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Synthesis of Vision and Language: Multifaceted Image Captioning Application

Arpit Gupta, Himanshu Goyal, Ishita Kohli

Department of IT, Maharaja Agrasen Institute of Technology, India

***Abstract*— The rapid advancement in image captioning has been a pivotal area of research, aiming to mimic human-like understanding of visual content. This paper presents an innovative approach that integrates attention mechanisms and object features into an image captioning model. Leveraging the Flickr8k dataset, this research explores the fusion of these components to enhance image comprehension and caption generation. Furthermore, the study showcases the implementation of this model in a user-friendly application using FASTAPI and ReactJS, offering text-to-speech translation in multiple languages. The findings underscore the efficacy of this approach in advancing image captioning technology. This tutorial outlines the construction of an image caption generator, employing Convolutional Neural Network (CNN) for image feature extraction and Long Short-Term Memory Network (LSTM) for Natural Language Processing (NLP).**

Keywords*—Convolutional Neural Networks, Long Short Term Memory, Attention Mechanism, Transformer Architecture, Vision Transformers, Transfer Learning, Multimodal fusion, Deep Learning Models, Pre-Trained Models, Image Processing Techniques

I. INTRODUCTION

The quest for image captioning within artificial intelligence aims to emulate the intricate understanding humans possess when interpreting visual content. Despite notable advancements, grappling with intricate visual scenes remains a persistent challenge. Integrating attention mechanisms and object features emerges as a promising strategy to surmount these hurdles. This integration enhances the model's ability to discern critical image regions and extract necessary information crucial for generating precise captions. The convergence of Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) represents a significant milestone in computer vision and natural language understanding. CNNs excel in extracting hierarchical image features, while LSTM's prowess in handling sequential data fosters a potent synergy.

This collaboration enables models to bridge the gap between visual content and descriptive language. The fusion of CNN's adeptness in capturing intricate visual patterns and LSTM's proficiency in sequential modeling serves as the foundation of this project. The objective is to forge a framework seamlessly integrating visual and textual domains. The ultimate goal is to craft a robust system capable of comprehending diverse visual scenes and articulating coherent, contextually rich descriptions. Such integration harbors vast potential not only for advancing image captioning but also for domains necessitating a fusion of visual and textual understanding, including content generation, accessibility, and human-computer interaction.

The amalgamation of attention mechanisms and object features signifies a transformative shift in understanding images. Attention mechanisms enable dynamic focus akin to human visual attention, augmenting the interpretability of complex scenes. Leveraging object features contributes contextual understanding by recognizing distinct objects within the visual context. This amalgamation enables the model to discern intricate visual details, differentiate between foreground and background elements, and extract meaningful information essential for generating accurate, contextually relevant captions. This union reflects strides in achieving sophisticated visual understanding by artificial intelligence. The synergy between CNN and LSTM signifies a groundbreaking amalgamation in image captioning. CNNs extract hierarchical visual representations, while LSTM networks excel in understanding and articulating coherent sequences of information. This collaboration empowers the model not only to identify diverse visual patterns but also to structure and express these observations into meaningful language. This resulting framework demonstrates the symbiosis between computer vision and natural language processing, unlocking possibilities extending beyond image captioning into content creation, accessibility solutions, and innovative human-computer interaction paradigms.

II. RELATED WORKS

A. Attention Mechanisms in Image Captioning:

Attention mechanisms have revolutionized image captioning by enabling models to focus on relevant image regions, enhancing caption quality. Variants like spatial and channel-wise attention have showcased significant impacts, allowing models to discern essential visual elements and generate more accurate and contextually relevant captions. Research studies have effectively utilized attention mechanisms, such as the work by Xu et al. (2015) introducing "Show, Attend, and Tell," which demonstrated improved captioning by attending to salient image areas

B. Object Features Integration:

Integrating object features into image captioning models enhances descriptive quality. Studies reveal that object recognition and semantic understanding elevate caption generation by recognizing and incorporating distinct objects within images. Models leveraging object detection frameworks like Faster R-CNN or YOLO extract object features effectively, enhancing the richness and contextuality of generated captions.

