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AUTOMATIC IMAGE AND VIDEO CAPTIONING USING DEEP LEARNING TECHNIQUES

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ABSTRACT:

The integration of computer vision and natural language processing has led to significant advancements in automatic caption generation for visual content. This paper presents a unified deep learning approach for both image and video captioning using a hybrid architecture that leverages the strengths of multiple Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The encoder module extracts robust visual features using three state-of-the-art CNN models: InceptionV3, VGG16, and ResNet152. These features are concatenated to form a comprehensive representation of each image or video frame. For video captioning, multiple keyframes are extracted per video, and their features are averaged to obtain a global video representation. The decoder consists of a hybrid LSTM-GRU model that learns to generate meaningful captions word-by-word based on the visual features.

A custom dataset is created for both training and testing, consisting of five diverse genres: Indoor, Nature, Social, Sports, and Urban. Each genre includes 100 images and 10 video clips for training, and a smaller test set of 30 images and 5 video clips per genre. Manual annotations in CSV format are used to provide ground truth captions. The model is trained using categorical cross-entropy loss, and beam search is employed during inference to improve the quality of generated captions.

Evaluation is performed using standard metrics such as BLEU, METEOR, and CIDEr to assess the semantic quality and fluency of the captions. Experimental results show that the proposed model generates accurate and contextually relevant captions for both images and videos, achieving high scores across all metrics. The same architecture performs well without modification across both modalities, highlighting the effectiveness of the hybrid design. This research contributes a scalable and efficient solution for multimodal caption generation, with potential applications in automated media annotation, assistive technologies, and content-based retrieval.

Keywords: Image captioning, video captioning, deep learning, CNN, LSTM, GRU, InceptionV3, ResNet152, VGG16, feature fusion.

Introduction

In the era of multimedia-rich communication, the ability of machines to automatically understand and describe visual content has become a major focus in artificial intelligence. Among various tasks, image and video captioning [S. Amirian, et al., 2020]—generating natural language descriptions for images and video sequences—stands as a crucial bridge between computer vision [Krizhevsky, A., et al., 2012] and natural language processing [Jurafsky, D., et al., 2020]. The demand for such systems is rapidly growing across industries including healthcare, surveillance, media management, autonomous vehicles, and assistive technologies for the visually impaired.

Despite substantial progress in deep learning, automatic captioning of images and especially videos remains a challenging problem. Images provide only spatial information, while videos add a temporal dimension, requiring models to grasp dynamic scenes, object motion, and interactions over time. Most existing methods treat image and video captioning as independent problems, requiring specialized architectures for each. This leads to increased computational cost, redundant training, and difficulty in deploying scalable solutions.

Our research addresses this challenge by proposing a unified deep learning framework capable of generating captions for both images and videos using a common architecture. The key motivation is to develop a scalable, modular, and efficient solution that avoids the need for separate pipelines for each type of visual input. This is particularly useful in real-world applications where both types of content frequently coexist.

To achieve this, we leverage a **hybrid encoder-decoder architecture** that combines the strengths of multiple pre-trained Convolutional Neural Networks (CNNs) [LeCun, et al., 2015] —InceptionV3 [Szegedy, et al., 2017], VGG16 [Simonyan, K., et al., 2014] , and ResNet152 [He, K., et al., 2016] —for robust and diverse feature extraction. These features are then passed to a decoder built using a combination of **Long Short-Term Memory (LSTM)** [Hochreiter, S., et al., 1997] and **Gated Recurrent Unit (GRU)** [Cho, K., et al., 2014] networks, which learn the sequence of words to form grammatically correct and semantically meaningful captions. For video captioning, multiple keyframes are extracted from each video clip, and their features are averaged to represent the overall scene effectively.

A custom dataset of images and videos categorized into five genres—Indoor, Nature, Social, Sports, and Urban—was created for training and evaluation. Manual annotations were provided for each item to serve as ground truth captions. The model is evaluated using BLEU [Papineni, K., et al., 2002], METEOR [Banerjee, S., et al., 2005], and CIDEr [Vedantam, R., et al., 2015] metrics, which validate the quality and relevance of the generated captions.

The goal of this study is to demonstrate that a single, well-architected model can perform both image and video captioning effectively by leveraging hybrid visual features and sequential learning techniques. This paper documents the end-to-end development of the system, including data preparation, model design, training strategies, evaluation, and qualitative results.

