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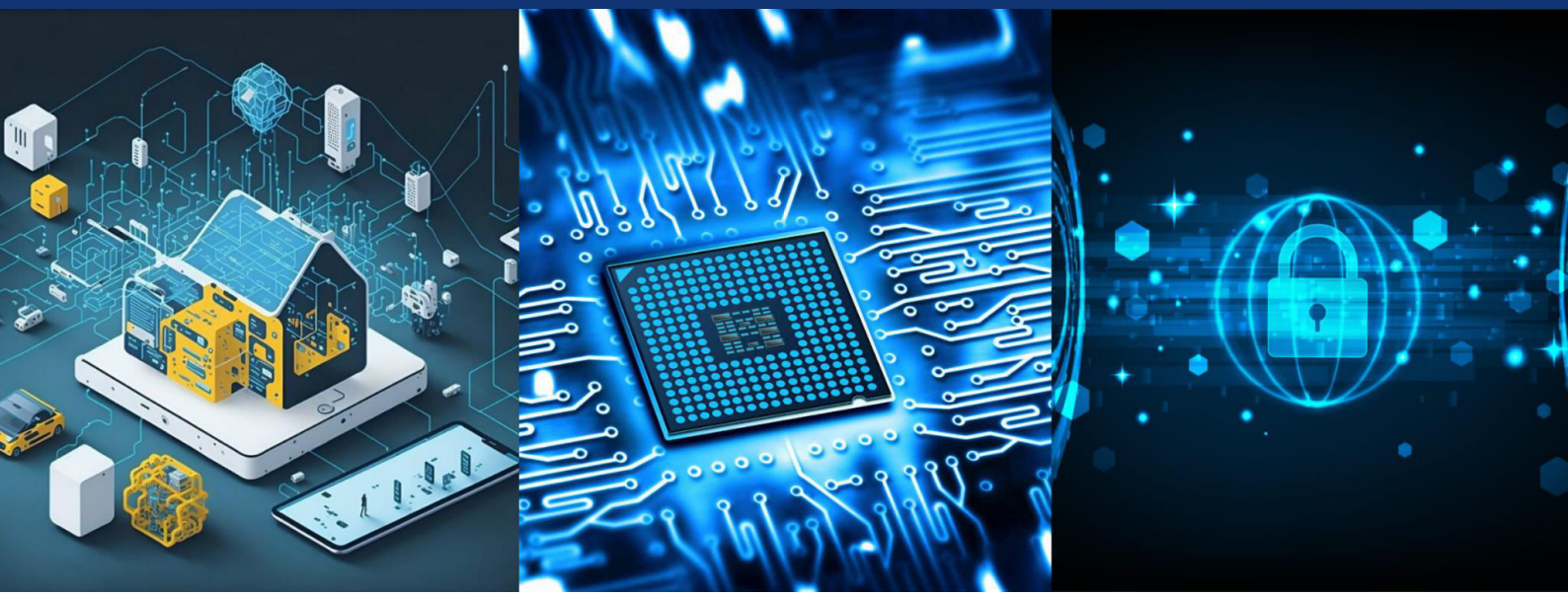

