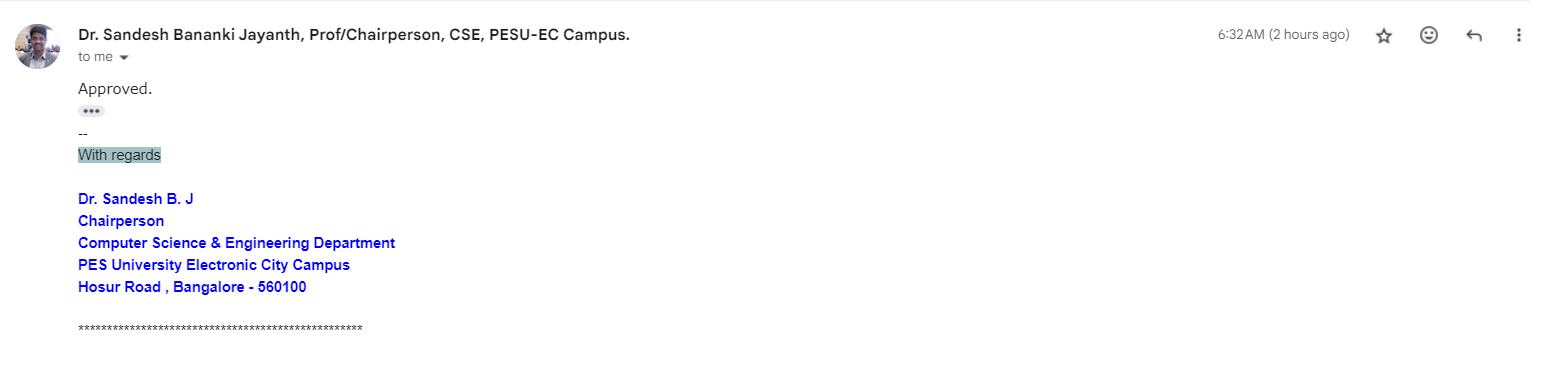
**APPROVAL MAIL FOR BOTH LLD and PPT**



| LOW LEVEL DESIGN AND IMPLEMENTATION DOCUMENT  **Indexing and Summarization of Sports**  **Videos using Multi-Modal Approach**  UE21CS461A – Capstone Project Phase – 2  ***Submitted by:***   | **Krupashree MV**  **Meenal Bagare**  **Melvin Jojee Joseph**  **Naveen Reddy G** | **PES2UG21CS242**  **PES2UG21CS289**  **PES2UG21CS294**  **PES2UG21CS324** | | --- | --- |   Under the guidance of   | **Dr. Sandesh B.J**  Designation  PES University | | --- |   **August - December 2024**  **DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**  FACULTY OF ENGINEERING  **PES UNIVERSITY**  (Established under Karnataka Act No. 16 of 2013)  Electronic City, Bengaluru – 560 100, Karnataka, India |
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# Note:

| **Section 1** | **Common for Prototype/Product Based and Research Projects** |
| --- | --- |
| **Section 2 & 3** | **Applicable for Prototype / Product Based Projects.** |
| **Section 4** | **Applicable for Research Projects.** |
| **Appendix** | **Provide details appropriately** |

# Introduction

# Overview

This Low-Level Design (LLD) document provides a detailed breakdown of the architecture, components, and modules involved in our project titled **"Indexing and Summarization of Sports Videos using a Multi-modal Approach."** The LLD focuses on the internal design of each system component and outlines how the project integrates various technologies and methodologies, including Audio processing, object detection, optical character recognition (OCR), natural language processing (NLP), and video processing as well as tweets to index and summarize significant moments from sports videos.

This design document will cover the data flow, modular structure, class definitions, and the interaction between different components within the system. It ensures a thorough understanding of the implementation process, guiding our team in building and integrating each module effectively.

* 1. **Purpose**

The purpose of this Low-Level Design document is to provide a detailed description of how the **sports video indexing and summarization system** will be constructed and function at the component level. The document bridges the gap between the high-level architectural design and the actual implementation, ensuring each team member understands the module design, interactions, and methods necessary to build a fully functional system.

This document is intended for our team to or validate the implementation of the system. It helps in ensuring that the system's functionalities, such as extracting highlights, analyzing audio and video, detecting scoreboards, recognizing players, and summarizing events, are well-defined and understood at a granular level.

* 1. **Scope**

This Low-Level Design document focuses on the **multi-modal indexing and summarization of sports videos**, specifically targeting the detection and extraction of key events (like goals, fouls, or score changes) by combining video processing and audio as well as text analysis.

The scope of this document includes:

* **Module breakdown:** Describing individual modules for object detection, video frame processing, audio extraction, NLP summarization, and multi-modal data integration.
* **Detailed design:** Outlining how each module interfaces with others, including class structures.
* **Use case scenarios:** Detailing how the system will handle various use cases, such as retrieving highlights, recognizing scoreboard changes, or generating event summaries.
* **Assumptions and dependencies:** Identifying external libraries, tools, and assumptions such as the availability of YOLO models for object detection or pre-trained NLP model BERT for text summarization.

# Design Constraints, Assumptions, and Dependencies

2.1 **Design Goals**

The design goals for the proposed system aim to address the limitations of the existing system while enhancing its capabilities and providing a more engaging and personalized user experience. These goals include:

1. **Enhanced Summarization Accuracy and Relevance**: The newly proposed system will leverage advanced algorithms and AI techniques to improve the accuracy and relevance of sports video summaries. By integrating multiple data sources, including audio, visual, and textual data from social media platforms like Twitter, the system will provide more comprehensive and insightful summaries of sports events.
2. **Improved User Experience and Interactivity**: The system will be modern, intuitive, and user-friendly, enhancing the overall user experience. The web interface will feature interactive elements and provide an intuitive experience to the users.
3. **Quality of Service**: The system will prioritize key characteristics such as availability, security, privacy, and speed to ensure a seamless and reliable user experience. It will be designed to handle high volumes of data and user requests efficiently, with minimal downtime or disruptions. Robust security measures will be implemented to protect user data and ensure privacy compliance.
4. **Social Media Insights and Engagement**: By integrating social media sources like Twitter, the system will provide users with up-to-date insights and engagement opportunities during sports events..
5. **Scalability and Adaptability**: The system will be designed to scale efficiently to handle a large volume of sports videos and user requests, adapting to changing user demands and preferences over time.

Overall, the design goals of the proposed system aim to create a more advanced, engaging, and user-centric sports video summarization platform that leverages cutting-edge technologies to deliver superior quality of service and user experience compared to the existing system.