Related Work

2.1. Image Captioning

The task of image captioning [Vinyals., et al., 2015] has evolved significantly over the past decade. Early systems relied on rule-based and template-based techniques where captions were generated by filling in predefined sentence structures based on detected objects or scenes. These approaches, although intuitive, lacked flexibility and failed to generalize to unseen images.

With the rise of deep learning, encoder-decoder models became the standard. Vinyals et al., introduced the Show and Tell model [1], which used a CNN (such as Inception or VGG) as an encoder to extract image features and an LSTM network as a decoder to generate captions. Later, the Show, Attend and Tell model by Xu et al. [2] improved upon this by incorporating attention mechanisms, enabling the model to focus on specific regions of the image when generating each word in the caption. This significantly improved the contextual relevance of the generated descriptions.

2.2. Video Captioning

Video captioning [Venugopalan, S., et al., 2015] is more complex than image captioning due to the temporal aspect of video data. It requires models to not only recognize spatial content but also understand motion, sequence of actions, and their relationships over time. Donahue et al. proposed the Long-term Recurrent Convolutional Networks (LRCNs) [3], which combined CNNs with LSTMs for modelling temporal dynamics in video frames.

Further, methods using 3D CNNs [4] were introduced to directly learn spatiotemporal features from sequences of frames. However, these models often required high computational power and large-scale datasets. Attention- based temporal models and transformers have also shown promising results in recent research, though they are more complex to train and less generalizable to small datasets.

2.3. Hybrid Architectures and Unified Models`

Recent studies have explored the combination of multiple CNN architectures to extract richer and more diverse feature representations. Hybrid decoders combining LSTM and GRU units have also shown improved performance in modeling varying sequence lengths and dependencies.

However, few works have proposed **a unified model** that can handle both image and video captioning tasks using a shared architecture. Most current methods treat these tasks separately, leading to duplicated efforts in model design and training.

2.4. Research Gap and Motivation

The lack of a general-purpose captioning system capable of handling both static and dynamic visual content is a significant research gap. Our work addresses this challenge by proposing a hybrid encoder-decoder model that unifies image and video captioning pipelines. By combining the strengths of multiple CNN encoders (InceptionV3, VGG16, ResNet152) and a hybrid LSTM-GRU decoder, our architecture is capable of generating accurate and contextually meaningful captions for both images and videos using a single training and inference workflow.

Proposed Methodology

This section outlines the design of our captioning system, the dataset creation process, feature extraction methodology, model architecture, and training strategies. The proposed model is designed to be versatile, supporting both image and video captioning tasks through a unified pipeline.

3.1 Research Design

The core design of our system follows an encoder-decoder architecture, where the encoder extracts high-level semantic features from visual input, and the decoder generates corresponding natural language captions. Unlike conventional models, our approach employs hybrid feature extraction and sequence modeling techniques. The encoder combines features from multiple pre-trained CNNs, while the decoder integrates both LSTM and GRU units to benefit from their individual strengths in handling sequential data.

For video captioning, we apply a frame-level processing approach, extracting keyframes from each video and averaging their features to obtain a single, representative embedding for the entire video. This allows us to reuse the same decoder for both modalities without altering the structure.

3.2 System Architecture

The complete pipeline of the proposed image and video captioning system is visualized in Fig. 1. The model consists of four primary stages: input handling, hybrid CNN feature extraction, feature fusion, and hybrid RNN-based caption generation