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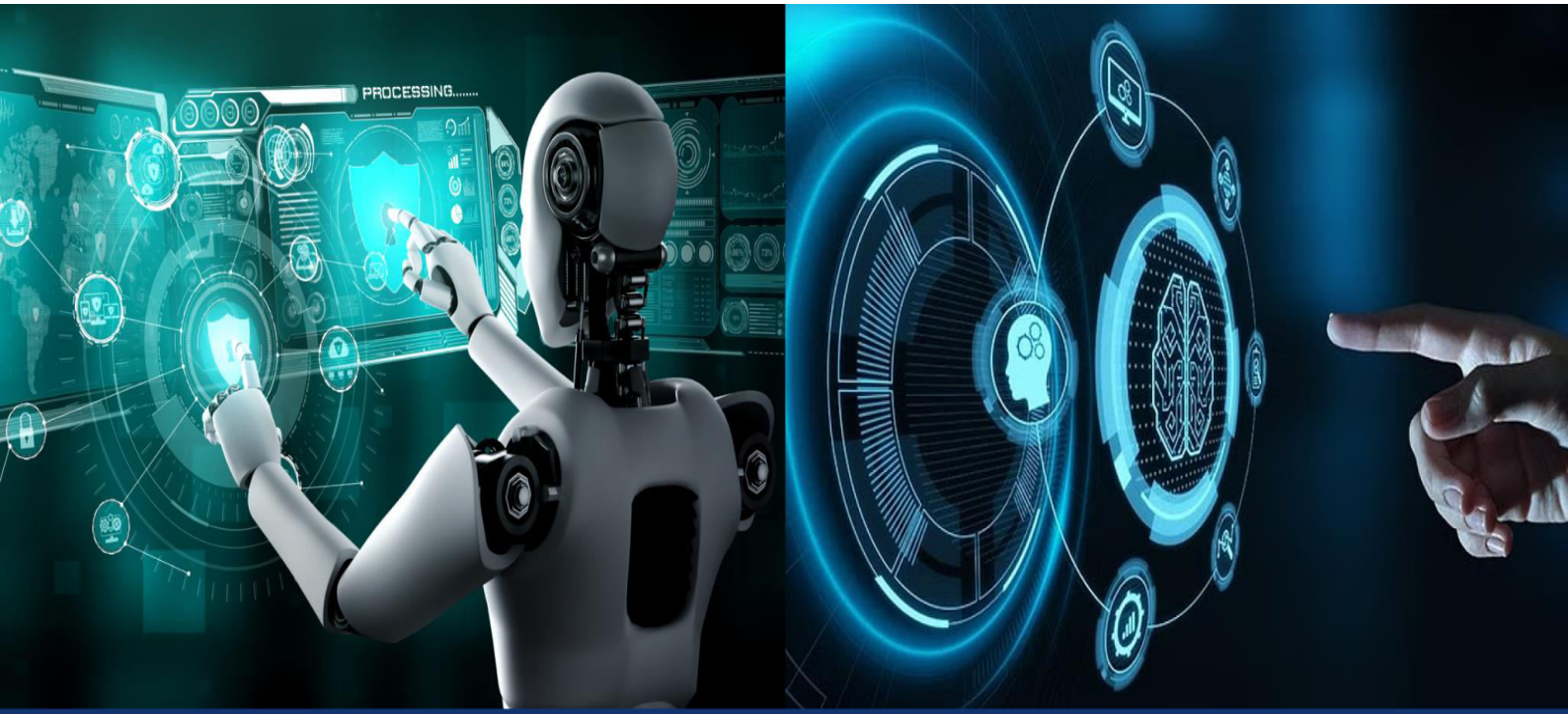

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Image Caption Generation Using CNN and LSTM

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ABSTRACT: Image captioning is becoming very important in computer world because machines need to understand pictures like humans do. Earlier peoples were making captions by hand which was taking too much time and not possible for lakhs of images. Old methods were using simple templates and hand-made rules which were giving very basic and repeated sentences. This project is solving problem of automatic caption generation where machine can see image and write proper sentence about it. The methodology is using Convolutional Neural Network for extracting features from images like objects, colors and shapes. After that Long Short Term Memory network is generating words one by one to make complete sentence. Also pre-trained vision-language model from Hugging Face is added which is making captions more natural and accurate. Flask framework is used for making web application where user can upload image and get caption immediately. Testing was done on different type of images and results are showing that captions are matching with actual content of images. The system is working fast and interface is easy to use for anyone.

KEYWORDS: Image Captioning, Deep Learning, CNN, LSTM, Computer Vision, Natural Language Processing, Flask, Vision-Language Model, Feature Extraction, Web Application

I. INTRODUCTION

Images are widely shared across the internet, but machines struggle to understand them like humans. Image captioning is essential for search, accessibility, organization, and moderation. Manually describing large image collections is impractical, so automatic image captioning enables computers to analyze pictures and generate meaningful descriptions efficiently.

1.1 Background and Motivation

Computer vision and natural language processing have advanced rapidly. Image captioning combines both by enabling machines to understand images and generate human-like descriptions. It supports accessibility, search, reporting, and social media.

