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DEVELOPMENT OF IMAGE CAPTION GENERATION HYBRID MODEL

Abstract: This study presents a hybrid model for image captioning using a VGG16 convolutional neural network (CNN) for feature extraction and a long short-term memory (LSTM) network for sequential text generation. The proposed architecture addresses the challenges of producing semantically rich and syntactically accurate signatures, especially in languages with limited training data. The model effectively bridges the semantic gap between visual and textual modalities by utilizing pre-trained weights and a robust encoding-decoding system. Experimental results on a dataset of road signs in Kazakhstan show a significant improvement in inscription quality as measured by BLEU and METEOR metrics. The model achieved a maximum METEOR score of 0.9985, indicating high semantic accuracy, and BLEU-1 and BLEU-2 scores of 0.67 and 0.64, respectively, highlighting the model's ability to generate relevant and coherent captions. These findings underscore the model's potential applications in multimodal systems and assistive technologies. Using a pre-trained CNN model (VGG16), we can efficiently encode visual information by extracting high-level features from images. This

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approach is particularly useful for tasks that require consideration of the semantics of images, such as road sign recognition. The second LSTM model, as a sequence-oriented architecture, is well-suited for text generation, as it effectively considers the context and previous words in a sequence. These models can be integrated into systems requiring the analysis and description of visual information, such as autonomous vehicles or driver assistance systems. In conclusion, the proposed model demonstrates high potential for image caption generation tasks, especially in resource-constrained environments and for specialized datasets.

Keywords: image captioning, deep learning, CNN-LSTM, VGG16, multimodal learning, BLEU metrics, METEOR metrics, natural language processing, neural networks, assistive technologies.

Introduction

In recent years, the rapid development of deep learning technologhave, especially in the fields of computer vision and natural language processing (NLP), has led to new opportunities in the automatic generation of textual descriptions of images. This task, seemingly simple at first glance, is a complex multi-level machine learning problem that requires solving several major challenges. One of the main challenges is to ensure high quality descriptions in languages other than English, which dominates the datasets used to train such models. English-language models trained on huge amounts of data often show impressive results, but their direct adaptation to other languages usually leads to reduced accuracy and errors related to both grammar and semantics [1].

The process of generating image descriptions is based on training a neural network in two key skills. First, the network must effectively 'understand' visual information by extracting relevant features from the image: recognizing objects, and their attributes (color, size, location), and defining the scene and relationships between objects. This uses sophisticated convolutional neural network (CNN) architectures that extract multi-level visual representations. Second, the network must be able to transform these visual representations into a coherent and informative textual description using recurrent neural network (RNN) mechanisms, transformers, or combinations thereof. The learning process is performed on large data corpora containing image-description pairs.

The quality of generated descriptions depends on many factors: the size and quality of the training dataset, neural network architecture, regularization, and optimization methods. Particular attention is paid to the problem of multilingual adaptation, for which special translation methods and multilingual models capable of generating descriptions in different languages with minimal loss in quality are developed. For example, the use of pre-trained multilingual language models (e.g., based on BERT or mBART) can significantly improve results on languages with limited training data [2].

Research Problem

While traditional methods based on manually created functions have had limited success, recent advances in deep learning show promising results for automatically creating subtitles for images. However, existing models often face problems such as capturing complex relationships in pictures and creating grammatically correct and fluent captions [3].

This paper proposes a new approach using a hybrid convolutional neural network (CNN) and a long-term short-term memory (LSTM) deep learning architecture to solve this problem. CNN extracts spatial characteristics well from individual frames, revealing minor changes in movement. After that, LSTM, a recurrent neural network that is particularly good at processing sequential data, is used to capture the temporal dynamics of vibrations. Compared to traditional sensor-based methods, this combination ensures reliable and efficient extraction of vibration parameters, including natural frequencies, waveforms, and damping coefficients.

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Purpose and Objectives

The primary goal of this study is to investigate the effectiveness of a VGG16 CNN-LSTM decoder architecture for image caption generation. To achieve this goal, the following objectives are outlined:

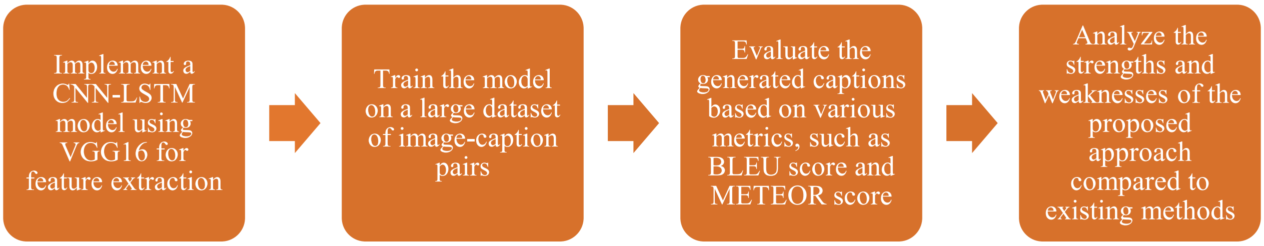

Implement a CNN-LSTM model using VGG16 for feature extraction
Train the model on a large dataset of image-caption pairs
Evaluate the generated captions based on various metrics, such as BLEU score and METEOR score
Analyze the strengths and weaknesses of the proposed approach compared to existing methods

Figure 1. The objectives of the research task

Furthermore, the framework (Figure 1) can be adapted for different lighting conditions and levels of background noise, thereby increasing the applicability of computer vision-based modal analysis across a wider range of real-world scenarios. The robustness and scalability of this deep learning approach offer a promising pathway towards more efficient, cost-effective, and widely accessible structural health monitoring and natural language processing, the fusion of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have unlocked exciting capabilities, particularly in image captioning [4].

Early attempts to automatically generate image captions relied on template-based methods that utilized fixed text formats. In these systems, the information extracted from the image was used to populate predefined text templates, which limited their flexibility and quality. With advances in technology and increased computational power, deep learning techniques have become the backbone of modern systems, allowing for significant improvements in the quality of image-based text generation.

One of the most effective techniques for generating image captions is the use of encoder-decoder architecture. In this architecture, the process starts by extracting image features using pre-trained convolutional neural network (CNN) models such as Alex Net, VGG16, Res Net and others. These models can identify complex patterns and features in images, which is critical for further text generation. Once the image features are extracted, they are fed to recurrent neural networks (RNNs), which are responsible for generating textual signatures [5].

