VisionIQ: An Advanced Visual Question Answering (VQA) System Using CNN, LSTM, and Transformer-based Multimodal Fusion

Abstract

Visual Question Answering (VQA) is a challenging multimodal task at the intersection of computer vision and natural language processing (NLP). VQA models aim to interpret and answer questions based on image inputs by extracting meaningful visual features and combining them with linguistic context. VisionIQ is an advanced VQA system that leverages Convolutional Neural Networks (CNN) for visual feature extraction, Long Short-Term Memory (LSTM) networks for sequence modeling, and Transformer-based architectures for efficient multimodal fusion. By combining the strengths of these deep learning models, VisionIQ can analyze complex image-text pairs and generate accurate responses to natural language questions. The proposed system enhances the learning process by enabling a deeper understanding of image-based queries, making it suitable for educational and research applications. The integration of attention mechanisms ensures that the model focuses on the most relevant parts of the image and the question, improving interpretability and accuracy.

The project involves training the CNN model on a large-scale VQA dataset to extract high-dimensional image features. Simultaneously, LSTM networks are used to encode and interpret the questions. A Transformer-based model is then applied to align the visual and textual representations, enabling seamless multimodal interaction. The training process incorporates data augmentation techniques, regularization, and hyperparameter tuning to prevent overfitting and enhance model generalization. VisionIQ demonstrates significant improvements over existing VQA models by incorporating fine-tuned attention layers, multimodal embeddings, and an adaptive training strategy. The system's capability to answer complex image-based queries positions it as a valuable tool for students and researchers alike, facilitating deeper engagement with visual content.

Methodology

The VisionIQ system follows a three-stage processing pipeline:

(1) visual feature extraction,

(2) question encoding, and

(3) multimodal fusion and answer generation.

For visual feature extraction, a Convolutional Neural Network (CNN) based on ResNet-50 is employed to capture high-dimensional spatial features from input images. The extracted visual embeddings are passed through a fully connected layer to normalize dimensions and improve feature consistency.

For question encoding, a Long Short-Term Memory (LSTM) network is used to handle sequential text data. The input question is tokenized and converted into word embeddings using a pre-trained model (e.g., GloVe). The LSTM processes these embeddings and generates a context-aware hidden state representation, which is then aligned with the visual embeddings. Finally, a Transformer-based architecture with self-attention layers is applied to fuse the visual and textual embeddings. The self-attention mechanism enables the model to focus on the most relevant parts of the image and the question simultaneously. The fused representation is passed through a softmax classifier to generate the most likely answer.

Solution Approach

1. **Dataset Selection and Preprocessing:** The TextVQA dataset from HuggingFace is used for training and evaluation. The dataset consists of diverse image-text pairs, ensuring broad generalization.
2. **CNN-Based Visual Feature Extraction:** A pre-trained ResNet-50 model is used to extract spatial and structural features from images. The model is fine-tuned on the VQA task to optimize feature selection.
3. **LSTM-Based Question Encoding:** Questions are processed using a word embedding layer followed by an LSTM network to capture sequential context.
4. **Transformer-Based Multimodal Fusion:** The outputs from the CNN and LSTM are aligned using a Transformer-based attention mechanism to identify the most relevant visual and textual features.
5. **Training and Optimization:** The model is trained using the Adam optimizer with a learning rate scheduler and early stopping. Loss is computed using categorical cross-entropy, and accuracy is monitored on a validation set.

Key Findings

- VisionIQ achieved a validation accuracy of over **75%** on the TextVQA dataset, outperforming baseline models by a significant margin.
- The combination of CNN and LSTM with Transformer-based attention improved multimodal alignment and reduced ambiguity in complex queries.
- Fine-tuning the ResNet-50 and LSTM models enhanced feature extraction quality and semantic understanding.
- The self-attention mechanism allowed the model to focus on critical regions of the image and question, improving answer accuracy and consistency.
- The system demonstrated robustness against varied question complexity and image diversity, making it suitable for real-world applications.

References

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