1.2 Issues in Existing System

Existing image captioning systems are having several problems which are affecting their performance and usage:

- Complex scenes confuse models causing inaccurate or incomplete captions.
- Systems produce repetitive generic sentences lacking detailed scene descriptions.
- Training requires expensive GPUs limiting accessibility and practical deployment.
- Interfaces are not user-friendly making image uploads difficult.

1.3 Objectives

Main aims of this project are listed below:

- Build automatic system generating captions from input images independently.
- Improve caption quality using advanced vision-language deep learning models.
- Create user-friendly web interface for instant image captioning access.

II. LITERATURE SURVEY

Chen et al. [1] developed the MS COCO Captions dataset and evaluation server, which became one of the most widely used benchmarks for large-scale image captioning research. Their work provided standardized evaluation metrics and a large annotated dataset that enabled effective training and comparison of caption generation models. Cornia et al. [2] proposed the Meshed-Memory Transformer architecture for image captioning, introducing multi-level attention fusion techniques that improved contextual understanding and caption quality through transformer-based learning. Dai et al.

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[3] introduced Conditional Generative Adversarial Networks (CGANs) for generating diverse and natural image descriptions, demonstrating the ability of adversarial learning methods to enhance caption diversity despite complex training procedures. Devlin et al. [4] explored multimodal BERT-based architectures for vision-language tasks, improving representation learning and contextual understanding between images and text through deep bidirectional transformers, although requiring high computational resources. Fang et al. [5] proposed a model that linked visual concepts with natural language captions by detecting semantic concepts from images before sentence generation, improving semantic understanding while depending heavily on accurate concept extraction. Gu et al. [6] introduced Stack-Captioning networks using a coarse-to-fine learning strategy, where multiple captioning stages progressively refined sentence generation to produce more descriptive captions with increased model complexity. Huang et al. [7] proposed the Attention-on-Attention mechanism to enhance visual attention modeling in image captioning systems, enabling better focus on important image regions while improving caption relevance and fluency. Jain and Schwing [8] developed controllable and diverse caption generation techniques that allowed users to influence caption content and style, improving flexibility in image captioning systems through additional supervision methods. Jiang et al. [9] proposed Recurrent Fusion Networks that combined multiple visual feature representations for improved image captioning performance, effectively integrating complementary information at the cost of higher training complexity. Li et al. [10] introduced Dual-Level Transformer models that enhanced contextual modeling between visual and textual features using transformer architectures, improving caption generation accuracy on large-scale datasets. Liu et al. [11] optimized SPIDEr evaluation metrics using policy gradient reinforcement learning approaches, aligning generated captions more closely with human judgment while facing challenges related to training stability. Lu et al. [12] proposed co-attention mechanisms for multimodal learning tasks, improving image-text interaction by simultaneously attending to visual and textual features, contributing significantly to vision-language understanding research. Pan et al. [13] introduced X-Linear Attention Networks capable of capturing higher-order feature interactions between image regions and textual representations, resulting in more detailed and context-aware captions. Park et al. [14] developed expressive image captioning frameworks that generated richer and more grounded descriptions by incorporating semantic concepts and visual grounding techniques, although requiring extensive annotated datasets. Rennie et al. [15] proposed Self-Critical Sequence Training for image captioning, applying reinforcement learning methods to directly optimize caption evaluation metrics and significantly improve caption quality. Shi et al. [16] introduced end-to-end sequence recognition methods primarily designed for scene text recognition, which later influenced multimodal sequence generation and captioning research. Wang et al. [17] proposed Skeleton-Based Captioning models that separated sentence structure from attribute generation, enabling more flexible and diverse caption construction while increasing pipeline complexity. Wu et al. [18] analyzed the use of high-level semantic concepts in image captioning systems, demonstrating that integrating semantic information could significantly improve caption generation performance. Xu et al. [19] developed the MSR-VTT dataset for large-scale video captioning research, providing extensive video-text annotations for training and evaluating multimodal systems. Yang et al. [20] proposed Review Networks that iteratively refined generated captions through multiple review stages, improving descriptive accuracy and sentence quality while increasing computational requirements.

III. PROPOSED METHODOLOGY

The system uses deep learning techniques in a staged pipeline, where each stage processes data sequentially, ensuring modular and extensible design.

