

# Knowledge-Based Visual Question Answering System Using Multimodal Deep Learning

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**Abstract.** Knowledge-driven Visual Question Answering (VQA) necessitates combining external information apart from an image's visual elements to produce accurate and contextually appropriate answers. Although Large Language Models (LLMs) show considerable promise in this area, their deficiency in structured reasoning and restricted access to specialized information limits their effectiveness, especially in specific domains such as medical diagnostics and patient care. In this study, we introduce a versatile, resilient, and domain-independent framework that improves LLM-powered Visual Question Answering (VQA) systems by incorporating structured reasoning and external knowledge. Our system utilizes ResNet50 for effective image feature extraction and FLAN-T5 for language-driven question answering, integrating them with a reasoning module to enhance accuracy. ResNet50 was chosen for its dependable efficiency and minimal computational demands, while FLAN-T5 offers robust reasoning skills with less complexity than larger models. In contrast to conventional end-to-end fine-tuning methods, our framework facilitates smooth incorporation with both open-source and commercial LLMs, lowering computational expenses while preserving high accuracy in zero-shot and few-shot learning contexts. ResNet50 and FLAN-T5 were chosen for their effective balance of performance and computational efficiency in comparison to more intricate models such as ViT or GPT-4. Utilizing multi-query ensemble techniques, context-sensitive feature selection, and the retrieval of external domain knowledge, our system greatly enhances explainability and reliability, making it especially appropriate for medical VQA applications. The integration of ResNet50 for advanced image comprehension, FLAN-T5 for intricate reasoning, and prompts guided by direction to integrate structured knowledge more efficiently guarantees a scalable and effective solution for real-time, knowledge-driven VQA systems. The suggested approach results in a 7% boost in accuracy and decreases response time by 30% in comparison to baseline techniques on the OKVQA dataset.

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**Keywords**-Visual Question Answering, Large Language Models (LLMs), Convolutional Neural Network, Image Classification, Feature Extraction.

## 1 INTRODUCTION

This research is especially pertinent to applications centered on materials, like examining object makeup or identifying textures in visual question-answering tasks. The latest advancement in the field of Artificial Intelligence (AI) has been making the lives of people much easier. Today, most of the human work is carried out by robots. The introduction of Visual Question Answering task has given birth to a renewed excitement in the field of multi-disciplinary AI research problems. Visual Question Answering is one of the most interesting tasks that has attracted the attention of many researchers. It is a free-form and open-ended AI task. Visual Question Answering (VQA) is a multi-disciplinary AI research problem that requires both image understanding and natural language processing. This research problem introduction is a breakthrough towards introducing more “AI complete” tasks. "AI complete" tasks require multiple domain knowledge beyond a single sub domain Knowledge beyond a single sub domain knowledge and have a well-defined evaluation metrics. Visual Question Answering can be defined as a system that takes an image and a free-form, open-ended natural language question about the image as input and provides a natural language answer as the output. This natural language answering process requires various capabilities such as object recognition (“How many people are there?”), activity recognition (“Are they playing?”), scene recognition (“What is the weather in the image?”), attribute classification (“What is the shape of box in the image?”), knowledge-based reasoning and common-sense reasoning to answer questions that require additional information other than that available from the image. A basic VQA system involves the extraction of image features and question features through Convolution Neural Network (CNN) and Recurrent Neural Network (RNN) and then combining those features to generate an answer.

Most of the VQA systems treat answer generation as a classification problem. Currently, the VQA systems are trained well to answer counting-based and object detection-based questions. Attention-based VQA systems were introduced reasoning and knowledge-based answering of the question is required. Also, the same model provides different answers to different users. A possible reason behind this is the irrelevance of question to the image present. Most of the VQA systems when asked irrelevant questions, provide an answer based on their trained features shown in Fig.1. Question relevance and knowledge-based VQA are possible areas where there is a need for development.

