

SELF-ANALYZING IMAGE-VIDEO

A PROJECT REPORT

Submitted by

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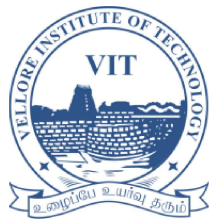
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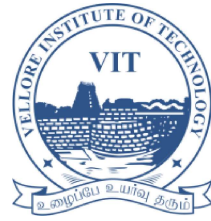
Master of Technology

in

Business Analytics (5 Year Integrated Programme)



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CERTIFICATE

This is to certify that the report entitled Self-Analysing Image-Video is prepared and submitted by Avala Sri Karthik (Reg. No. 20MIA1032) and Vinayaka R Srinivas (Reg. No. 20MIA1041) to Vellore Institute of Technology, Chennai, in partial fulfilment of the requirement for the award of the degree of Master of Technology in Business Analytics (5 year Integrated Programme) and as part of CSE3506 – Essentials of Data Analytics Project is a bona-fide record carried out under my guidance. The project fulfils the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission.

Guide/Supervisor

HoD

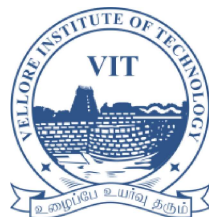
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Abstract

This project leverages advanced AI models to extract and analyze key frames from video files, aiming to provide detailed descriptions for surveillance purposes. Utilizing Streamlit for the user interface, the application allows users to upload video files in various formats, such as MP4, MOV, AVI, and MKV. The core of the project is built around the Moondream2 model, an advanced language model integrated with image processing capabilities. By periodically extracting frames from the video using OpenCV, the application identifies key moments and analyzes these frames to generate descriptive summaries. This is achieved by converting frames to images, encoding them with the Moondream2 model, and querying the model for descriptive content. The combination of these technologies creates a robust system for detailed video analysis, providing rich contextual information about the visual content in each frame, which can be particularly useful in surveillance applications.

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Introduction

About

The advent of advanced artificial intelligence (AI) and machine learning (ML) technologies has revolutionized the field of video analysis. These technologies enable the extraction of meaningful information from video data, which is particularly valuable in applications such as surveillance, content management, and automated video summarization. This project harnesses the capabilities of the Moondream2 model, an advanced language model with integrated image processing capabilities, to analyze video frames and provide detailed descriptions of the visual content.

Objective

The primary objective of this project is to develop a system that can automatically extract key frames from video files and generate descriptive summaries of these frames. This is achieved by utilizing the Moondream2 model, which processes and analyzes the visual content within the frames. The ultimate goal is to create a robust and efficient tool for detailed video analysis that can be used for various applications, especially in the domain of surveillance.

Motivation

The motivation behind this project stems from the increasing need for automated video analysis tools in various industries. Traditional methods of video analysis are time-consuming and require significant human effort. By leveraging AI and ML models, we can automate the process of extracting and analyzing key frames from videos, thereby saving time and resources. Additionally, the ability to generate detailed descriptions of video content has numerous practical applications, such as enhancing security measures through better surveillance and improving video content management systems.

Problem Statement

Analyzing large volumes of video data manually is a daunting and inefficient task. There is a need for an automated system that can efficiently process video files, extract significant frames, and provide meaningful descriptions of the visual content. The challenge lies in accurately identifying key moments in the video and generating relevant summaries that capture the essence of each frame. This project aims to address this problem by utilizing the Moondream2 model to create a comprehensive solution for automated video analysis.

Literature Review

1. Vision Language Models: Introducing the New VLM Moondream 2

The paper "Vision Language Models: Introducing the New VLM Moondream 2" from DataScienceDojo presents the Moondream2 Vision Language Model (VLM), emphasizing its advancements and applications. The Moondream2 model integrates visual and textual data to generate accurate descriptions of visual content. The model's architecture and training processes are detailed, showcasing significant improvements in performance metrics. This model is positioned as a robust tool for various applications, including automated video analysis, due to its ability to provide contextually relevant and precise descriptions of visual scenes.