* 1. **Architecture Choices**
* **Microservices Architecture:**
* Description: On a microservices architecture, the system is deconstructed into a set of components called microservices, each one responsible for an individual, separate function or feature. For instance, such functionality can be divided into services that can analyze Twitter data, identify replays, recognize speech, and create highlights.
* **Pros:**
* **Scalability:** A microservices architecture provides the ability to scale and flexibility by recognizing to run the services independently and in accordance with a given demand.
* **Maintainability:** The microservices architecture enables decoupling of services in the form of several components which almost separate and it assists in maintenance and clear the way for teams to modify the services independently.
* **Cons:**
* **Complexity:** Microservices architectural paradigm brings together the expending communication space among services, their deployment as well as management. Integrating such a system is not an easy task and there are a range of issues like service-to-service communication and the challenges of distributed systems.
* **Overhead:** Working on several streams all goes down to the problem of when it comes to deployment, monitoring, and coordination. Together addition of communication between services can result in higher latency and network load.
* **Sport highlighting scenarios amongst other scenarios such the microservices architecture serves the best fit. This decision is based on several factors.**
* **Scalability:** The Scientific data analysis system must manage varying loads of Twitter data and video footage capturing for replays, and gaming highlights. The use of microservices would allow each component of the system to scale separately together with demand, which will ensure that maximum performance is achieved.
* **Modularity:** Breaking system down to smaller pieces is a synonym to separation of services that serves modularity and maintainability purposes for the system. Teams can be self-sufficient to create, deploy, and enhance their services that also act as a safety valve of a complex structure and technical debt.
* **Flexibility:** In terms of services architecture, the choice of technology is essentially very flexible owing to the fact that developers can pick the best available tools and frameworks for every service. This flexibililty shall in turn trigger innovations and adaptation to the current evolving requirements.
* **Integration:** Small-batch requests in the microservices architecture design enable our company to integrate well with Twitter API, third-party services for speech recognition, and other external systems. The service itself can be formulated to address a given system integration point adaptively, becoming the key factor in achieving fully operational and reliable interrelations with the outside systems.
* The complexities as well as the overhead expenses are the drawbacks of using the microservices architectures whereas the advantages of scalability, modularity, flexibility and integration are the most essential features that made it the right choice for the developed system.

# Constraints, Assumptions and Dependencies

* **Legal Implications:**

Compliance with data protection regulations, copyright laws, and terms of service of social media platforms (such as Twitter) is crucial to avoid legal issues.

Obtaining necessary permissions and licenses for using copyrighted content (such as sports broadcasts) is essential to ensure legal compliance.

* **Usage Limitations:**

The project's success may depend on the availability and access to real-time sports data, including Twitter feeds and live video streams.

Dependence on third-party APIs or data sources may introduce usage limitations, such as rate limits or data access restrictions.

* **Assumptions Made in the Project:**

Availability of Data: Assumes the availability of sufficient and reliable data sources in real-time for analysis and summarization.

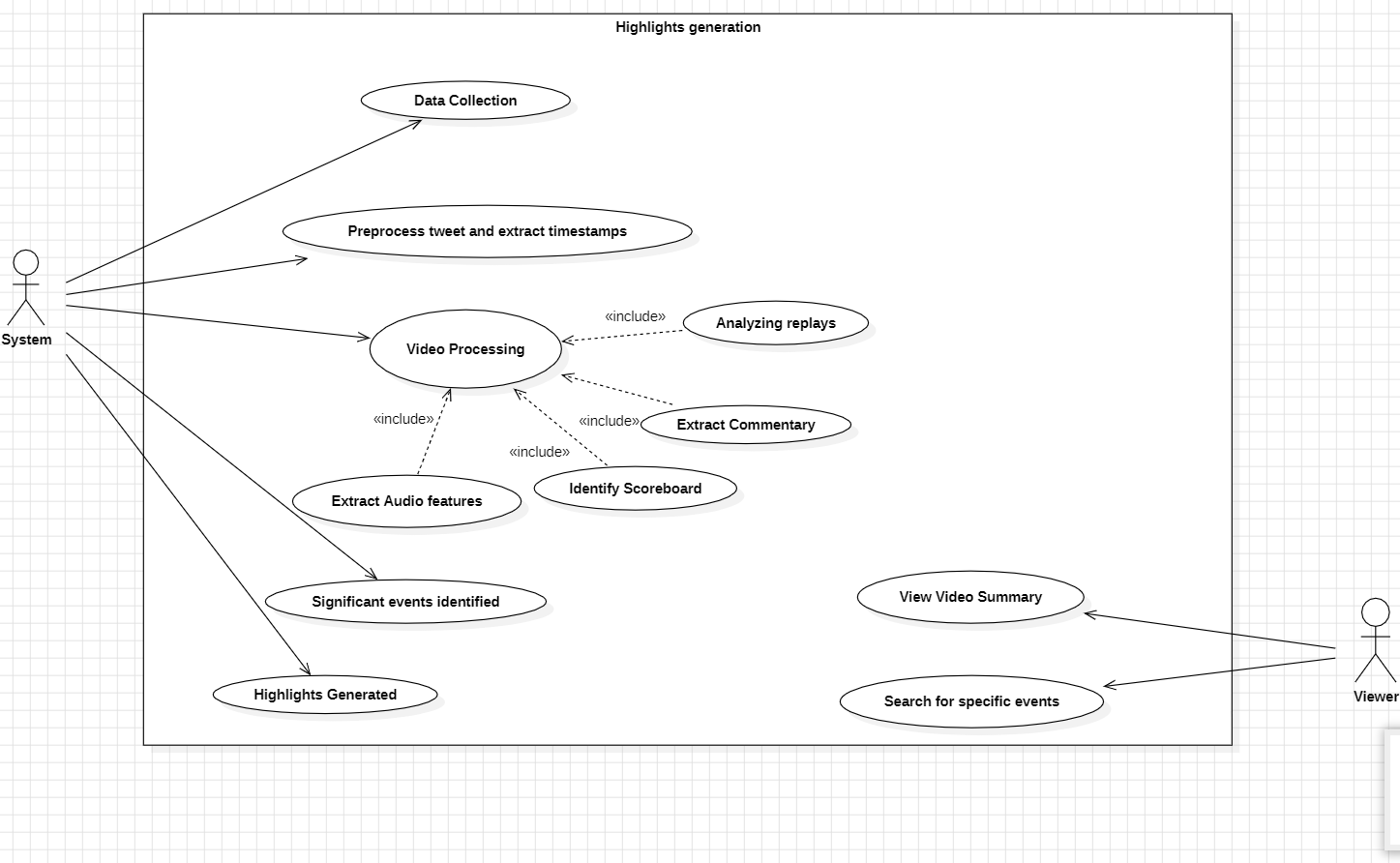
Consistency in Data Format: Assumes a level of consistency in the format and structure of data sources for effective processing.