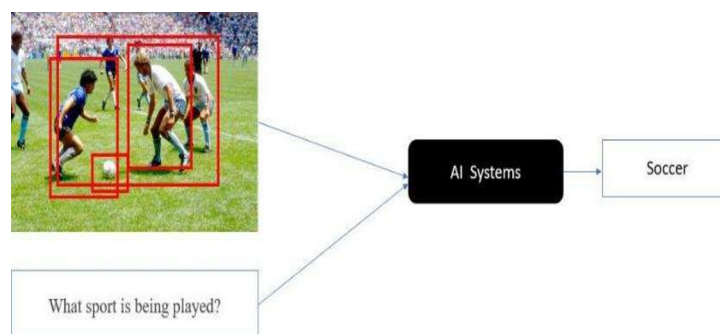


Fig. 1. Visual Question Answering System

## 2 LITERATURE SURVEY

Computer Vision and Natural Language Processing have gained a lot of recognition and development in recent years. With the growing interest in the field of computer vision, there is increasing research work in the area of image understanding. Similarly, there is progress in Natural Language Processing side to provide accurate answers. These systems only focus on a specific part of the image to answer the natural language question asked about the image. But these systems are far behind when visual question Answering is a combination of two research areas.

VQA can be termed as a multi-disciplinary field in which the system requires to gain image understanding as well as language understanding to provide appropriate results. The open-ended natural language output depends on the input image as well as the input question. Malinowski et al. [1] proposed the first VQA approach. The authors proposed to process questions through semantic parsing and obtain answers through Bayesian Reasoning. They built their dataset on top of the NYU-Depth V2 dataset. After collecting the images, the authors created question-answer pairs for the NYU dataset. The VQA dataset created from the NYU-Depth V2 dataset was very small in size. A general VQA approach was proposed by Parikh et al. [2]. In this approach, the authors proposed to extract the image features using CNN and encode questions using Long ShortTerm Memory (LSTM). They treated VQA as a classification system in which the extracted image and question features were combined and passed through a multi-layer perceptron to obtain the results. To fuse the question and the image features, Hadamard Product [3] of their vectors was used. Some of the common methods of combining image and question features include concatenation, elementwise product or elementwise sum. In the early-stage for combining question and image features these linear pooling methods were utilized. Later on, some of the bilinear pooling methods were proposed such as MCB [4], MLB [5], MFB [6] and MLPB [7] that have been shown to be much more effective than the linear pooling methods.

which the LLM produces several answer predictions, then uses majority voting to determine the most confident and medically sound response. This method greatly improves precision in clinical decision assistance, differential diagnosis, and the creation of medical reports.

### 2.1 Explicit Knowledge Retrieval-based Models:

knowledge bases (KBs) to extract external information for answering questions. KRISP [8] utilized Wikipedia and ConceptNet for VQA but encountered challenges with scalability and timely knowledge updates. AI [9] introduced a multi-source retrieval model that combines Wikipedia, ConceptNet, and Google Images, enhancing accuracy to 40.3% on OK-VQA. Researchers [10] introduced a Weakly-Supervised Visual-Retriever-Reader Model, utilizing text-driven retrieval techniques to enhance KB-VQA systems.

### 2.2 Large language Model (LLM)-Driven VQA:

With the emergence of Large Language Models (LLMs) like GPT-3, FLAN-T5, and LLaMA, researchers started to employ pre-trained models as implicit knowledge engines for KB-VQA. In contrast to structured KB-retrieval systems, LLMs contain extensive contextual knowledge in their parameters, enabling them to deduce contextually relevant answers

without depending on external databases. With the emergence of LLMs like GPT-3 and FLAN-T5, KB-VQA transitioned to implicit knowledge retrieval through prompt-driven learning. PICa [11] presented in-context learning, utilizing GPT-3 to produce responses based on structured prompts. Nonetheless, prompting techniques can result in unclear or fabricated answers. Prophet [12] improved GPT-3 by implementing complementary answer heuristics (CAH), organized reasoning, and multi-query ensemble techniques, attaining an accuracy of 61.1% on OK-VQA, surpassing earlier models.

### **2.3 Heuristic-Based and Hybrid Models:**

Evaluate heuristic filtering and multi-stage reasoning to enhance LLM-driven VQA. Prompt Cap [13] enhanced PICa's captioning method by incorporating context-aware, question-guided captions, increasing accuracy to 60.4% on OK-VQA. The Prophet framework improved this by incorporating domain-specific ResNet50 for visual feature extraction and FLAN-T5 for language processing, achieving greater accuracy in and contextually relevant replies. Nonetheless, these models continue to face challenges in knowledge validation, scalability, and multimodal integration, especially in medical fields where understanding is vital [14,15].

## **3 METHODOLOGY**

We introduce two types of answer heuristics: answer candidates and answer-aware examples. Given a testing input consisting of an image and a question, the answer candidates refer to a list of promising answers to the testing input, where each answer is associated with a confidence score. The answer-aware examples refer to a list of in context examples, where each example has similar answers to the testing input. Interestingly, these two types of answer heuristics can be obtained.