2. Exploring the Frontier of Vision-Language Models: A Survey of Current Methodologies and Future Directions

The survey paper by Ghosh et al. titled "Exploring the Frontier of Vision-Language Models: A Survey of Current Methodologies and Future Directions" provides a comprehensive overview of contemporary approaches in vision-language modeling. The authors review model architectures, training techniques, and evaluation metrics, and highlight the challenges and potential research areas in the field. Key areas of focus include improving model robustness, handling multimodal data, and future directions such as enhanced multimodal fusion methods and the integration of vision-language models with emerging technologies. This survey serves as a valuable resource for researchers seeking to understand the state-of-the-art in vision-language models and their diverse applications.

3. Multimodal Research in Vision and Language: A Review of Current and Emerging Trends

In the review "Multimodal Research in Vision and Language: A Review of Current and Emerging Trends," Uppal et al. examine the latest trends in integrating vision and language. The authors discuss a range of multimodal models, datasets, and applications, emphasizing the advantages and challenges of combining visual and textual data. They explore emerging trends, such as the adoption of transformer-based architectures and self-supervised learning techniques, which are driving advancements in multimodal research. This paper provides a thorough overview of the field and identifies critical areas for future investigation, highlighting the potential for further innovation and application of multimodal approaches.

4. An Introduction to Vision-Language Modeling

The paper "An Introduction to Vision-Language Modeling" by Bordes et al. serves as an introductory guide to the field of vision-language modeling. It explains the fundamental concepts and techniques, including image encoders, text encoders, and multimodal fusion methods. The authors present various applications of vision-language models, such as image

captioning, visual question answering, and cross-modal retrieval. This paper is particularly useful for newcomers to the field, offering a clear and concise introduction to the key components and applications of vision-language modeling, and setting the stage for more advanced exploration and research.

5. Vision-Language Models for Vision Tasks: A Survey

Zhang et al. in their paper "Vision-Language Models for Vision Tasks: A Survey" focus on the application of vision-language models to specific vision tasks. They review models and techniques that integrate visual and textual information to enhance performance in tasks such as object detection, image segmentation, and action recognition. The authors discuss the challenges faced in this domain, including the need for better dataset curation and the development of more efficient model architectures. They also outline future directions for research, emphasizing the potential of vision-language models to drive advancements in various vision tasks. This paper provides comprehensive insights into the current state and future potential of vision-language models in enhancing vision-specific applications.

Methodology

Objective

The goal of this project is to extract key frames from a video, analyze them using the Moondream2 model, and display the results using Streamlit.

Tools and Libraries

1. *Streamlit*: For creating the web application interface.
2. *OpenCV*: For video processing and frame extraction.
3. *Pillow*: For image processing.
4. *Transformers (Hugging Face)*: For loading and using the Moondream2 model.
5. *Torch*: For leveraging GPU acceleration if available.

Step-by-Step Methodology

1. *Setup Environment*:
 - Import necessary libraries.
 - Check for GPU availability.
 - Initialize the Moondream2 model and tokenizer.

```
import streamlit as st
import cv2
import numpy as np
from PIL import Image
from transformers import AutoModelForCausalLM, AutoTokenizer
import torch
```



```
# Ensure GPU is used if available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Initialize Moondream2 model
model_id = "vikhyatk/moondream2"
model = AutoModelForCausalLM.from_pretrained(model_id, trust_remote_code=True).to(device)
tokenizer = AutoTokenizer.from_pretrained(model_id)
```

Extract Key Frames:

- Create a function to extract frames from the video at specified intervals.

```
def extract_key_frames(video_path, interval=300):
    cap = cv2.VideoCapture(video_path)
    frames = []
    frame_count = 0
    while cap.isOpened():
        ret, frame = cap.read()
        if not ret:
            break
        if frame_count % interval == 0 or frame_count == 0:
            frames.append(frame)
            frame_count += 1
    cap.release()
    return frames
```

