocab_size)(x)
out = Activation('softmax')(x)
model = Model(inputs=[image_model.input, language_model.input], outputs = out)

# model.load_weights("../input/model_weights.h5")
model.compile(loss='categorical_crossentropy', optimizer='RMSprop', metrics=['accuracy'])
model.summary()
```

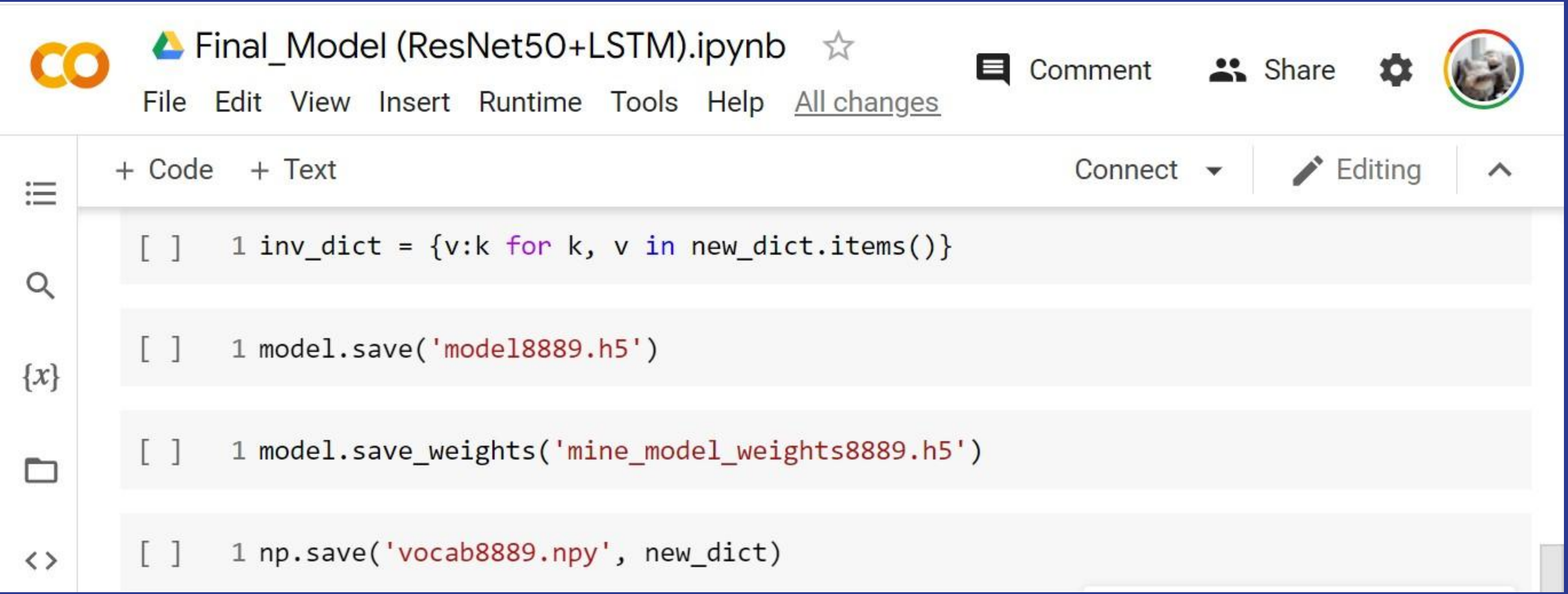
Fitting the Model