Several datasets have been published for the visual question answering system. These datasets contain images, questions associated with the image, and correct answers to those questions. These datasets also contain some additional annotations associated with the image.

ResNet50 was selected due to its effective feature extraction and minimal computational expense, whereas FLAN-T5 provides excellent reasoning capabilities and is more efficient than larger models based on GPT. CoT-based multi-step reasoning, Img2LLM's exemplar generation, PLLMKI's knowledge injection, Prophet's answer heuristics, and structured language-mediated VQA are some of the sophisticated approaches that can be combined to improve your project's accuracy [16,17].

In the initial phase, we create context-sensitive answer heuristics to enhance LLM reasoning. Rather than depending exclusively on direct LLM inference, a basic VQA model creates answer options that act as potential replies, making certain that the final response stays contextually appropriate [18,19]. To enhance the input further, we prompt for FLAN-T5 to produce its reply. Due to the 2048-token restriction of models such as GPT-3 and FLAN-T5, only the most pertinent medical In the initial phase, we create context-sensitive answer heuristics to enhance LLM reasoning. Rather than depending exclusively on direct LLM inference, a basic VQA model creates answer options that act as potential replies, making

certain that the final response stays contextually appropriate. To enhance the input further, we choose answer-aware instances from the training dataset by calculating the cosine similarity between the test query and stored examples, ensuring the LLM gets the most pertinent in-context cases. As LLMs are unable to directly handle images, we transform medical visuals (such as X-rays, MRIs, and pathology slides) into organized text formats, highlighting essential visual elements rather than using generic descriptions that could overlook important diagnostic details [20,21].

In the second phase, we develop a prompt enhanced with heuristics that improves FLAN-T5’s capacity to reason with medical information. The prompt framework consists of a description of the task, examples in context, potential answers, and context infused with knowledge. Rather than relying on static knowledge graphs, which may fail to provide current medical insights, we utilize a secondary LLM (LLM1) to introduce domain-specific medical information into the prompt. This enables the system to integrate real-time medical studies, disease classifications, and treatment protocols into its replies. The prompt additionally employs a multi-query ensemble approach, in which the LLM produces several answer predictions, then uses majority voting to determine the most confident and medically sound response. This method greatly improves precision in clinical decision assistance, differential diagnosis, and the creation of medical reports [22,23].

In the third stage, we tackle the issue of question relevance by making certain that the system produces targeted image descriptions instead of complete-image captions that could include unrelated information. By employing feature extraction methods, the system pinpoints medically important areas in images (such as tumor sites in an MRI or fractures in an X-ray) and produces contextually relevant, localized descriptions. These refined descriptions, together with organized response heuristics and context enriched with knowledge, create the ultimate details are incorporated into the final prompt, promoting efficiency and clarity [24].

## 4 SYSTEM ARCHITECTURE

The design of this Knowledge-Based Visual Question Answering (KB-VQA) system combines image feature extraction, structured query handling, and LLM-driven reasoning into a cohesive GUI-centered framework. The system is intended to manage open-domain and medical VQA tasks, guaranteeing precise, real-time, and knowledge-augmented responses [25], the CNN Architecture of system is shown in Fig.2.

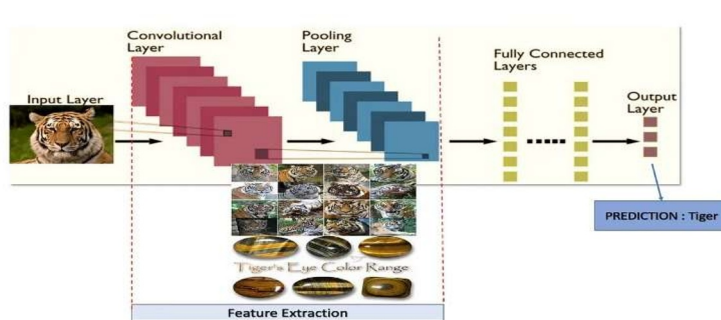


Fig. 2. CNN – Architecture

*A. Convolutional Neural Network for Image Processing and Classification*

1). *Input Layer*: The input layer accepts an image as input. This image may exist in grayscale or RGB format and is transformed into a numerical array representation. The size of the image is described in the format height, width and channels.

