Image Captioning using EfficientNetV2 based on Encoder-Decoder Framework

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***Abstract*- In this work, a deep neural network-based framework consisting of a "Gated Recurrent Unit (GRU)" decoder and an "EfficientNetV2B0-based Convolutional Neural Network (CNN)" encoder is used to offer a unique method of automatic picture captioning. The framework is designed to perceive information points within images and their contextual relationships, facilitating the generation of meaningful and contextually relevant captions. The CNN encoder built on the EfficientNetV2B0 architecture is very good at identifying objects in pictures and extracting features while preserving spatial information. Next, a language describing the visual information collected in the photographs is created using these qualities. To improve the captioning process, the GRU decoder is essential in word prediction and sentence construction using the retrieved characteristics. The suggested neural network system combines the GRU model with the effectiveness and precision of the EfficientNetV2B0 model as an image feature extractor to provide fixed-length output vectors for ultimate predictions. Popular open-source datasets like Flickr-8k and Flickr-30k are used in the study to train and evaluate the model. Using Python-Keras and TensorFlow backend, the framework is implemented, demonstrating the effectiveness of the GRU-based model and EfficientNetV2B0 in automatic picture captioning tasks. The suggested method for producing correct and contextually appropriate picture captions is shown to be successful and accurate when performance evaluation is carried out using the BLEU (BiLingual Evaluation Understudy) measure.**

Keywords*- Image Captioning, Convolutional Neural Networks (CNN), EfficientNetV2, Gated Recurrent Unit (GRU), Recurrent Neural Network (RNN).

I. INTRODUCTION

Captioning an image involves providing a brief description of the image. When composing a caption for an image, it is necessary to first recognize the main components or elements, together with their attributes and connections, and then offer a fitting explanation. The employment of computer vision techniques in conjunction with a language pattern built from Natural-Language-Processing (NLP) is necessary to verify picture words convey images of objects and their interactions.

The study is about, the ability to identify objects, actions, and relationships is necessary for image understanding. These methods mostly rely on the encoding and decoding framework, which is separated into 2 essential stages. Firstly, CNN model is trained to make it as image encoder. 2nd , the input decoder which creates captions (picture description) is the hidden layer RNN model ImageNet is used to add model weights after CNN is used to extract features from the picture using the EfficientNetV2 model. Nonetheless, the bulk of contemporary encoder-decoder frameworks encode the input picture using a CNN, transform it into a dense feature vector,and then employ an architecture called a "Gated-Recurrent-Unit (GRU)" to translate the vector into an illustrative language.

In short, RNN performs effectively with any type of sequential knowledge, including building a group of words, while CNN is better at storing spatial data including recognize things in photos. Ultimately, performance comparisons against the most advanced approaches are shown, including a BLEU score for image captioning systems on datasets with multiple related datasets, such as Flickr30k and Flickr8k.The standard datasets from Flickr30k and Flickr8k, together with a few local datasets, have been used to study the suggested image caption generator.

II. LITERATURE SURVEY

Creating captions for characterization, regression, and prediction issues using natural language, the attention module, and CNN [1]. In order to integrate high-level semantic information into image captioning, this paper suggests a dynamic semantic attention technique. It enhances caption accuracy and richness by separating visual and non-visual word production, as demonstrated by encouraging trial findings [2]. "Natural language processing" and "machine learning" have the ability to automatically identify an image's content [3]. In order to improve the encoder-decoder model by incorporating geometric attention and capturing spatial relationships between identified objects, this study develops the Object Relation Transformer for picture captioning [4].

Provide a trainable, deterministically or stochastically trained attention-based model for visual description. The model gains the ability to create descriptive terms and concentrate on noticeable items [5]. Images are captioned using GRU [6]. Using EfficientNetB0 along with GRU, local tourist image captioning was built [7]. Three main issues plague the more recent approaches to traffic scene: vehicle detection, TSR recognizes traffic signs and detects pedestrians.VGG16 along with LSTM are utilized for sequential caption generation in order to comprehend traffic scenes with different vehicle types (autonomous automobiles)[8].