```python
model.fit([X, y_in], y_out, batch_size=512, epochs=200)
```

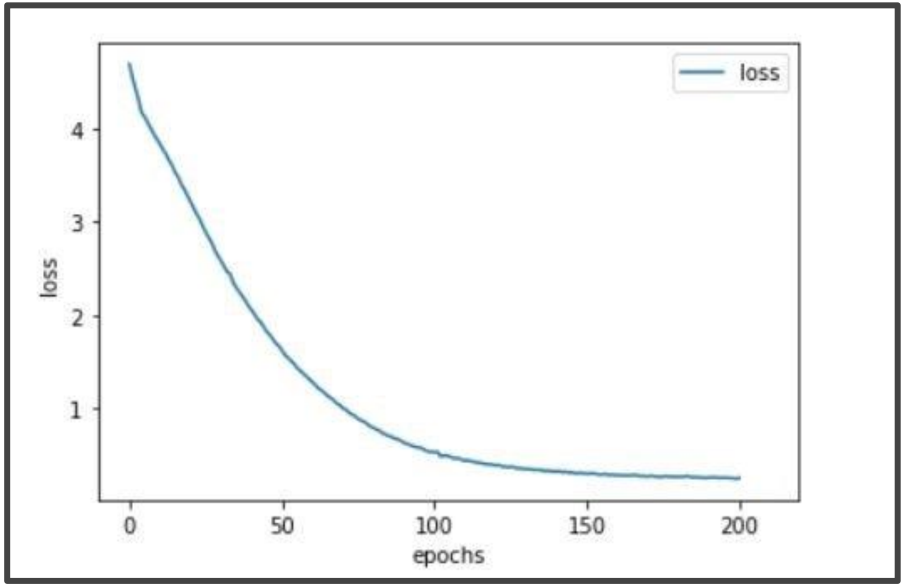
Final_Model (ResNet50+LSTM).ipynb

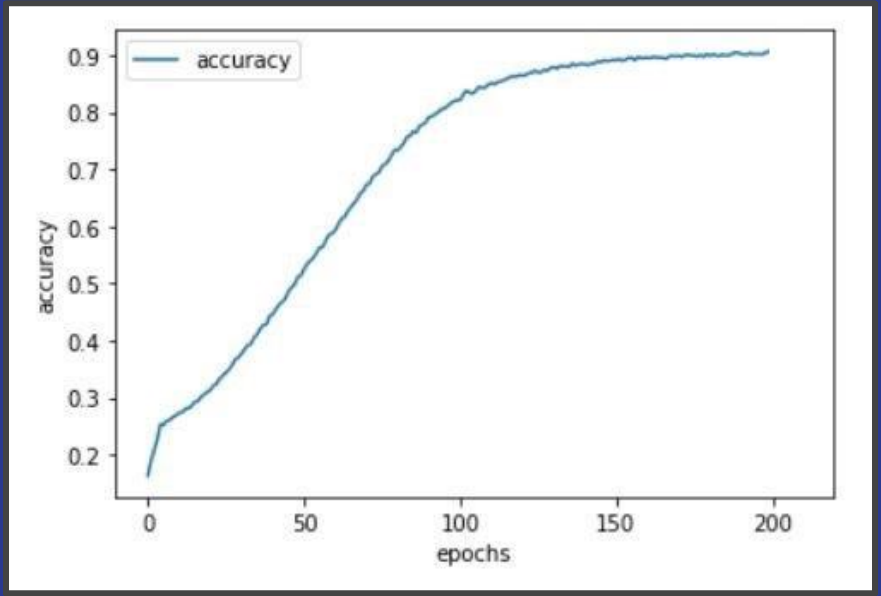
```
203/203 [==============================] - 16s 77ms/step - loss: 0.3561 - accuracy: 0.8886
Epoch 193/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3614 - accuracy: 0.8868
Epoch 194/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3611 - accuracy: 0.8878
Epoch 195/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3570 - accuracy: 0.8875
Epoch 196/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3576 - accuracy: 0.8878
Epoch 197/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3544 - accuracy: 0.8884
Epoch 198/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3539 - accuracy: 0.8889