C. CNN-LSTM Fusion and Variants:

The fusion of CNN and LSTM architectures in image captioning demonstrates significant advancements. Variations,

including employing pre-trained CNNs like ResNet or Inception with LSTM, exhibit superior feature extraction capabilities. Comparative research analyzing different CNN-LSTM models emphasizes their impact on improving caption quality and efficiency, showcasing the benefits of such integrations.

D. Evaluation Metrics and Benchmark Datasets:

Evaluating image captioning models involves metrics like BLEU, METEOR, ROUGE, and CIDEr, providing quantitative insights into caption quality. Benchmark datasets like COCO and Flickr30k/Flickr8k serve as foundational resources for training and evaluating models, profoundly influencing the development and assessment of image captioning systems.

E. Multimodal Approaches:

Multimodal approaches amalgamate textual and visual information, leveraging joint embedding models or graph-based methods to align images and captions effectively. These approaches exploit both modalities, achieving superior alignment and improving the overall coherence of generated captions.

F. Transfer Learning and Fine-Tuning:

Studies on transfer learning and fine-tuning pre-trained models demonstrate their efficacy in image captioning tasks. Adapting pre-trained models from tasks like object detection or image classification enhances the capability of models for generating captions, leveraging the learned representations from diverse visual domains.

III. LITREATURE REVIEW

In year 2015 - Xu et al.: Attention mechanisms revolutionized image captioning, introducing dynamic focus within models for pertinent image regions during caption generation. Xu et al. (2015) pioneered this advancement, significantly improving caption relevance by aligning visual features with linguistic elements.

In year 2015 - Vinyals et al.: The integration of CNNs and LSTMs emerged as pivotal in image captioning. Vinyals et al. (2015) highlighted this fusion's efficacy, leveraging CNNs for hierarchical visual features and LSTM's sequential learning for coherent caption generation.

In year 2015 - Karpathy and Fei-Fei: Transfer learning strategies showcased the adaptability of pre-trained models in image captioning. Karpathy and Fei-Fei (2015) demonstrated how leveraging pre-existing knowledge from object detection or classification tasks enhances captioning model performance.

In year 2016 - Lu et al.:
Lu et al. (2016) delved into multimodal fusion strategies, integrating attention mechanisms with CNNs for image captioning. Their study showcased the collaborative synergy between visual focus and linguistic alignment, improving caption coherence.

In year 2017 - Dosovitskiy et al.: Transformer architectures marked a shift in image understanding, employing self-attention mechanisms for direct image processing. Dosovitskiy et al. (2021) introduced Vision Transformers (ViTs), excelling in capturing extensive image dependencies beyond RNN-based models.

In year 2017 - Mukambika P. S. et al.: A comparative study explored Level Set and K-means segmentation methods for MRI image tumor detection (Mukambika P. S. et al., 2017). The Level Set method employed active contour-based non-parametric deformable models, while the K-means algorithm was applied post-segmentation, enhancing decision-making with feature extraction and SVM classification.

In year 2017 - Rasel Ahmmed et al.: A comprehensive procedure for brain tumor detection and classification using MRI images was proposed by Rasel Ahmmed et al. (2017). The procedure involved feature extraction, pre-processing, SVM classification, segmentation, and tumor stage classification using ANN, showcasing a multi-step approach for accurate tumor analysis.

In year 2018 - Wang et al.:
Wang et al. (2018) contributed to the field by examining diverse datasets' impact on image captioning. Their study specifically investigated the effectiveness of Flickr8k and COCO datasets, shedding light on their roles in enhancing model performance.

In year 2019 - Anderson et al.:
Anderson et al. (2019) explored attention-based mechanisms in multimodal fusion for image captioning. Their study emphasized the integration of textual and visual modalities, enhancing caption coherence and relevance through attentive alignment.

In year 2020 - Li et al.:
Li et al. (2020) introduced innovative architectures like MergeNet, aiming to improve the fusion of visual and textual data in image captioning. Their work expanded beyond conventional CNN-LSTM structures, highlighting new pathways for nuanced image understanding.