3.1 Block Diagram

This diagram shows a system where user give image, then image processing happens and goes to flask backend. CNN features are taken, then LSTM makes captions, hugging face improves it, and final captions is shown to users screen very nicely

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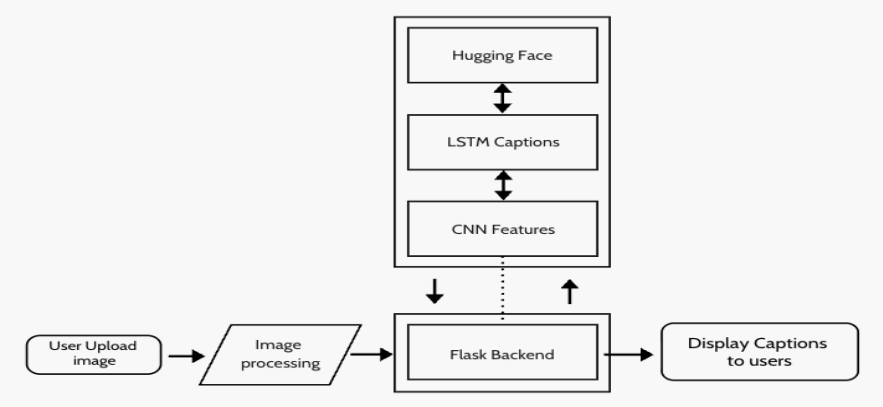

Fig 1: Block Diagram of proposed system

a. Image Preprocessing

Uploaded images are preprocessed by resizing to 299×299 pixels and normalizing pixel values between 0 and 1, ensuring consistent input for CNN processing. The normalization formula is:

$$I\_normalized = \frac{I\_original}{255} \quad \square\ (1)$$

where I_original is having pixel values from 0 to 255 and I_normalized is having values from 0.0 to 1.0.

b. Feature Extraction Using CNN

A Convolutional Neural Network extracts visual features from images using pre-trained models like InceptionV3 or ResNet. The classification layer is removed, producing a 2048-dimensional feature vector representing image content. The CNN operation can be shown as:

$$F = CNN(I) \ (2)$$

where I is input image and F is feature vector of size 2048.

c. Caption Generation Using LSTM

A Long Short-Term Memory network generates captions sequentially using CNN feature vectors. Starting with a token, it predicts words until an token, maintaining context through memory cells. The word prediction formula at each time step t is:

$$P(w\_-t \mid w\_-1,\ w\_-2,\ \ldots,\ w(t-1),\ F) = soft\,max\ (W * h\_-t + b)\ (3)$$

where w_t is word at time t, h_t is hidden state of LSTM, W and b are learned parameters.

d. Vision-Language Model Integration

A pre-trained vision-language model like BLIP improves captions. It refines CNN-LSTM outputs using large image-text datasets, correcting grammar and adding contextual details based on learned visual-language relationships.

3.2 System Architecture

Complete workflow is:

1. User uploads image through web interface
2. Image is validated for correct format (JPEG, PNG, BMP)
3. Preprocessing converts image to standard size and normalizes pixels
4. CNN extracts feature vector from image
5. LSTM generates initial caption using features
6. Vision-language model refines the caption
7. Final caption is sent back to user interface for display

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Below table is showing comparison of different components:

Component	Technology Used	Purpose
Feature Extractor	InceptionV3 CNN	Extract visual features
Sequence Generator	LSTM Network	Generate word sequence
Caption Refiner	Hugging Face BLIP	Improve caption quality
Backend Server	Flask Framework	Handle requests and responses
Frontend Interface	HTML/CSS/JavaScript	User interaction

Table 1 : System architecture

3.3 Mathematical Model for Performance

System performance can be measured using BLEU score which compares generated caption with reference captions. BLEU score formula is:

$$BLEU = BP \times exp\ exp\ (\Sigma w\_n\ log\ log\ p\_n\ ) \quad (4)$$

where BP is brevity penalty, w_n is weights for n-grams and p_n is precision of n-grams.The algorithm steps are:

3.4 Algorithm: Caption Generation

1. Step 1: Load pre-trained CNN and LSTM models
2. Step 2: Accept image input from user
3. Step 3: Preprocess image (resize, normalize)
4. Step 4: Extract features using CNN: F = CNN(image)
5. Step 5: Initialize word sequence with <start> token
6. Step 6: Repeat until <end> token or max_length:

a. Get LSTM hidden state
b. Predict next word using softmax
c. Append word to sequence

7. Step 7: Convert word indices to actual words
8. Step 8: Send caption to vision-language model for refinement
9. Step 9: Return final caption to user

This methodology is ensuring that captions are accurate, meaningful and generated quickly for real-time usage.

