

BSSE FINAL PROJECT

Software Design Specification

Video Similarity Detection



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Software Design Specification

SDP Phase II

Video Similarity Detection

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Table of Contents

Table of Contents	i
Revision History	ii
Abstract.....	3
1. Introduction.....	4
1.1 Product	4
1.2 Background	4
1.3 Objective(s)/Aim(s)/Target(s).....	5
1.4 Scope	5
1.5 Business Goals	7
2. Overall Description	8
2.1 Product Features.....	8
2.2 Functional Description	10
2.2.1 Use-Case 1	10
Table 1: UC-1.....	10
2.2.2 Use-Case 2	11
Table 2: UC-2.....	11
2.2.3 Use-Case 3	11
Table 3: UC-3.....	12
2.3 User Classes and Characteristics.....	12
2.4 Design and Implementation Constraints	12
2.5 Assumptions and Dependencies.....	12
3. Technical Architecture	14
3.1 Application and Data Architecture.....	14
3.1.1 Figure 1: System Demonstration.....	16
3.1.2 Figure 2: System Use Cases.....	17
3.2 Component Interactions and Collaborations	17
3.3 Design Reuse and Design Patterns.....	18
3.4 Technology Architecture.....	19
4. Screenshots/Prototype	20
4.1 Workflow	20
4.1.1 Figure 3: System Swim Lane.....	21
4.2 Screens	22
4.2.1 Figure 4: System Prototype 1.....	22
4.2.2 Figure 5: System Prototype 2.....	23
4.2.3 Figure 6: System Prototype 3.....	24
5. Revised Project Plan	25
5.1.1 Figure 7: Project Planner 3	25
6. References	25
Appendix A: Glossary.....	1
Appendix B: IV & V Report	2

Revision History

Name	Date	Reason For Changes	Version

Abstract

With the rise of internet socialization went to a next level, people share a lot of text, images and videos to socialize with others, this limits less sharing of visual content bring lot of problems like copy right protection, duplication, misinformation, sensitive and harmful content. The solution to this problem is very costly, time-taking, and effort-seeking, because tens of thousands of videos are uploaded daily on different social media platforms. In these circumstances performing these tasks manually is not possible and if possible, to an extent will be so costly, to harness this problem there should be a model which will be capable to accurately detecting the derived video content from the reference videos data set with minimum resource consumption. Paying attention especially to video copy detection, there are two main challenges. The first is to detect the manipulated and edited video derived from the dataset and utilization of minimum time and resource consumption. Video copy detection challenge encompasses two tasks, first is descriptor track in which the model should predict that the query video is derived video from the dataset or not by confidence score. Secondly matching track, the model will provide the temporal segment of the copied part in query video. The model will be trained on specially designed dataset for video similarity detection model by Meta named as YFCC100M containing 0.8 million videos with noise removal approximately 15 to 25 seconds which are being dividing into three-part training, validation and testing and the dataset will be shrink due to resource limitation.

The method of the first placed group in the competition will be discussed in this paper. The query video pattern is categorized in three groups: first, not edited, second, and the third, in which frames contain more than one scene. Dual level method with video editing detection (VED) will tell whether the query video is edited or not. For unedited video the random vectors with norms and bias will be replaced with negative value in descriptor. For editing video for the multiple scenes, the traditional image processing method will be used. By using dual level detection, the computation cost will be reduced. Frame Scene Detection (FSD) is used to deal with the major problems of video copy detection.

For the matching track there are two problems how to extract the features, with embedding or similarity matrix and matching of copy segments in video. Both tracks required the features; by using embedding changing descriptor model, embedding also must change, as compared to embedding similarity matrix doesn't change, so similarity matrix is used. And for video segment copy we used similarity alignment model (SAM) which takes similarity matrix as an input and gives results in the score matrix.

1. Introduction

1.1 Product

The product of this project is a simple user-friendly web-based graphical interface designed to enhance content moderation on social media platforms. This interface serves as a powerful tool for detecting manipulated clips within query videos. Users would be able to drag a video or give link of the video containing subpart of the referenced video on which the model has been trained, press retrieve replicas button to get same pairs and run temporal segment button to play the same section. Interface would display the possible matched pairs of query and reference video from the dataset according to the confidence score with their potential temporal location providing users with confidence scores and temporal localization information. The primary goal is to offer a solution to the challenges associated with content manipulation, misinformation, and the presence of inappropriate content in the realm of social media.

This graphical interface represents the culmination of advanced deep learning algorithms, particularly focusing on video copy detection. Leveraging the capabilities of artificial intelligence, computer vision, and deep learning techniques, the product aims to deliver a reliable and efficient solution for moderating and ensuring the integrity of visual content shared on various social media platforms.