Image description methods are top-down and bottom-up [9] by producing a suitable natural-language explanation of the visual subject, deep neural network algorithms can effectively address the challenges associated with image captioning [10]. An encoder-decoder model utilizing Wavelet-based CNN for visual feature extraction and attention processes is presented. By combining contextual data, channel, and spatial attention, this approach creates captions [11]. The favored method makes use of deep-learning techniques, like Recurrent-Neural-Networks (RNNs) for caption creation and Convolutional-Neural-Networks (CNNs) for extracting features from images [12].

III. Methodology

The proposed encoder-decoder framework is dependent on following steps:

1) *Data Acquisition and Exploration:*

Conduct the exploratory data analysis (EDA) which gains insights into the Flickr8k and Flickr30k datasets used in the project.

Validate data completeness and accuracy through data comprehension techniques, ensuring reliable inputs for the image captioning model.

2) *Data Preprocessing:*

Implement data preprocessing steps, including image resizing, normalization, and tokenization of captions, to prepare the data for model training.

3) *Model Architecture Design:*

Create a deep learning architecture for picture captioning that is built on the Encoder-Decoder framework and uses EfficientNetV2B0 and GRU layers. To maximize performance, try out several model iterations, adjust hyperparameters, and try out alternative architectures.

4) *Training and Evaluation:*

Train the deep learning model on the pre-processed data, utilizing technique like batch training to enhance convergence.

Evaluate the model's performance using BLEU metrics to assess caption quality and overall effectiveness.

Conduct a comparison analysis with existing techniques to demonstrate the advantages of our proposed model in generating accurate and relevant image captions.

5) *Experimentation and results analysis:*

Conduct experiments to examine the impact of varying parameters, such as batch size, learning rate, and model complexity, on caption generation quality.

Demonstrate the model's capacity to provide a variety of different and semantically relevant captions for a range of images by presenting specific findings and performance data.

A. *Data preprocessing and datasets:*

The accompanying subsections provide instructions on how to prepare associated photo and text data for the deep learning models after obtaining the relevant images and captions from datasets:

1) *Related Image/photos and Caption Datasets:* By using popular open-source datasets, including Flickr-8k, containing 8000 photographs, and Flickr-30k, containing 30000 images.

2) *Photographic data preparation:* The image quality is viewed using a pre-trained model. The goal of the study was to find out how the depth of Convolutional networks influences how accurate they are in large-scale picture recognition. To minimise the amount of parameters in the provided network models, all collected pictures are reduced to 224 x 224 pixels. A pre-trained model called EfficientNetV2 is then used to extract image properties. Lastly, the suggested caption generating method is applied to a particular image of the dataset by means of these attributes.

3) *Text Data Preparation:* Each image in the both datasets have five captions, which results in a long vocabulary. Together with changing words to lowercase letters, the procedure also eliminates newlines and punctuation from the descriptions (captions).

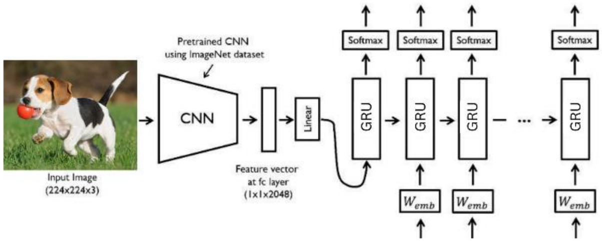


Fig.1. Merging GRU layers with CNN models for image captioning.[13]

B. *The Proposed methodology:*

The CNN encoder and the GRU decoder are the two main deep learning models included in the suggested framework. Both textual data and sequences are covered under “Natural Language Processing (NLP)”.

- CNN Encoder: Finally, because this model projects the picture's attributes and advances them to the next level, it discovers that extracting features from an image is simpler. The CNN architecture, such as EfficientNetV2B0, efficiently captures spatial details and identifies relevant image features, facilitating a rich representation of the visual content.

- GRU Decoder: A Gated Recurrent Unit (GRU) decoder must first scan the encoded image before producing a sequential caption. The next step is to generate a text description, sometimes called the "Language Model" via word sequence formation.

1) *Model Creation:*

The three main parts of the suggested deep learning-based merging model are an image feature extraction, sequence processor, and a decoder, as seen in Figure 1.