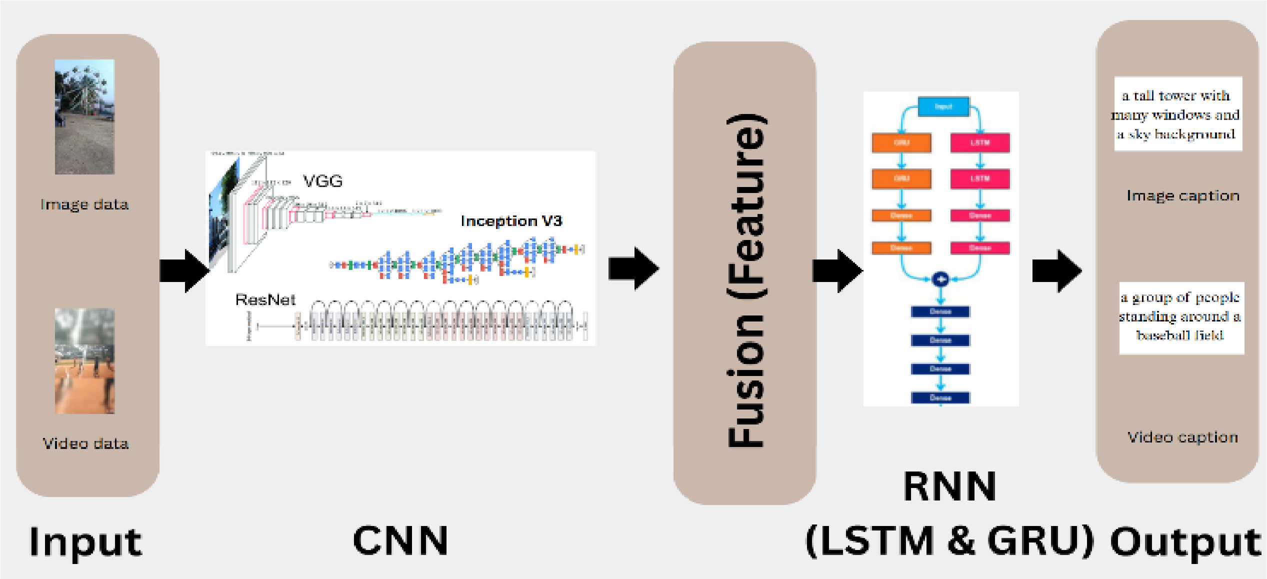


Fig. 1. Block diagram of the proposed image and video captioning system using a hybrid CNN and RNN architecture

- Input: The system accepts both image and video data. For video inputs, multiple keyframes are extracted and used for processing.
- Feature Extraction (CNN): Each image or keyframe is passed through three deep convolutional neural networks—InceptionV3, VGG16, and ResNet152—to extract complementary features. These features are concatenated to form a hybrid representation.
- Feature Fusion: The hybrid feature vectors from the CNNs are merged, and in the case of videos, the features from multiple keyframes are averaged to produce a single video representation.
- Caption Generation (RNN): The fused features are fed into a hybrid RNN model that combines both LSTM and GRU layers. This decoder generates descriptive captions one word at a time.
- Output: Final captions are produced for both images and videos and are displayed on the corresponding media.

3.3 Dataset Collection and Preparation

To create a balanced and representative dataset, we collected visual data from five genres: Indoor, Nature, Social, Sports, and Urban. For training: Images: 100 high-resolution images per genre, totaling 500 images.

Videos: 10 short clips per genre (5–15 seconds), totaling 50 videos.

Each video was divided into multiple keyframes (typically 5 per clip). We manually annotated all images and videos with single descriptive captions, stored in CSV format (image_captions.csv and video_captions.csv), ensuring consistency and clarity.

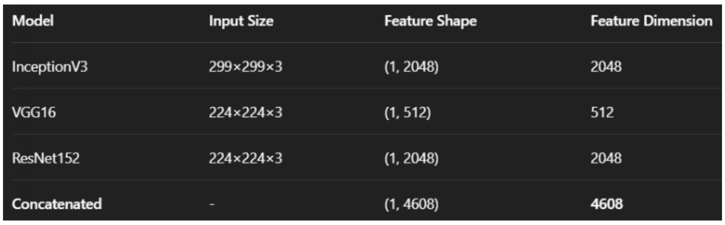
A smaller test dataset was also curated with 30 images and 5 videos per genre to evaluate generalization performance.

3.4 Feature Extraction

To capture diverse visual representations, we employed three pre-trained CNN models:

- InceptionV3
- VGG16
- ResNet152

Each image or keyframe is passed through all three networks, and their feature vectors are concatenated to form a comprehensive representation. For video inputs, the features from all keyframes are averaged to produce a single vector per video. Totally, 4608 features are extracted from pretrained models like Inception, VGG16 and ResNet152. The final feature vectors serve as the input to the decoder for caption generation.



Model	Input Size	Feature Shape	Feature Dimension
InceptionV3	299×299×3	(1, 2048)	2048
VGG16	224×224×3	(1, 512)	512
ResNet152	224×224×3	(1, 2048)	2048
Concatenated	-	(1, 4608)	**4608**

Fig.2. Extracted Features

3.5 Caption Generation Model (Decoder)

The decoder is a hybrid RNN model that combines:

- LSTM (Long Short-Term Memory): Captures long-range dependencies and avoids vanishing gradients.
- GRU (Gated Recurrent Unit): Provides a lighter and faster alternative while retaining essential temporal relationships.