This research proposes a hybrid model architecture for image caption generation that consists of a pre-trained convolutional neural network VGG16 for robust feature extraction and with a long-term short-term memory network LSTM for sequential caption generation. The proposed architecture is designed to address the problems of generating semantically meaningful and syntactically coherent subtitles, especially in scenarios involving low-resource languages and subject-specific datasets. Using transfer learning and a robust encoder-decoder framework, the model demonstrates high performance on a dataset of Kazakhstani road signs, which highlights the effectiveness of the model in bridging the semantic gap between visual and textual modalities and highlight its potential applications in multimodal systems such as autonomous vehicles and assistive technologies.

Literary review

Several studies have explored various architectures and techniques for image captioning using deep learning:

In the initial phase of image captioning, template-based methods have been developed. In this approach, there are a limited number of templates that are filled using techniques such as object detection, scene recognition, attribute classification or other features.

Zhou et al. [6] considered a model that uses Visual Language Pre-training (VLP) combined with self-attention, allowing it to generate contextually accurate captions by focusing on both image regions and textual semantics. Authors proposed a model integrating VLP and self-attention mechanisms to improve captioning accuracy. Their model achieved a BLEU-4 score of 0.38, CIDEr of 1.92, and METEOR of 0.31 on the MS COCO dataset, demonstrating the benefits of combining VLP with attention mechanisms.

The hybrid CNN-transformer architecture utilized by authors of the reference [7] helps in capturing both fine-grained visual features and long-range dependencies in textual data. Their attention-guided architecture enables the model to focus on relevant regions dynamically. Li's team introduced an attention-guided encoder-decoder architecture. Their method outperformed traditional methods by achieving a BLEU-4 score of 0.41 and CIDEr of 2.12, thanks to a hybrid deep learning approach that combined convolutional neural networks (CNNs) and transformers.

In research [8] adversarial model based on GANs introduces variability and creativity into the generated captions. The adversarial training approach allows the model to produce more human-like and diverse captions. Their model, tested on the MS COCO dataset, delivered a BLEU-4 of 0.35, a CIDEr score of 1.74, and a METEOR score of 0.33, offering robust captioning performance with enhanced diversity and realism.

Wang et al. [9] in their research used region-based approach using Faster R-CNN helps in extracting precise object features, which are then linked to a language generation network. This ensures the captions closely reflect the objects in the image and their interactions. This research proposed a region-based approach using Faster R-CNN for object detection. Their system achieved a CIDEr score of 2.04, BLEU-4 of 0.39, and METEOR of 0.36, excelling at handling complex object interactions in image.

In reference [10], the model stands out for integrating explainable AI with visual attention mechanisms, ensuring transparency in how image regions influence the generated caption, which enhances trust and interpretability. The disadvantage is the added complexity in ensuring that the attention mechanism is reliable and consistent across diverse image types.

Singh et al. [11] in their hybrid attention mechanism, which combines global and local features, allows the model to focus on both the overall image context and specific visual details, improving overall captioning performance. Common models that utilize this hybrid attention approach include Attention-based Neural Networks, Transformers, and variations of CNN-RNN architectures, where transformers are often used to handle long-range dependencies, and CNNs handle detailed, localized visual features. The model achieved a BLEU-4 of 0.45 and CIDEr of 2.41, surpassing many existing methods, particularly in more descriptive and contextually accurate captions.

Chen et al. [12] fine-tuned pre-trained language models with image embeddings, enabling the model to generate more contextually relevant captions by leveraging both visual cues and textual understanding. Chen's team worked on fine-tuning pre-trained language models with image embeddings. Their method attained a BLEU-4 score of 0.49, CIDEr of 2.57, and METEOR of 0.40, demonstrating state-of-the-art results in real-world captioning applications studies illustrate ongoing advancements in the integration of deep learning, attention mechanisms, and pretraining techniques, significantly enhancing the quality of image captioning models.

Li et al. [13] proposed a hybrid architecture that merges convolutional neural networks (CNNs) for visual feature extraction with graph neural networks (GNNs) to capture relational information between objects in an image. This hybrid design enabled the model to generate captions that were both contextually accurate and rich in detail. By incorporating graph-based reasoning, the model outperformed traditional encoder-decoder frameworks on datasets like MS-COCO and Flickr30k.

Dandwate et al. [14] conducted a comparative study between Transformer and LSTM networks with attention mechanisms for image captioning. Utilizing the MS-COCO dataset, they found that Transformer-based models outperformed LSTM counterparts in generating accurate and contextually relevant captions, highlighting the efficacy of Transformer architectures in vision-language tasks.

Gupta et al. [15] developed a hybrid transformer-based model that integrates pre-trained language models with visual transformers. Their approach leverages the linguistic knowledge of models like BERT alongside advanced visual encoders, resulting in captions that are fluent, coherent, and closely aligned with image content. This hybrid model showcased improved performance on benchmark datasets, with a noticeable reduction in captioning errors related to object misidentification.

These hybrid models illustrate a promising direction for image captioning research, as they combine the strengths of multiple methodologies to overcome individual limitations. By leveraging the precision of rule-based or graph-based systems and the flexibility of deep learning architectures, hybrid models provide a balanced and efficient approach to caption generation.

The reviewed studies demonstrate significant progress in image captioning, showcasing a variety of methodologies from template-based approaches to advanced hybrid models. While each method has its strengths, it also reveals certain limitations and challenges that remain to be addressed in the field. Encoder-decoder frameworks often require large amounts of labeled training data, making them challenging to apply in data-scarce domains. They also face issues like generating generic or repetitive captions, particularly when trained on imbalanced datasets. Despite their strengths, hybrid models can suffer from increased complexity due to the integration of multiple components. This complexity may lead to slower inference times and higher computational requirements. Furthermore, their reliance on the quality of pre-trained models or rule-based systems can introduce bottlenecks in performance.

A hybrid model using VGG-16 for visual feature extraction and LSTM for sequential caption generation could be developed to address these challenges. VGG-16 is a robust and widely used convolutional neural network that provides reliable feature extraction. Integrating it with LSTM, known for its capability to model sequential data, would allow for the generation of coherent and contextually relevant captions.