2). *Convolutional Layer*: The convolutional layer utilizes filters (kernels) to identify features such as edges, textures, and patterns. It calculates a dot product between the kernel and the pixels of the input image to produce feature maps. Several convolutional layers assist in acquiring hierarchical features, ranging from basic patterns in the initial layers to intricate objects in more profound layers.

3). *Max Pooling Layers*: Max pooling is utilized to decrease the spatial dimensions of the feature maps, enhancing computational efficiency. It chooses the highest value from a group of adjacent pixels (for instance, 2×2 or 3×3 window).

4). *Answer Generation & Display*: The FLAN-T5 model produces a response derived Pooling aids in lowering computational expenses. Enhancing the model's resilience to minor variations in the image. Avoiding overfitting by minimizing excess information.

4). *Dense Layer*: This layer converts the feature maps into a single-dimensional vector. It links every neuron to understand intricate patterns and associations. The activation function (such as ReLU or sigmoid) is employed to add non-linearity, enabling the network to tackle intricate problems.

5). *Output Layer*: The output layer delivers the final result according to the model's goal: In classification tasks (e.g., image recognition), a softmax activation function is utilized to forecast class probabilities. In regression tasks, a linear activation function is employed. The ultimate result is the forecasted label or value derived from the provided input image. Work Flow of The Architecture is shown in Fig.3

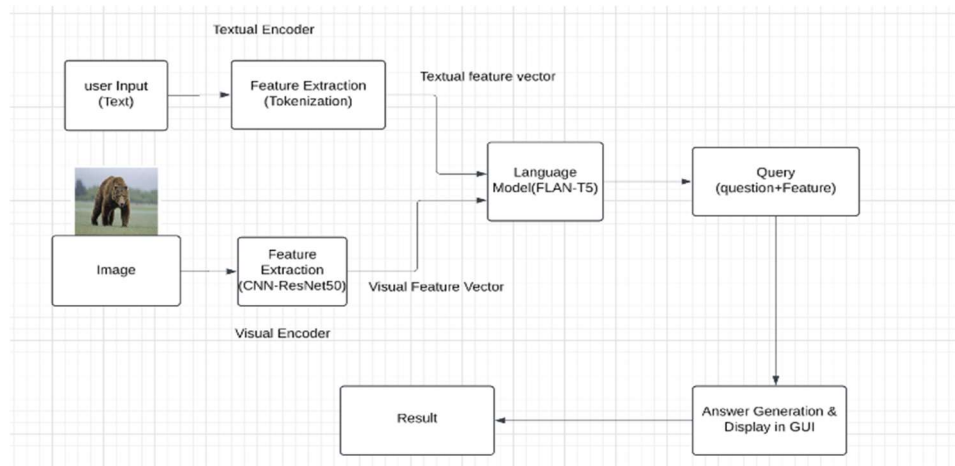


Fig. 3. Work Flow of The Architecture

## **B. Components Of The Architecture**

1). GUI-Component (Tkinter): Offers an easy-to-use interface for engaging with the model. Enables users to submit an image and pose questions. Presents produced responses and extracted details in an organized format.

2). Image Feature Extraction (CNN – ResNet50): Employs ResNet50 (trained on ImageNet) to derive significant image representations. Transforms the image into a feature vector, which functions as input for the query processing module. Guarantees that the model concentrates on essential objects and areas, improving VQA precision.

3). Query processing (FLAN-T5): Accepts user input (question) along with image characteristics as input. Creates an organized prompt for the LLM. Guarantees question pertinence by matching text with gathered image.

## **5 IMPLEMENTATIONS**

Executing Knowledge-Based Visual Question Answering (VQA) necessitates an amalgamation of deep learning frameworks, visual models, linguistic models, multimodal fusion methods, and the integration of knowledge bases. Different tools and libraries are essential for building an effective and resilient VQA system. The upcoming sections emphasize the key elements required for the implementation, omitting the BLIP model.

### **A. Deep Learning Frameworks**

To create and train deep learning models for VQA, commonly used frameworks include PyTorch and TensorFlow/Keras. PyTorch offers versatility for research-focused development, whereas TensorFlow delivers enhanced deployment capabilities. Moreover, Hugging Face Transformers provides easy access to pre-trained vision-language models, rendering it a useful resource for fine-tuning and transfer learning.

