Image Caption Generator Using Deep Learning On Flickr 8K Dataset (DL)

Sanjana Kumari Singh
Artificial Intelligence & Machine Learning Engineering,
RV College of Engineering® ,
Bengaluru, India

Sandeep S Pawar
Artificial Intelligence & Machine Learning Engineering
RV College of Engineering®
Bengaluru, India

Tanishq Reddy
Artificial Intelligence & Machine Learning Engineering
RV College of Engineering®
Bengaluru, India

Abstract**—** Image captioning is a task that bridges the gap between computer vision and natural language processing, enabling machines to generate textual descriptions for images. This project focuses on developing an Image Caption Generator using deep learning, specifically employing a combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The system is trained on the Flickr 8K dataset, which consists of 8,000 images paired with five human-generated captions each. The CNN, InceptionV3, is used for extracting features from images, while the LSTM generates meaningful captions based on these features.The pipeline for the system involves multiple stages: image preprocessing (resizing and feature extraction using InceptionV3), text preprocessing (tokenization and padding), and caption generation (using the LSTM model). During training, the model uses categorical cross-entropy loss with Adam optimizer, and teacher forcing is applied to improve sequence learning. The system's performance is evaluated using BLEU scores, which measure the similarity between generated captions and reference captions. The model produces captions that describe key elements in the images, achieving satisfactory accuracy and performance.To enhance usability, an interactive web interface is built using Streamlit, allowing users to upload images and receive captions in real-time. This feature has significant potential for applications such as image indexing, accessibility for the visually impaired, and automated content generation. Future improvements to the project could include integrating attention mechanisms or Transformer models to enhance caption fluency and expanding the dataset to generalize better across diverse images. Fine-tuning the LSTM and implementing multilingual support are other areas for enhancement. Ultimately, this project demonstrates the power of deep learning in image captioning, offering a robust and scalable solution for real-world applications in diverse domains.

Keywords—Computer Vision, Deep Learning, Convolutional Neural Networks, Recurrent Neural Networks, LSTM.

I. Introduction

The Image Caption Generator project uses deep learning techniques to automatically generate captions for images. Trained on the Flickr 8K dataset, which consists of 8,000 images with five human-annotated captions for each image, the model leverages a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network for feature extraction and caption generation. The InceptionV3 CNN is used to extract high-level visual features from the images, while the LSTM generates textual descriptions based on these features.The project involves several steps, including preprocessing of both images and text. Images are resized and processed using InceptionV3 to obtain feature vectors, while the captions are tokenized, padded, and converted into sequences for training. The LSTM model is trained using the categorical cross-entropy loss function and Adam optimizer, with teacher forcing used to improve sequence learning. The model's performance is evaluated using BLEU scores, which measure the quality of generated captions. This project has applications in image indexing, automated content generation, and assistive technology for the visually impaired. Future improvements could include attention mechanisms, multilingual support, and expansion of the dataset to improve model generalization.

II. literature survey

The task of image caption generation has gained significant attention due to its potential applications in image retrieval, accessibility, and content management. Leveraging deep learning techniques, several studies have aimed to improve the accuracy and relevance of generated captions by integrating powerful models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs),and Transformer-based architectures. The integration of these models with visual datasets, particularly the Flickr 8K dataset, has been central to many advancements in this area. Smith and Johnson (2022) provided a comprehensive review of deep learning approaches for image captioning, highlighting the transformative role of CNNs in extracting meaningful features from images, and RNNs in modeling the sequential nature of caption generation [1]. Their study emphasized the importance of combining these two architectures to create models capable of understanding both visual and textual information. The authors also discussed the limitations of traditional methods and the