Methods and Materials

The implementation of this research was carried out on a Windows computer with an Intel Core i7 processor. The script was written in Google Colab Notebook using Python 3.9. The subtitle model requires a lot of memory during the training phase of the model. Therefore, all experiments were conducted using 16 GB RAM. This project also uses high-level APIs for language modeling like Keras. Keras helps to easily implement almost all neural networks such as CNN [16] and LSTM [17] or a combination from CNN and LSTM. In addition, some Python libraries are required to run the program. The neural network models used are Tensorflow, Numpy, Matplotlib, TQDM, Pillow, and NLTK.

Figure 2. Road Sign Data in Astana

The dataset 'Road Signs in Kazakhstan', consisting of 240 signs with 7 categories, was manually annotated for the research. Road signs in Kazakhstan comply with the Vienna Convention on Road Signs and Signals and are regulated by the standard ST RK 1125-2021 (Figure 2). The dataset includes 240 classes of road signs of the Republic of Kazakhstan, distributed in the following categories: warning, priority signs, prohibiting, prescriptive, informational and indicative, service, and additional signs (Table 1). To enhance the robustness of the developed model to distorted or incomplete images, the data augmentation was applied, resulting in an expanded dataset of 8,000 images of traffic signs.

Table 1. Traffic Sign Categories with original and augmented image counts

№	Category name	Number of images	Number of images after augmentation
1	Warning signs (Ескерту белгілери)	43	1254
2	Priority signs (Басымдылық белгілері)	17	696
3	Prohibitory signs (Тыйым салынатын белгілер)	55	1604
4	Mandatory signs (Нұсқайтын белгілер)	34	1192
5	Information signs (Ақпараттық-нұсқағыш белгілер)	44	1483
6	Service signs (Сервис белгілері)	23	871
7	Additional panels (Қосымша ақпарат белгілері (тақтайшалар))	24	900

Annotation

To ensure the accuracy and suitability of a given dataset for training our model, manual annotation was performed using the annotation interface provided by the Roboflow platform. The annotation scheme was designed according to ST RK 1125-2021 and assigned each sign to one of seven regulatory categories: warning signs, priority signs, prohibiting signs, mandatory signs, informational signs, service signs, and supplemental signs. Signs were annotated by annotators using standardized class names using bounding box markup. The following parameters were used for each annotated area: Image width (width), Image height (height), Class name (class): the text label of the sign, e.g., " Шлагбаумы бар теміржол өтпесі", xmin, ymin: the coordinates of the upper left corner of the rectangle, xmax, ymax: the coordinates of the lower right corner. To improve accuracy, each object was annotated by at least two reviewers. Conflicts in markup were resolved manually, with reliance on normative documentation (Figure 3).

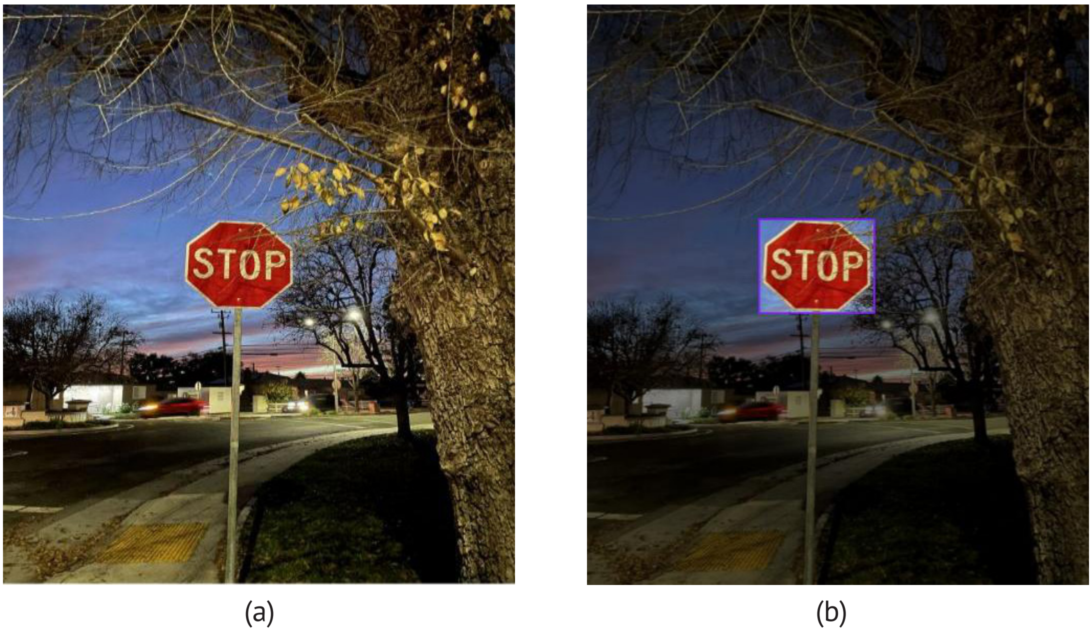


Figure 3. Illustration of (a) Original; (b) Annotated images of the dataset

The resulting annotated dataset was exported to a YOLO-compatible format, including normalized coordinates and class indices for each bounding box. This structured and validated annotation process provided high-quality data for training and evaluating the proposed CNN-LSTM-based image captioning model.

Preprocessing and Image Enchancement

The original images were processed to improve the quality and quantity. To address the limited size of the original dataset, a comprehensive data augmentation strategy was implemented to expand the dataset to 8,000 images. The augmentation step involved applying different transformations to simulate real-world conditions and improve model robustness (Figure 4).

