## Composed Video Retrieval via Enriched Context and Discriminative Embeddings (Supplementary)

## A. Description Generation

We used recent open-source multi-model conversational model such as MiniGPT-4 [3] to generate the detailed description of input video using middle frame of the video. We utilize pre-determined prompts in the given format ###Human :< Img >< ImageFeature >< /Img >< Instruction > ###Assistant : ###Human, corresponds to the prompt. ###Assistant, serves the purpose of determining the system role, which in our case is defined as "You will be able to see the image once I provide it to you. Please answer my questions." < Instruction > refers to a the instruction given to LLM which is "Describe the given image in details". Both text queries undergo tokenization and fed into the LLM [1] which generates the detailed description of the input image.

Fig. 1 and 2 plays a crucial role in emphasizing the significance of the detailed captions generated by our method for effective target video retrieval. The figure distinctly illustrates the limitations of the default short captions used in WebVid dataset. These conventional captions often lack the essential contextual details needed to accurately matched with the corresponding target videos. By contrast, our generated detailed captions encompass a broader range of contextual elements, ensuring that the key aspects of the reference video are effectively preserved and mirrored in the retrieved target videos. This comparison in both the figures 1 and 2 not only highlights the deficiencies in webvid captions but also underscores the enhanced performance and accuracy achieved through our approach using these detailed descriptions. The examples serves as a compelling visual representation of the added value brought by our detailed descriptions for composed video retrieval.

Problem with generating descriptions from multi-modal conversational LLM is it's hallucinated outputs. These hallucinations refer to the occurrences where the model generates responses or outputs that are either irrelevant or factually incorrect, deviating from the expected or logical outcome based on the input data. The process of identifying these hallucinatory examples is detailed in Section 3.2 of the paper. In this section, we describe the methodol-

ogy used to detect and categorize these instances. Our approach involves setting a threshold for hallucination detection, which, in this case, is determined to be 0.2. This threshold represents a quantifiable measure or criterion used to filter out responses that are likely to be hallucinations.

Once these examples are filtered based on the hallucination threshold, we then undertake a manual review and correction process. This manual intervention is crucial as it not only helps in rectifying the inaccuracies in the model's outputs but also provides valuable insights into the nature and characteristics of the hallucinations produced by the model. Through this correction process, we can refine the model's performance, enhancing its reliability and accuracy.

## **B.** Additional Qualitative Results

Fig. 3 and 4 shows the additional qualitative comparison with our baseline CoVR-BLIP [2] where the top row represents the baseline [2] results and bottom row represents the our approach. For each example video, top-10 retrieved videos with their similarity scores were shown. Our approach correctly retrieved targeted video as highlighted in green tic whereas the baseline CoVR-BLIP [2] not able to retrieve correct target video with the highest similarity score.

Figures 3 and 4 illustrate a qualitative comparison between baseline CoVR-BLIP [2] and our approach. These figures highlights the advancements and improvements our method offers over the baseline in the context of composed video retrieval accuracy and relevance. In both figures, the top row displays results obtained using the baseline CoVR-BLIP model, while the bottom row showcases the outcomes achieved with our approach. This side-by-side arrangement allows for a direct and intuitive comparison between the two methods. For each example video featured in these figures, the top-10 retrieved videos, along with their respective similarity scores, are presented. These similarity scores are key indicators of how well the retrieved videos match the input query video in terms of content, context, and change elements.

A significant aspect highlighted in these figures is the ef-

ficacy of our approach in accurately retrieving the targeted video. This is visually represented by a green tick mark, indicating instances where our model successfully identified the correct target video with the highest similarity score. In contrast, the baseline CoVR-BLIP model often fails to retrieve the correct target video with the highest similarity score. This difference is critical as it underscores the enhanced precision and effectiveness of our method in identifying and ranking relevant video content in response to a given input. With these comparative examples, Figures 3 and 4 not only demonstrate the superiority of our approach over the baseline but also offer tangible evidence of the practical improvements our model brings to the field of composed video retrieval using detailed descriptions. This comparison is useful in showcasing the real-world applicability and benefits of the advancements our approach contributes to the domain. Additionally, Fig. 5 shows the qualitative examples for our proposed approach where our approach successfully retrieve the correct target video as highest similarity.