1.2 Background

Image and Video copy detection has been one of the hottest working domains for the past ten years. In 2007 on Muscle-VCD dataset video copy detection work done as a series of TRACvid [8], in 2007 another work found like current web video search (CWeb) [9] was based on keywords or tags and the near duplicate video use to come in the result the model this by matching the signatures derived from color histograms even if this did not work then feature based near-duplicate detection but was comparatively expensive. In 2008 The content-based copy detection (CCD) [10] benchmark worked with a large collection of synthetic queries, which is atypical for TRECVID, as was the use of a normalized detection cost framework. In 2011 Near Duplicate Video Retrieval (NDVR) [11] became popular when it solves the problem of accuracy as previous models was extracting single feature to retrieve duplicate video, but single feature was not enough to do so, here the Multiple Feature Hashing (MFH) technique begets the comparatively good accuracy. In 2013 Event retrieval through Circulant Temporal Encoding (CTE) [12] was very effective in this domain this model works by embedding the frame descriptors to jointly represent the appearance and temporal order and product quantization to complex vectors to compress the descriptors on the new datasets of EVVE. Art Vision base article by Lukas Klic which represents computer

vision APIs with the Research Space platform, allowing for the matching of similar artworks and photographs across cultural heritage image collections [5]. TransVLC: an attention-enhanced video copy localization network which is optimized directly from initial framelevel features and trained end-to-end with three main components: customized Transformer, correlation and SoftMax layer for similarity matrix generation, and a temporal alignment module for copied segments localization [6]. George Awad and Keith Curtis evaluated video retrieval tasks at TRECVID 2022 in which TRECVID, a national institute, was researched on in content-based video retrieval [7]. In the context of image similarity 2008 the GIST [12] descriptor had recently received increasing attention in the context of scene recognition. In this paper we evaluate the search accuracy and complexity of the global GIST descriptor for two applications, for which a local description is usually preferred: same location/object recognition and copy detection. We identify the cases in which a global description can reasonably be used. The comparison is performed against a state-of-the-art bag-of-features representation. To evaluate the impact of GIST's spatial grid, we compare GIST with a bag-of-features restricted to the same spatial grid as in GIST.

1.3 Objective(s)/Aim(s)/Target(s)

The project's primary target is to generate vector representations of videos using advanced deep learning algorithms by classifying the content in three classifications edited, unedited and multi frame videos using with dual level detection method with video editing detection. In the Matching Track, specific emphasis is placed on creating a model capable of directly detecting clips within a query video, corresponding to segments within a larger amount of reference videos by Frame level video decomposition and using Similarity Alignment Model.

1.4 Scope

Ads recommendation system:

Video similarity detection can analyze the content of videos that users have engaged with or viewed. By identifying patterns and similarities in users' video consumption behavior

Video content classification:

Video similarity detection can be used to classify videos into different genres based on visual and thematic similarities. For example, it can group together action movies, comedies, or dramas by identifying common visual elements or themes within the content.

Crime events investigation:

In the context of crime events investigation, video similarity detection can serve as a valuable tool for law enforcement agencies and investigative teams.

Video surveillance:

Video similarity detection can analyze surveillance footage to identify similarities between different incidents. This helps investigators link events, recognize patterns, and track the movements of individuals involved in criminal activities.

Street crime detection:

Video similarity detection enables real-time monitoring of street surveillance cameras. The system can continuously analyze video feeds to identify patterns or anomalies associated with criminal behavior, such as theft, vandalism, or assault.

Plagiarism and Copyright Infringement:

Video similarity detection models can be used to identify instances of video content that has been copied or plagiarized from other sources, helping content creators and copyright holders to protect their intellectual property.

Content Duplication:

Video platforms and content aggregators can use video similarity detection to identify and remove duplicated or near duplicated content, ensuring that their platforms offer original and diverse content to users.

Content Moderation:

Video platforms can employ similarity detection to identify and flag videos that violate community guidelines or contain inappropriate or offensive content, improving content moderation efforts.

Video Verification:

In cases where the authenticity of a video is questioned, similarity detection models can be used to compare the video in question with other videos to determine if it has been manipulated or altered.

Video Analytics:

Similarity detection can help content creators and marketers analyze their video performance by identifying patterns of similarity among different videos, providing insights into what types of content resonate with their audience.

Educational Content:

Video similarity detection can help educators and students discover educational videos that cover similar topics, enabling more comprehensive learning experiences.

1.5 Business Goals

The business goals in this project are like big targets we want to hit.

Content Moderation in Social Media:

Social media platforms employing video similarity detection aim to moderate and filter content effectively. This ensures compliance with regulations, protects users from inappropriate content, and maintains a positive user experience.

Data-Driven Decision-Making:

Businesses leveraging video similarity detection aim to make informed, data-driven decisions. This includes using insights from video analytics to adapt strategies, improve security protocols, and enhance operational efficiency.