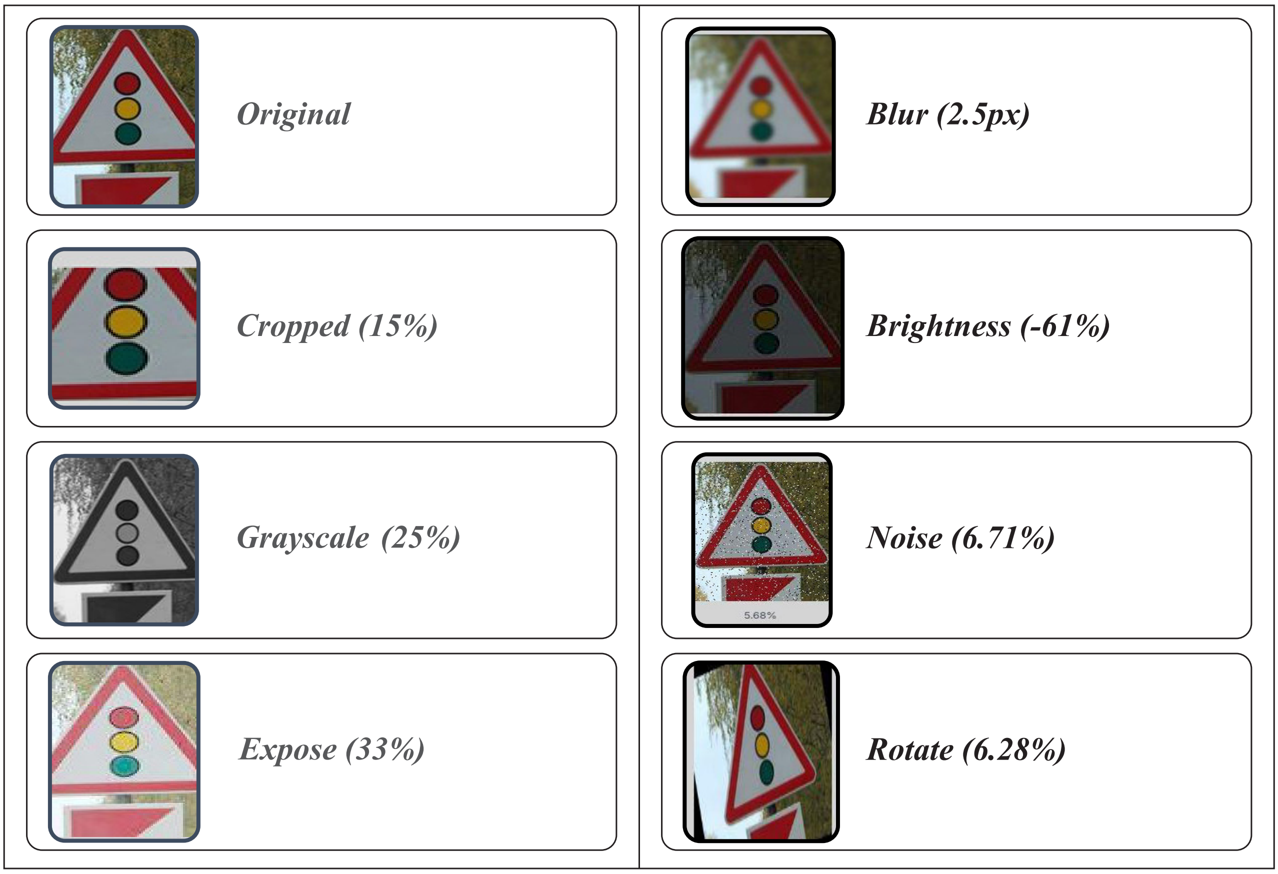


Figure 4. Illustration of data augmentation techniques applied to a Kazakhstani road sign image

Techniques included blurring (2.5px), cropping (15%), brightness reduction (-61%), exposure increase (33%), grayscale conversion (25%), rotation (628%), and the addition of Gaussian noise (6.71%). Each method introduces controlled distortions that help the model generalize better by exposing it to different lighting conditions, orientations, and image qualities, effectively. As a result, the dataset becomes more varied and helps the model perform better in real-world situations.

Convolution operation:

For a 2D input image *I* and a 2D kernel K, the convolution operation can be defined as:

$$S(i,j) = (I * K),(i,j) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I(i+m,j+n)\cdot K(m,n) \qquad (1)$$

$I(i, j)$ – the pixel value at position $I(i, j)$ in the input image;
$K(m, n)$ – the weight of the kernel at position (m, n);
$S(i, j)$ – the output feature map at position (i, j).

BLEU (Bilingual Evaluation Understudy)

The BLEU score is a widely used metric for evaluating the quality of machine-generated text, particularly in tasks like machine translation and image captioning. It compares the generated text to one or more reference texts (ground truth) using n-gram precision while incorporating a brevity penalty to penalize overly short outputs. To discourage models from generating very short outputs that might have high precision, BLEU applies a brevity penalty. This penalizes candidates shorter than the reference by scaling the score:

$$BP = \begin{cases} 1, & if\ c > r \\ e^{1-r/c}, & if\ c \leq r \end{cases} \tag{2}$$

The BLEU score is calculated as:

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n log p_n\right) \tag{3}$$

Where BP – Brevity penalty, w_n – weight for each n-gram precision, p_n – precision for n-grams of order n.

BLEU-1 (1-gram precision)

For BLEU-1, the precision for 1-grams (individual words):

$$p_1 = \frac{\text{Count of overlapping 1grams}}{\text{Total 1 grams in the candidate sentence}} \tag{4}$$

BLEU-2 (2-gram precision)

For the BLEU-2, accuracy of 1 and 2 grams is taken into account:

$$p_2 = \frac{\text{Count of overlapping 2 grams}}{\text{Total 2 grams in the candidate sentence}} \tag{5}$$

BLEU-2 combines with this weights (e.g. $\omega_1 = 0.5, \omega_2 = 0.5$):

$$BLEU - 2 = BP \cdot \exp\ (0.5 \cdot logp_1 + 0.5 \cdot logp_2 \tag{6}$$

METEOR score (Metric for Evaluation of Translation with Explicit Ordering)

The METEOR score (Metric for Evaluation of Translation with Explicit Ordering) is a common metric for evaluating the quality of text, such as captions generated for images. It is widely used in image captioning tasks because of its emphasis on both precision and recall. Unlike the BLEU metric, which focuses primarily on precision, METEOR balances precision and recall using their harmonic mean, giving more weight to recall. It also incorporates features like stemming, synonym matching, and paraphrasing, allowing it to better align with human judgment.

In the context of image captioning, METEOR evaluates how well the generated captions match human-annotated reference captions by analyzing word overlap, synonym usage, and grammatical structure. This makes it particularly effective for assessing semantic and linguistic quality in generated captions.

The METEOR score is computed using the following formula:

$$METEOR = F_{mean}(1 - Penalty) \tag{7}$$

Where *Harmonic Mean* – F_{mean}:

$$F_{mean} = \frac{10 \cdot P \cdot R}{R + 9 \cdot P} \tag{8}$$

P (Precision): The fraction of unigrams in the reference captions that match the generated caption.