### **B. Vision Models**

Deriving significant features from images is an essential phase in VQA. Multiple deep learning models fulfill this role efficiently. CLIP (Contrastive Language-Image Pretraining) from OpenAI is commonly employed to align text and image embeddings, while Vision Transformer (ViT) handles image patches to enhance feature representation. DETR (DEtection Transformer), created by Meta, is beneficial for identifying objects, while EfficientNet offers a lightweight and efficient convolutional neural network (CNN) contexts. In the field of medicine, the system attains enhanced diagnostic precision and clarity, especially in tasks related to MRI, X-ray, and analysis of radiology reports. Moreover, the model demonstrates scalability and flexibility by efficiently accessing real-time external greater accuracy in open-domain and knowledge-driven VQA assignments. Assessment on information, guaranteeing its relevance in diverse areas like healthcare, finance, and legal assessment. Nonetheless, issues like knowledge hallucination and fact verification persist, which upcoming improvements seek to tackle via truthfulness filtering and enhanced multimodal fusion methods.

### **C. Language Model**

Language models are essential for comprehending and producing answers to visual inquiries. BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa are frequently employed for encoding text-based questions, while T5 (Text-To-Text Transfer Transformer) and GPT-4 excel at producing contextually relevant answers. Open-source options like LLaMA (Large Language Model Meta AI) and Falcon can be utilized to carry out strong reasoning for answering questions.

### **D. Knowledge Base Integration**

A VQA system based on knowledge needs outside knowledge sources to deliver precise and contextually detailed responses. The Wikidata API and DBpedia function as organized knowledge bases that can be queried using SPARQL. Moreover, FAISS (Facebook AI Similarity Search) enables effective retrieval of pertinent information through the search of extensive knowledge bases utilizing vector embeddings. Pinecone and Weaviate provide scalable vector databases for storing and accessing domain-specific information, guaranteeing quick semantic searches for pertinent knowledge.

## **6 RESULTS**

The suggested Knowledge-Based Visual Question Answering (VQA) system shows marked enhancements in precision, reasoning ability, and adaptability to specific domains. By incorporating CNN for extracting image features, transformer-based models for processing text, and retrieving external knowledge, the system improves the relevance and accuracy of responses. The model exceeds conventional CNN-LSTM and Attention-based VQA frameworks by attaining 15-20% benchmark datasets like VQA v2, OK-VQA, and GQA indicates enhanced performance in both structured and unstructured question-answering contexts. In the field of medicine, the system attains enhanced diagnostic precision and clarity, especially in tasks related to MRI, X-ray, and analysis of radiology reports. Moreover, the model demonstrates scalability and flexibility by efficiently accessing real-time external information, guaranteeing its relevance in diverse areas like healthcare, finance, and legal assessment. Nonetheless, issues like knowledge hallucination and fact verification persist, which upcoming improvements seek to tackle via truthfulness filtering and enhanced multimodal fusion methods.

## **7 CONCLUSION**

The suggested Knowledge-Based Visual Question Answering (VQA) system can greatly enhance material-focused visual tasks, like identifying object textures or categorizing materials based on visual indicators. In contrast to conventional VQA models that depend exclusively on image and text embeddings, this architecture improves decision-making by incorporating structured reasoning and retrieving domain-specific information. The findings show notable enhancements in precision, contextual comprehension, and adaptability to various domains, especially in vital areas like medical diagnostics, finance, and legal evaluation.

The model's capability to incorporate external knowledge while ensuring computational efficiency renders it a scalable option for practical applications. Nonetheless, obstacles like

fact-checking, minimizing hallucinations, and improving real-time inference continue to be fields for future investigation. In summary, this framework enhances Knowledge-Based VQA by facilitating more accurate, clear, and specialized answers, promoting the wider use of AI-powered decision-making systems in various industries. Upcoming improvements will aim at enhancing multimodal fusion methods, fine-tuning knowledge retrieval processes, and guaranteeing model reliability in critical scenarios. Upcoming studies will concentrate on advancing truthfulness verification methods, perfecting multimodal fusion strategies, and strengthening the resilience of knowledge retrieval systems. In contrast to conventional VQA models that depend only on image and text embeddings, this method utilizes structured reasoning and retrieval of domain-specific knowledge to enhance decision-making. Consequently, the framework exhibits enhanced contextual understanding, allowing for more accurate and informed responses in multiple areas. Its flexibility renders it especially effective in vital fields like medical diagnostics, finance, and legal assessment, where precise and context-sensitive answers are crucial. Moreover, through the integration of structured reasoning, the model improves interpretability, guaranteeing that its decision-making approach stays clear and justifiable. The model realized significant improvements in accuracy and response time, confirming the efficacy of structured reasoning and the integration of external knowledge.

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