Plagiarism and Copyright Infringement:

Video similarity detection models can be used to identify instances of video content that has been copied or plagiarized from other sources, helping content creators and copyright holders to protect their intellectual property.

Content Duplication:

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Similarity detection can help content creators and marketers analyze their video performance by identifying patterns of similarity among different videos, providing insights into what types of content resonate with their audience.

Educational Content:

Video similarity detection can help educators and students discover educational videos that cover similar topics, enabling more comprehensive learning experiences.

2. Overall Description

2.1 Product Features

The project is organized into two primary tracks:

Plagiarism Verification:

In this track, the system is designed to verify whether the queried video is directly copied from the videos present in the reference dataset. It aims to detect instances of plagiarism or unauthorized use of copyrighted material by comparing the queried video with the reference dataset.

Duplicate Videos:

This track focuses on identifying pairs of videos in the reference dataset that are highly similar or duplicate to the queried video. It helps in detecting instances where multiple versions of the same content exist, facilitating content management and copyright enforcement.

Similar Videos:

The system provides pairs of potentially similar videos from the reference dataset, arranged in chronological order based on their confidence scores. This feature assists in identifying videos with similar content or themes, enabling users to explore related content efficiently.

Temporal Segments:

This feature highlights the temporal segments within the queried video that match with segments from videos in the reference dataset. It allows users to pinpoint specific portions of the video that are similar to existing content, aiding in content analysis and investigation.

Manipulation Verification:

In this track, the system verifies whether the queried video has undergone manipulation, such as edits or multi-frame alterations. It helps in detecting instances of video tampering or manipulation, ensuring the integrity and authenticity of the content.

2.2 Functional Description

2.2.1 Use-Case 1

Identifier	Drag videos.	
Purpose	Uploading videos.	
Priority	High.	
Pre-conditions	Query video must be contained by reference video set.	
Post-conditions	Model must provide a pair of similar videos with temporal segments.	
Typical Course of Action		
S#	Actor Action	System Response
1	Drag a query video in the video section.	Perform the description and embedding.
Alternate Course of Action		
S#	Actor Action	System Response
1	Corrupt or unseen query video dragged.	Suspicious mark.

Table 1: UC-1

2.2.2 Use-Case 2

Identifier		Feature Extraction.
Purpose		Create Embeddings
Priority		High.
Pre-conditions		Query video must be contained by reference video set.
Post-conditions		Model must provide a pair of similar videos with temporal segments.
Typical Course of Action		
S#	Actor Action	System Response
2	Press “Retrieve Replica” button.	Shows Possible pairs of similar videos.
...		
Alternate Course of Action		
S#	Actor Action	System Response
2	Press “Retrieve Replica” button.	Replica not found.
...		

Table 2: UC-2

2.2.3 Use-Case 3

Identifier	Temporal segments.	
Purpose	Time Stamps Segments.	
Priority	High.	
Pre-conditions	Query video must be contained by reference video set.	
Post-conditions	Model must provide a pair of similar videos with temporal segments.	
Typical Course of Action		
S#	Actor Action	System Response
3	Press “Run Temporal Segments” button.	Shows the query and referenced matched video segments parallely.
...		
Alternate Course of Action		
S#	Actor Action	System Response
3	Press “discard drag” button	Video discarded.
...		

Table 3: UC-3

2.3 User Classes and Characteristics

User classes are identified based on their interest in content tracing, copyright enforcement, and ensuring the safety of social media platforms. Characteristics of each user class are considered, including frequency of use, technical expertise, and security levels.

2.4 Design and Implementation Constraints

Various constraints, including corporate policies, hardware limitations, interfaces with other applications, and design conventions, are considered during the development phase.

2.5 Assumptions and Dependencies

Assumptions include the prerequisite knowledge of AI and deep learning, while dependencies involve external datasets, such as YFCC100M and hardware resources like GPUs.

Assumptions:

Availability of Sufficient Data:

YFCC100M contains 0.8 million videos with noise removal approximately 15 to 25 seconds which are being divided into three-part training, validation and testing and the dataset will be shrink due to resource limitation.

Quality of Footage:

It is assumed that the dataset footage used for training and testing the system is of sufficient quality, with clear visuals.

Compliance with Legal Regulations:

The project assumes compliance with legal regulations related to video surveillance, copyright, and data privacy.

Stable Internet Connection:

The system relies on accessing and processing video data, which requires a stable internet connection. An unstable connection could disrupt the data retrieval and analysis process, affecting the system's performance.

Dependencies:

Availability of Skilled Personnel:

The successful development and deployment of the Video Similarity Detection System depends on the availability of skilled personnel with expertise in artificial intelligence, machine learning, computer vision, and software development.