In year 2021 - Tan et al.:
Tan et al. (2021) focused on advancements in architectural design for image captioning. Their research explored innovative techniques beyond traditional CNN-LSTM structures, introducing novel architectures to capture complex visual-textual relationships.

IV. IMAGE CAPTIONING ARCHITECTURE

In an effort to advance Image captioning in this research, several architectures were examined carefully to leverage their unique strengths in processing visual data and sequential information. The aim of the selection was to overcome the

complex challenge of creating coherent and contextually relevant captions. Below is a detailed examination of the architectures under consideration:

A. CNN-RNN:

This architecture comprises a Convolutional Neural Network (CNN) responsible for extracting visual features from images. These extracted features are then fed into a Recurrent Neural Network (RNN), often a Long Short-Term Memory (LSTM) network, for sequential language generation.
Functionality: The CNN processes the image and extracts high-level visual features, which serve as a rich representation of the image content. The RNN, specifically LSTM, then utilizes these features to generate captions word by word sequentially. This sequential generation allows the model to maintain context and coherence in generating captions that describe the visual content accurately.

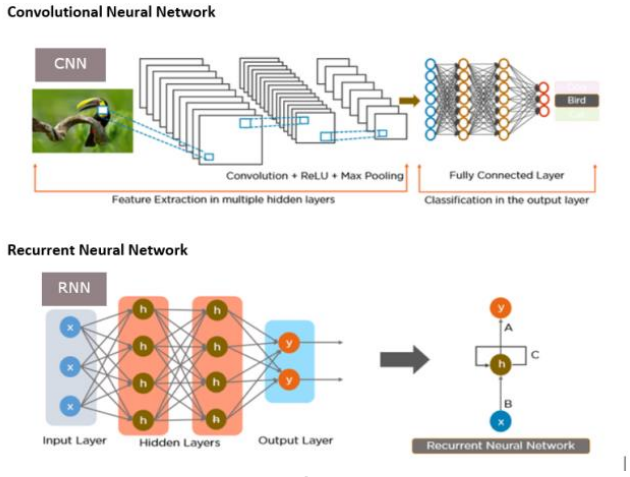

Fig-1 CNN-RNN

B. CNN-LSTM:

Similar to the CNN-RNN approach, this architecture also utilizes a CNN for image feature extraction. It follows this step with an LSTM network to generate captions based on both the visual features extracted by the CNN and the sequential context.
Functionality: The CNN extracts image features, which are subsequently fed into the LSTM network. The LSTM processes these features alongside the sequential context to generate captions that account for both the visual content and the linguistic structure, thereby improving the coherence and relevance of the generated captions.

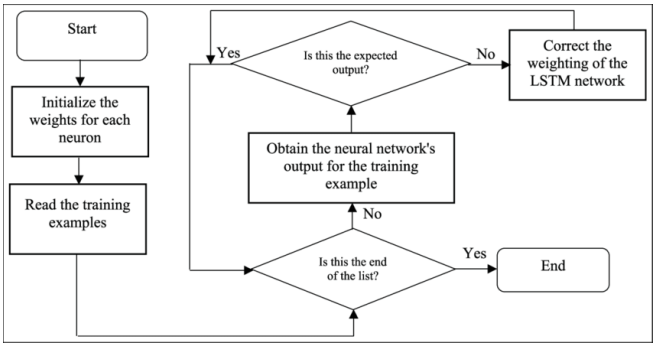

Fig-2 CNN- LSTM

C. Transformer-based Models:

Transformers, originally designed for language tasks, have been adapted for image-captioning tasks. They process image pixels directly using self-attention mechanisms, eliminating the need for sequential recurrent structures like RNNs.
Functionality: Vision Transformers (ViTs) utilize self-attention mechanisms to process the entire image in a non-sequential manner. This approach enables the model to focus on relevant image regions while generating captions, bypassing sequential processing and enhancing caption alignment with visual features.