Epoch 199/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3523 - accuracy: 0.8887
Epoch 200/200
203/203 [==============================] - 16s 78ms/step - loss: 0.3503 - accuracy: 0.8889
<keras.callbacks.History at 0x7f1f0bfb69d0>
```

Save Model & Vocabulary

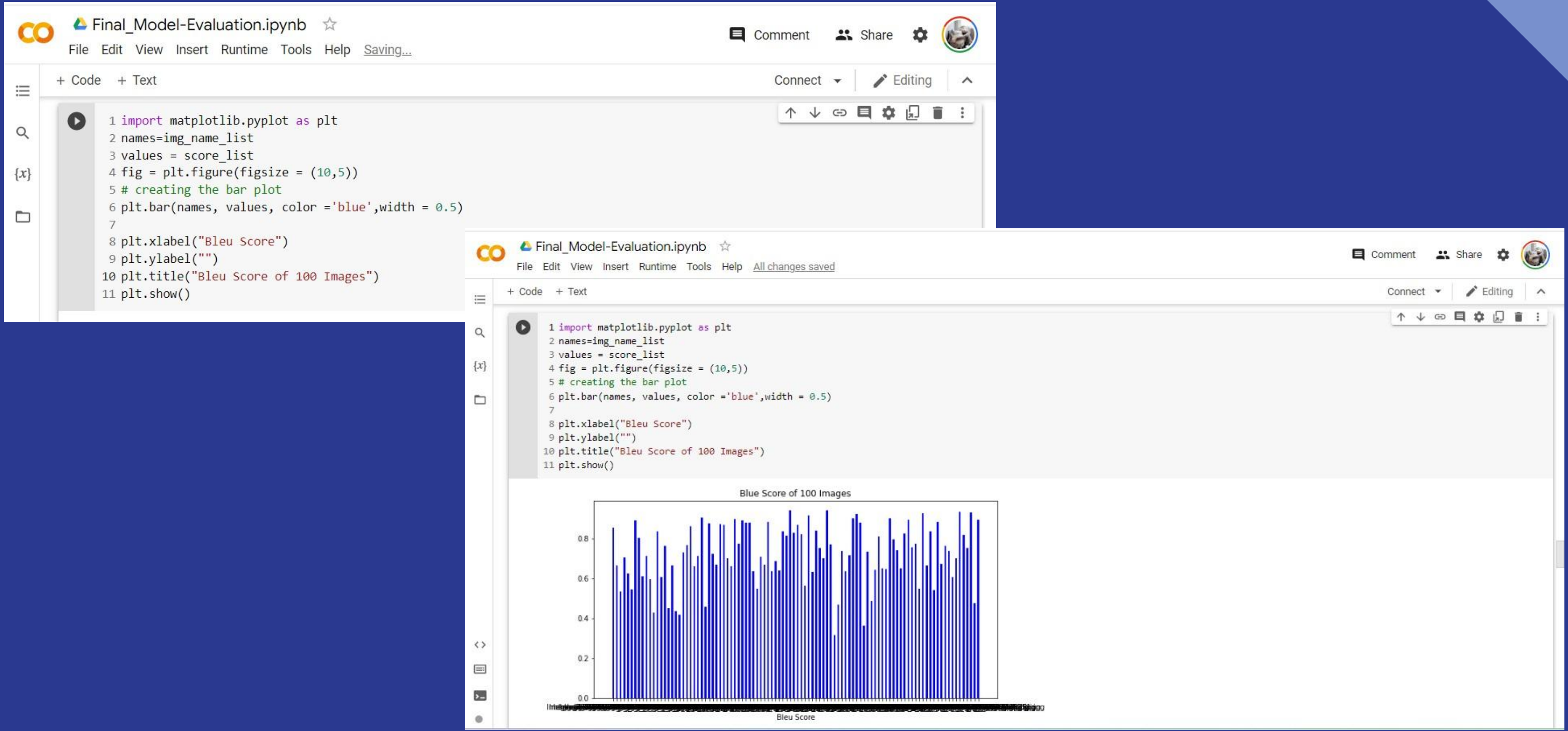


Performance Measure





BLEU Score (on 100 images)



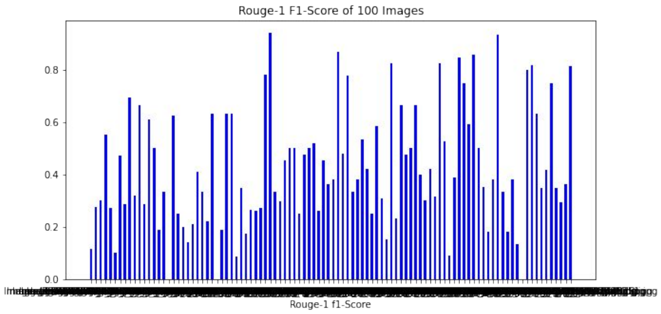
Average BLEU Score = 0.7238

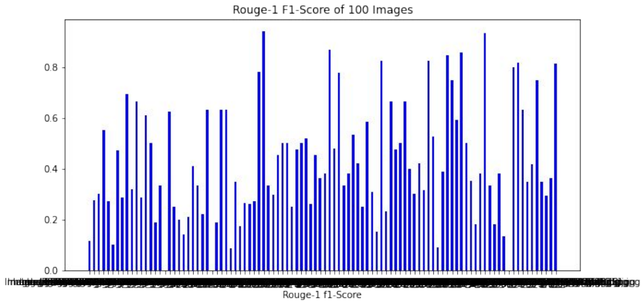
ROUGE Score

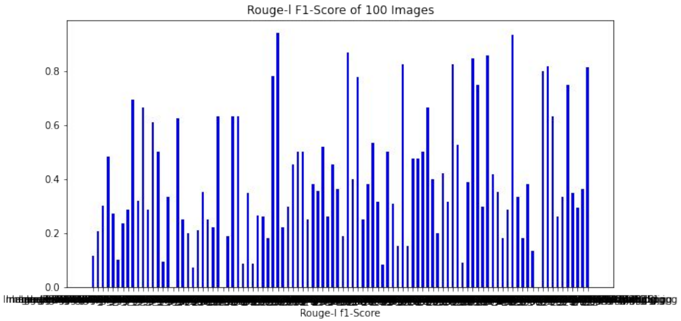
Rouge-1 F1-Score

Rouge-2 F1-Score

Rouge-l F1-Score







Average ROUGE Score

Final_Model-Evaluation.ipynb

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```
rogue_1_s=0
for i in range(100):
  rogue_1_s=rogue_1_s+rouge_1_f[i]
print(rogue_1_s)
```