Access to Hardware Resources:

The project depends on access to adequate hardware resources, including powerful computers or servers equipped with four A100 GPUs with 8GB storage for efficient video processing and analysis.

Integration with Existing Infrastructure:

The system may rely on integration with social media platforms for data collection, storage, and deployment.

Continuous Updates and Maintenance:

The system's effectiveness depends on continuous updates and maintenance to address emerging challenges, improve performance, and adapt to changing user needs.

3. Technical Architecture

3.1 Application and Data Architecture

Application architecture:

Video editing detection:

The system employs a dual level detection method to categorize queried videos based on their editing status. This method helps in distinguishing between unedited videos, edited videos, and videos containing multiple scenes.

Descriptors:

The descriptor in the proposed video similarity detection system extracts meaningful features from videos, transforms them into compact embeddings, calculates similarity between videos, and aids in detecting manipulations within queried videos.

Matching module:

The matching module in the video similarity detection system aligns temporal segments between a query video and reference videos, measures similarity, and provides localization information for matched segments.

APIs and Services:

APIs and services facilitate communication between backend and frontend components of the system. This includes APIs for data retrieval, model inference, and result delivery.

User-Friendly Web Page:

This is your portal to our system. It's a simple webpage where you ask our system to check videos. You must upload video and it gives you which part of video is copied or similar, making the whole process user-friendly.

Data architecture:

Reference Video Repository:

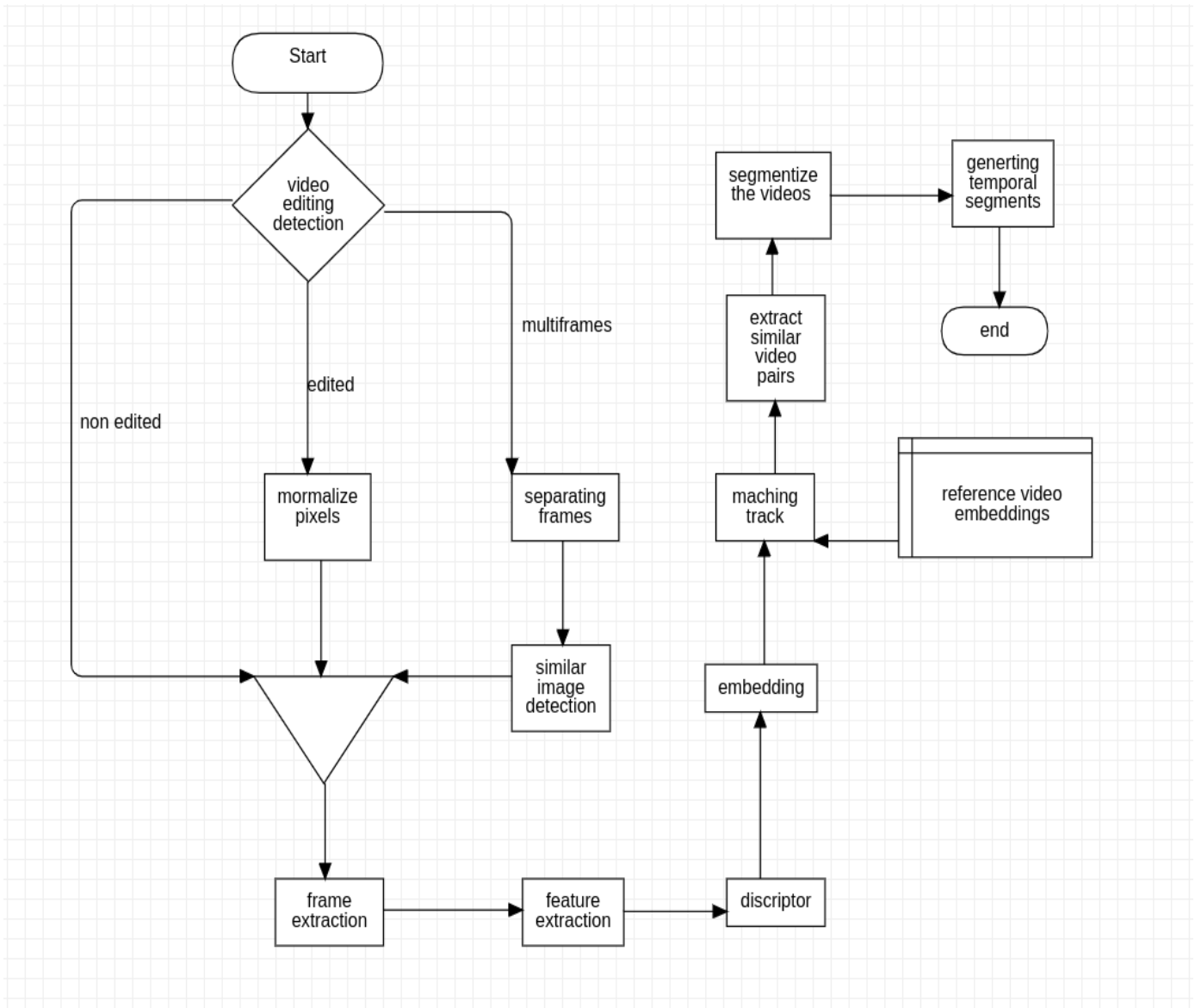
The data architecture includes a repository for storing reference videos used for comparison and similarity detection. These videos may be organized based on categories, tags, or other metadata to facilitate efficient retrieval and analysis.