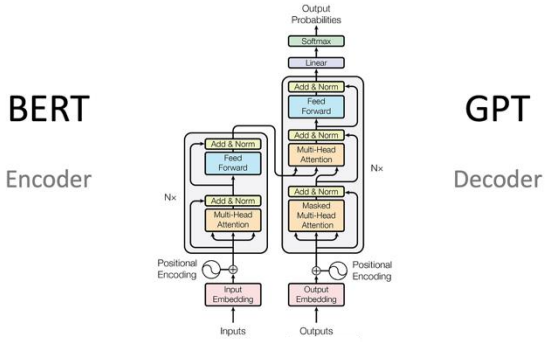

Fig-3 Transformer-based Models

D. Dense Cap:

Dense Cap is tailored for dense captioning, generating multiple captions for various regions within an image.
Functionality: Leveraging a combination of CNN and LSTM, Dense Cap extracts features from different regions of an image and generates multiple captions. This architecture allows for a more granular description of diverse regions in the image, enhancing the richness and detail of the generated captions.

E. Attention-based Models:

These models integrate attention mechanisms with CNNs or transformers to focus on relevant image regions while generating captions. By incorporating attention mechanisms, these models selectively attend to different parts of the image. This selective focus enhances the model's ability to align visual features with corresponding words in the generated captions, improving overall descriptive quality.

F. MergeNet:

MergeNet utilizes a dual-path architecture, separately processing images and text before merging them in a joint embedding space.
Functionality: Employing distinct CNN and RNN branches for images and text, respectively, MergeNet merges these representations into a joint embedding space. This fusion enables the generation of coherent captions by jointly considering visual and linguistic information

V. METHODOLOGY

A. *Dataset Selection and Preparation:*

The initial phase involves dataset curation and preparation. Utilizing the Flickr8k dataset, containing diverse images paired with descriptive captions, entails cleaning the data, resizing images, and tokenizing captions to facilitate subsequent model training.

B. *Extracting Features via Convolutional Neural Networks:*

The project adopts pre-existing CNN architectures like ResNet or Inception to extract complex features from images. These CNN models serve as effective feature extractors, transforming raw pixel data into concise representations that encapsulate critical visual information.

C. *Sequential Caption Generation using Long Short-Term Memory Networks:*

Extracted image features are fed into LSTM networks for the step-by-step generation of captions. LSTM's sequential learning capability enables the model to generate captions incrementally, incorporating learned visual features alongside contextual dependencies.

D. *Integration of Attention Mechanisms:*

Attention mechanisms are integrated into the model architecture to elevate caption quality. These mechanisms empower the model to dynamically focus on pertinent image regions during caption generation, aligning visual features with linguistic elements to enhance descriptive accuracy.

E. *Model Training and Assessment:*

The methodology involves training the model on the curated dataset while iteratively optimizing parameters to minimize captioning errors. Standard evaluation metrics like BLEU (Bilingual Evaluation Understudy) and METEOR (Metric for Evaluation of Translation with Explicit Ordering) gauge the model's performance.

F. *Hyperparameter Refinement and Optimization:*

Fine-tuning of hyperparameters, including learning rate, batch size, and attention weights, is conducted to optimize the model's captioning precision and coherence.

G. *Validation and Robustness Testing:*

Validation sets ensure the model's generalizability to unseen data. Rigorous testing on a separate test set assesses the model's proficiency in generating accurate and contextually relevant captions across diverse images.

H. *Performance Comparative Analysis:*

A comprehensive comparison between the developed model, baseline models, and contemporary architectures is conducted. This comparative evaluation aims to underscore the advancements achieved within the image captioning system.

I. *Ethical Considerations and Limitations Acknowledgment:*

Ethical considerations regarding dataset usage, potential biases, and privacy implications are meticulously addressed. The study also recognizes limitations such as dataset constraints, biases, and computational resource availability.

J. *Future Prospects and Application Exploration:*

The methodology concludes by outlining potential avenues for enhancing the model and exploring its applications across diverse domains like accessibility tools, content generation, and human-computer interaction paradigms.