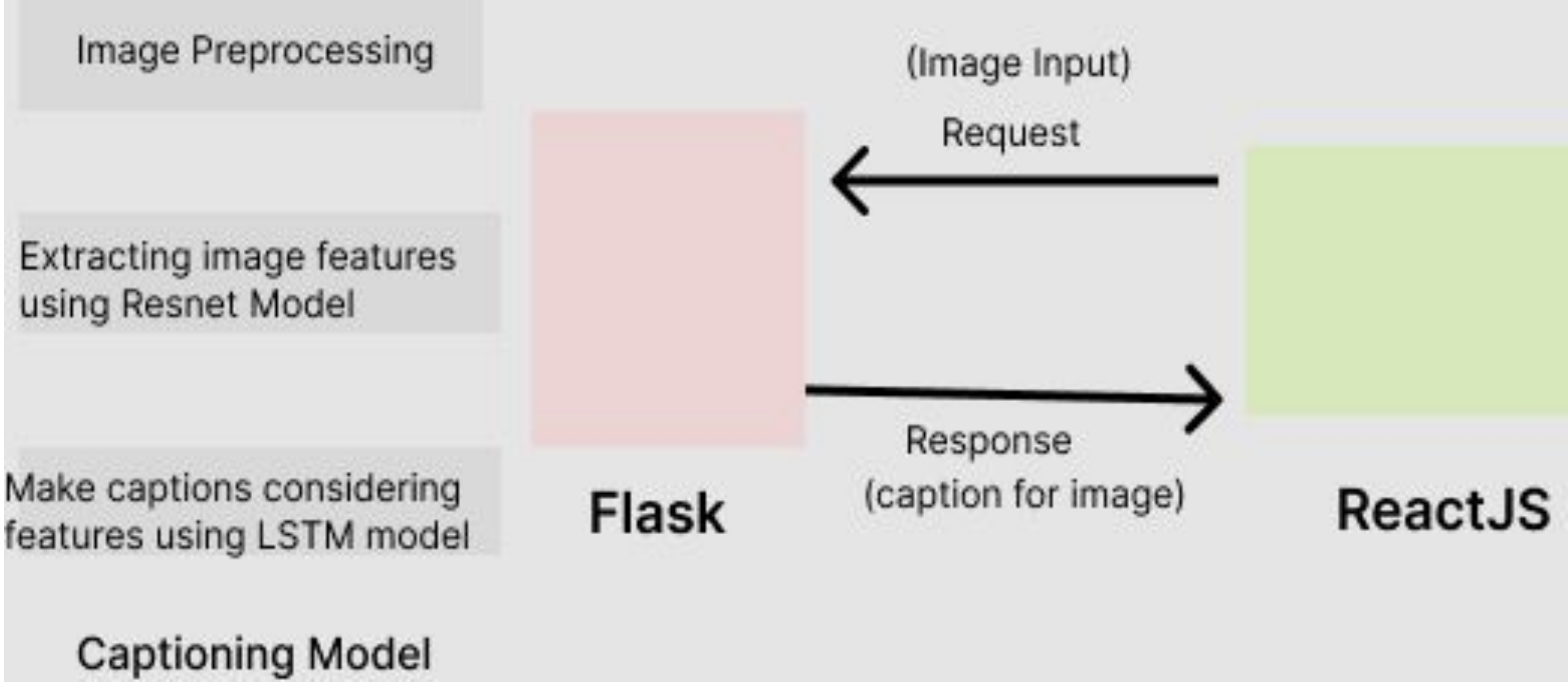
```
42.605771931299316
```

```
avg_rouge_1=sum(rouge_1_f)/100
avg_rouge_2=sum(rouge_2_f)/100
avg_rouge_l=sum(rouge_l_f)/100
```

```
print("Average Rouge-1 F1-score : " + str(avg_rouge_1))
print("Average Rouge-2 F1-score : " + str(avg_rouge_2))
print("Average Rouge-l F1-score : " + str(avg_rouge_l))
```

```
Average Rouge-1 F1-score : 0.42605771931299313
Average Rouge-2 F1-score : 0.21421628278383217
Average Rouge-l F1-score : 0.3967502175885946
```