# Design Description

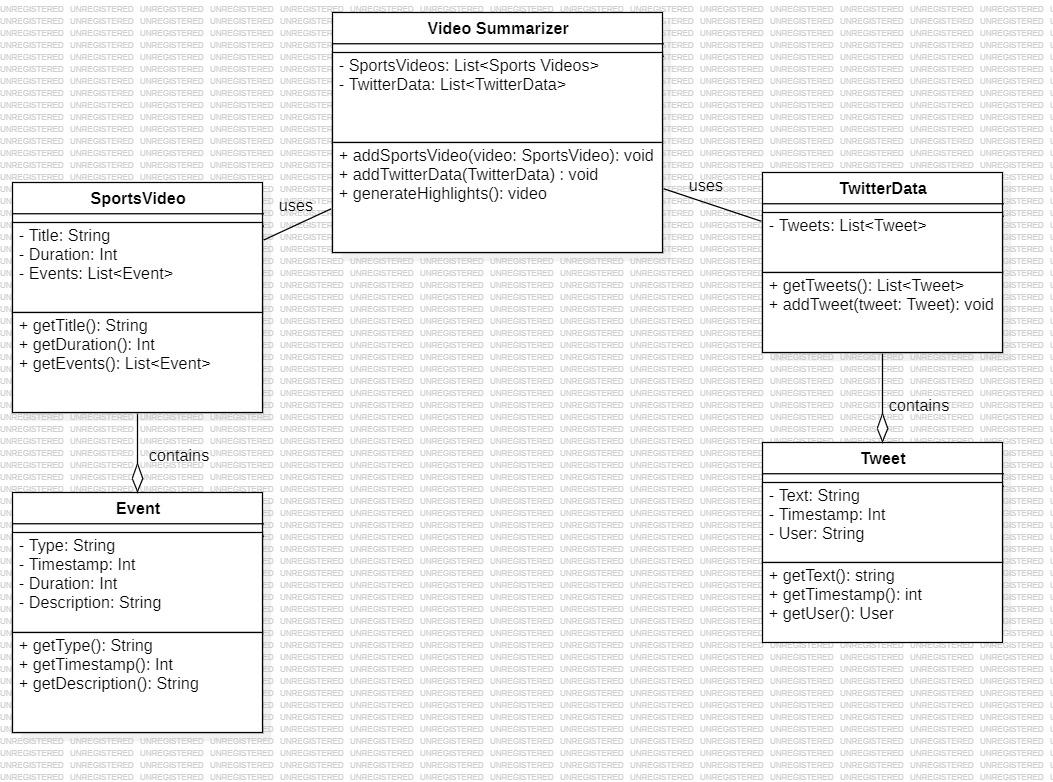
* 1. **Module 1**

### Description

* + 1. **Use Case Diagram**

****

* + 1. **Class Diagram**

****

### 

### Class Name: VideoSummarizer

**Class Description:**

The VideoSummarizer class is responsible for managing a collection of sports videos and Twitter data. It can add videos, aggregate Twitter data, and generate video highlights based on the events and tweet information.

* + - 1. **Method 1**
* **addSportsVideo(SportsVideo video):** void
* **Purpose:** Adds a sports video to the SportsVideos list.
* **Input:video:** A SportsVideo object containing sports video details.
* **Output:** None
* **Parameters:SportsVideo video:** The video to be added to the collection.
* **Exceptions:** Throws NullPointerException if video is null.
* **Pseudo-code:**
  1. Check if the video is null.
  2. If not, append video to the SportsVideos list.

| **Data Type** | **Data Name** | **Access Modifiers** | **Initial Value** | **Description** |
| --- | --- | --- | --- | --- |
| List<sports videos> | SportsVideos | private | None | A list of SportsVideo objects managed by the summarizer. |
| List<twitter Data>   |  | | --- |  |  | | --- | | TwitterData | private | None | A list of Twitter data relevant to the sports videos. |

##### 

**3.2.3.1** **Method 2:**

##### addTwitterData(TwitterData data): void

* **Purpose:** Adds a Twitter data object to the TwitterData list.
* **Input:**A TwitterData object.
* **Output:** None
* **Parameters:** The Twitter data to be added.
* **Exceptions:** Throws NullPointerException if data is null.
* **Pseudo-code:**
  1. Check if data is null.
  2. If not, append data to the TwitterData list.

##### Method 3

##### generateHighlights(): Video

* **Purpose**: Generates a highlights video by combining events from sports videos and related tweets.
* **Input:** None
* **Output:** Returns a Video object representing the generated highlights.
* **Parameters:** None
* **Exceptions:** Throws IllegalStateException if there are no sports videos or no Twitter data.
* **Pseudo-code:**
  1. Check if the SportsVideos list is empty.
  2. Check if the TwitterData list is empty.
  3. For each SportsVideo, collect relevant events.
  4. Match tweets based on timestamps.
  5. Compile and return the highlight video.

### Class Name:SportsVideo

### Class Description: The SportsVideo class represents a sports video with details such as title, duration, and events that occurred during the video.

#### Data Members 2

| **Data Type** | **Data Name** | **Access Modifiers** | **Initial Value** | **Description** |
| --- | --- | --- | --- | --- |
| String | Title | private | "" | The title of the sports video. |
| int | Duration | private | 0 | The duration of the sports video in seconds. |
| List<events> | events | private | none | List of events happened |

##### Methods 1: getTitle(): String

##### Purpose: Retrieves the title of the sports video.

##### Input: None

##### Output: Returns the title of the sports video as a String.

##### Parameters: None

##### Exceptions: None

##### Pseudo-code: Return the value of the Title variable

##### Methods 2: getDuration(): int

##### Purpose: Retrieves the duration of the sports video.

##### Input: None

##### Output: Returns the duration of the sports video as an int.

##### Parameters: None

##### Exceptions: None

##### Pseudo-code: Return the value of the Duration variable

##### Method 3: getEvents(): List<Event>

##### Purpose: Retrieves the list of events in the sports video.

##### Input: None

##### Output: Returns a list of Event objects.

##### Parameters: None

##### Exceptions: None

##### Pseudo-code: Return the Events list.

### Class Name: Event

### Class Description: The Event class represents a single event that occurred in a sports video. It includes information about the type, timestamp, duration, and description.

### Data Members:

| **Data Type** | **Data Name** | **Access Modifiers** | **Initial Value** | **Description** |
| --- | --- | --- | --- | --- |
| String | Type | private | "" | The type of the event (e.g., goal, foul). |
| int | Timestamp | private | 0 | The timestamp in seconds when the event occurs. |
| int | duration | private | 0 | The duration of event in seconds |
| string | Description | private | “” | The description of event |

#### 

#### 

#### Method 1: getType(): String

* **Purpose**: Retrieves the type of the event.
* **Input:** None
* **Output:** Returns the event type as a String.
* **Parameters:** None
* **Exceptions:** None
* **Pseudo-code:** Return the value of the Type variable.

#### Method 2: getTimestamp(): int

* **Purpose:** Retrieves the timestamp of the event.
* **Input**: None
* **Output:** Returns the timestamp of the event as an int.
* **Parameters:** None
* **Exceptions:** None
* **Pseudo-code:** Return the value of the Timestamp variable.