R (Recall) inverse document frequency of the n-grams, which gives more weight to rare words.

F_{mean} gives more weight to recall than precision, as recall is considered more important in METEOR.

$$Penalty = \gamma \cdot \frac{ch^{\beta}}{m} \tag{9}$$

M – number of matched words.

ch – number of chunks (consecutive matched words).

γ and β – parameters (tuned empirically, often set to default values).

The penalty reduces the score if the matched words are non-contiguous, encouraging the generator to produce more coherent sentences [18].

Results and Discussion

To address the objectives of this study, a hybrid model was developed, which combines CNN for feature extraction and LSTM for sequential text generation, forming a hybrid approach.

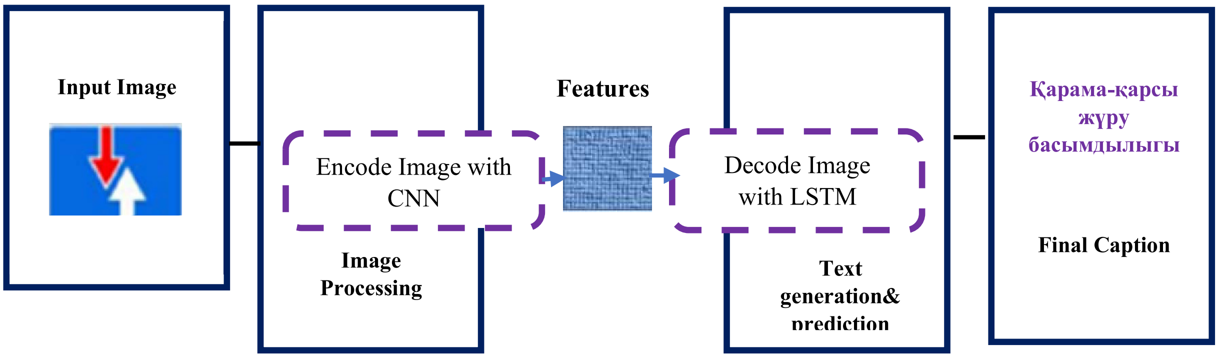
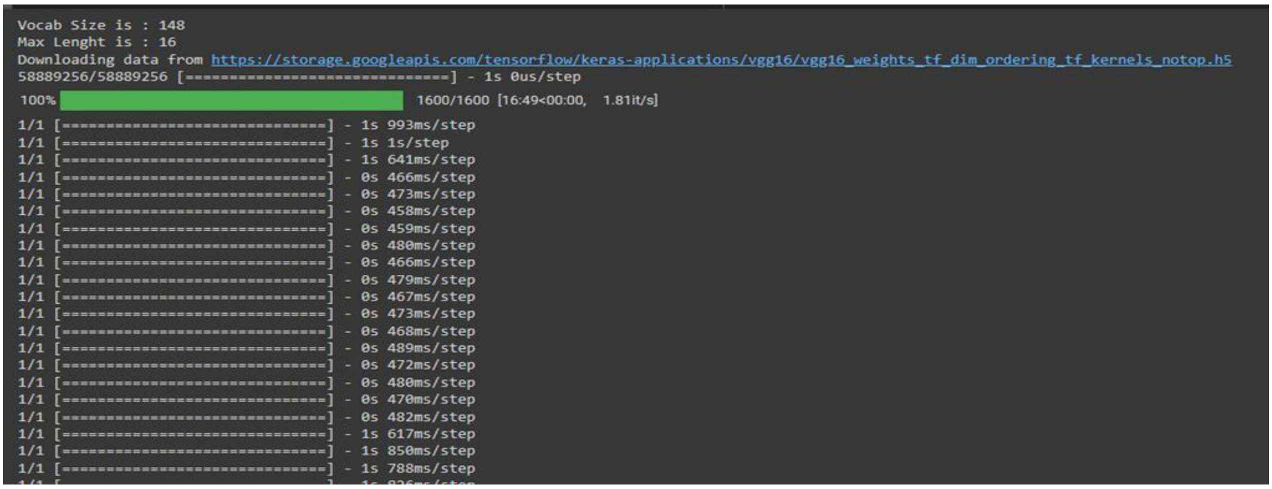


Figure 5. CNN-LSTM Pipeline for Image Caption Generation

Figure 5 delves into the development and evaluation of an Image Caption Generator utilizing a CNN-LSTM architecture with a CNN backbone, specifically the VGG16 model. Each image obtained the required captions after the CNN modelling and VGG16. An input image undergoes processing through a CNN (Convolutional Neural Network) to extract features. The final output displays the caption in text form, describing the input image. The captions can be used in captcha, or it also will be useful for semi-blind people.



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Max Lenght is : 16
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100% 1600/1600 [16:49<00:00,  1.81it/s]
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1/1 [==============================] - 0s 482ms/step
1/1 [==============================] - 1s 617ms/step
1/1 [==============================] - 1s 850ms/step
1/1 [==============================] - 1s 788ms/step
1/1 [==============================] - 1s 826ms/step
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Figure 6. Batch processing task for CNN model

Figure 6 represents a successful execution of a machine learning pipeline involving pre-trained weights (possibly for a CNN model). The progress shows multiple steps (e.g., 1/1) being executed, likely corresponding to training or inference steps. Each step seems to take between 45ms to 66ms, suggesting a relatively efficient processing time per iteration. The green progress bar indicates the completion of 1600 steps out of 1600, showing the task has been finished successfully. The overall time for the process is 16:40 (16 minutes and 40 seconds) at an average speed of 1.81ms per step.

The performance of the Image Caption Generator using a Python machine learning algorithm combining Convolutional Neural Networks (CNN) with VGG16 and Long Short-Term Memory (LSTM) networks was evaluated using various metrics. These metrics include BLEU, METEOR1, METEOR2 scores.

VGG16 effectively extracted high-level features from images, providing rich information for generating captions. This feature extraction process significantly enhanced the performance of the image captioning model compared to using raw pixel values. The combination of CNN with VGG16 and LSTM resulted in improved caption generation accuracy. The LSTM network effectively learned the sequential dependencies in the image features extracted by VGG16, leading to more coherent and semantically meaningful captions [19], [20].