## References

- [1] Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%\* chatgpt quality, 2023.
- [2] Lucas Ventura, Antoine Yang, Cordelia Schmid, and Gül Varol. CoVR: Learning composed video retrieval from web video captions. *AAAI*, 2024. 1, 5, 6
- [3] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023. 1

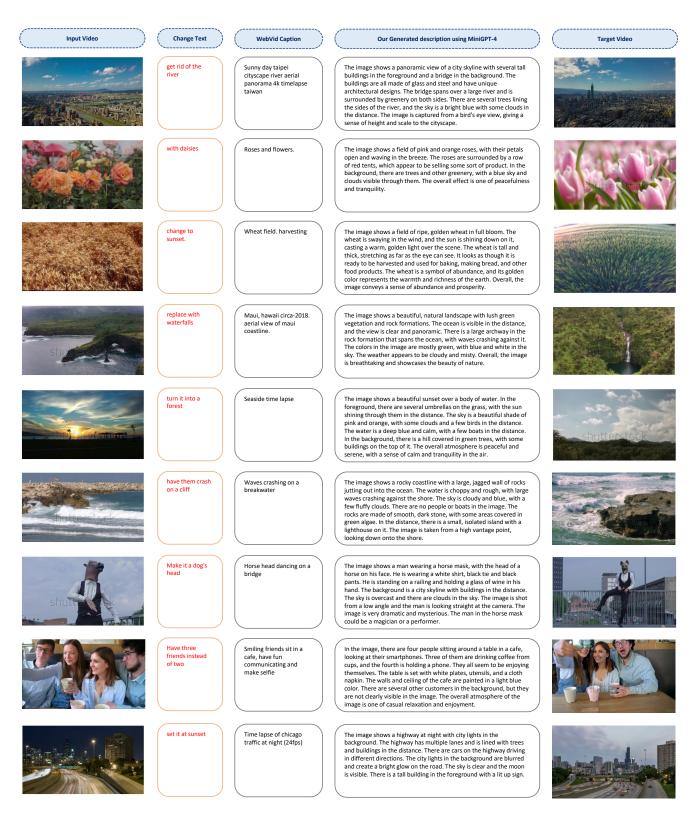


Figure 1. Examples of our detailed descriptions providing richer information for reference video compared to default Webvid-CoVR Captions. Our detailed descriptions enhance the understanding and interpretation of the reference video, offering more context, clarity, and specific information that the default webvid captions may lack.