Smart Descriptions:

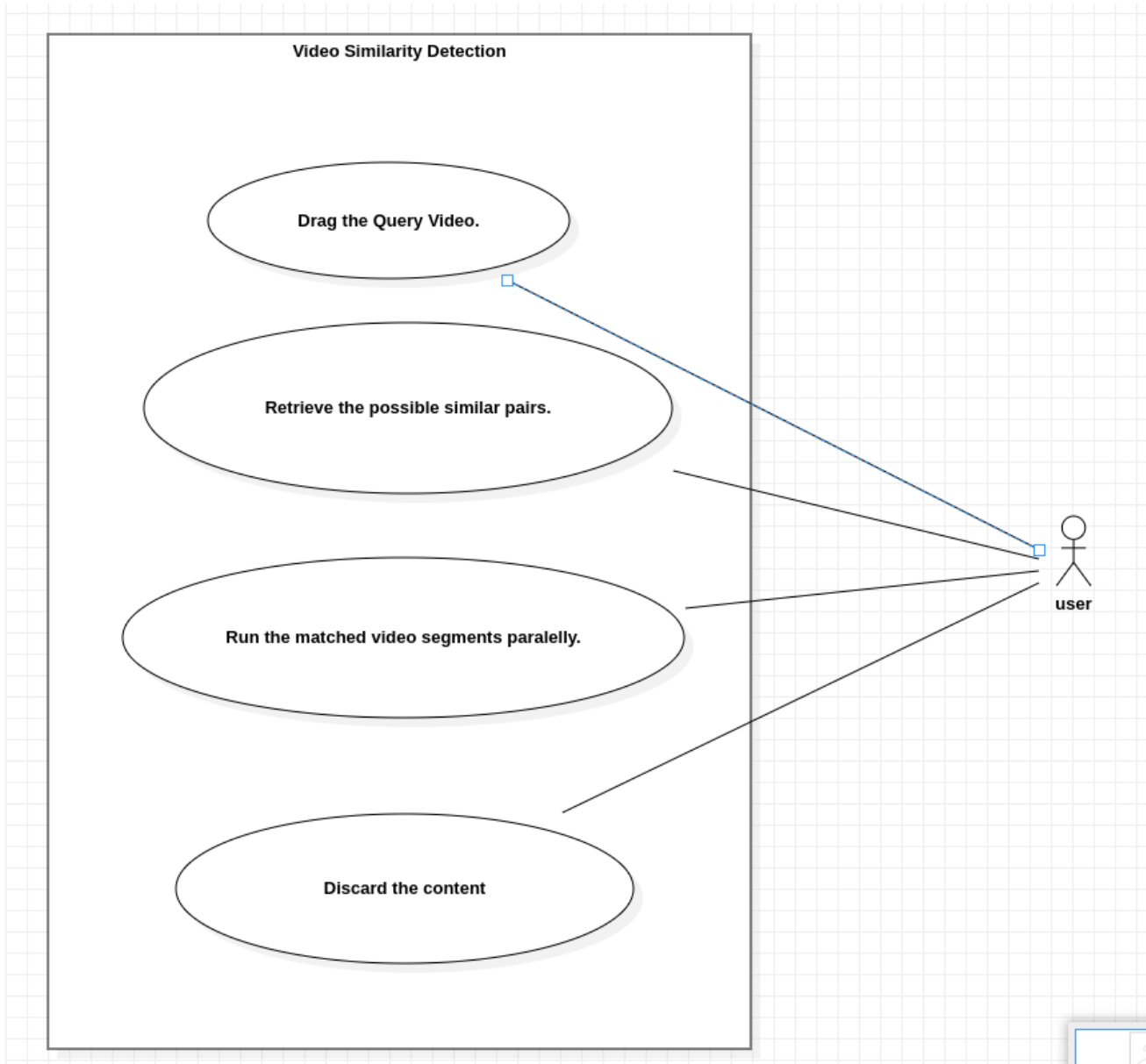
These are like smart summaries of each video. They help our system quickly grasp and compare videos, making the analysis faster and more accurate.

