Smart Assistant for the Visually Impaired
Project Proposal

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Motivation

People with visual impairments or disabilities face significant challenges in their daily lives, especially when it comes to navigating unfamiliar environments or accessing information. Smart assistants can provide a valuable tool to assist these individuals in their day-to-day lives. By leveraging cutting-edge computer vision and natural language processing technologies, we can build a smart assistant that can interpret the user's surroundings and answer their questions in real-time, making it easier for them to navigate the world around them. Questions can be general or based on the environment like “Is the traffic light red?”, “Is the coffee store open?”, “How crowded is the Post Office?”, etc. Also, the applications of this system are limitless.

Hypothesis

We hypothesize that by combining state-of-the-art Computer Vision and Natural Language Processing techniques, we can develop a smart assistant that can answer a wide range of questions asked by visually impaired or disabled individuals based on real-time video feed captured using a camera. Furthermore, we expect that integrating the system with other modules such as GPS, Google Maps, and other APIs will seamlessly increase its convenience and usability for users.

Experiments

We propose to conduct the following experiments to evaluate the performance of our system:

Experiment 1: Question Answering Accuracy: We will evaluate the accuracy of the question-answering module of our system by comparing its responses to a set of human-generated answers for a variety of questions, including both general knowledge questions and questions specific to the user's surroundings. We will use standard evaluation metrics such as accuracy, precision, recall, and F1 score to measure the performance of our system.

Experiment 2: Real-time human evaluation: We are going to create a couple of (let’s say 30 question and image pairs) and manually evaluate the performance of the model on those samples. This will function as a small dev set to ensure that our model can handle the use cases we are actually interested in.

Experiment 3: Integration with APIs: We will evaluate the effectiveness of integrating our system with commonly available APIs and services like GPS, Google Maps and Places APIs, Folium, Nominatim, etc. We will test if our system is correctly identifying the user's location and answering based on the location, if relevant. To the best of our knowledge, there are no datasets we could use for automatic evaluation, so this will have to be done manually.

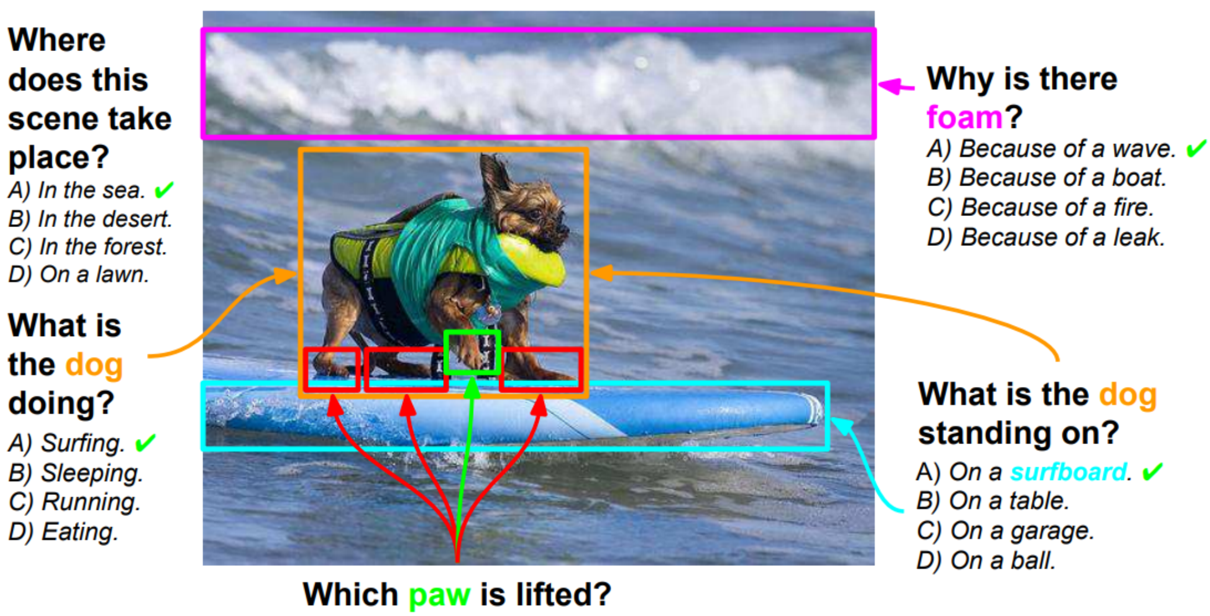
Datasets

We will use the following Visual Question Answering datasets for training and evaluating our system:

COCO: The Microsoft Common Objects in Context (COCO) dataset will be used to train and evaluate our computer vision models. COCO consists of over 330,000 images with more than 2.5 million object instances labeled with bounding boxes. Note: This is not used directly since VisualQA (defined below) has more relevant data that draws from COCO.

VisualQA data: VQA has ~205k images from COCO, 1M questions, and 11M ground truth answers.

Visual7W: Visual7W is a dataset of images with lots of questions that amount to a very dense annotation of the image.



Baseline Model

We will use the model BEiT Pretraining for All Vision and Vision-Language Tasks by Wang, et al. (2022) out of the box.

Methodology

We propose to use the following methods to build our system:

1. Use DroidCam as a camera that will record the environment via a live video feed. Later, it can be replaced by an embedded camera in smart glasses. It records the videos and sends them to the system.
2. A speech2text module will be used on the audio spoken by the user to convert the user's query from audio to natural language - let's say we call the text the question.
3. As soon as speech2text activates, we will capture a few frames at regular intervals (frequency to be experimented with - let's say 5 frames every second) and save these images.
4. Feed the image and question to ChatGPT 4 API if available (most likely it will not be made available). If ChatGPT 4 API is not available, then we will use the BEiT model as mentioned above. Time permitting, we will look into training our own model that will encode the image using CLIP. CLIP (Contrastive Learning Image Pretraining) is a state-of-the-art model that can simultaneously perform image and text classification. Sheng S et al. (2021) shows that CLIP can be used as an image encoder in QA contexts, which is capable of generating high-quality answers to a wide range of questions.
5. During the eval phase, get the model answer and decode it to get the answer to the question.
6. We will integrate our system with common APIs like GPS and Google Maps to provide additional information based on the user's surroundings. This will help with questions like “How long will it take me to walk to the nearest medical store?”, “Is there traffic on the Saint Paul Street?”

Halfway Milestone

By halfway, we hope to get the speech2text, video live stream capture, and modules set up. We should have the architecture for preprocessing input to BEiT set up.
In the second half, we plan to integrate it with APIs and look at training a new model, rather than just integrating one out of the box.

Extensions and Future Scope

Given that we implement the proposed system mentioned above, here are some possible experiments/extensions that we might work on, time permitting:

Experiment 3: Provenance/Localization: We will evaluate the effectiveness of our system in providing provenance or localization information for the answers generated. We will use a set of annotated images to test if our system is correctly identifying the regions of the image that the answer corresponds to.

Expected Outcome

We expect that our system will be able to accurately answer a wide range of questions asked by visually impaired or disabled individuals based on real-time video feeds captured using a camera. We also expect that integrating the system with other modules such as GPS, Google Maps, and other APIs will increase its convenience and usability. We hope to improve the daily lives of blind and disabled individuals by making some tasks and activities convenient for them.

References

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