Input Video WebVid Caption **Change Text** Our Generated description using MiniGPT-4 **Target Video** Wind on a wheat Poppy on a wheat field The image shows a field of tall, green grass and red poppies growing in it. The grass is waving in the breeze and the poppies are in full bloom, their bright red petals swaying in the wind. The sky is clear and blue, with a few white clouds floating overhead. The sun is shining down on the scene, casting dappled shadows on the grass. In the distance, there is a small farmhouse with a red roof and white picket fence. The farmhouse looks like it is surrounded by trees and has a small barn in the back. In the field The image shows a bride and groom walking down a street on their wedding day. The bride is wearing a white dress and holding a bouquet of red roses. The groom is wearing a black tuxedo and Lovely couple walking in holding her hand. They are walking down the street holding hands and looking at each other with smiles on their faces. Behind them, there is a stone wall with trees and shrubs growing on it. The scene bathed in warm sunlight, casting shadows on the wall. In the background, there are buildings and cars driving on the street change to be a bridge Aerial view of village in 1. The image shows a small town nestled along the banks of a river with trees and houses lining the sides of the river.2. The town hoi an, vietnam appears to be quite old and quaint with wooden houses and a few appears to be quite or used in the town is surrounded by green trees and bushes, giving it a serene and peaceful atmosphere. 3. There are a few boats tied up to the banks of the river, suggesting that the town has a riverfront. The river is fairly wide and appears to have some water flowing through it. Young woman drinking tea and admire view from window at home at The image shows a woman standing at a window in a modern office building, looking out at the city at night. She is holding a mug of hot coffee and smiling at the view. The background is lit up by city lights, instead of tea night and there are some trees and buildings visible in the distance. The woman is wearing a dark sweater and jeans, and her hair is dark and casual. The overall feeling of the image is one of warmth and make it more Seamlessly looped flight The image depicts a sunset over a vast ocean with a cloudy sky in the fantasy-like over ocean at blue background. The sun is setting behind the clouds, casting a warm glow on the water. The colors in the sky are shades of orange and pink, with a slight purple tint to them. The water is calm, with a few small waves lapping at the shore. In the foreground, there are some trees on the shore, their branches swaying in the breeze. The overall mood of the image is peaceful and calming. make it cloudy Bird of prey flying against This image shows a large bird flying in the blue sky. The bird has a the blue sky long black tail and a large wingspan. Its body is brown with black feathers and its wings are spread open as it flies. The background is a bright blue sky with a few clouds in the distance. The image is quite detailed and allows for a clear view of the bird's anatomy and flight movements. The image shows a large bridge spanning a body of water with several cars driving under it. On either side of the bridge are tall buildings with palm trees in the foreground. The sky is clear and blue Clearwater, united states Make it a dog's may, 2017: bridge in clearwater with a few clouds in the distance. The water is calm and reflective in the sunlight. There are no people or boats visible in the image. The bridge appears to be made of concrete and steel. Overall, the image is a view of a large, modern bridge spanning a body of water with tall buildings in the background. Change to the 3d rendered, medically The image shows a human skeleton with an X-ray view of the body's larynx accurate illustration of organs and bones. The skeleton appears to be a male adult, with a head and limbs visible. The image is in a blue color, with no other visible features or background. The organs and bones appear clear and visible, with the heart and lungs in the chest area, the liver and the human gallbladde spleen in the upper abdomen, and the kidneys and adrenal glands in the lower abdomen. Have a waterfall Roofs mostar This image shows a small town with old buildings and a rocky terrain in the background. The buildings are made of stone and have wooden shutters on the windows. The roofs are made of clay tiles and there are mountains in the background. There are no trees or other vegetation in the foreground, only rocks and the buildings. The town seems to be located in a mountainous area with steep slopes and rocky terrain. There is no road or other infrastructure visible in the image.

Figure 2. Additional examples of our detailed descriptions providing richer information for reference video compared to default Webvid-CoVR Captions. Our detailed descriptions enhance the understanding and interpretation of the reference video, offering more context, clarity, and specific information that the default webvid captions may lack.

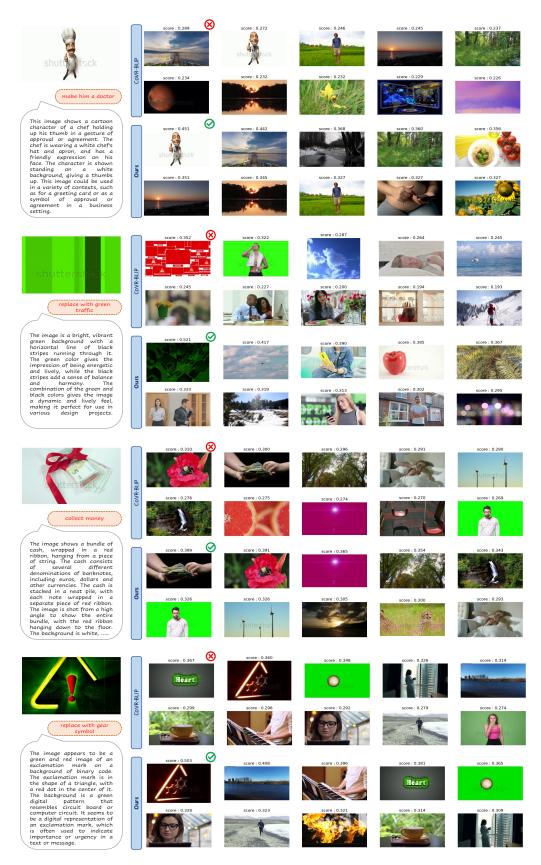


Figure 3. The comparison between the baseline CoVR-BLIP [2] and our approach on selected video samples from the WebVid-CoVR test set. The correct target video retrieved is highlighted with green marks with highest similarity score. The results demonstrates the superior accuracy and relevance of the retrieved videos using our method in comparison with baseline [2] for a given input video, highlighting the significant improvements and refinements our approach brings to video content analysis and retrieval.