High-Level Architecture Diagram:

The Smart Video Checker and Matching Finder are like the main cities, and the Video Library and Smart Descriptions are like the big databases connecting everything. Your interaction through the web page is like the road that connects you to these smart cities.



3.1.1 Figure 1: System Demonstration



3.1.2 Figure 2: System Use Cases

3.2 Component Interactions and Collaborations

Dual level detection and descriptor Module Interaction:

Form dual level detection the normalized edited videos are given to the descriptor module extracts features from videos, which are then used by the matching module to compare and find similarities between the query video and reference videos.

Descriptor and Matching Module Interaction:

The descriptor module extracts feature from videos, which are then used by the matching module to compare and find similarities between the query video and reference videos.

Matching Module and reference videos descriptions:

The matching module collaborates with the reference videos descriptions to identify any discrepancies between the queried video and reference videos, helping to flag potential manipulations.

3.3 Design Reuse and Design Patterns

Design Reuse:

Utilizing existing libraries and frameworks:

The project can leverage established libraries and frameworks for tasks such as feature extraction, similarity calculation, and manipulation detection. Libraries like TensorFlow or PyTorch can be used for deep learning-based feature extraction, while OpenCV can assist in video processing tasks.

Reusing pre-trained models:

Pre-trained deep learning models for tasks like object detection or image classification can be reused and fine-tuned for specific aspects of the video similarity detection system, saving time and computational resources.

Adopting modular architectures:

Reusing modular design architectures, such as descriptors and matching tracks as microservices or component-based architectures, allows for the integration of existing components and facilitates scalability and maintainability.

Desing Patterns:

Observer pattern:

The descriptor module responsible for extracting features from videos could act as the subject, while the matching module that identifies similar segments could be an observer.

Adapter pattern:

Our system has a couple of components that are written in C++ language for achieving the time efficiency, the other components written in python for their interactions adapter pattern is used.

3.4 Technology Architecture

Backend Development:

Machine learning and deep learning algorithms for video similarity detection. Python libraries like scikit-learn, Keras, or TensorFlow for implementing machine learning models.

Descriptor module: Descriptor Track, we propose a dual-level detection method with Video Editing Detection (VED) and Frame Scenes Detection (FSD) to tackle the core challenges on Video Copy Detection.

Matching module: We propose a Similarity Alignment Model (SAM) for video copy segment matching.

Frontend Development:

This architecture leverages Streamlit's capabilities to create a seamless and responsive user interface for the video similarity detection system, all within the Python environment.

API development:

Descriptor Track, we propose a dual-level detection method with Video Editing Detection (VED) and Frame Scenes Detection (FSD) to tackle the core challenges on Video Copy Detection.