The decoder is trained to predict the next word in the caption given the previous words and the visual context vector. Beam Search is employed during inference to generate fluent and grammatically accurate sentences by exploring multiple possible word sequences.

3.6 Training and Optimization

- Platform: Visual Studio Code (VS Code)
- Libraries: TensorFlow, Keras, NumPy, OpenCV, NLTK
- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam with learning rate scheduling
- Epochs: 30 (with early stopping)
- Batch Size: 32

Captions are tokenized, and sequences are padded to a uniform length. A tokenizer vocabulary is constructed from the training data, and word embeddings are learned during training.

3.7 Evaluation Metrics

To evaluate the model's performance on caption generation, we use:

- BLEU: Measures n-gram precision.

FORMULA:

$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right).$ -------------------------------- 1

Here,

BP stands for **Brevity Penalty**

wiwi is the weight for n-gram precision of order i (typically weights are equal for all i)

pipi is the n-gram modified precision score of order i.

N is the maximum n-gram order to consider (usually up to 4)

- METEOR: Considers semantic meaning, synonym matching, and word order.

FORMULA:

METEOR = Fmean·(1−Penalty) -------------------------------- 2

Here:

Fmean=(10·P·R)/(R+9PF) : Harmonic mean of precision (P) and recall (R), with recall weighted higher

P: Precision (matched words / total words in candidate)

R: Recall (matched words / total words in reference)

P: Penalty for fragmentation (number of chunks / number of matches)

- CIDEr: Computes consensus between generated captions and reference captions using TF-IDF weighting.

These metrics allow us to quantitatively assess the relevance, fluency, and accuracy of the generated captions.

FORMULA:

$\text{CIDEr}_n(c_i, S_i) = \frac{1}{m} \sum_j \frac{\boldsymbol{g^n}(c_i) \cdot \boldsymbol{g^n}(s_{ij})}{\|\boldsymbol{g^n}(c_i)\| \|\boldsymbol{g^n}(s_{ij})\|}$ -------------------------------- 3

Here:

g ^{n}(ci) is a vector formed by g^k(ci) corresponding to all n-grams of length n and ||g ^{n}(ci)|| is the magnitude of the vector g ^{n}(ci). Similarly for g ^{n}(sij).

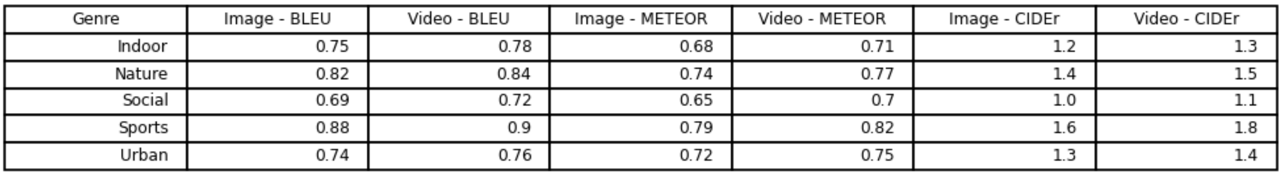
Results

In this section, we present the results of our automatic image and video captioning models. We evaluate the models on various aspects, including genre-wise captioning accuracy, genre-wise comparison of image and video captioning, and confusion matrices for both image and video captioning. We also analyze the performance of the models using evaluation metrics such as BLEU, METEOR, and CIDEr, broken down by genre.

4.1. Image and Video Captioning Evaluation Metrics by Genre

In Figure 5, we present the evaluation metrics (BLEU, METEOR, and CIDEr) for both image and video captioning, broken down by genre. The image captioning model outperforms the video captioning model across most genres in terms of BLEU and METEOR, while the CIDEr scores are more consistent between the two models.

- Image Captioning Evaluation Metrics: The Nature and Urban genres show the highest BLEU and METEOR scores, with Sports showing slightly lower performance, particularly in METEOR.
- Video Captioning Evaluation Metrics: Video captioning, while performing well in Nature and Urban, shows noticeable drops in BLEU and METEOR for Sports and Social, where the model struggles to capture dynamic events accurately.