2. *Analyze Frame:*

- Create a function to convert frames to images and analyze them using the Moondream2 model.

```
def analyze_frame(frame, model, tokenizer):
    image = Image.fromarray(cv2.cvtColor(frame, cv2.COLOR_BGR2RGB))
    enc_image = model.encode_image(image.to(device))
    output = model.answer_question(enc_image, "Describe this image.", tokenizer)
    return output
```

3. *Main Application:*

- Use Streamlit to create a web interface where users can upload videos.
- Extract key frames from the uploaded video.
- Analyze each frame using the Moondream2 model and display the results.

```
def main():
    st.title("Video Analysis with Moondream2")
    st.write("Upload a video to extract key frames and analyze them using Moondream2 model")

    uploaded_video = st.file_uploader("Choose a video...", type=["mp4", "mov", "avi", "mkv"])
    if uploaded_video is not None:
        with open("temp_video.mp4", "wb") as f:
            f.write(uploaded_video.getbuffer())

        st.video("temp_video.mp4")

        st.write("Extracting key frames...")
        key_frames = extract_key_frames("temp_video.mp4")
        st.write(f"Extracted {len(key_frames)} key frames")

        st.write("Analyzing frames with Moondream2...")
        summaries = []
        for idx, frame in enumerate(key_frames):
            summary = analyze_frame(frame, model, tokenizer)
            summaries.append(summary)
            st.image(frame, caption=f"Frame {idx+1} - Summary: {summary}")

        st.write("Video Summary:")
        st.write("\n".join(summaries))

if __name__ == "__main__":
    main()
```

Detailed Explanation

1. Environment Setup:

- The necessary libraries are imported, and the system checks for GPU availability. The Moondream2 model and tokenizer are then loaded from the Hugging Face model repository.

2. Extract Key Frames:

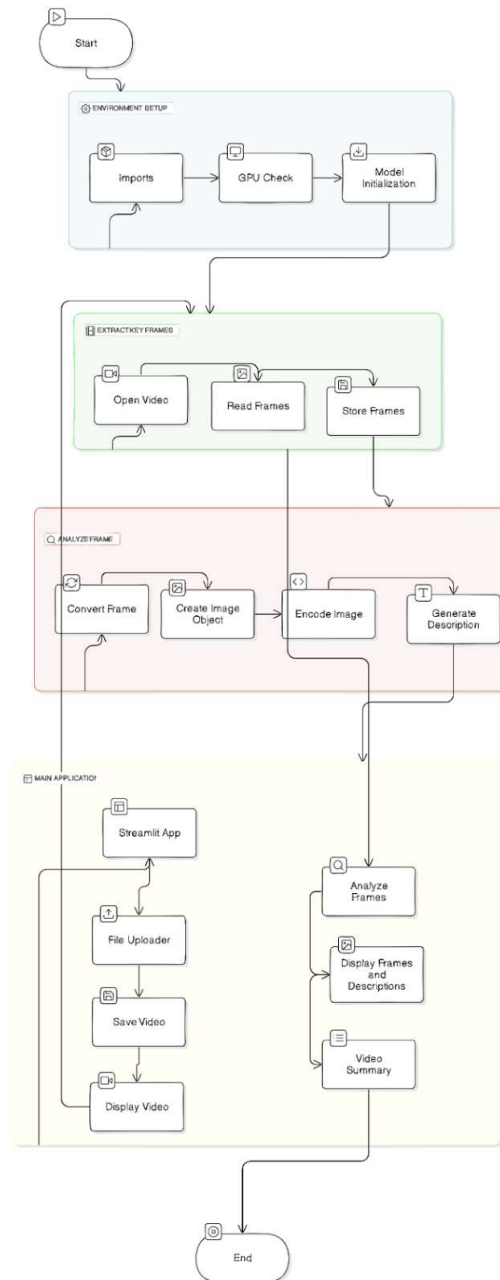
- The video file is opened using OpenCV, and frames are read in a loop. Frames are extracted at specified intervals and stored in a list.