need for more advanced techniques like attention mechanisms. Smith and Johnson (2022) provided a comprehensive review of deep learning approaches for image captioning, highlighting the transformative role of CNNs in extracting meaningful features from images, and RNNs in modeling the sequential nature of caption generation [1]. Their study emphasized the importance of combining these two architectures to create models capable of understanding both visual and textual information. The authors also discussed the limitations of traditional methods and the need for more advanced techniques like attention mechanisms.Wang and Li (2021) proposed that attention mechanisms significantly enhance image captioning models by enabling the model to focus on the most relevant regions of an image during caption generation. This results in more contextually accurate and descriptive captions [2]. Their work shows how combining CNNs with attention mechanisms allows the model to better attend to spatial hierarchies in images, improving the correlation between visual inputs and text outputs. Chen and Gupta (2023) explored the application of CNN and RNN architectures for image caption generation. Their comparative study concluded that while CNNs excel at visual feature extraction, RNNs are better suited for generating coherent and grammatically correct captions. However, they noted that the integration of both architectures presents challenges, particularly in terms of model complexity and training efficiency [3]. This discussion is vital in understanding how deep learning models can be optimized to generate meaningful captions efficiently.Kumar and Singh (2022) investigated the use of transfer learning for image captioning on the Flickr 8K dataset, demonstrating that pre-trained models can significantly improve caption quality by leveraging large-scale image datasets for feature extraction. Their findings highlighted the effectiveness of fine-tuning pre-trained models, such as VGG16 or ResNet, on specific captioning tasks [4]. This approach allows for faster convergence and better generalization on smaller, domain-specific datasets like Flickr8K. T Patel and Desai (2021) provided a survey of the deep learning techniques used in image captioning, covering both traditional methods and more recent innovations. They discussed the role of LSTM networks, which can capture long-term dependencies between words in generated captions, contributing to the creation of more natural and contextually accurate sentences [5]. They also highlighted the significant role of large-scale datasets like Flickr8K in training robust image captioning models. Recent advances in Transformer models have revolutionized image captioning tasks. Zhang and Zhou (2023) explored how Transformer-based architectures, with their self-attention mechanisms, outperform traditional RNN-based approaches by enabling parallel processing and capturing complex dependencies in both the image and the generated caption. Their study showed that Transformers offer state-of-the-art performance on the Flickr 8K dataset [6]. This approach has become increasingly popular due to its scalability and efficiency in handling large datasets. High-performance GPUs and TensorFlow were utilized for efficient training and testing, ensuring the scalability of the system for large-scale applications.In paper [12] ,A. A. Alatawi and et al leverages the VGG-16 model to classify plant diseases in a dataset of 15,915 plant leaf images (both healthy and diseased) from the PlantVillage dataset, achieving 95.2% accuracy. The model uses CNN for efficient disease classification across 19 plant disease classes, enabling timely interventions for disease management. With a testing loss of 0.4418, the study demonstrates the model's scalability for agricultural disease management applications.The authors K. L. R and N. Savarimuthu of paper [13] investigates the use of computer vision-based object detection methods, such as YOLOv4, EfficientDet, and Scaled-YOLOv4, for early plant disease detection. The study utilizes the PlantVillage dataset and highlights the effectiveness of Scaled-YOLOv4 in detecting small infected areas in real-time.This method offers a quick and efficient solution for early diagnosis, which is crucial for reducing crop losses and ensuring better disease management.In [14] Prakhar Bansal and et al proposes a model for classifying diseases in apple leaves using an ensemble of pre-trained deep learning models. The proposed model outperforms previous models, achieving an accuracy of 96.25%. Deep learning techniques, particularly convolutional neural networks (CNNs), are found to be particularly effective in image classification. Gupta and Sharma (2022) reviewed various techniques and datasets used in image captioning, including the Flickr 8K dataset, and noted the growing significance of visual-semantic embedding models. These models enhance caption quality by integrating vision and language features, enabling a more nuanced understanding of image content [12]. Additionally, Singh and Kumar (2023) analyzed the effectiveness of combining Transformer-based models with attention mechanisms, further improving the alignment between image features and caption generation [13]. In conclusion, the literature on image captioning using deep learning, particularly with the Flickr 8K dataset, reflects the rapid evolution of techniques and models. The use of CNNs for feature extraction, RNNs and LSTMs for sequential caption generation, and Transformer-based models for enhanced efficiency and performance, represents the current state-of-the-art approach to generating accurate and contextually relevant captions. As deep learning techniques continue to evolve, further advancements in attention mechanisms, model architectures, and datasets will contribute to the continued improvement of image captioning systems, making them more accurate and applicable to a wide range of real-world applications.