WEB APPLICATION



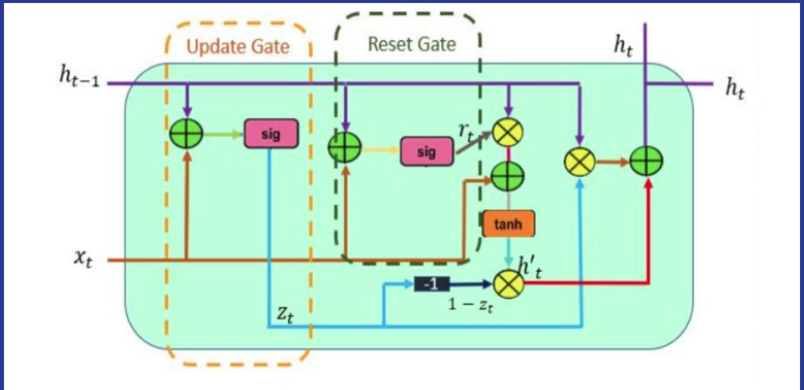
CONCLUSION & FUTURE

Estimated time for processing and result

Can we still improve it?

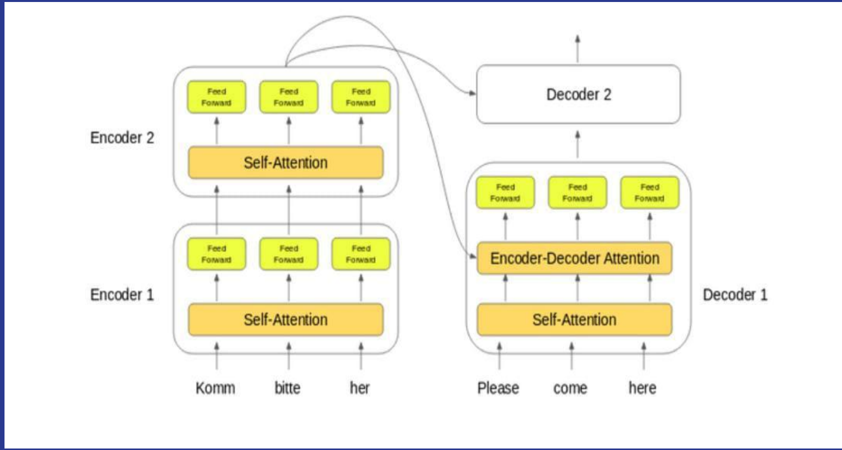
GRU(Gated Recurrent Units) for captioning

- More efficient computation wise compared to LSTM
- uses less training parameter and therefore uses less memory and executes faster (29.3% faster)than LSTM



Transformers

- solve sequence-to-sequence tasks while handling long-range dependencies
- relies entirely on self-attention mechanism
- Parallel processing
- Way more accurate and faster training time



GITHUB REPOSITORY:

https://github.com/saumyapanda17/image-captioning-dell

Thank You!