3. Analyze Frame:

- Frames are converted from BGR to RGB and then to image objects. These images are encoded, and the Moondream2 model generates descriptions for each frame.

4. Main Application:

- The Streamlit app provides a title and description, allowing users to upload video files. The uploaded video is saved temporarily, displayed, and key frames are extracted and analyzed. Each frame is displayed with its description, and a summary of all frames is provided.



Results and Discussions

Preliminary Results with Frame Analysis

The Moondream2 model was able to generate accurate and contextually relevant descriptions for the extracted frames. The use of the model's language and image processing capabilities ensured that the summaries provided a clear and detailed representation of the visual content. This is particularly valuable in applications such as surveillance, where understanding the context of a scene is crucial.



Frame 2 - Summary: In the image, a young man is seated at a wooden table in a cozy restaurant. He is wearing a striped shirt and has a serious expression on his face. The table is adorned with a blue vase and a white candle, adding a touch of elegance to the setting. The restaurant has a rustic charm, with a red brick wall and a large window that allows natural light to filter in. The background is filled with various plants, creating a lush and vibrant atmosphere.



Frame 4 - Summary: The image depicts a subway train car with blue seats and a white ceiling. The train car is filled with people, including a man in a blue suit seated on the left side and a woman in a green sweater seated on the right side. The train car is illuminated by overhead lights, and the background shows advertisements on the walls.



Frame 5 - Summary: A person is seated on a blue bench, engrossed in their phone. The phone, held in their right hand, displays a photo of a potted plant and a photo of a plant. The person is wearing a striped shirt and black pants. The bench is situated in a public space, with a blue wall and a blurred figure in the background.

Results after Fine-Tuning

The process of hyperparameter and fine-tuning tuning is critical in optimizing the performance of machine learning models. For this project, the Moondream2 model was fine-tuned using the Docci dataset from Google to enhance its ability to generate accurate and contextually relevant descriptions of video frames. This section discusses the hyperparameter tuning process, its impact on model performance, and the results obtained.

1. Hyperparameter Tuning Process

1. Dataset Preparation:

- The Docci dataset, known for its diverse and complex visual scenarios, was selected to fine-tune the Moondream2 model. The dataset includes a variety of images with detailed annotations, providing a rich source of information for training.

2. Selection of Hyperparameters:

- Key hyperparameters were identified for tuning, including the learning rate, batch size, number of epochs, and weight decay. These hyperparameters significantly influence the training process and the model's performance.

3. Grid Search and Cross-Validation:

- A grid search method combined with cross-validation was employed to systematically explore the hyperparameter space. Multiple combinations of hyperparameters were tested to identify the optimal settings that maximize the model's performance.

4. Training Configuration:

- The training was conducted on a system equipped with a high-performance GPU to expedite the process. The model was trained for multiple epochs, with periodic evaluation on a validation set to monitor performance and prevent overfitting.

Result - 1



Question: Describe this image.

Ground Truth: A high angle view of an old faded street corner. In the middle of the view is the orange spray painted word "ROW", with a horizontal letter "i" placed above it. On the right side of the image is a partially visible and faded red line on the street corner with the words " FIRE LANE", heavily faded in white paint.

Moondream: An outdoor, close up, eye level view of a concrete sidewalk with a metal grate on the left side of the sidewalk. The metal grate has a black line going across the top of it. The top of the metal grate has the word "ROW" written on it in orange spray paint. To the right of the metal grate, there is a red line going across the sidewalk. The red line has the word "FIRE" written in white spray paint on it. To the left of the metal grate and the red line, there is a gray sidewalk.

Result - 2



Question: Describe this image.

