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**Abstract** - In Artificial Intelligence, automatically describing what's there in a photograph or image has always been a context of study. This paper includes the implementation of Automatic Caption Generator using CNN and RNN-LSTM models. It combines recent studies of machine translation as well as computer vision. The datasets used were Flickr8k. For evaluation of the performance of the described model we have used BLEU scores. Through the scores, one can apart the generated captions as good captions and bad captions. Main applications of this model include usage in virtual assistants, for image indexing, for social media, for visually impaired people, recommendations in editing applications and much more.

*Key Words*: CNN, RNN-LSTM, BLEU, VGG16, Deep Learning

### **1.INTRODUCTION**

Image Caption Generator models is based on encoderdecoder architecture which use input vectors for generating valid and appropriate captions. This model bridges gap between natural language processing as well as computer vision. It's a task of recognizing and interpreting the context described in the image and then describing everything in natural language such as English. Our model is developed using the two main models i.e., CNN (Convolutional Neural Network) and RNN-LSTM (Recurrent Neural Networks- Long Short-Term Memory). The encoder in the derived application is CNN which is used to extract the features from the photograph or image and RNN-LSTM works as a decoder that is used in organizing the words and generating captions. Some of the major applications of the application are self-driving cars wherein it could describe the scene around the car, secondly could be an aid to the people who are blind as it could guide them in every way by converting scene to caption and then to audio, CCTV cameras where the alarms could be raised if any malicious activity is observed while describing the scene, recommendations in editing, social media posts, and many more.

#### 2. RELATED WORK

The application is merged with two main architectures CNN and RNN which describes attributes, relationships, objects in the image and puts into words.

CNN is an extractor that extracts features from the given image.

RNN- LSTM will be fed with the output of the CNN and following it will describe and generate a caption.

CNN is a Convolutional Neural Network which process the data having the input shape similar to two-dimensional matrix. CNN model has many layers including input layer, Convo Layer, Pooling Layer, Fully-connected layers, Softmax, and Output layers. Input layer in CNN is an image. Image data is presented in form of 3D form of matrix. Convo Layer also known as feature extractor where it performs the convolutional operation and calculate the dot products. ReLU is sub layer in Convo layer that converts all negative values to zero. Pooling layer is one where the volume of the image is being reduced once the convolution layer executes. Fully-Connected layers is connection layer that connects one neuron in a layer to other neuron in other layer involving neurons, biases and weights. Softmax layer is used for multi- classification of objects where using formula the objects are classified. Output layer is last layer at CNN model and has the encoded result to be fed to LSTM model.

RNN is Recurrent Neural Network where output of previous step is fed to ongoing step. LSTM (Long Short-Term Memory) is an extended version of RNN that are used to the predict the sequence based on the previous step where in it remembers all the steps and also the predicted sequence at every step. It grasps the required information from the processing of inputs as well as forget gate and also it does remove the non-required data 3. DATA FLOW DIAGRAM

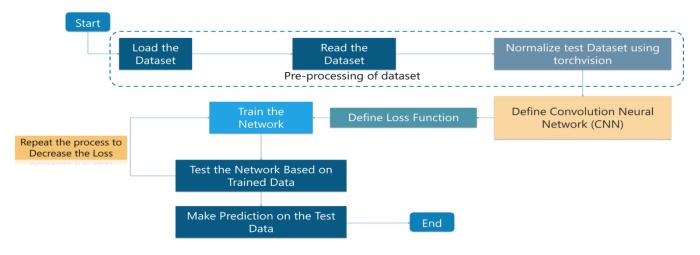


Fig -1: DFD Diagram

### 4. PROPOSED ARCHITECTURE

#### 4.1 Three Phases of the application

- Features Extraction: The extraction of the features from images are being extracted. It creates vector features also known as embeddings. The CNN model extract features from original images after which they are compressed to smaller and RNN compatible feature vector. Thus, it's also known as Encoder.
- Tokenization: The next phase in the application is RNN, that decodes the feature vectors that were fed to it from CNN. Here the sequence of the words is predicted and however the captions are generated.
- Prediction: After the tokenization, the last step is Prediction. Here the vectors are decoded and the final output is being generated using get\_prediction() function.

#### 4.2 Flow of the project

• Importing the libraries

### 5. LITERATURE SURVEY

- Configuring the GPU memory to be used for training purposes
- Importing the image dataset and its respective captions
- Plotting few images and their captions from the dataset
- Cleaning captions for further analysis
- Cleaning the captions for further processing
- Plotting the top 50 words that appear in the cleaned dataset
- Loading VGG16 model and weights to extract features
- Extracting features
- Plotting similar images from the dataset
- Tokenizing the captions for further processing
- Processing the captions and images as per the requires shape by the model
- Building the LSTM model
- Training the LSTM model
- Plotting the loss value
- Generating captions
- Evaluating the performance using BLEU scores