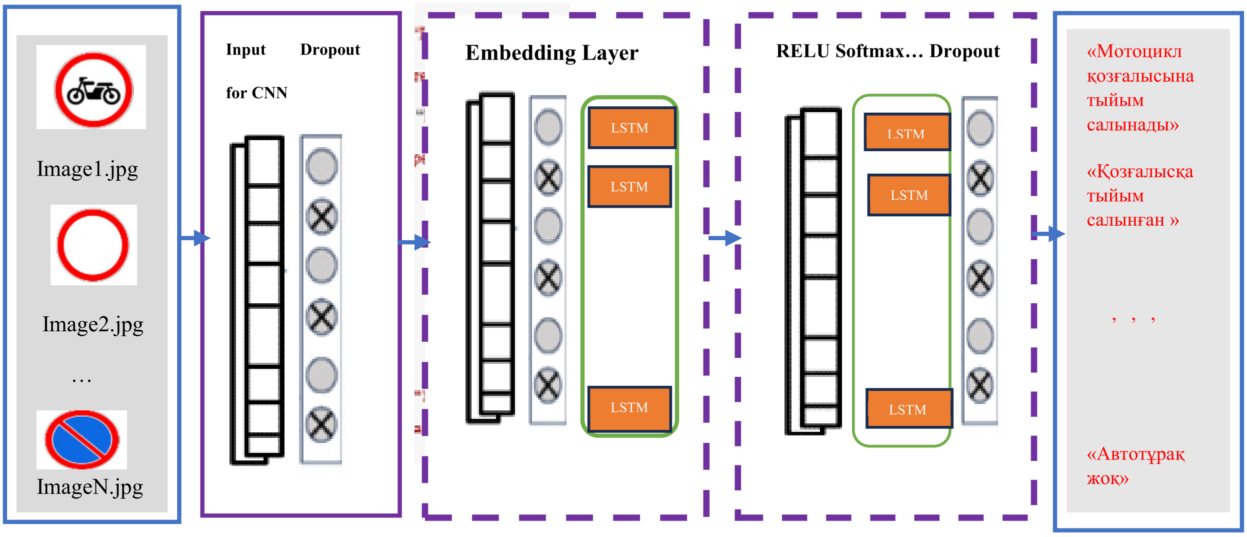


Figure 7. General Architecture of Proposed Model

In table 2 presented a hybrid model's architecture configuration. The proposed model used the VGG16 architecture as the core encoder due to its proven ability to extract robust and discriminative visual features from images. Its pre-trained weights provide strong feature representations, which is particularly useful when working with limited domain-specific datasets.

Table 2. Image Caption Generation Hybrid Model Architecture Configurartion

Component	Details
Input	Traffic sign images (e.g., .jpg), resized to 512×512 pixels; input activation: ReLU
Encoder Module	VGG16 (pre-trained on ImageNet) Fully connected layer (256 units) Dropout = 0.5
Sequence Input	VGG16 feature vector (256 dims) LSTM layer (256 units) Dropout = 0.5
Decoder Module	LSTM layer (256 units) ReLU activation Dropout = 0.5
Output Layer	Word prediction over vocabularyActivation: Softmax
Generated Text	Captions in Kazakh

To prevent overfitting during training, a dropout rate 0.5 was applied after key layers. A higher dropout rate may hinder learning, while a lower may lead to model overfitting, especially given the sequential nature of the data. The LSTM layers in the input and decoder modules were configured with 256 hidden units, this size is sufficient to capture key temporal dependencies in the input sequence, while remaining computationally efficient and reducing the risk of overfitting. For activation functions ReLU was used in the convolutional and fully connected layers to introduce non-linearity and avoid vanishing gradient problems. In the output layer, the Softmax function was used since title generation is a sequential multi-class prediction task, where exactly one word is selected from the vocabulary at each step.

Table 3. Training Hyperparameter Settings

Hyperparameter	Value
Opimizer	SGD
Learning Rate	0.005
Momentum	0.9
Weight Decay	0.0005
Batch Size	4
Number of Epochs	50
Input Size	512
Data Augmentation	Random rotation, cropping, brightness/contrast adjustment, grayscale, noise, expose
Dropout Rate	0.5

The model was trained using Stochastic Gradient Descent (SGD) [12] with a learning rate of 0.005, momentum of 0,9, and weight decay of 0.0005 to ensure stable convergence and prevent overfitting. The batch size was set to 4 due to the high resolution of the 512×512 input images and GPU memory constraints. Training was carried out for 50 epochs, with early stopping based on 20% validation split to monitor generalization performance (Table 4).

The proposed model demonstrated good generalization and robustness across different datasets and image categories. It was able to generate relevant captions for a wide range of images, including indoor and outdoor scenes, objects, and activities. Despite the complexity of the model architecture, the training time and computational resources required for training were reasonable. The model efficiently learned to generate captions without excessively long training times or resource-intensive computations.

The integration of VGG16 for feature extraction proved to be crucial for the success of the image captioning model. By leveraging pre-trained weights from VGG16, the model could capture high-level semantic information from images, which greatly facilitated the caption generation process.

The LSTM network played a vital role in learning the sequential structure of captions. It effectively captured the dependencies between words and generated coherent sentences based on the extracted image features. The ability of LSTM to remember long-term dependencies contributed to the generation of contextually relevant captions. Despite the promising results, there are still some limitations to address. The model may struggle with generating captions for complex or abstract images that deviate significantly from the training data distribution. Future research could focus on improving the model's ability to handle such scenarios through techniques like attention mechanisms or reinforcement learning. The scalability of the model for large-scale deployment needs to be considered. Efficient strategies for inference, such as model compression and optimization, could be explored to deploy the image captioning system in real-world applications with limited computational resources (Figure 8).