- *Image feature extractor:* The process of extracting features from photographs is known as image feature extraction. With the exception of the output layer, a pre-trained 237-layer EfficientNetB2V0 model is used to extract the content from the photos. After pre-processing Ultimately, the model discovers that it is easier to extract features from a picture because it projects the image's attributes and advances them to the next level.

- *Sequences processor:* Text data is handled by a word embedding layer, which is followed by a GRU-based recurrent layer. Sequence modelling challenges are well-known for the competitive performance and computational efficiency of GRU units. When combined, these elements allow for the accurate creation of captions by capturing the textual data's sequential relationships.

- *Decoder:* The decoder takes charge of producing the ultimate textual descriptions, while a "Dense layer" integrates and processes the fixed-length vectors from the sequence processor and captions feature extractor.

Our objective was to establish an expansive lexicon while ensuring brevity, resulting in a more streamlined model conducive to quicker training. Each description undergoes segmentation into individual words. The model proceeds to analyze each word in conjunction with its corresponding photo, predicting subsequent words accordingly. The next word in the series is then predicted by the model using the first two words in the text description together with the corresponding image. This deep learning architecture is intended to function as a "merge-model," where a thick layer creates a condensed representation of the picture. In addition, the sequence processor part accepts input sequences with predetermined lengths. These sequences are then sent via an embedded layer, that employs a masking method to ignore padded data. Dropout regularization is used to reinforce both input models in order to prevent overfitting to the data set for training and take advantage of the model's quick learning speed.

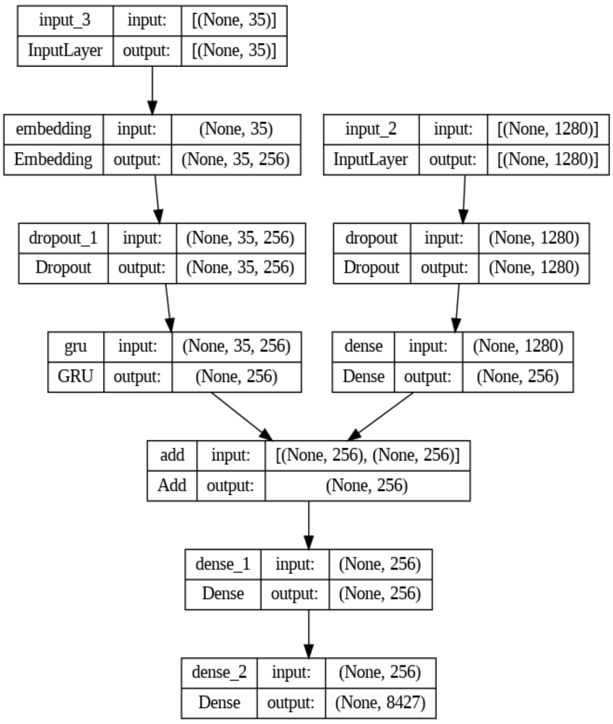

input_3 | input: | [(None, 35)]
InputLayer | output: | [(None, 35)]
embedding | input: | (None, 35)
Embedding | output: | (None, 35, 256)
input_2 | input: | [(None, 1280)]
InputLayer | output: | [(None, 1280)]
dropout_1 | input: | (None, 35, 256)
Dropout | output: | (None, 35, 256)
dropout | input: | (None, 1280)
Dropout | output: | (None, 1280)
gru | input: | (None, 35, 256)
GRU | output: | (None, 256)
dense | input: | (None, 1280)
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, 8427)

Fig.2. Model Summary

2) *Training Procedure:*

The training process starts by taking useful information from images using a model that has already been trained, and then proceeds to process text data. This process includes changing captions to lowercase, eliminating non-alphabetic characters, and inserting start and end tokens. Afterwards, the text undergoes tokenization using the Tokenizer class, and the vocabulary size is determined by the number of distinct words. within the dataset known as corpus. The data is split into test and training sets, with 80% of the data designated for training, after the maximum caption length for padding is established. During the training of the model, a data generator function is used to produce batches of training data. This function pre-processes text and generates pairs of input and output for the training. The model architecture is built using TensorFlow Keras and consists of an encoder-decoder structure. It includes dropout regularization and dense layers. The image features are handled by the encoder, while the decoder utilizes GRU layers to incorporate sequence features. This particular model consists of distinct input layers for image attributes and encoded text. These layers are combined by utilizing the add function to create the network model. A predetermined number of epochs are processed to train the model, during which the Adam optimization algorithm and categorized cross-entropy loss are used to construct the model. Every period is made up of several stages, where the data generator supplies batches of training data to be used for model adjustment. The model learns to create descriptions for images using the given training data by going through this repeated process.