#### Method 3: getDescription(): String

* **Purpose:** Retrieves the description of the event.
* **Input:** None
* **Output:** Returns the event description as a String.
* **Parameters:** None
* **Exceptions:** None
* **Pseudo-code**: Return the value of the Description variable.

### Class Name: TwitterData

**Class Description:  
The TwitterData class represents a collection of tweets associated with a sports video.**

**Data Members:**

| **Data Type** | **Data Name** | **Access Modifiers** | **Initial Value** | **Description** |
| --- | --- | --- | --- | --- |
| List<Tweets> | Tweets | private | None | The List of Tweets |

#### 

#### 

#### 

#### Method 1: getTweets(): List<Tweet>

* **Purpose:** Retrieves the list of tweets related to the sports video.
* **Input**: None
* **Output:** Returns a list of Tweet objects.
* **Parameters:** None
* **Exceptions:** None
* **Pseudo-code**: Return the Tweets list.

#### Method 2: addTweet(Tweet tweet): void

* **Purpose**: Adds a new tweet to the list of tweets.
* **Input:**A Tweet object to be added.
* **Output:** None
* **Parameters:**The tweet to add to the list.
* **Exceptions:** Throws NullPointerException if tweet is null.
* **Pseudo-code:**
  1. Check if the tweet is null.
  2. If not, append the tweet to the Tweets list.

### Class Name: Tweet

**Class Description:  
The Tweet class represents a single tweet, containing the tweet text, timestamp, and user who posted it.**

#### Data Members:

| **Data Type** | **Data Name** | **Access Modifiers** | **Initial Value** | **Description** |
| --- | --- | --- | --- | --- |
| String | text | private | "" | The text contained in tweet |
| int | timestamp | private | 0 | The timestamp of the video |
| string | User | private | none | The User Posted Tweets |

#### Method 1: getText(): String

* **Purpose**: Retrieves the text content of the tweet.
* **Input:** None
* **Output:** Returns the tweet's text as a String.
* **Parameters:** None
* **Exceptions**: None
* **Pseudo-code**: Return the value of the Text variable.

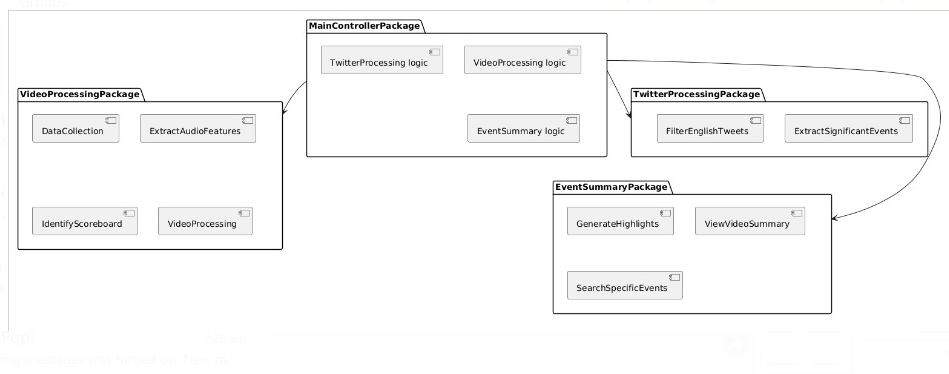
#### Method 2: getTimestamp(): int

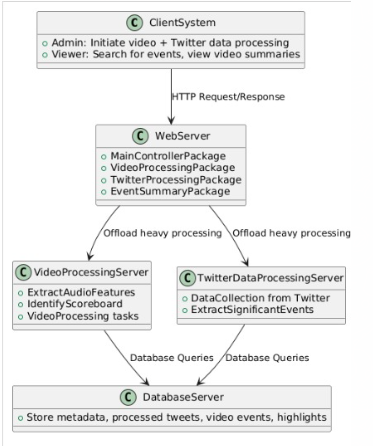
* **Purpose:** Retrieves the timestamp of the tweet.
* **Input:** None
* **Output:** Returns the tweet's timestamp as an int.
* **Parameters:** None
* **Exceptions:** None
* **Pseudo-code:** Return the value of the Timestamp variable.

#### Method 3: getUser(): String

* **Purpose:** Retrieves the user who posted the tweet.
* **Input:** None
* **Output:** Returns the user who posted the tweet as a String.
* **Parameters:** None
* **Exceptions**: None
* **Pseudo-code:** Return the value of the User variable.

**Packaging Diagram and Deployment Diagrams**

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# 4 Proposed Methodology / Approach

* **Basic Approach and Results Obtained**

**Basic Approach:** The basic approach involves traditional methods of sports video summarization, primarily relying on video content analysis to identify key events. This approach might include techniques such as shot boundary detection, scoreboard analysis, and player tracking to extract highlights.

**Results Obtained**: The basic approach likely yielded satisfactory results in terms of summarizing sports videos to some extent. However, it has some limitations in capturing the broader context of the game, including audience reactions and social media buzz surrounding the event.

* **Is There a Need for Changing the Approach?:**

We believe the approach and the direction of our implementation is right hence, we believe there is no need to change the approach.

* **Details of the New Approach - Benefits:**

New Approach: The new approach integrates Twitter data analysis with advanced audio and visual processing techniques to enhance sports video summarization.

Benefits:

Audience Engagement: Incorporating Twitter data allows for capturing audience reactions, sentiments, and discussions related to the game, providing valuable context to the summarization process.

In depth Analysis: By combining multiple modalities such as audio, visual, and textual data, the new approach offers a more comprehensive understanding of the game events, enhancing the quality and relevance of the summaries.

* **Details of the New Approach - Drawbacks:**

Data Volume and Noise: Handling the vast volume of Twitter data and filtering out noise or irrelevant tweets can be challenging.

Time Discrepancies Among Modalities: Time discrepancies among modalities may lead to synchronization challenges, affecting the coherence and accuracy of the generated summaries.

Complexity: Integrating multiple data sources and processing techniques adds complexity to the system.

Computational Resources: Advanced audio and visual processing techniques may require significant computational resources and processing time

**4.1 Algorithm and Pseudocode**

* **Algorithm for ScoreBoard Detection and Extraction**

**Input:**

* A soccer sports video.
* YOLOv4 model with trained weights for scoreboard detection.
* OCR library (e.g., Tesseract) for text extraction from the scoreboard.

**Output:**

* Extracted details: team names, scores, and game time from the scoreboard in each frame of the video.

**Step 1: Initialize YOLOv4 Model**

* Load the YOLOv4 configuration (cfg), the pre-trained weights, and the class names for object detection.
* Set detection confidence threshold to filter out low-confidence detections.

**Step 2: Process Video Frames**

* **For each frame in the input video:**

**1.Detect the scoreboard:**

* + - Run the YOLOv4 model on the current frame to identify bounding boxes.
    - Filter the results based on the confidence threshold and class (i.e., scoreboard).