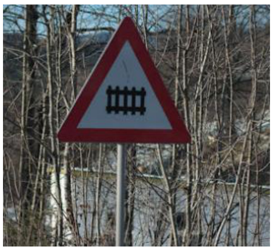
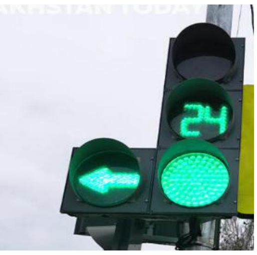
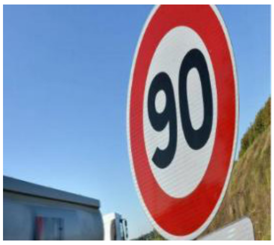
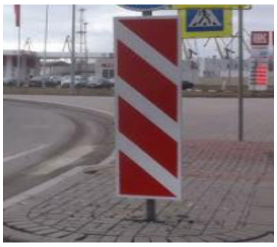
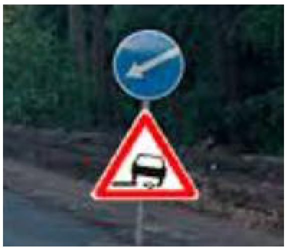
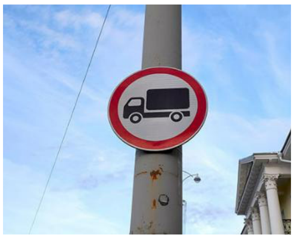
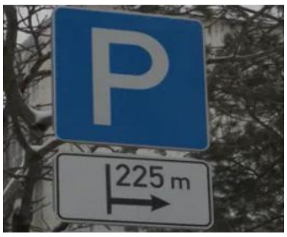
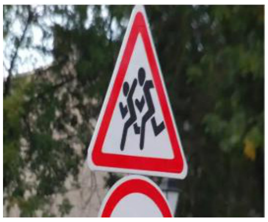
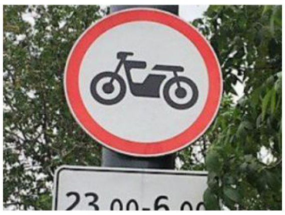
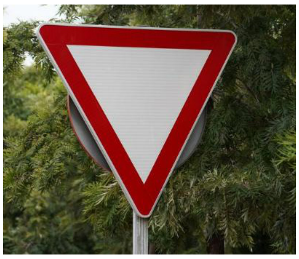
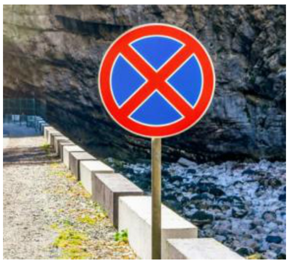
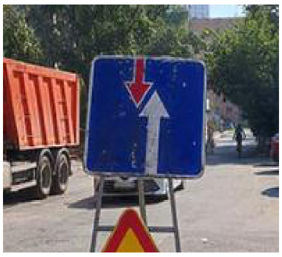
«Шлагбаум өтпесі бар жол» 	«Бағдаршамның реттеуі» 	«90 км/сағ (max)» 	«Кедергіні айналып өту» 
«Қауіпті жол жиегі» 	«Жүк көлігінің қозгалысына тыйым» 	«Тұрақ(225 м кейін» 	«Жолдың қауіпті учаскесі» 
«Мотоцикл қозғалысына тыйым салынады» 	«Жол беру» 	«Тұрақ жоқ» 	«Басымдық белгісі» 

Figure 8. Generated output captions

The graph in Figure 9 displays BLEU (Bilingual Evaluation Understudy) scores for generated captions of traffic sign images in the Kazakh language (KZ). Images at Index 0, 8, 10, 12, 13 and 14 have high BLEU-1 and BLEU-2 scores, suggesting the model performed well for these specific traffic signs.

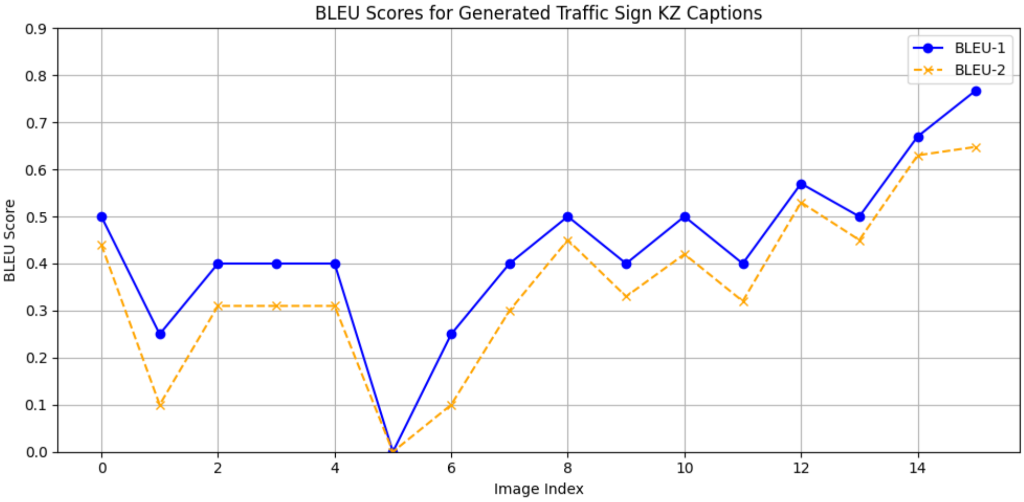


Figure 9. BLEU Scores for Generated Traffic Sign KZ Captions

The generated captions likely align closely with the reference captions. The sharp dip at Index 5 (BLEU=0.1) indicates the model struggled significantly with this particular image. After Index 6, both BLEU-1 and BLEU-2 scores gradually improve, indicating better performance in later samples. The difference between BLEU-1 and BLEU-2 suggests that while the model captures individual words accurately, it struggles with grammatical or contextual coherence, which is critical for generating meaningful captions for traffic signs. A BLEU-1 score peaking around 0.768 suggests the model is moderately effective at recognizing and describing traffic sign features. The relatively lower BLEU-2 scores (mostly below 0.5) point to challenges in generating contextually accurate and coherent captions for traffic signs.