4. Screenshots/Prototype

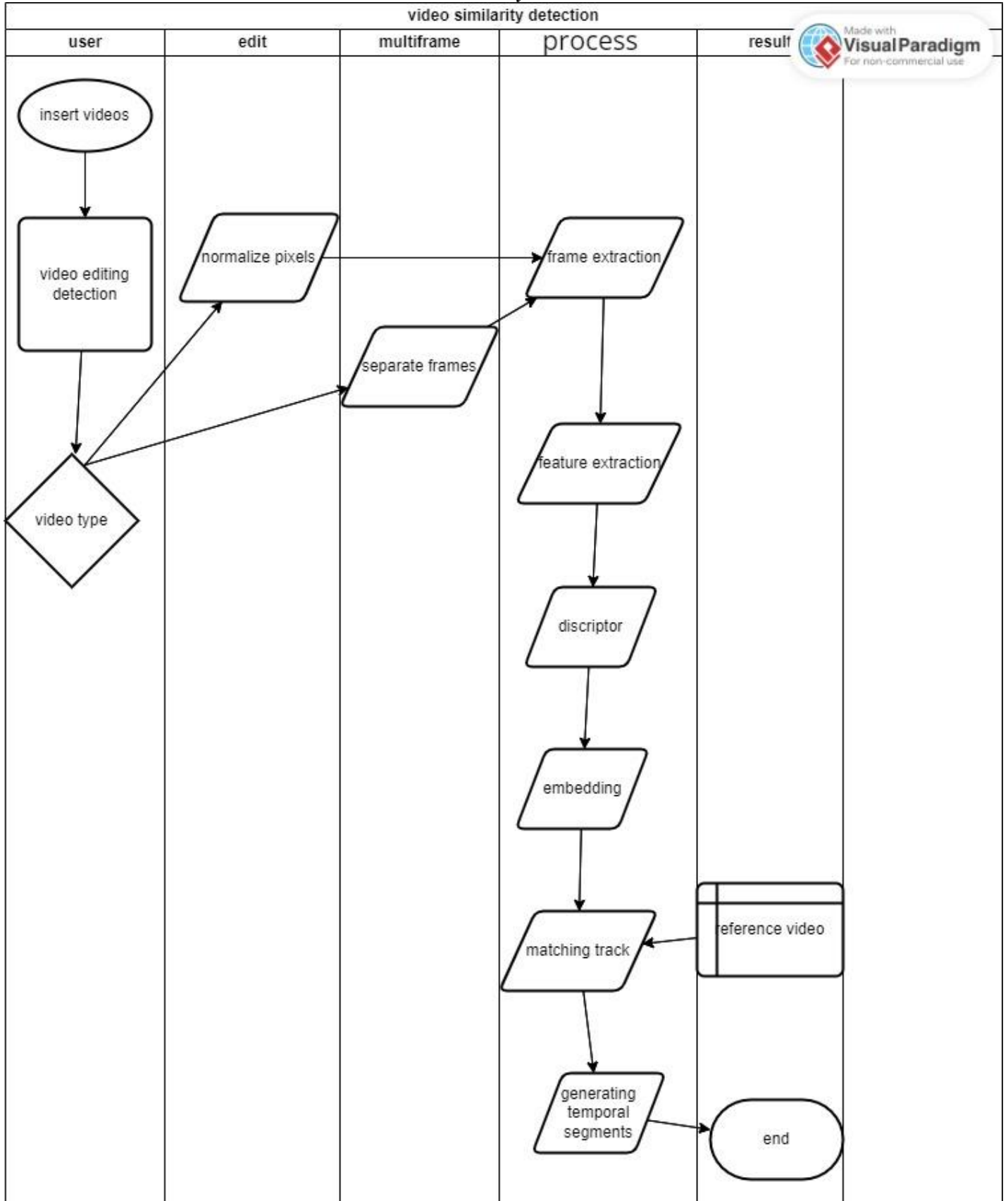
4.1 Workflow

When a user uploads a video, the system initiates a process to determine its authenticity and similarity with reference videos. Initially, it examines whether the video has undergone any editing. If the uploaded video appears unedited, the system swiftly extracts its features and compares them with those of the reference videos. If no significant deviations or manipulations are detected, the process concludes, affirming the video's originality.

Conversely, if the uploaded video shows signs of editing or manipulation, the system delves deeper into its content. It begins by dissecting the video into smaller segments, examining each fragment for resemblances with videos in the reference dataset. This meticulous analysis involves employing advanced techniques, such as similar image detection, to identify any matching components within the uploaded video and the reference set. Furthermore, if the uploaded video comprises multiple frames, the system meticulously separates and analyzes each frame individually. By scrutinizing every frame in isolation, the system ensures comprehensive coverage in detecting similarities or discrepancies between the uploaded video and the reference dataset. The video is split into single frames, from each frame the features are extracted then its embeddings are made which is the digital representation of the of media. These representations are then compared from the embeddings of the referenced data set and provide the original source of the video and possible potential pairs of videos are shown on the screen and temporal segments are highlighted.

Video Similarity Detection

video similarity detection



4.1.1 Figure 3: System Swim Lane

4.2 Screens

The image shows a web application interface for 'SimiVid'. At the top, there is a dark header bar with the 'SimiVid' logo on the left, a search bar with a magnifying glass icon and the text 'Search' in the center, and 'Login' and 'SignUp' buttons on the right. The main content area has a dark background. It features a title 'Check Video Similarity' in white, followed by the subtitle 'Easily check similar videos by giving two videos.' Below this, there are two columns. The left column is titled 'Your Video' in red and contains a white box with a large black plus sign. Below the box is a text input field with the placeholder 'Paste your Link here' and a chain-link icon. The right column is titled 'A Similar Video' in red and contains a similar white box with a plus sign and a text input field with the placeholder 'Paste your Link here' and a chain-link icon. Below these columns, there is a section titled 'Please Chosse any Recommendation or Batton' in red. This section contains three radio buttons: 'Retrive the Possible Similar Pair', 'Run the match Sagment', and 'Not Sure'. Below the first two radio buttons are dropdown menus labeled 'Recomendation' and 'Recomended Reason'. Below the third radio button is a text input field with the placeholder 'Recomended video is Harmful or Disturbing'. At the bottom of this section is a green 'Submit' button. On the left side of the main content area, there is a dark grey 'Help' button.

4.2.1 Figure 4: System Prototype 1

Check Video Similarity

Easily check similar videos by giving two videos.