Table -1:

| No. | Authors                   | <b>Research Paper</b> | Publication | Dataset and   | Conclusions   |
|-----|---------------------------|-----------------------|-------------|---------------|---------------|
|     |                           |                       | Year        | methodology   |               |
| 1   | Pranay Mathur, Aman Gill, | Camera2Caption:       | 2017        | Dataset: MS   | The model     |
|     | Nand Kumar Bansode,       | A real-time           |             | COCO          | proposed      |
|     | Anurag Mishra             | image caption         |             | Method:       | generates the |
|     | -                         | generator             |             | Advanced      | real time     |
|     |                           |                       |             | deep          | environment   |
|     |                           |                       |             | reinforcement | high quality  |
|     |                           |                       |             | learning      | captions with |
|     |                           |                       |             | based on NLP  | the help of   |



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|---|--|---|------|--|--|
|   |  |   |      | and Computer   | tenserflow.  |
|   |  |   |      | vision   |  |
| 2 | Simao Herdade, Armin<br>Kappeler, Kofi Boakye, Joao<br>Soares                              | Automatic Image<br>Captioning using<br>Convolution<br>Neural Networks<br>and LSTM | 2019 | Dataset: MS<br>COCO<br>Method:<br>architecture<br>model using<br>CNN as well<br>as NLP<br>techniques   | Using CNN and<br>LSTM models<br>the image's<br>caption is<br>generated.  |
| 3 | Manish Raypurkar,<br>Abhishek Supe, Pratik<br>Bhumkar, Pravin Borse, Dr.<br>Shabnam Sayyad | Deep learning-<br>based image<br>caption<br>generator                             | 2021 | Dataset:<br>Flickr_8k<br>Method: CNN<br>and LSTM<br>model to<br>extract<br>features and<br>sequence the<br>words and<br>finally<br>generating<br>captions. | Proposed model<br>is based on<br>multi label<br>Neural<br>networks   |
| 4 | B.Krishnakumar,K.Kousalya,<br>S.Gokul,R.Karthikeyan,<br>D.Kaviyarasu                       | Image caption<br>Generator using<br>Deep Learning                                 | 2020 | Method: Deep<br>learning-<br>based model<br>using CNN to<br>identify<br>featured<br>objects with<br>the help of<br>OpenCv.                                 | Proposed model<br>could generate<br>captions<br>successfully in<br>Jupyter<br>Notebook using<br>keras as well as<br>tenserflow |
| 5 | R. Subash  | Automatic Image<br>Captioning using<br>Convolution<br>Neural Networks<br>and LSTM | 2019 | Dataset: MS<br>COCO<br>Method: NLP<br>and CNN-<br>LSTM based<br>model  | Using CNN-<br>LSTM and NLP<br>techniques the<br>model for image<br>captioning is<br>generated                                  |

### 6. Datasets

- For the application of image caption generator, we used the dataset named Flickr\_8k dataset.
- This dataset contains a wide range of images that has many different types of situations and scenes.
- Flickr\_8k dataset has 8000 images and every image has 5 captions.
- We divided the entire dataset of 8000 images as 6000, 1000 and 1000 as training, validation and testing sets respectively
- Every image has different dimensions.

#### **7. SYSTEM REQUIREMENTS**

OS: Windows 7 and above, Recommended: Windows 10.

CPU: Intel processor with 64-bit support

Disk Storage: 8GB of free disk space.

For Execution: Anaconda Framework in Python.

For Deployment: Python

#### 7.1 Libraries Used:

- Tensorflow: Its an open-source library that supports deep learning using Python etc frameworks.
- Keras: Its an open-source Python library that allows to evaluate the deep learning models.
- Pillow: Pillow is a Python Imaging Library (PIL), that adds support for opening, manipulating, and saving images.
- Numpy: To work with arrays, Numpy library is used.
- Matpolib: Library to create static and animated visuaizations in Python framework.