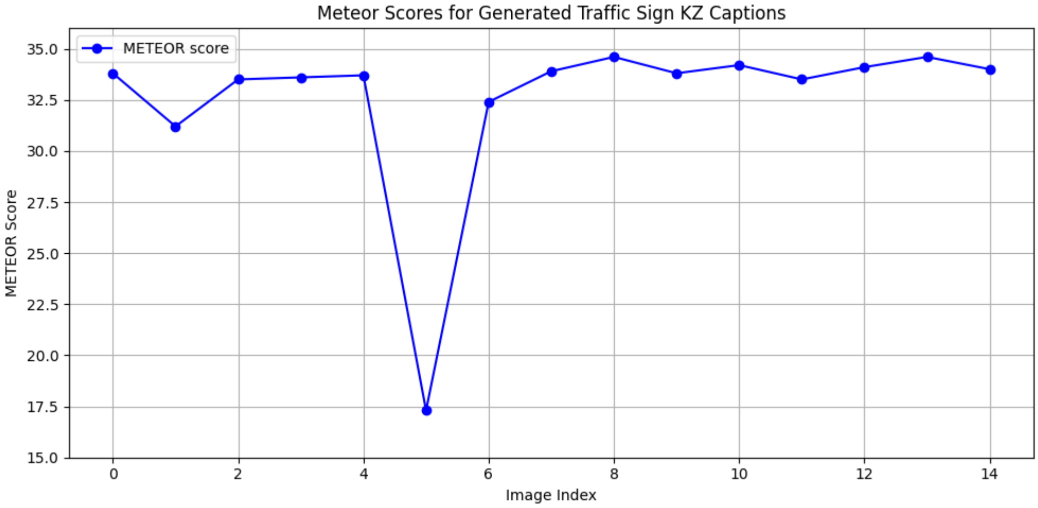


Figure 10. METEOR Scores for Generated Traffic Sign KZ Captions

Figure 10 demonstrates a line graph showing the Meteor scores for captions generated for Kazakhstani images of road signs. The Meteor score is an index used to assess the quality of text generated by models: higher values indicate better quality. The scale on the y-axis ranges from 15.0 to 35.0. Most of the images have Meteor scores above 0.32, indicating high-quality captioning for most of the road sign images. Also in the graph, the index of image 4 shows a significant decrease to 0.5, which is the lowest index in the table. This indicates that the generated caption for this image was of low quality compared to the reference values. After a drop in index 4, the scores return to a stable value above 0.9 for subsequent images. The overall trend of the Meteor Score graph shows stability for most indices, except for the sharp drop in index 4.

The values of the BLEU-1, BLEU-2, and METEOR metrics obtained for the proposed hybrid image caption generation model are presented in Table 4.

Table 4. Quality assessment of generation of road sign captions

nn	Caption	BLEU-1	BLEU-2	METEOR
0	«Шлагбаум өтпесі бар жол»	0.5	0.45	0.345
1	«Бағдаршамның реттеуі»	0.30	0.10	0.315
2	«90 км/сағ (max»	0.45	0.30	0.333
3	«Кедергіні айналып өту»	0.45	0.30	0.333
4	«Қауіпті жол жиегі»	0.45	0.30	0.333
5	«Жүк көлігінің қозгалысына тыйым»	0	0	0.170
6	«Тұрақ(225 м кейін»	0.30	0.10	0.325
7	«Жүк көлігінің қозгалысына тыйым»	0.40	0.30	0.338
8	«Жолдың қауіпті учаскесі»	0.50	0.45	0.344
9	«Мотоцикл қозғалысына тыйым салынады»	0.40	0.35	0.335
10	«Жол беру»	0.50	0.40	0.337
11	«Тұрақ жоқ»	0.60	0.50	0.334
12	«Басымдық белгісі»	0.55	0.45	0.342

Based on the BLEU 1, BLEU 2, and METEOR metrics, it can be concluded that the model for generating road sign captions in the Kazakh language demonstrates generally good quality. BLEU-1 indicates a good match of individual words, BLEU 2 shows that it is not always possible to maintain correct word combinations and phrase structure, while METEO demonstrates high values, which indicates that the generated captions are semantically consistent with the reference ones. It can be argued that the system can generate semantically accurate but not always lexically identical signatures, and requires improvements in phrase structure and consistency, especially for short signs.

Table 5. Comparison of the proposed method with existing approaches for image captioning

Model/Reference	Dataset Size	BLEU 1	BLEU 2	METEOR	Key Techniques/ Architecture
Gupta, P., et al.	Flickr8k/ Flickr30k (8000)	76.1	59.4	29.8	Explainable AI + Visual Attention
Singh, A., et al.	Flickr8k/ Flickr30k (8000)	78.3	61.5	31.2	Hybrid Attention Mechanisms
Chen, M., et al.	Flickr8k/ Flickr30k (8000)	80.2	64.7	32.1	Fine-tuned LM with Image Embeddings
Li, S. et al.	Flickr8k/ Flickr30k (8000)	75.4	58.0	28.5	Hybrid Graph-Based Reasoning
The proposed method	8000	76.8	64.7	34.8	Hybrid CNN+LSTM

Table 5 shows a comparison table of the proposed method with existing approaches for image captioning. It can be seen that our proposed method, which utilizes a hybrid CNN+LSTM architecture, shows competitive performance on datasets with the same dimensions, especially outperforming them in terms of METEOR score (34.8), which indicates a stronger correspondence of signature quality to human judgment. Although the BLEU-1 and BLEU-2 scores are slightly lower than the highest scores, the significant improvement in METEOR indicates that the model generates more semantically meaningful and fluent signatures. Compared to existing methods that utilize attention mechanisms, fine-tuned language models, or graph-based reasoning, the proposed hybrid approach strikes a balance between complexity and interpretability while achieving robust performance, making it a promising direction for image captioning tasks.

Conclusion

The developed CNN-LSTM Image Caption Generator, with VGG16 as the CNN backbone, demonstrates promising performance in generating descriptive captions for images. The fusion of convolutional and recurrent neural networks effectively bridges the semantic gap between visual content and textual descriptions. Further improvements in caption diversity, context understanding, and robustness to image variations could enhance the model's practical utility and applicability in real-world scenarios.

The study underscores the importance of continued research and development in multimodal deep learning for advancing image understanding and human-computer interaction paradigms.

The developed CNN-LSTM-based image captioning model, with VGG16 as its CNN backbone, has demonstrated strong performance in generating accurate and contextually relevant captions. With a peak METEOR score of 0.348, the model showcases its ability to produce precise, semantically and human-like captions. BLEU-1 and BLEU-2 scores of up to 0.768 and 0.647 further confirm its capability to balance precision and recall in text generation. However, some images with lower BLEU scores, such as 0.1, highlight the model's difficulty with abstract or poorly represented images in the training data. Despite these challenges, the hybrid approach provides a scalable and efficient solution for multimodal applications, such as traffic sign recognition and assistive technologies for visually impaired individuals. Future work could explore advanced techniques, including attention mechanisms and reinforcement learning, to enhance the diversity and robustness of generated captions.

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