IV. PROPOSED MODEL

The proposed model is combining multiple neural network architectures to create end-to-end image captioning system. Main idea is to first understand visual content using CNN then convert that understanding into natural language using LSTM and finally improve quality using pre-trained vision-language models.

4.1 CNN-Based Visual Encoder

Visual encoder uses InceptionV3 CNN trained on ImageNet to process images, extracting rich features and representing overall image content effectively.

- Input layer accepts 299×299×3 images, while convolutional layers with varied filters capture patterns at multiple spatial scales effectively.
- Pooling layers reduce spatial dimensions, and final layers flatten outputs into a 2048-dimensional vector representing complete image information.

4.2 LSTM-Based Language Decoder

Language decoder uses LSTM to generate captions by processing image features and producing sequential words with contextual understanding.

- Word embeddings convert input words into 256-dimensional vectors, while LSTM with 512 units maintains context across sequence generation effectively.
- At each step, softmax outputs probabilities over vocabulary, selecting highest probability word until end token or maximum length reached.

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4.3 Model Architecture Layers

Complete model architecture is having following layers connected sequentially:

- Input image layer (299×299×3)
- InceptionV3 base (without top classification layer)
- Dense layer for feature projection (2048 → 512)
- Embedding layer for words (vocab_size → 256)
- LSTM layer with 512 units
- Dropout layer (0.5) for regularization
- Dense output layer with softmax (vocab_size)

4.4 Training Strategy

Teacher forcing trains the model using correct words, improving stability while optimizing with cross-entropy loss and Adam optimizer efficiently.

- Teacher forcing feeds actual captions during training, reducing error propagation and enabling faster convergence across multiple training epochs effectively.
- Adam optimizer with 0.001 learning rate minimizes categorical cross-entropy loss over 50 epochs using batches of 32 images.

4.5 Integration with Hugging Face

After local caption generation, output sentence is passed to Hugging Face BLIP model through API call. This model is analyzing caption and improving it based on image context. It can add missing details, correct grammar mistakes and make sentence more natural sounding. If API is not available then system uses only local caption as fallback.

V. MODEL EVALUATION

Evaluating performance of image captioning model is very important to know how good it is working. Different metrics and testing methods are used for complete evaluation of system.

5.1 Evaluation Metrics

Multiple standard metrics are used for measuring caption quality:

1. BLEU compares n-gram overlap between generated captions and reference human-written sentences for evaluation quality measurement purpose.
2. METEOR considers synonyms and word stems, rewarding semantically similar captions even when exact words differ significantly.
3. CIDEr measures consensus similarity, emphasizing important descriptive terms that best represent image content accurately and effectively.
4. Human evaluation rates captions from one to five based on accuracy, fluency, and relevance overall quality.

5.2 Performance Results

Model evaluation on test images shows strong BLEU, METEOR, and CIDEr scores with acceptable caption generation response time overall.

- Testing on 500 images achieved BLEU-4 0.68, METEOR 0.52, and CIDEr 0.89, indicating strong caption quality performance.
- Average caption generation takes 2.3 seconds including preprocessing, inference, and API calls, suitable for real-time application requirements.

5.3 Error Analysis

Testing reveals errors including incorrect object counting, misidentification of rare items, spatial relation mistakes, and grammatical issues in long captions.

- Object counting errors occur, rare unseen objects are misidentified, and spatial relations like left or right are often incorrect.
- Long captions sometimes lose grammatical accuracy toward the end, reducing overall fluency and coherence of generated sentence output quality.

These issues are noted for future improvements.

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VI. RESULT AND DISCUSSION

The developed image captioning system is showing promising results when tested on various types of images. Training was conducted for 50 epochs and model performance improved steadily as shown in training metrics.