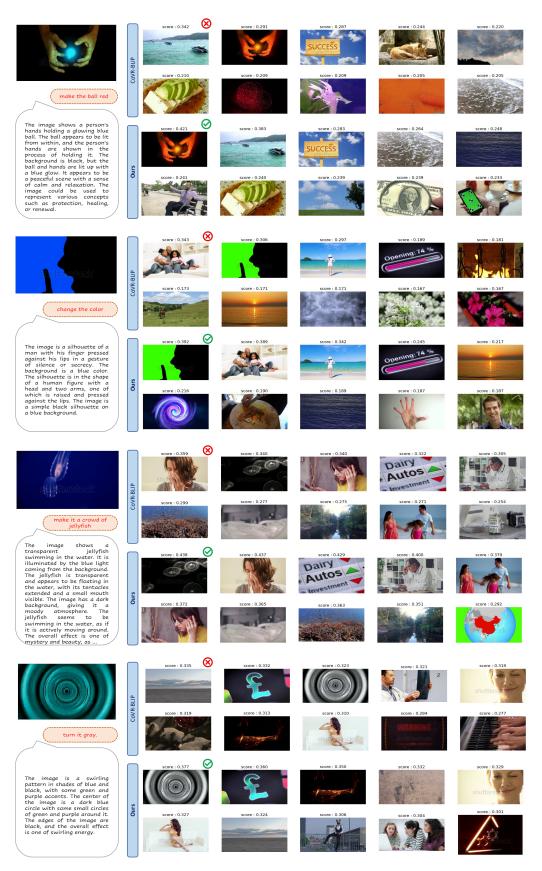


Figure 4. Our approach, as illustrated in the comparison with the baseline CoVR-BLIP [2], showcases its efficacy on chosen video samples from the WebVid-CoVR test set. Videos retrieved by our method that precisely match the target are marked in green, indicating the highest similarity scores.

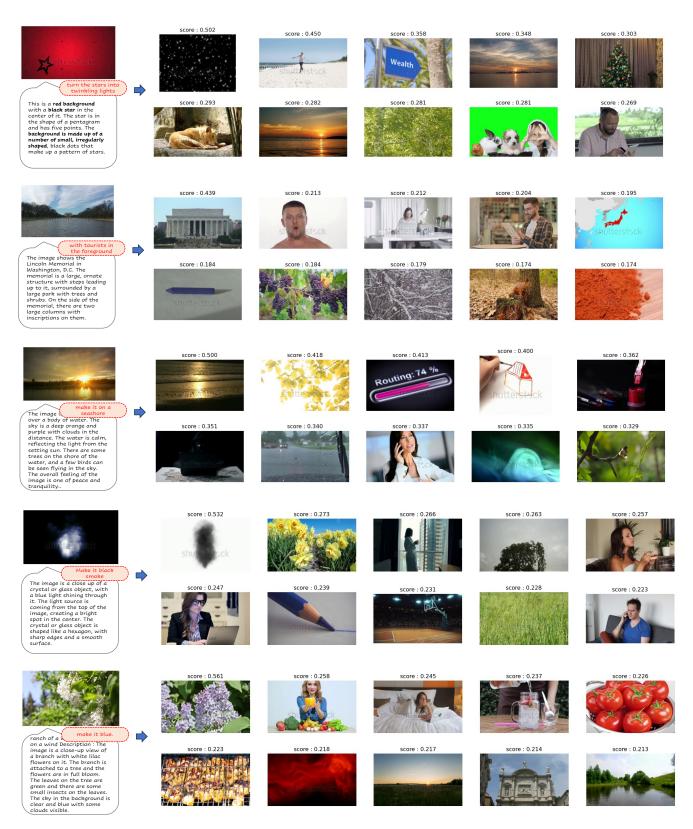


Figure 5. Positive Outcomes Demonstrated by our approach on WebVid-CoVR Test Set. The figure presents the top-10 videos retrieved for an input video, showcasing the effectiveness of our approach. Each video is accompanied by a similarity score, indicating the degree of correlation between the input composition and the retrieved target video, thus emphasizing the precision and relevance of our retrieval system in identifying closely matched content.