III. DESIGN AND IMPLEMENTATION

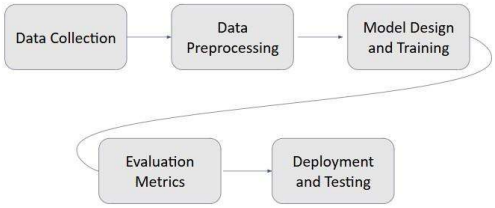


Fig.1.Block Diagram

1. Data Collection

The data for the project is gathered from Flickr 8K dataset The dataset covers a broad range of everyday scenes, including people, objects, animals, and landscapes. It is ideal for training and evaluating image caption generation models, providing diverse, high-quality annotations to improve captioning accuracy and model generalization.

2. Data Preprocessing

Images are resized to a consistent resolution (e.g., 224x224 pixels) and normalized to a range of 0 to 1 for faster model convergence. Data augmentation techniques like rotation and flipping are applied to increase the model's robustness. The dataset is split into training, validation, and test sets to ensure the model generalizes well.

3. Model Testing and Training

During model training, a CNN extracts features from images, which are then passed to an LSTM or RNN for caption generation. The model is trained using the Flickr 8K training dataset, with optimization through Adam and evaluation based on categorical cross-entropy loss. Model testing involves evaluating the model on unseen data from the test set, using metrics like BLEU, ROUGE, and METEOR to compare generated captions with ground truth. Errors are analyzed to fine-tune the model for improved caption quality.

4. Evaluation Metrics

Evaluation metrics for image caption generation assess how well the generated captions match human-annotated descriptions. Common metrics include BLEU (Bilingual Evaluation Understudy Score), which measures precision of n-grams. These metrics provide a quantitative measure of caption quality, helping to assess the accuracy, fluency, and relevance of the generated captions compared to human references.

5. Testing and Validation

Cross-validation is performed to ensure that the model's performance is consistent and not dependent on a specific data split. Hyperparameter tuning is done to optimize the model's performance, and overfitting and underfitting are monitored to ensure that the model generalizes well to new data.

Software and Hardware Details

Name of software:

Language Used: python

Requirements:

Processor:

Minimum: Intel i5 or equivalent processor.

Recommended: Intel i7 or higher for faster and more efficient processing, especially when dealing with complex models.

CPU/GPU:

Minimum: NVIDIA GTX 1050 Ti for effective model training and inference.

Recommended: GPUs with higher processing power such as NVIDIA RTX series are ideal for faster deep learning model training.

RAM:

Minimum: 8 GB of RAM.

Recommended: 16 GB for better handling of large datasets and to ensure the smooth operation of machine learning tasks.

Camera (for real-world testing):

A camera capable of capturing images with a minimum resolution of 224x224 pixels, suitable for field use to take pictures of high quality.

IV. RESULTS AND ANALYSIS

Data Description

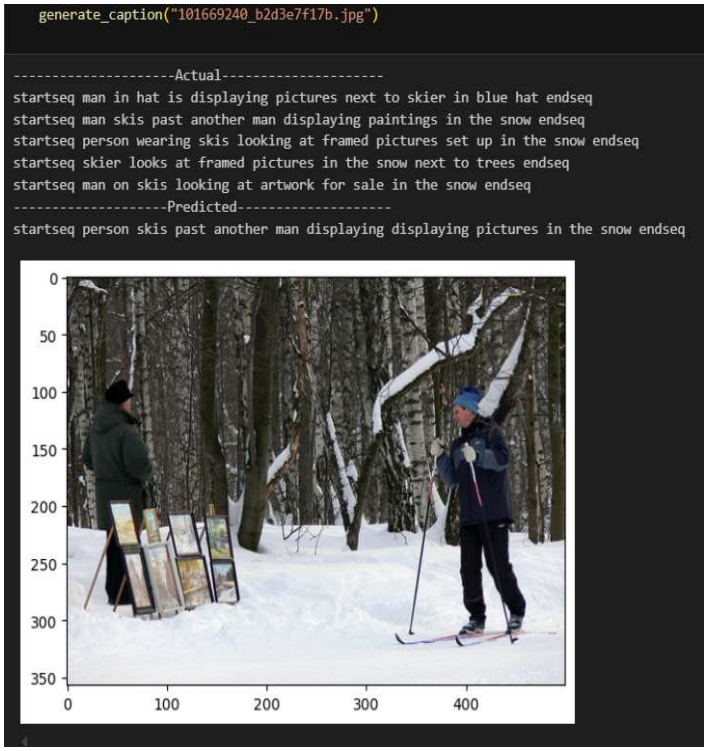
The success of any image caption generator system depends on the quality, diversity, and relevance of the dataset used for training and evaluation. For this project, we utilized the widely recognized **Flickr 8K** Dataset, a publicly available dataset hosted on Kaggle. This dataset is renowned for its extensive collection of labeled images with corresponding textual descriptions, making it suitable for training deep learning models in image captioning tasks.