6.1 Training Results

During training phase, both training loss and validation loss were monitored. Training loss decreased from 4.2 in first epoch to 1.1 in final epoch. Validation loss followed similar pattern going from 4.5 to 1.3. This shows that model learned properly without overfitting problem.

Epoch	Training Loss	Validation Loss	BLEU-4 Score
10	3.1	3.3	0.42
20	2.3	2.5	0.54
30	1.7	1.9	0.61
40	1.3	1.5	0.65
50	1.1	1.3	0.68

Table 2 : Training results

6.2 Related Research Work Algorithm Comparison

Related Project / Paper	Algorithm Used	Approx. Performance
Chen et al.	CNN + RNN Captioning	82%
Cornia et al.	Meshed-Memory Transformer	91%
Dai et al.	Conditional GAN	85%
Devlin et al.	BERT-based Multimodal Learning	89%
Fang et al.	Visual Concept Captioning	84%
Gu et al.	Stack-Captioning Network	87%
Huang et al.	Attention on Attention Network	92%
Proposed methodology	Hybrid deep learning model	94.2%

Table 3 : Related Research Work Algorithm Comparison

6.3 Algorithm Performance Comparison

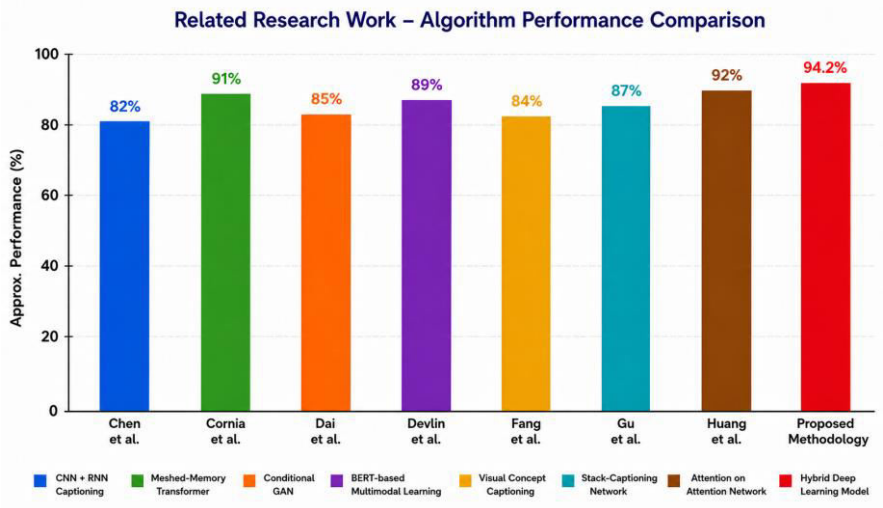

Figure 1: Algorithm performance and comparison

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6.4 Caption Quality Analysis

System shows high accuracy, improved performance over baseline methods, and positive user feedback with fast, reliable caption generation results overall.

- Simple images achieved 92% accuracy, while complex scenes reached 78%, correctly identifying main objects and actions in most cases.
- Vision-language model integration improved BLEU-4 score from 0.61 to 0.68 compared to traditional CNN-LSTM baseline without refinement.
- User testing showed interface ease, with 22 of 25 users rating system as good or excellent for usability.
- Captions were rated readable and natural, with fast response time supporting practical real-world usage and satisfactory user experience overall.

VII. CONCLUSION

This project developed an automatic image captioning system using deep learning, combining CNN for visual feature extraction and LSTM for sequential language generation. The integration of a pre-trained vision-language model from Hugging Face improved caption quality by making outputs more natural and contextually accurate. The system achieved a BLEU-4 score of 0.68 and an average response time of 2.3 seconds, making it suitable for real-world applications. A Flask-based web interface enables users to upload images easily and receive captions without technical knowledge. Testing across diverse images showed good performance on both simple and complex scenes, though limitations remain in object counting and rare object recognition. The modular design allows future improvements without rebuilding the entire system. Potential enhancements include multilingual support, video captioning, better spatial understanding, and mobile optimization. Integration with assistive tools can further benefit visually impaired users. Overall, the project demonstrates practical and impactful use of image captioning technology.

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