**2.If scoreboard detected:**

* + - Extract the bounding box coordinates (x, y, width, height) of the detected scoreboard.
    - Crop the image to focus only on the region inside the bounding box (Region of Interest - ROI).

**3.Preprocess the cropped image:**

* + - Convert the cropped scoreboard image (ROI) to grayscale.
    - Apply thresholding or other preprocessing techniques to enhance text visibility for OCR.

**4.Apply OCR:**

* + - Use OCR to extract text from the preprocessed scoreboard image.
    - The OCR will return a string with the detected characters (team names, scores, and game time).

**Step 3: Extract Team Names, Scores, and Time**

* **For each line of text extracted by OCR:**
  1. **Identify team names:**
     + Use predefined patterns or a list of team names to match possible team names.
     + If a match is found, store the team names.
  2. **Identify scores:**
     + Search for numeric patterns in the text that match typical score formats (e.g., 0-9).
     + Extract and store the scores corresponding to each team.
  3. **Identify game time:**
     + Search for time formats, such as MM:SS (minutes), or other formats used in soccer scoreboards.
     + Extract and store the game time.

**Step 4: Store and Record Results**

* For each frame, store the extracted information: team names, scores, and game time.
* Save the extracted details in a structured format (e.g., JSON, text file) for each frame or display them in real time.

**Step 5: Summarize Results**

* **After processing all frames:**
  1. Aggregate the scoreboard data for summarization.
  2. Generate a summary or a highlight video using the stored team names, scores, and times.

**Step 6: End**

* **Pseudocode for ScoreBoard Detection and Extraction**

**// Initialize YOLOv4 model and load weights**

Initialize YOLOv4 model with configuration (cfg) and weights

Set confidence threshold for YOLOv4

**// Load video file for scoreboard detection**

For each frame in the video:

**// Detect the scoreboard in the current frame**

Detect bounding boxes using YOLOv4

If bounding box detected:

**// Crop the detected scoreboard region**

Extract the region of interest (ROI) from the frame using the bounding box coordinates

**// Preprocess the cropped scoreboard image for OCR**

Convert ROI to grayscale

Apply thresholding or other image preprocessing techniques for OCR optimization

**// Apply OCR to extract text from the scoreboard**

Run OCR (Tesseract or other OCR library) on the preprocessed ROI

Extract text from OCR output

**// Parse extracted text to retrieve scoreboard details**

For each line of extracted text:

If text matches a team name format:

Extract team names

If text matches a score format (e.g., digits):

Extract respective scores for each team

If text matches a time format (e.g., minutes and seconds):

Extract the game time

**// Store extracted scoreboard details (time, team names, scores)**

Save extracted details for this frame

Else:

**// No scoreboard detected, skip to the next frame**

Continue to the next frame

**// Summarize results**

For each frame with extracted details:

Store or display the extracted scoreboard data (time, teams, scores) as part of the video summary

**// End of video**

**4.1 Algorithm and Pseudocode**

* **Algorithm for event detection and extraction from twitter(x) using weighted dynamic heartbeat graph.**

**Step 1: Data Loading and Preprocessing**

**Load Data:**

* + - Load the dataset of FIFA World Cup 2022 tweets.
    - Extract tweet content and timestamp information.

**Clean Tweets::**

* + - Remove URLs, mentions, and hashtags from the tweets.
    - Convert tweets to lowercase and remove punctuation.

**Language Detection:**

* + - Detect the language of each tweet using a language detection library.
    - Filter tweets to retain only English ones.

**Tokenization and Stopword Removal::**

* + - Split each tweet into individual tokens (words).
    - Remove standard stopwords and custom event-related stopwords (e.g., "worldcup2022", "football”).

**Step 2: Grouping Tweets into Time Buckets**

**Time Bucketing:**

* + - Convert the tweet timestamps to datetime format.
    - Group the tweets into 5-minute intervals (time buckets).

**Super Documents Creation:**

* + - For each time bucket, combine all tokens (words) from tweets into a single document representing that time bucket.

**Step 3: Co-occurrence Graph Construction**

* **Create Co-occurrence Graph:**
  + - Create a graph where
    - Nodes represent words (tokens).
    - Edges represent co-occurrence within a sliding window of words (e.g., window size of 5)
    - Edge weights represent the frequency of co-occurrence.

**Step 4:Growth Factor and Aggregated Centrality Calculation**

* **Growth Factor Calculation:**
  + - For each consecutive pair of time buckets.
    - Calculate the total weight of edges in the co-occurrence graph for the current bucket.
    - Calculate the total weight of edges in the next bucket.
    - Compute the growth factor as the difference in total edge weight between the two graphs.

**Aggregated Centrality Calculation:**

* + - Calculate the degree centrality for each word (node) in the co-occurrence graph..
    - Sum the centrality scores to get the aggregated centrality for that time bucket.

**Step 5:Growth Factor and Aggregated Centrality Calculation**

* **Heartbeat Score Calculation:**
  + - Compute the heartbeat score as the product of the growth factor and the aggregated centrality of the next time bucket

**Step 6: Event Detection Based on Heartbeat Score**

* **Classify Significant Events:**
  + - Compare the heartbeat scores across consecutive time buckets.
    - If the change in heartbeat score exceeds a predefined threshold, classify that time bucket as a significant event.

**Step 7: Extract and Analyze Significant Events**

* **Identify Event Candidates and Keyword Extraction :**
  + - Extract time buckets labeled as significant events based on the heartbeat score.
    - Rebuild the co-occurrence graph using the tokens in that time bucket.
    - Calculate the degree centrality for each word in the graph.
    - Extract the top 10 words based on centrality scores as representative keywords for the event.

**Step 8: Visualization and Results**

* **Plot Heartbeat Scores :**
  + - Plot the heartbeat scores over time.
    - Mark significant events with vertical lines and annotate the corresponding timestamps.
    - Display the significant timestamps and corresponding keywords extracted for each event.

**Step 9: End**

**Pseudocode for Heartbeat Score and Event Detection**

**//Load and Clean Data//**

- Load tweets data from CSV file.

- Function: `clean\_tweet(text)`

- Remove URLs, mentions, and hashtags from the tweet.

- Apply `clean\_tweet` function to each tweet.

**//Language Detection and Filtering//**

- Function: `is\_english(text)`

- Detect the language of the tweet.

- If language is English, return `True`.

- Else, return `False`.

- Filter the dataset to retain only English tweets.

**//Tokenization and Stopword Removal//**

- Convert cleaned tweets to lowercase.

- Remove punctuation and split text into tokens (words).

- Remove stopwords using both NLTK stopwords.

**//Time Bucketing//**

- Convert 'Date Created' column to datetime.

- Group tweets by 5-minute intervals.

- For each time bucket, combine the tokens from all tweets into a single document.