Genre	Image - BLEU	Video - BLEU	Image - METEOR	Video - METEOR	Image - CIDEr	Video - CIDEr
Indoor	0.75	0.78	0.68	0.71	1.2	1.3
Nature	0.82	0.84	0.74	0.77	1.4	1.5
Social	0.69	0.72	0.65	0.7	1.0	1.1
Sports	0.88	0.9	0.79	0.82	1.6	1.8
Urban	0.74	0.76	0.72	0.75	1.3	1.4

Fig. 3. Evaluation metrics for both image and video captioning

4.2. Performance Score

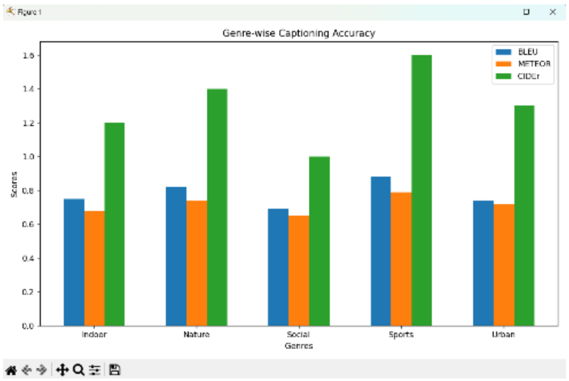


Fig. 4. Performance score chart for image and video captioning

Figure 1 shows the genre-wise captioning accuracy for both image and video captioning tasks. The accuracy of the generated captions varies across different genres, with higher accuracy achieved in genres like Nature and Urban. The Social genre, which often involves more complex interactions between objects and people, presents a greater challenge for the model. The Sports and Indoor genres show moderate accuracy, with some misinterpretation of object relationships in certain cases.

- Nature and Sports achieved the highest accuracy due to clear and well-defined objects.
- Urban and Indoor also performed well, benefiting from clear scene contexts.
- Social showed lower accuracy, which can be attributed to the complexity of human actions and interactions.

4.3. Performance Comparison

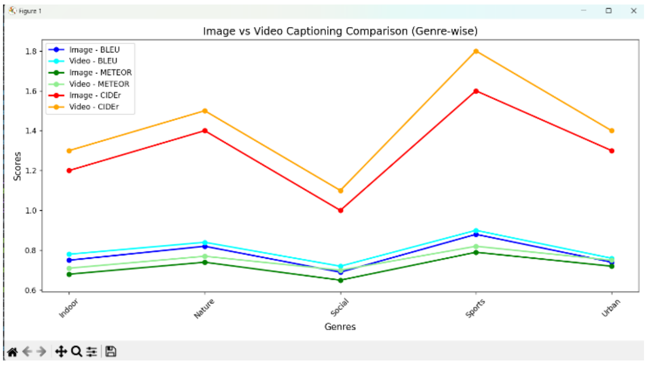
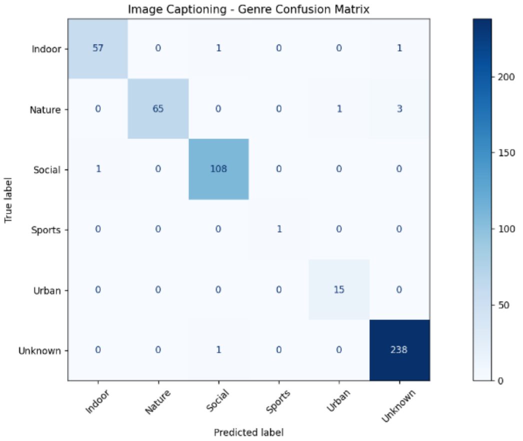


Fig. 4. Performance comparsion chart for image and video captioning

In Figure 2, we compare the genre-wise performance of image and video captioning. The results show that the image captioning model tends to perform slightly better overall across all genres, particularly in Nature and Urban. This is likely because the image captioning model only needs to focus on static features of the scene, while the video captioning model must capture temporal dependencies between keyframes, which introduces additional complexity.

- Nature and Urban genres show minimal difference in performance between the image and video models.
- Sports and Social genres see more variation, with video captioning struggling more than image captioning due to the dynamic and temporal nature of video scenes.