3) *Computational resources used & hyperparameters:*

We made use of Colab Pro's powerful NVIDIA Tesla V100 GPU with 32GB VRAM, a subscription service that offers enhanced GPU capabilities and longer runtime. Our model training process was greatly expedited by this configuration, with the training and testing stages being finished in around three hours. To provide a stable development environment, we used TensorFlow, Keras, NumPy, pandas, tqdm, matplotlib, NLTK, and pickle in our software stack. We used Colab Pro's cloud data storage management feature and batch processing with a 64-batch size to achieve effective training iterations. The performance of our model was further enhanced by adjusting hyperparameters such as the optimizer (Adam), embedding dimensions (256), and dropout rate (0.4). Once we reached convergence after 11 epochs of training, we saved the trained model as 'best_model.h5' for further analysis and assessment.

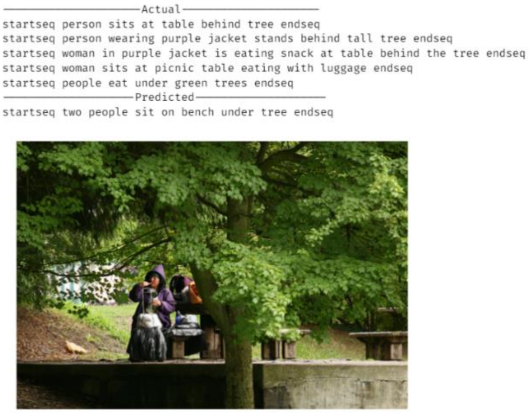
IV. EXPERIMENTAL RESULTS

A. *Datasets:*

The Flickr8k, Flickr30k shared datasets were the two common datasets utilized in the research. These datasets were chosen because of their reasonable size-small enough to be generated on a desktop computer with a single CPU-realism, and open-source nature. The dataset contains eighty different categories of items depicted in the photos. Each image is associated with five captions stored in token.txt. Additionally, the proposed model underwent testing on a local dataset. Prior to processing, Every image is cropped to 224 by 224 pixels. Additionally, the suggested model was integrated into datasets used for testing & training.

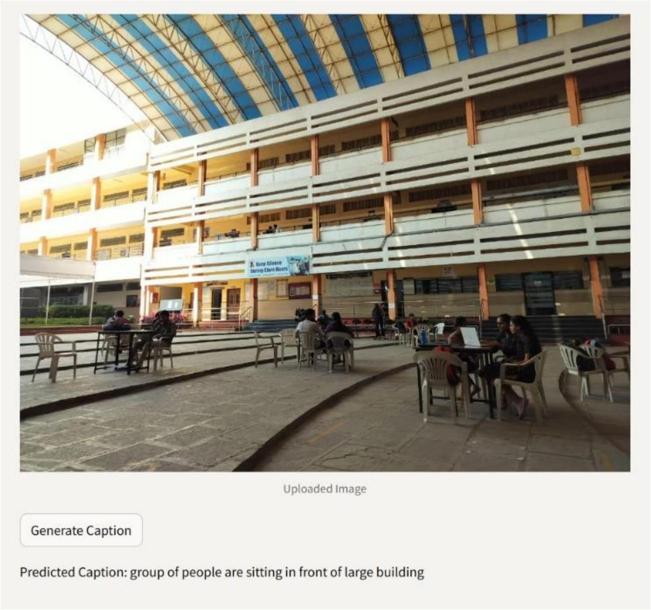
B. *Outcomes:*

The proposed approach focuses on providing image captions that describe the pictures. A few anticipated results of deep learning-driven image description generator are shown in the figure, which depicts the user interfaces of the proposed system. It was observed that images featuring people or other human subjects achieved the highest accuracy, as most training images are individual photos. Local images sourced from local camera shots, university websites, and other platforms were also utilized to evaluate the suggested model, which yielded satisfactory results in captioning the images.



```
─────────────────────Actual─────────────────────
startseq person sits at table behind tree endseq
startseq person wearing purple jacket stands behind tall tree endseq
startseq woman in purple jacket is eating snack at table behind the tree endseq
startseq woman sits at picnic table eating with luggage endseq
startseq people eat under green trees endseq
────────────────────Predicted────────────────────
startseq two people sit on bench under tree endseq
```