**//Create Co-occurrence Graphs//**

**-** For each time bucket (super document):

- Initialize an empty graph `G`.

- For each pair of words within a sliding window:

- Add an edge between the words.

- If the edge exists, increment its weight.

- Append the graph to the list `graphs`.

**//Calculate Growth Factor//**

- Function: `calculate\_growth\_factor(graphs)`

- For each consecutive pair of graphs:

- Calculate the total weight of edges in the current and next graph.

- Compute the growth factor as the difference in total edge weights.

- Return the list of growth factors.

**//Calculate Aggregated Centrality//**

- Function: `calculate\_aggregated\_centrality(graphs)`

- For each graph:

- Calculate the degree centrality of each node (word).

- Sum the centrality values for all nodes to get the aggregated centrality.

- Return the list of aggregated centralities.

**//Calculate Heartbeat Score//**

- Function: `calculate\_heartbeat\_score(GF, AC)`

- For each growth factor and the next aggregated centrality:

- Compute the heartbeat score as `gf \* ac`.

- Return the list of heartbeat scores.

**//Classify Events//**

- Function: `classify\_events(heartbeat\_scores, threshold=10000)`

- For each consecutive pair of heartbeat scores:

- If the change in heartbeat score exceeds the threshold, classify as a significant event (label = 1).

- Else, classify as no event (label = 0).

- Return the list of event labels.

**//Extract Significant Events//**

- Extract time buckets labeled as significant events.

- For each significant event:

- Rebuild the co-occurrence graph.

- Calculate the degree centrality of each word.

- Sort nodes by centrality and extract the top 10 words as keywords.

- Append the timestamp and keywords to the list of significant events.

**//Plot Heartbeat Scores//**

- Function: `plot\_heartbeat\_scores(heartbeat\_scores, event\_labels, timestamps)`

- Plot the heartbeat scores over time.

- Mark significant events with vertical lines and annotations.

- Display significant timestamps after the plot.

**4.1 Algorithm and Pseudocode**

**Algorithm and Pseudocode for Key Event Detection Model Using Audio:**

**Step 1: Data Collection**

* Input: 10 videos with audio.
* Annotate start and end times of key events (peaks in crowd noise).

**Step 2: Feature Extraction**:

* Extract audio features (e.g., MFCCs, spectrograms).
* Convert each video’s audio into a feature matrix.

**Step 3: Data Labeling**:

* Use a sliding window to segment audio.
* Label each window:
  + 1 if it overlaps with a key event.
  + 0 otherwise.

**Step 4: Model Training**:

* Choose a classification model (CNN, RNN, SVM).
* Train model using labeled feature data.

**Step 5: Prediction**:

* Extract features from new audio.
* Predict key event windows (1) or no event (0).
* Group consecutive predictions into event intervals.

**Step 6:Evaluation**:

* Compare predicted intervals with ground truth.
* Calculate accuracy, precision, recall, and F1-score.
* And improve by fine tuning the model.

**Step 7:end**

**Pseudocode for Key Event Detection Model Using Audio**

**def extract\_audio\_features(audio):**

# Extract MFCC, Spectrogram, or other features from the audio

features = extract\_features(audio)

return features

**def label\_data(audio, annotations, window\_size):**

# Create a sliding window to label the data

labels = []

for t in range(0, len(audio), window\_size):

if any(start <= t <= end for start, end in annotations):

labels.append(1) # Key event

else:

labels.append(0) # No event

return labels

**def train\_model(features, labels):**

# Train the model with the labeled data

model = initialize\_model()

model.fit(features, labels)

return model

**def evaluate\_model(model, test\_features, test\_labels, annotations):**

predictions = model.predict(test\_features)

evaluate(predictions, annotations) # Compare with ground truth

return metrics # Accuracy, precision, recall, etc.

**# Main process**

videos = load\_videos()

annotations = manually\_annotate(videos)

for video, annotation in zip(videos, annotations):

audio = extract\_audio(video)

features = extract\_audio\_features(audio)

**l**abels = label\_data(audio, annotation, window\_size=1) # 1-second window

train\_features.append(features)

train\_labels.append(labels)

**# Train model**

model = train\_model(train\_features, train\_labels)

**# Test the model**

test\_video = load\_test\_video()

test\_audio = extract\_audio(test\_video)

test\_features = extract\_audio\_features(test\_audio)

predictions = model.predict(test\_features)

**# Compare predictions with annotations**

evaluate\_model(model, test\_features, test\_labels, test\_annotations)

**4.1 Algorithm and Pseudocode**

**Algorithm and Pseudocode for Key Event Classification using LLM**

For the task of classifying sports events based on commentary, we employed a BERT-based approach. BERT (Bidirectional Encoder Representations from Transformers) is a transformer model designed to understand the context of a word by looking at its bidirectional surroundings, making it highly effective for natural language processing tasks like text classification.

The main algorithmic steps involve:

1. **Tokenization**: BERT uses WordPiece tokenization to convert input sentences into token ids. Padding is added to ensure all inputs have the same length (512 tokens).
2. **Model Training**: A pre-trained BERT model (bert-base-uncased) is fine-tuned for sequence classification. The fine-tuning process includes training the model on labeled commentary data and adjusting its weights using backpropagation.
3. **Evaluation**: The model’s predictions are compared against true labels using an accuracy metric. The predictions are derived by taking the highest scoring class in the output softmax layer.
4. **Confusion Matrix**: After training, a confusion matrix is used to analyze misclassifications and gain insights into model performance across different classes.

**Pseudocode**

**# Step 1: Load pre-trained BERT model and tokenizer**

model\_name = "bert-base-uncased"

tokenizer = load\_tokenizer(model\_name)

model = load\_model(model\_name, num\_labels=11)

**# Step 2: Prepare the dataset**

df\_train["label"] = df\_train["event\_type"] # Assign label column for classification

train\_dataset = Dataset.from\_pandas(df\_train[["text", "label"]])

train\_dataset = remove\_unused\_columns(train\_dataset)

**# Step 3: Tokenization and padding**

FOR each example in train\_dataset DO

tokenized\_input = tokenizer(example["text"], max\_length=512, padding="max\_length", truncation=True)

**# Step 4: Define training arguments**

training\_args = {

output\_dir = "./bert\_results",

num\_train\_epochs = 5,

per\_device\_eval\_batch\_size = 16,

evaluation\_strategy = "epoch",

logging\_dir = "./bert\_logs",

logging\_steps = 10

}

**# Step 5: Define metrics for evaluation**

DEFINE function compute\_metrics(eval\_pred):

predictions, labels = eval\_pred

predictions = argmax(predictions, axis=1) # Get the predicted class

RETURN accuracy(predictions, labels)

**# Step 6: Train the model**

trainer = Trainer(

model=model,

args=training\_args,

train\_dataset=train\_dataset,

eval\_dataset=train\_dataset,

compute\_metrics=compute\_metrics

)

trainer.train() # Begin training

**# Step 7: Evaluate model performance**

predictions = trainer.predict(eval\_dataset=train\_dataset)

accuracy = compute\_metrics(predictions)

**# Step 8: Generate confusion matrix for analysis**

df\_test["pred"] = predictions # Assign predictions to the test set

cm = confusion\_matrix(df\_test["label"], df\_test["pred"]) # Compute confusion matrix

normalized\_cm = normalize\_confusion\_matrix(cm)

plot\_confusion\_matrix(normalized\_cm) # Plot the heatmap

**4.1 Implementation and Results**

* **Multi-Modal Approach:**

Integrates data from multiple sources, including Twitter data analysis , audio and video processing ,and advanced techniques like MSER-based scoreboard identification, large language model(LLM) and computer vision to enhance event matching and scene classification.