### 8. RESULTS

| 1  | А                      | В                   | С                           | D      | E                     | F                               | G                     | Output          |
|----|------------------------|---------------------|-----------------------------|--------|-----------------------|---------------------------------|-----------------------|-----------------|
| 2  | DEEP LEARNING MODEL    | ACTIVATION FUNCTION | COST FUNCTION               | EPOCHS | GRADIENT ESTIMATION   | NETWORK ARCHITECTURE            | NETWORK INITIALIZATIO | Mean BLEU score |
| 3  | Gradient Estimation    |                     |                             |        |                       | <i>*</i>                        |                       |                 |
| 4  | 1                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.37            |
| 5  | 2                      | ReLU                | Cross-Entropy               | 6      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.351           |
| 6  | 3                      | ReLU                | Cross-Entropy               | 5      | Adagrad               | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.404           |
| 7  | 4                      | ReLU                | Cross-Entropy               | 5      | RMSProp               | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.374           |
| 8  | 5                      | ReLU                | Cross-Entropy               | 5      | Adadelta              | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.353           |
| 9  | 6                      | ReLU                | Cross-Entropy               | 5      | Nadam                 | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.353           |
| 10 | 7                      | ReLU                | Cross-Entropy               | 5      | SGD                   | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.028           |
| 11 | Cost Function          |                     |                             |        |                       |                                 |                       |                 |
| 12 | 1                      | ReLU                | mean squared error          | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.215           |
| 13 | 2                      | ReLU                | hinge                       | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0               |
| 14 | 3                      | ReLU                | kullback leibler divergence | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.373           |
| 15 | 4                      | ReLU                | cosine proximity            | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0               |
| 16 | Network Initialization |                     |                             |        | and the second second |                                 | 1                     | 1               |
| 17 | 1                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | glorot uniform        | 0.381           |
| 18 | 2                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | random uniform        | 0.388           |
| 19 | 3                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | lecun_uniform         | 0.367           |
| 20 | 4                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | he_uniform            | 0.389           |
| 21 | 5                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | glorot_normal         | 0.398           |
| 22 | Activation Function    |                     |                             |        |                       |                                 |                       |                 |
| 23 | 1                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.374           |
| 24 | 2                      | tanh                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.384           |
| 25 | 3                      | elu                 | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.392           |
| 26 | 4                      | selu                | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.363           |
| 27 | 5                      | linear              | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.192           |
| 28 | 6                      | sigmoid             | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.375           |
| 29 | 7                      | softsign            | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.396           |
| 30 | 8                      | softplus            | Cross-Entropy               | 5      | Adam                  | 3 layer, 256 nodes, LSTM, vgg16 | default               | 0.381           |
| 31 | Epochs                 |                     |                             |        |                       |                                 |                       |                 |
| 32 | 1                      | ReLU                | Cross-Entropy               | 3      | Adam                  | 3 layers, 256 nodes each        | default               | 0.429           |
| 33 | 2                      | ReLU                | Cross-Entropy               | 4      | Adam                  | 3 layers, 256 nodes each        | default               | 0.394           |
| 34 | 3                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layers, 256 nodes each        | default               | 0.408           |
| 35 | 4                      | ReLU                | Cross-Entropy               | 6      | Adam                  | 3 layers, 256 nodes each        | default               | 0.38            |
| 36 | 5                      | ReLU                | Cross-Entropy               | 7      | Adam                  | 3 layers, 256 nodes each        | default               | 0.405           |
| 37 | Network Architecture   |                     |                             |        |                       |                                 |                       |                 |
| 38 | 1                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layers, 256 nodes each        | default               | 0.407           |
| 39 | 2                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layers, 128 nodes each        | default               | 0.405           |
| 40 | 3                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 3 layers, 512 nodes each        | default               | 0.394           |
| 41 | 4                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 4 layers, 256 nodes each        | default               | 0.406           |
| 42 | 5                      | ReLU                | Cross-Entropy               | 5      | Adam                  | 4 layers, 128 nodes each        | default               | 0.386           |

### **Fig-3: Model results**

# **Table: BELU Scores**

| No. | Research Works i.e.,<br>Models | BELU Scores |
|-----|--------------------------------|-------------|
| 1.  | LRCN                           | 0.669       |
| 2.  | NIC                            | 0.277       |
| 3.  | VSA                            | 0.584       |
| 4.  | CNN-LSTM                       | 0.681       |
| 5.  | Our Model                      | 0.398       |



## 8.1 Some good and bad captions





true: little girl covered in paint sits in front of painted rainbow with her hands in bowl pred: group of people are sitting in the street BLEU: 0.2601300475114445

true: black and white dog is running in grassy garden surrounded by white fence pred: brown dog is running on the grass BLEU: 0.1744739429575305



true: collage of one person climbing cliff pred: man in blue shirt is standing on the air in the air BLEU: 0



true: black and white dog jumping in the air to get toy pred: dog is jumping in the grass BLEU: 0.22083358203177395



true: couple and an infant being held by the male sitting next to pond with near by stroller pred: man in black shirt is standing in the street BLEU: 0.23735579159148829

#### Fig-5: Bad Captions



true: black dog and spotted dog are fighting pred: black and white dog is playing in the grass BLEU: 0.7598356856515925



true: man drilling hole in the ice pred: man in blue shirt is jumping on the air BLEU: 0.7598356856515925

BLEU: 0.7598356856515925

true: man and baby are in yellow kayak on water pred: man in blue wetsuit is playing in the water





true: man and woman pose for the camera while another man looks on pred: man in black shirt and blue shirt is standing in the street BLEU: 0.7071067811865476



true: the children are playing in the water pred: girl in blue shirt is playing on the beach BLEU: 0.7598356856515925

### Fig-6: Good Captions



## 9. CONCLUSION AND FUTURE WORK

The model has been successfully trained and tested to generate the valid captions for the loaded images.

The proposed model is based on multi label classification that uses CNN-RNN approach to generate the captions where CNN works as an encoder and RNN works as a decoder. The CNN architecture used is VGG16.

Some of the future enhancements would include describing the captions based on on multiple targets. The generated caption should be in variety of languages. Training and testing the model with larger datasets and on different architectures with different CNN architectures such as LeNet, AlexNet, GoogLeNet, ResNet and more. Also, the values generated of BeLU i.e., BeLU scores must be high in order to achieve the maximum accuracy of the model.

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