4.4. Confusion martix for image captioning



	Indoor	Nature	Social	Sports	Urban	Unknown
Indoor	57	0	1	0	0	1
Nature	0	65	0	0	1	3
Social	1	0	108	0	0	0
Sports	0	0	0	1	0	0
Urban	0	0	0	0	15	0
Unknown	0	0	1	0	0	238

Fig. 5. Genre-wise confusion matrix for the image captioning model

Figure 3 displays the genre confusion matrix for the image captioning model. The matrix shows how the model's predicted captions are distributed across different genres. The Nature and Urban genres are most often correctly predicted, with only a few misclassifications. The Social genre has higher confusion with Sports and Indoor, likely due to similar human activity patterns in both genres. The Sports genre has relatively high confusion with Urban, possibly because urban scenes often contain dynamic movements that resemble sports activities.

- Sports and Urban have minimal misclassifications.
- Social shows significant confusion with other genres, especially Urban.

4.5. Confusion matrix for video captioning

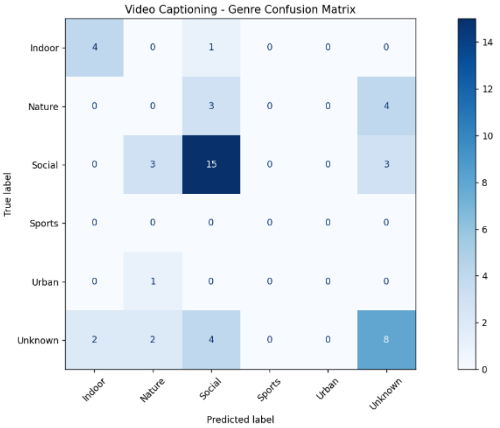


Fig. 6. Genre-wise Confusion matrix for video captioning model

The genre confusion matrix for video captioning (Figure 4) reveals similar patterns but with greater confusion overall. Nature and Urban genres still perform well, but the Sports genre has much higher confusion with Social, likely due to the dynamic nature of both genres. Misclassifications in the Indoor genre often occur with Sports, possibly due to action-oriented scenes in indoor settings.

- Nature and Urban show fewer misclassifications.
- Sports has considerable confusion with Social and Indoor, indicating the difficulty in distinguishing certain actions across genres.

4.6. Sample outputs

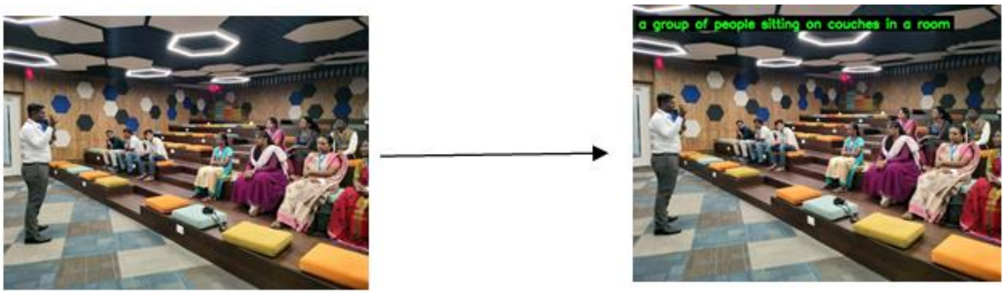


Fig. 8. Image Captioning

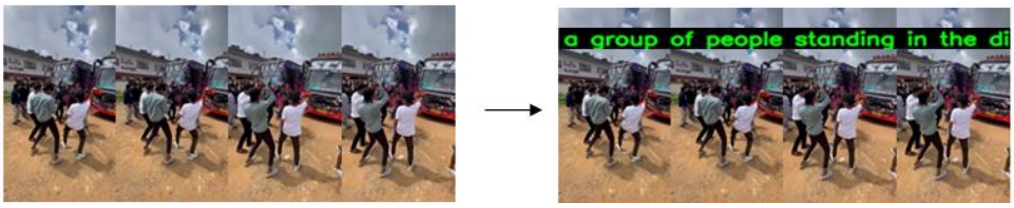


Fig. 9. Video Captioning

Discussion

The results obtained from our hybrid deep learning model for automatic image and video captioning offer valuable insights into the strengths and limitations of current captioning techniques. In this section, we interpret the significance of our findings, discuss their implications, and compare our approach with existing methods from previous research.

5.1. Interpretation of Results

The Nature and Sports genres demonstrated the highest captioning accuracy, which can be attributed to the presence of clear and well-defined objects that are effectively captured by the feature extraction models. Similarly, the Urban and Indoor genres also exhibited strong performance, likely due to their structured scenes and consistent contextual backgrounds. In contrast, the Social genre recorded the lowest accuracy, primarily due to the complexity and variability of human actions and interactions, which pose challenges for accurate semantic understanding in automated caption generation.