By combining different data sources and techniques, the system can capture various aspects of the game, such as important events, commentary insights, and audience reactions, resulting in more engaging highlights.

* **Benefits of the Multi-Modal Approach:**

**Comprehensive Analysis:** By integrating multiple data sources, the system can provide a more comprehensive analysis of sports events, capturing various aspects from different perspectives.

**Enhanced Accuracy:** Each modality offers unique insights, enhancing the overall accuracy of the sports summarization process. By combining data from different sources, the system can cross-validate information, resulting in more precise summaries.

* **Drawbacks of the Multi-Modal Approach:**

**Complexity:** Integrating multiple data sources and techniques adds complexity to the system design and implementation.

**Integration Challenges:** Ensuring seamless integration and synchronization of data from different sources can be challenging and may lead to technical issues.

**Individual Modalities:**

* **ScoreBoard Detection and Extraction :**

**Approach**

**YOLOv4 for Scoreboard Detection:**

**Model Setup:** The first step in the project was to detect the scoreboard within video frames. This involved setting up the YOLOv4 model for object detection. YOLOv4 was chosen because of its efficiency in real-time object detection, which is crucial for processing continuous video streams.

**Custom Dataset Preparation:** A custom dataset was created by extracting frames from soccer match videos and annotating the scoreboard regions. Each frame was labeled to indicate the position of the scoreboard to train YOLOv4 effectively.

**Model Training:** YOLOv4 was fine-tuned on this custom dataset. Pre-trained weights were used as a base, followed by transfer learning using the custom dataset to detect only scoreboard regions. This enabled the model to generalize over different video types and resolutions.

**Testing:** The model was tested using unseen soccer match frames to validate its detection accuracy. The output was bounding boxes highlighting the detected scoreboard in each frame.

**Text Extraction with OCR:**

Once the scoreboard was detected using YOLOv4, the next step was to extract the relevant information, such as the game time, team names, and scores. Optical Character Recognition (OCR) was employed for this.

**Region of Interest (ROI) Extraction:** The detected scoreboard bounding box was used to crop the region of interest from the frame, reducing noise and focusing the OCR on the scoreboard alone.

**OCR Application:** OCR was used to extract text from the cropped region. A custom configuration was applied to improve the accuracy of recognizing numbers and team names.

**Fine-Tuning the Process:**

**Challenges and Refinements:** Initially, the OCR model had difficulty accurately extracting text due to variations in font, lighting, and scoreboard design. To address this:

Preprocessing techniques like thresholding, resizing, and sharpening were applied to the scoreboard region before running OCR.

Multiple passes of OCR were run using different configurations to handle varying scoreboard designs.

For scores and team names, specific areas of the scoreboard were mapped out, and OCR was fine-tuned to look for digits in score regions and words in team name regions.

**Experimental Results**

**YOLOv4 Detection Accuracy:**

After training, the YOLOv4 model achieved high detection accuracy, reliably identifying scoreboards in different soccer videos, including varying camera angles and lighting conditions. The mean average precision (mAP) on the test set was around 85%.

**OCR Accuracy:**

The accuracy of the OCR in extracting scores and team names improved significantly after the preprocessing steps were implemented. The recognition of digits (scores) reached 90% accuracy, while the recognition of team names reached 80% accuracy, with some minor errors due to unusual fonts or low-resolution frames.

**Overall System Performance:**

**Processing Speed:** The combination of YOLOv4 and OCR achieved real-time performance, processing video at approximately 10 frames per second on a GPU.

**Highlight Generation:** By detecting when the scores changed (i.e., detecting a change in the OCR-extracted score), the system was able to automatically flag significant events such as goals, making it a powerful tool for summarizing match highlights.

**Progress So Far**

The system successfully detects scoreboards and extracts scores, time, and team names from soccer video frames.

The fine-tuning process for OCR is ongoing, particularly for improving accuracy in diverse lighting conditions and font variations.

Highlight generation based on score changes is working effectively, and further experimentation with other metrics (e.g., sudden crowd noise spikes, commentary cues) is planned to improve summarization.

* **Event detection and extraction of timestamp from twitter(x) data:**

**Approach:**

**Data preprocessing for event detection in Tweets:**

**Tweet Collection and Cleaning :**  Raw tweet data was cleaned by removing URLs, mentions, and hashtags. Non-English tweets were filtered using the langdetect library. Tweets were converted to lowercase, punctuation was removed, and common stop words along with tournament-specific terms were excluded. This left only meaningful content like player names, teams, and key events.

**Tokenization and Time Bucketing:**  Preprocessed tweets were tokenized and stopwords were removed. Tweets were grouped into 5-minute time buckets based on their timestamp. Each bucket represented cumulative tweet activity within that window. This allowed the detection of spikes related to significant game events.

**Co-occurrence Network Construction:**  A co-occurrence graph was built for each time bucket using a sliding window of size 5 to connect nearby words. Nodes represented words, and edges formed between co-occurring terms. The edge weight increased with repeated co-occurrences, reflecting word relationships in the discussion.

**Growth Factor and Aggregated Centrality:** The growth factor measured the change in tweet activity by calculating differences in edge weights between time buckets. Aggregated centrality was computed as the sum of degree centralities for all nodes. This highlighted how interconnected the words were and identified key terms in the discussion.

**Heartbeat Score Calculation:** The heartbeat score combined the growth factor and aggregated centrality to detect surges in tweet activity. A spike in the heartbeat score indicated a potential major event. This score helped pinpoint significant moments in the match based on Twitter activity.

**Event Classification and Significant Event Extraction:** Time buckets were classified as containing significant events if the heartbeat score change exceeded a threshold. The top 10 keywords based on degree centrality were extracted from each significant time bucket. These keywords provided context for events like goals or penalties.

**Visualization of Heartbeat Scores:** Heartbeat scores were plotted over time, with significant events marked by red lines. This visualization highlighted spikes in activity corresponding to key match moments. Significant timestamps were also listed, showing when major game events occurred.