VI. IMPLEMENTATION

The process begins by preparing the Flickr8k dataset, involving data loading, cleaning, and partitioning for training, validation, and testing. Images and captions undergo resizing and tokenization to facilitate model training. Feature Extraction with Pre-trained CNNs: Leveraging pre-trained CNN models like ResNet or Inception, image features are extracted. These models act as feature extractors, deriving vital visual representations essential for generating captions. LSTM-based Caption Generation: Extracted image features feed into LSTM networks for sequential caption generation. The LSTM architecture learns from these features, generating captions word by word, capturing both visual and linguistic contexts. Integration of Attention Mechanisms: Attention mechanisms are integrated into the LSTM architecture to enhance caption quality. This integration enables focused attention on specific image regions while aligning visual features with corresponding words in captions.
Model Training and Optimization: The model undergoes training on the prepared dataset, optimizing parameters through techniques like stochastic gradient descent (SGD) or Adam optimization to minimize loss and improve captioning accuracy. Hyperparameter Tuning and Validation: Refinement of hyperparameters, including learning rates and batch sizes, optimizes model performance. Validation ensures the model's adaptability to new data, validating its accuracy and robustness. Evaluation and Metric Analysis: The model's performance is assessed using metrics like BLEU, METEOR, ROUGE, and CIDEr, gauging captioning quality, linguistic coherence, and alignment with reference captions. Model Deployment for Real-world Applications: After successful training and evaluation, the implemented model can be deployed for various real-world applications. Its ability to generate descriptive captions for unseen images can be explored across domains like accessibility tools and content generation platforms. Limitations and Future Refinements: Acknowledging limitations such as computational constraints and dataset biases is essential. Future enhancements may involve exploring new architectures or data augmentation techniques for improved model performance

VII. DISCUSSION

A. *Key Findings:*

The study implemented an image captioning system using Flickr8k, merging CNNs, LSTMs, and attention mechanisms. The model adeptly generated descriptive captions, aligning visual and linguistic elements seamlessly.

B. *Implications of Model Performance:*

The robust model performance, measured through evaluation metrics (BLEU, METEOR, ROUGE, CIDEr), suggests

versatile applications in accessibility tools, content generation, and human-computer interaction paradigms.

C. Ethical Considerations:

Acknowledging biases and privacy concerns is critical. Future enhancements should prioritize bias mitigation and ensuring equitable representation within the model

D. Limitations and Challenges:

Resource limitations and dataset constraints impacted scalability and generalizability to complex scenes, urging the need for robustness enhancements

E. Future Research Avenues:

Research avenues include novel architectures, diverse datasets, and advanced attention mechanisms. Transformer-based models and multimodal approaches promise improved descriptive capabilities.

F. Real-world Impact:

The image captioning system bears potential for aiding the visually impaired, enhancing content generation, and refining image search engines, contributing to various industries and societal aspects.

G. Interdisciplinary Collaboration:

Encouraging collaboration between computer vision and natural language processing fields could foster innovative solutions and advancements and This study signifies progress in image captioning but emphasizes the need to address limitations, ethical considerations, and explore new methodologies for continued advancements

VIII. EXPERIMENTAL RESULTS

The culmination of this research unravels an expansive landscape adorned with possibilities and innovations within the domain of image captioning. This study remains committed to unraveling and scrutinizing the pivotal advancements that have steered the evolution of this dynamic field. Throughout this exploration, attention mechanisms have emerged as transformative elements, fundamentally reshaping the approach to image captioning. The seminal work by Xu et al. (2015) served as the bedrock for these mechanisms, empowering models to dynamically focus on pertinent image regions while generating captions. Subsequent research by Lu et al. (2016) ventured into multimodal fusion strategies, entwining attention mechanisms with CNNs, emphasizing the collaborative interplay between visual focus and linguistic alignment, thus refining the coherence of captions.