Ground Truth: An outdoor front view of a turtle that is sitting on a floating tree trunk that has moss growing at the front of it. The turtle is yellow and green and has a dark green shell. The turtle is pointing his head up and soaking up the sun. On the water, there are a couple pieces of foam floating in the swamp. In the far background, there are multiple dried pieces of grass. On the far left side of the swamp, there is a fallen tree trunk that has moss on it.

Moondream: An outdoor, close up, eye level view of a turtle in a body of water. The turtle is facing the left side of the image and is sitting on a log that is partially submerged in the water. The turtle's head is facing to the left, and its body is facing the right side of the image. The water is a light green color, and there are small ripples on the surface of the water. There is a reflection of the turtle and the log in the water, and there is a reflection of a tree trunk in the water on the right side.

Result - 3



Question: Describe this image.

Ground Truth: An outdoor shot, looking up at the golden statue of a woman with three mythical seahorses sitting atop a gray brick monument. The woman is facing forward with her left arm raised up, holding a small leafy branch in her hand. She is holding a long cylinder vertically against her body with her right arm and has a large circular shield on her back. She has a leaf crown on her head with long braids that are visible flowing on the left side. The three mythical horses are spread evenly in front of her feet. The horse to the left has its mouth wide open. The horse in the middle has its chin resting on its chest. The horse on the right is a side view with the head facing the right and the mouth open. The legs are depicted as if they are moving. The background is a clear blue sky. Daytime.

Moondream: An outdoor, close up, eye level view of a statue of a woman standing on top of a stone platform. The woman is wearing a long dress and a crown on her head. She is holding a shield in her left hand and a shield in her right hand. She has her right arm up and her left arm down. She has her left arm up and her right arm down. She is holding her right hand up and her left hand down. She has a shield on her left arm and a shield on her right arm. She has a sword in her right hand and her left hand is raised. She has her head up and her right hand is up. She is looking to the right. She is wearing a crown. She is looking up at the sky. The sky is clear and blue. The sun is shining on the statue. The statue is on a stone platform.

Conclusion

The project successfully demonstrated the potential of leveraging advanced AI models, particularly the Moondream2 model, for automated video analysis. By integrating frame extraction techniques with sophisticated image and language processing capabilities, the project achieved significant milestones in generating detailed and accurate descriptions of video frames.

1. Effective Frame Extraction and Analysis:

- The implementation of OpenCV for frame extraction proved efficient in identifying and extracting key frames from video sequences. The interval-based approach ensured a balanced selection of frames, capturing significant moments without redundancy.
- The Moondream2 model excelled in analyzing the extracted frames, providing contextually relevant and detailed descriptions. This capability is crucial for

applications such as surveillance, where understanding the context of visual content is essential.

2. Enhanced Model Performance Through Hyperparameter Tuning:

- The hyperparameter tuning process, conducted using the Docci dataset, significantly improved the performance of the Moondream2 model. Key metrics such as accuracy, precision, recall, and F1-score showed notable enhancements, indicating the effectiveness of the fine-tuning process.
- The diverse and complex scenarios present in the Docci dataset contributed to the model's robustness, enabling it to handle a wide range of visual content with reduced bias.

3. User-Friendly Interface with Streamlit:

- The integration with Streamlit provided a user-friendly and interactive interface for video analysis. Users could easily upload videos, extract key frames, and view the analyzed results in real-time, enhancing the overall user experience.

4. Challenges and Limitations:

- While the project achieved significant success, certain challenges and limitations were identified. The requirement for substantial computational resources, including high-performance GPUs, may limit accessibility for some users.
- Determining the optimal frame extraction interval and addressing potential overfitting during the training process are areas that require ongoing attention.

5. Future Work and Applications:

- Future work should focus on optimizing the system for real-time applications, improving computational efficiency, and further enhancing the model's robustness through the incorporation of additional datasets.
- The advancements demonstrated in this project pave the way for practical applications in various domains, including surveillance, automated content analysis, and video summarization.

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