Your Video



Paste your Link here



Upload from Device

Please Chosse any Recommendation or Button



Retrive the Possible Similar Pair



Run the match Sagment



Not Sure

Recomendation



Recomended Reason

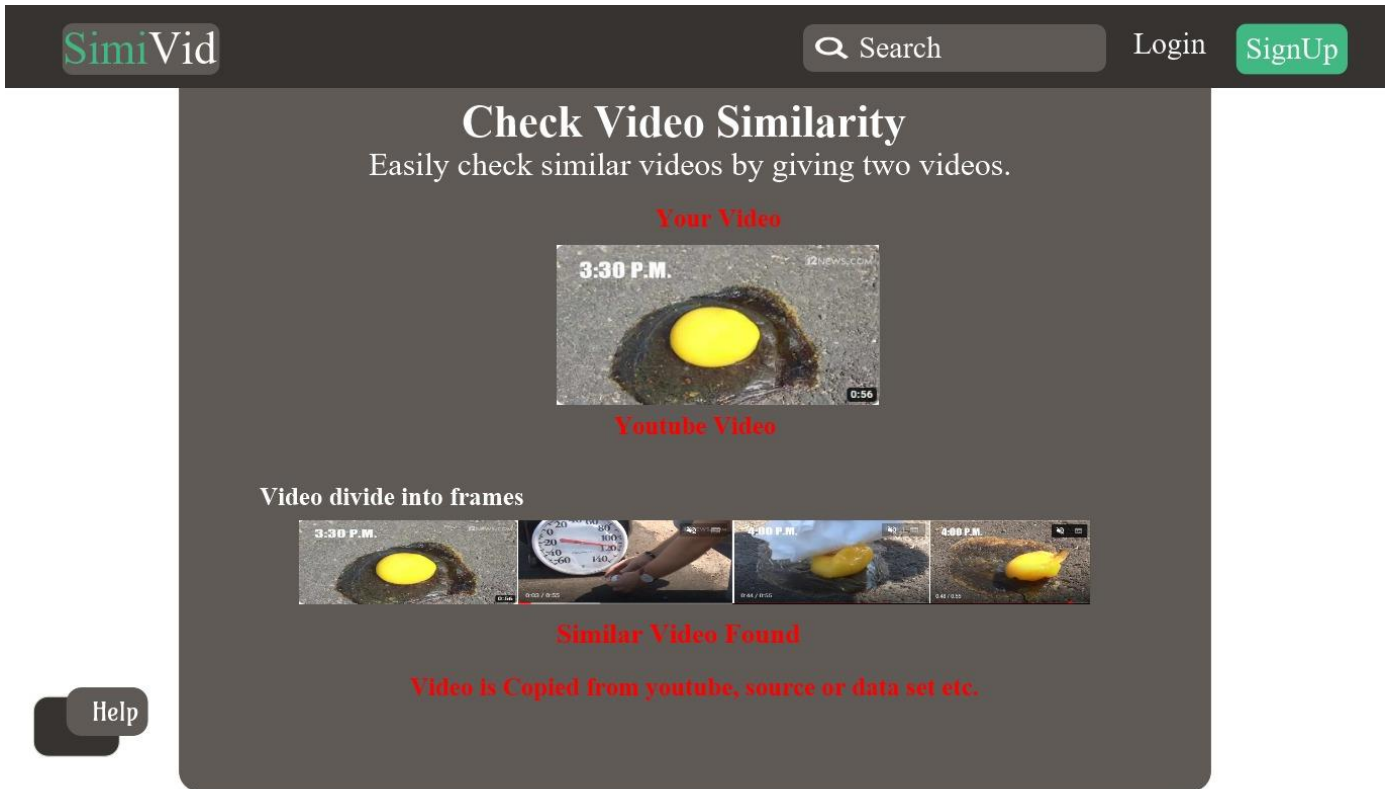


Recomended video is Harmful or Disturbing

Submit

Help

4.2.2 Figure 5: System Prototype 2



4.2.3 Figure 6: System Prototype 3

5. Revised Project Plan

5.1.1 Figure 7: Project Planner 3

6. References

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Video Similarity Detection

Jenicek, Maxim Maximov, Laura Leal-Taixé, Ismail Elezi, et al. The 2021 image similarity dataset and challenge. ArXiv preprint arXiv:2106.09672, 2021.

Appendix A: Glossary

CNN: Convolutional Neural Network.

YOLO: You Only Look Once.

FSD: Frame Scene Detection.

VED: Video Editing Detection.

SAM: Similarity Alignment Model.

TTA: Test Time Augmentation.

TN: Temporal Network.

FCPL: Features Compatible Progressive Learning.

CCD: Content Based Copy Detection.

CWEB: Current Web Video Search.

NDVR: Near Duplicate Video Retrieval.

Appendix B: IV & V Report

(Independent verification & validation)

IV & V Resource

Name

Signature

S#	Defect Description	Origin Stage	Status	Fix Time	
				Hours	Minutes
1					
2					
3					
...					

Table 1: List of non-trivial defects

This document has been adapted from the following:

1. Previous project templates at UCP
2. High-level Technical Design, Centers for Medicare & Medicaid Services. (www.cms.gov)