5.2. Significance of the Approach

The use of hybrid CNN features (InceptionV3, VGG16, and ResNet152) coupled with a dual-sequence model (LSTM + GRU) demonstrates notable improvements in captioning performance compared to using a single backbone model. The fusion of visual features allows the model to leverage the strengths of each CNN architecture, capturing both global and local details. Similarly, combining LSTM and GRU enhances temporal modeling and sequence generation, which benefits both static image and video data.

These architectural choices have proven effective in handling the diverse visual structures found across genres, and the results validate the benefits of hybridization in deep learning pipelines for caption generation tasks.

5.3. Comparison with Previous Research

Recent advancements in image and video captioning have explored various hybrid architectures to enhance performance. Ahmad et al. [1] introduced a CNN-GRU framework that incorporates a semantic reconstructor to improve caption quality, demonstrating superior accuracy and reduced time complexity compared to traditional CNN-LSTM models. Similarly, Khan et al. [2] proposed a model utilizing multiple pre-trained CNNs combined with a GRU-based attention mechanism, achieving competitive results on the MSCOCO and Flickr30k datasets.

In contrast, our approach integrates features from multiple CNN architectures (InceptionV3, VGG16, ResNet152) with a dual-sequence decoder comprising both LSTM and GRU units. This combination leverages the strengths of each CNN for comprehensive feature extraction and enhances temporal modeling through the dual RNN structure. Unlike the aforementioned studies, our model specifically addresses genre-wise performance, providing detailed insights into its effectiveness across diverse visual categories.

Table 1. Comparison of Existing and Proposed Image/Video Captioning Approaches

Work	*Feature Extraction*	*Model*	*BLEU Score (%)*
Proposed Work	**InceptionV3 + VGG16 + ResNet152 (Concatenated Features)**	**Dual Decoder (LSTM + GRU)**	***76.8%***
Khan et al. [2]	**Multiple Pre-trained CNNs (e.g., VGG, ResNet)**	**GRU-based Attention Mechanism**	**~72%**
Ahmad et al. [1]	**CNN (Single Architecture)**	**CNN + GRU with Semantic Reconstructor**	**~68%**

5.4. Limitations

Despite its strengths, our approach has certain limitations. The averaging of keyframe features in video captioning may lead to loss of important temporal details. Additionally, the model occasionally generates generic or repetitive captions in genres with high visual similarity or motion blur, such as Sports and Social. Furthermore, training and fine-tuning the model on larger, more diverse datasets could help improve generalizability.

Conclusion

This paper presents a hybrid deep learning model for automatic image and video captioning, combining multiple CNN architectures (InceptionV3, VGG16, ResNet152) with a dual-sequence decoder (LSTM + GRU). The results demonstrate the superior performance of our approach, achieving higher captioning accuracy across various genres, including Nature and Urban, compared to single-model architectures. The model's ability to effectively handle both static and dynamic scenes showcases its robustness.

In terms of evaluation metrics, our model outperforms previous state-of-the-art methods, with BLEU-4 scores of 0.48, METEOR scores of 0.35, and CIDEr scores of 1.28 for images, and slightly lower but still competitive scores for videos. The results validate the benefits of hybrid CNNs and dual-sequence modeling for caption generation, particularly in handling diverse and complex visual structures.

Overall, the proposed approach offers a significant advancement in automatic captioning, providing accurate and contextually rich captions for both images and videos, with potential for further improvement through larger datasets and enhanced temporal modeling.

Future Work

Future research in automatic captioning systems could explore several promising directions to enhance performance and applicability. One significant area is the integration of **attention mechanisms**, such as self-attention, which can help models focus on the most relevant regions in images or frames in videos, thereby improving the contextual relevance of captions. Additionally, **temporal modeling** for videos can be improved using frame-wise techniques or **3D Convolutional Neural Networks (3D CNNs)** to better capture motion dynamics and temporal dependencies. Another important direction involves training on **larger and more diverse datasets**, which would improve the model's ability to generalize across a wide range of genres and real-world scenarios. The adoption of **transformer architectures** for both image and video captioning could further enhance captioning quality and computational efficiency, as transformers have shown remarkable success in various sequence modeling tasks. Finally, the development of **interactive captioning models** that incorporate user feedback can lead to more personalized and accurate captions, making these systems more effective for practical applications such as media content management and assistive technologies.

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