Fig.3. Actual and predicted captions for image from the dataset



Predicted Caption: group of people are sitting in front of large building

Fig.4. Predicted caption for custom image

C. *Performance Evaluation:*

BLEU Metric	Flickr8k	Flickr30k
BLEU-1	0.625841	0.598135

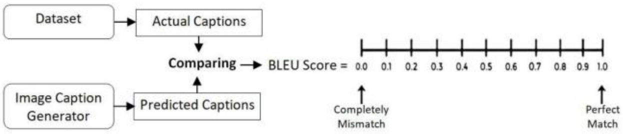


Fig.5. The process of generating BLEU score [13]

The test set is used to predict picture captions, and these predictions are then evaluated using an established metric to evaluate the proposed model. BLEU ('Bilingual-Evaluation-Understudy'), a bilingual assessment metric, was used to gauge how effective the proposed photo captioning method was.

To calculate BLEU score, a predicted sentence is compared to a reference sentence. The corresponding BLEU score perfection and examples of relevant captions are displayed. The Python NLTK module was used to produce the BLEU score for the evaluation of the candidate text. The quality of machine-generated versions is evaluated using the BLEU (Bilingual-Evaluation-Understudy) score. Phrase BLEU Score for each sentence and Corpus BLEU Rating for groups of sentences are the two levels at which it works. Comparing comparable grammes in a preset order—for example, one gramme for single words and two grammes for word pairs—determines the N-gram scores. Every N-gram match receives a weight, usually 0 for non-matches and one for matches. Balanced geometric averages of N-gram scores over a range of orders—from 1 to n—are computed to determine the BLEU score. The Collective N-gram values

(BLEU-N), which are produced by calculating the weighted geometrical average of the individual N-gram scores, are a crucial factor in determining the overall BLEU score.

V. CONCLUSION

Constructing a system for encoding and decoding for deep neural networks for a practical photo captioning system was the aim of this effort. After processing and passing through the RNN layers for all relevant keywords, text strings, and captions, The CNN algorithm layer aids in extracting features from the images. Adding anticipated words to the feedforwarding model is the last step. This produces a final word description that is based on the input image's features (derived by CNN) and the data source's words (words from a dataset by RNN). Suggested deep-learning model (BLEU metrices) for picture caption creation was assessed in the experiments with two standard datasets (Flickr-8k and Flickr-30k) and images from various local sources. The image captioning test produced satisfactory results and showed that photographs with people or other humans in them are the most accurate. The suggested system, however, has significant computational expenses and needs powerful GPU hardware in order to operate. This prevented us from training the entire dataset, resulting in a vocabulary reduction that is insufficient for precise item detection.

VI. FUTURE SCOPE

- *Attention mechanisms:* Attention mechanisms will be leveraged in future image captioning developments to allow models to concentrate on important picture aspects for improved relevance and accuracy in captions.
- *Teacher forcing:* Implementation of teacher forcing techniques to improve training stability and convergence, ensuring more accurate and coherent caption generation by leveraging ground truth information during model training.
- *Real-time and optimization:* Innovations in real-time captioning will make it easier to generate captions instantly. This will be especially helpful for live events and video streams that need precise captions right away.
- *Fine-tuning:* To increase model performance, fine-tuning approaches will be used to incorporate transfer learning, improve hyperparameters, and guarantee flexibility across a variety of datasets.
- *Scalability:* Improvements in scalability will guarantee effective handling of big datasets and instantaneous picture analysis, rendering the model adaptable and useful in a range of industries, including media, healthcare, and industrial automation.

All things considered, these developments hold up the possibility of more precise, contextually appropriate, and adaptable picture captions, increasing the image captioning technology's usefulness in a variety of fields and applications.

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