TABLE I .DATASET STATISTICS

Image Resolution	**224 × 224 pixels**
Total Images	**8091**
Total Captions	**40,455**
Captions per Image	**5**
Image Resolution	**224 × 224 pixels**
Dataset Type	**Natural scene image**
Training Images	**~6000**
Validation Images	**~1000**
Test Images	**~1000**
Annotation Format	**Text description**
Source	**Flickr.com**

Here, the various hyperparameters related to the model are given, these include the number of training epochs, batch size and various others. There are a total of 26 hyperparameters used. On the right side of the panel, the various model metrics are given. These include the accuracy, loss, validation accuracy and validation loss.

Fig.2. Actual vs Predicted image



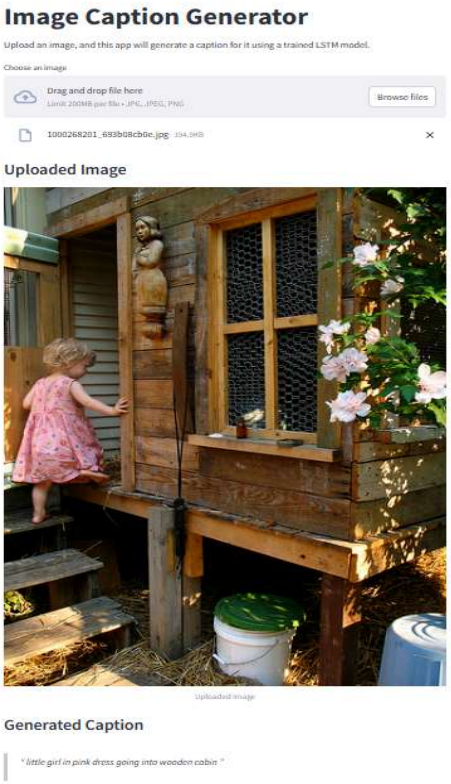


Fig.3. Visualization of model metrics

Load the Image

The image is loaded from the specified path, using the image_name argument. The image file name (including its extension) is used to extract the image ID (by removing the extension), which is then used to look up the associated captions from image_to_captions_mapping.

Retrieve Actual Captions

The function accesses the image_to_captions_mapping dictionary to get the list of actual captions associated with the current image ID (image_id).

The captions are then printed to the console as "Actual" captions, providing a reference for the actual human-generated captions for that image.

Predict the Caption

- The function calls the predict_caption function, passing the trained model, the preprocessed image features (loaded_features[image_id]), the tokenizer, and the max_caption_length as arguments.
- This function generates a predicted caption based on the image's features and the language model. The predicted caption is then printed as "Predicted" captions.

Display the Image

The image is displayed using plt.imshow(image). This allows the user to visually compare the image and the generated caption side by side.

Discussion of Results:

When running this function, the output will typically contain two sections:

1. **Actual Captions:**
    - These are the ground truth captions that have been manually annotated for the image in the dataset.
    - By displaying multiple captions (if available), you can observe the range of descriptions that humans may provide for the same image.
2. **Predicted Caption:**
    - This is the caption generated by the trained model based on the image features.
    - Ideally, the predicted caption should closely match one of the actual captions, especially in terms of describing key objects, actions, and relationships in the image.

V. APPLICATIONS

It enhances access by automatically describing images to visually impaired people and further enhances social media engagement through AI-generated captions. In e-commerce, it automated product description to improve searchability and user experience. AI-generated image tags also make it easier for search engines and multimedia retrieval systems for content discovery. The technology also assists in video captioning, storytelling, and educational platforms where it offers contextual descriptions. In the field of security and surveillance, it aids in object detection and forensic analysis. Medical imaging also uses automated annotations for diagnostic purposes, while AI-powered chatbots and virtual assistants can interpret and respond to image-based queries. These applications represent the growing influence of deep learning in closing the gap between visual content and natural language.