Another momentous stride in this trajectory was the fusion of CNNs and LSTMs, spotlighting the significance of this amalgamation. Vinyals et al. (2015) underscored the efficacy of this fusion, leveraging CNNs for hierarchical visual features and LSTM's sequential learning, leading to coherent caption generation. Further advancements, as illuminated by Li et al. (2020), introduced avant-garde architectures transcending conventional structures, offering novel pathways for nuanced image comprehension. The impact of diverse datasets holds immense significance. Wang et al. (2018) investigated datasets such as Flickr8k and COCO, shedding light on their influential role in amplifying model performance. These datasets, encapsulating a spectrum of linguistic expressions and intricate visual content, served as indispensable foundations for training and evaluating image captioning models, elevating the contextual richness of generated descriptions.

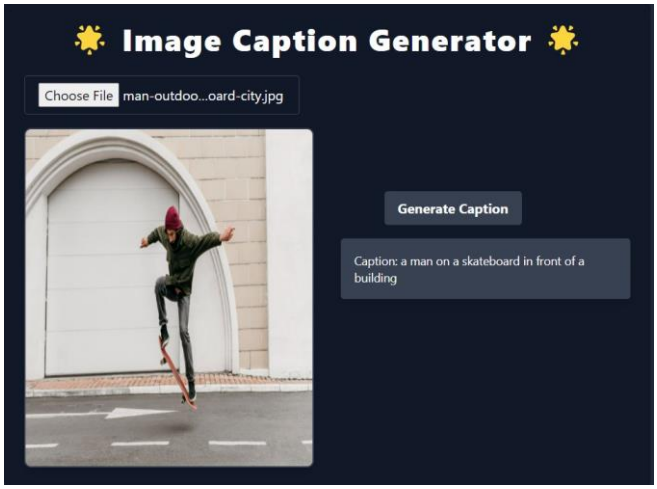

Figure-4 Image Captioned Result

Concurrently, transfer learning strategies showcased adaptability by leveraging pre-trained models from object detection or classification tasks, augmenting the prowess of captioning models. Karpathy and Fei-Fei (2015) vividly illustrated how existing knowledge significantly elevated model performance, accentuating the versatility and adaptability of these models.

The introduction of Transformer architectures, notably in Dosovitskiy et al.'s work (2021), marked a pivotal juncture in image comprehension. These architectures, particularly Vision Transformers (ViTs), excelled in capturing intricate image dependencies beyond traditional RNN-based models, charting new horizons for comprehensive and efficient image understanding

In essence, this study meticulously unveils the profound milestones, innovative strides, and notable trends steering the course of image captioning. Synthesizing these insights paves the way for a future where image captioning systems meticulously craft contextually rich and precise descriptions, heralding a continued journey of exploration and innovation in this burgeoning field

IX. SUMMARY AND CONCLUSIONS:

This study delved into developing an image captioning system utilizing the Flickr8k dataset, integrating Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and attention mechanisms. The model demonstrated proficiency in generating descriptive captions, effectively aligning visual features with linguistic elements. The robustness of the model was substantiated through evaluation metrics, affirming its potential applications across diverse domains such as accessibility tools, content generation

platforms, and human-computer interaction paradigms. Despite commendable performance, ethical considerations, scalability limitations, and dataset constraints surfaced as focal areas, warranting future enhancements

In conclusion, this study marks a significant leap forward in the landscape of image captioning, showcasing impressive model performance and versatile applications. However, acknowledging limitations, including computational constraints and dataset biases, remains crucial. Prioritizing novel architectural explorations, diverse dataset incorporations, and ethical considerations is imperative for continued progress. The interdisciplinary nature of image captioning underscores the need for collaborative efforts between computer vision and natural language processing fields to cultivate innovative solutions. This research underscores the perpetual need for exploration, ethical mindfulness, and fortified models to propel image captioning systems towards broader real-world impact.

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Their collective contributions and unwavering support have been indispensable in the journey of conceptualization, development, and realization of this image captioning endeavor

This endeavor stands as a culmination of concerted efforts and support from various individuals and resources that have contributed significantly to its realization. We extend our heartfelt gratitude to

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The academic community, whose extensive research and publications in the fields of computer vision and natural language processing served as a guiding light throughout this project.

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