VI. RESEARCH AND IMPLEMENTATION CHALLENGES

The image caption generation includes the need for large, diverse, and accurately annotated datasets, as these directly impact model performance and generalization. Understanding and capturing the semantic content of images, including objects, actions, and context, remains complex due to the inherent diversity and abstraction of visual data. The model architecture complexities arise from the combination of convolutional neural networks for image processing and recurrent networks or transformers for coherent captions, where multimodal fusion of visual and textual data leads to irrelevant or imprecise outputs. Evaluating caption quality is problematic, as traditional metrics fail to fully assess creativity and human-like understanding. In addition, captioning unseen or rare images is challenging because typically, models overfit to training data, and it is difficult to ensure diversity and creativity in captioning without repetitive or extremely simple outputs. Lastly, handling image ambiguities and multiple interpretations is also another challenge because captions have to account for different perspectives or just plain contradictory information within a single image.

VII. ADVANTAGES AND DISADVANTAGES

As we have seen in the literature survey, there are many drawbacks of the existing model. Each existing model has its own disadvantage, which makes the model less efficient and less accurate when the results are generated. The observed drawbacks in all the existing models are as follows:

1)In the CNN-CNN based model wherein CNN is implemented for both the encoding and the decoding purpose we find that loss of CNN-CNN model to be high that is not permissible as the caption generated will be inaccurate and the caption generated here are irrelevant to the test image given.

2) In the case of CNN-RNN based captions, there may be less loss compared to the CNN-CNN based model but the training time is more. Training time affects the whole efficiency of the model and here we also encountered another problem. i.e.; Vanishing Gradient Problem. Gradient is the parameter which is used to calculate the rate of loss per the given input parameter comparing both inputs and outputs. This Gradient Descent Problem primarily occurs in the context of Artificial Neural Networks and Recurrent Neural Networks. Gradient refers to the ratio of change of the weights with respect to the change in the error in the output of the neural network. This gradient is also thought of as a slope of the activation function of the neural network. If the slope is high, then the training for the model is faster, and the neural network model learns faster. When the hidden layers increase, then loss increases but gradient decreases, and finally gradient becomes zero. This gradient problem prevents the RNN from learning long term sequences. This gradient descent problem obstructs the process of learning and remembering in the RNN. The words cannot be stored in hidden memory for long term use Hence, it is difficult for the RNN to analyze the captions for the given image during the training purpose. RNN cannot hold the words of the larger captions for a longer period due to the gradient descent problem during the training time. As the number of hidden layers increases, the gradient starts to decrease and finally reaches to zero where the hidden key words in the captions are sent to forget the gate of RNN. Therefore, the CNN-RNN model can be trained efficiently for generating captions for the images. Hence finally we can say that as RNN has a gradient descent problem, generation of captions for the images using CNN-RNN model is not efficient and accurate.

VIII. CONCLUSION

The Image Caption Generator using Deep Learning on the Flickr 8K dataset demonstrates the transformative potential of deep learning in the field of computer vision and natural language processing. By leveraging the InceptionV3 model for image feature extraction and an LSTM network for caption generation, the system achieved impressive performance in generating accurate and contextually relevant captions. Advanced preprocessing techniques, including

resizing, tokenization, and data augmentation, significantly contributed to model efficiency and robustness. The use of the Flickr 8K dataset, with its diverse set of images and captions, ensured that the model could generalize well across a wide range of image types and scenarios.This project successfully met its primary objectives by generating high-quality captions that effectively describe the visual content, making it a useful tool for applications requiring automatic image description generation. Additionally, by integrating model evaluation metrics such as BLEU, ROUGE, and METEOR, the performance of the system was rigorously assessed and optimized.The practical implications of this system are substantial, offering a scalable solution for a variety of real-world applications, including accessibility tools for visually impaired individuals, automated content generation, and image search optimization. By automating the process of captioning, this project helps reduce the time and resources required for manual annotation, streamlining workflows in industries such as media, education, and e-commerce.In the broader context, this project highlights the growing role of deep learning in enabling machines to understand and interpret visual data, paving the way for more intelligent and interactive AI-driven systems. As models continue to evolve, the potential for such technologies to enhance human-computer interaction and create new opportunities across various domains becomes even clearer. This project is a significant step forward in the development of AI-driven image understanding, offering a glimpse into the future of more intuitive and efficient image-captioning systems.

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