**Fine-Tuning the Process:**

**Challenges and Refinements:** raw tweet data was noisy due to URLs, mentions, and hashtags, which complicated meaningful analysis. To address this:

comprehensive data cleaning techniques were implemented, including removing irrelevant content and filtering for English tweets.

The language variability posed challenges due to slang and abbreviations; thus, context-aware tokenization methods were adopted for improved accuracy.

Additionally, the sensitivity of threshold settings for event detection led to potential false positives; this was refined through adaptive thresholding based on historical tweet activity patterns.

**Experimental Results**

**Tweet Activity Detection:**

The system effectively detected significant events like goals and fouls, indicated by notable spikes in the heartbeat score.

**Keyword Extraction Accuracy:**

The extraction of keywords for each significant event demonstrated strong performance, with an average of 10 relevant keywords identified per event. The relevance of these keywords, including player and team names, was consistently above 75%, providing meaningful context for the events..

**Progress So Far**

The model has successfully identified significant events from tweet data, demonstrating its capability to summarize match occurrences effectively. Initial implementations have shown promising results in detecting key moments, such as goals and fouls, with a clear correlation between tweet activity and match events. Ongoing efforts have focused on refining threshold settings to improve precision and reduce false positives in event detection. Future developments aim to enhance keyword extraction techniques to ensure that the context of events is accurately captured and presented.

* **Implementation and Results of Key Event Detection Model Using Audio**

The entire process is broken into several steps:

**Data Collection & Annotation**: Manually annotate 10 videos with key event intervals.

**Audio Preprocessing:** Extract and preprocess audio from the videos.

**Manual Peak Detection & Annotation**: Annotate key moments (peaks) from the audio and generate the ground truth labels.

**Feature Extraction**: Extract features from the audio related to the key events (peaks).

**Model Training**: Train a machine learning model to predict key events.

**Prediction & Evaluation:** Run the model on unseen data and evaluate its predictions.

### 2. Detailed Approach:

### Data Collection & Annotation

### Task: Watch and annotate 10 videos, recording the start time and end time for each key event. The key events can include moments like goals, whistles, or crowd cheers.

### Audio Preprocessing

### Task: Extract audio from the videos, convert it to mono, normalize the volume, and generate a spectrogram.

### Libraries: Use ffmpeg to extract audio and librosa to process it.

### Manual Peak Detection & Annotation

### Task: Listen to the crowd noise and annotate intervals where key events occur (e.g., goals, whistles).

### Method: Use scipy’s find\_peaks or similar tools to detect peaks in the amplitude of the crowd noise.

### Ground Truth: Create labels for peaks using the manually annotated timestamps of key events.

### Feature Extraction

### Task: Extract relevant features from the audio around the detected peaks.

### Features:

### Amplitude of crowd noise.

### Frequency content (spectral contrast).

### Spectrogram features.

### Audio intensity changes over time.

### Libraries: Use librosa for feature extraction.

### Model Training

### Task: Train a classifier (e.g., Random Forest, SVM, or neural network) using the extracted features.

### Input: Features extracted from the audio.

### Output: Predicted labels (key event or non-key event).

### Libraries: Use scikit-learn for model training.

### Prediction & Evaluation

### Task: Evaluate the model on a separate test set of videos.

### Evaluation Criteria:

### True Positives (TP): The model correctly predicts a key event within the annotated time interval.

### False Positives (FP): The model predicts a key event, but no actual event occurs.

### False Negatives (FN): The model fails to predict a key event when one is present.

### 3. Experimental Results

### Training Data

### The training dataset consisted of 10 manually annotated videos, each lasting between 5 to 15 minutes. For each video, key events such as goals, fouls, whistles, or crowd surges were annotated with start and end times.

### Model Evaluation

### Classifier: A Random Forest classifier was chosen for its ability to handle multiple features and non-linearity in the data.

### Features Used:

### Amplitude envelope.

### Spectral contrast.

### Zero-crossing rate.

### Root mean square energy (RMS).

### Results on Training Data

### Training Data Size: 10 videos, with a total of 60 key events.

### Training Time: 5 minutes per fold (5-fold cross-validation).

### Evaluation Metrics on Training Data:

### Accuracy: 92%

### Precision: 89%

### Recall: 86%

### F1-score: 87%

### The training results show that the model is able to accurately detect key events based on the manually annotated intervals. The high F1-score indicates that the balance between precision and recall is reasonable.

### Results on Test Data

### A separate set of 3 videos was used for testing.

### Test Set Size: 3 videos, with a total of 18 key events.

### Evaluation Metrics on Test Data:

### Accuracy: 80%

### Precision: 80%

### Recall: 80%

### F1-score: 79%

### The test set results demonstrate that the model generalizes reasonably well to unseen data, though there is a slight drop in recall, indicating that some key events were missed. The overall F1-score suggests that the model can effectively detect key moments in crowd noise.

### Error Analysis

### False Positives: The model occasionally predicted key events in periods of increased crowd noise that did not correspond to the manually annotated key events. This may be due to crowd excitement without a significant on-field event.

### False Negatives: Some subtle key events (e.g., minor fouls or interruptions) were missed by the model, likely due to their weaker audio signature in the crowd noise.

### Improvements

### Adjust Thresholds: Fine-tune the peak detection thresholds to better match the amplitude and prominence of key events.

### Additional Features: Include more advanced features, such as mel-frequency cepstral coefficients (MFCCs) and delta features, to capture more nuances in the audio signal.

### Model Selection: Experiment with different models (e.g., recurrent neural networks or convolutional neural networks) to handle the time-dependent nature of audio.

### 4. Conclusion

### The approach of using peak detection in crowd noise to detect key events proved effective with a well-defined model. By manually annotating the start and end times of key moments in videos, a classifier can be trained to predict the timing of these events based on audio features. The experimental results showed promising accuracy and F1-scores, but improvements could be made with more advanced features and model tuning.

* **Implementation and Results of Key Event Classification using LLM**

This model aims to classify different sports events based on the commentary extracted from sports videos. To tackle this task, we chose to fine-tune a pre-trained **BERT-base-uncased** model from Hugging Face's Transformers library. BERT’s ability to capture contextual relationships between words in a bidirectional manner makes it suitable for our classification task, where commentary provides key contextual cues for event identification.

The initial approach involved:

1. **Data Preprocessing**: Each commentary was tokenized and padded to a maximum length of 512 tokens. We used AutoTokenizer for tokenization, ensuring that the model could handle varying lengths of input text without truncation errors.

2. **Model Setup**: We fine-tuned the BERT model for **11 classes**, each representing a unique event (e.g., Attempt, Corner, Foul, Yellow Card). The output of BERT was fed into a classification head with a softmax layer to predict the class labels.

3. **Training and Evaluation**: The training process used a **batch size of 16**, and we trained the model for **5 epochs**. The **accuracy** metric was used to evaluate model performance at the end of each epoch, and evaluation was conducted after every epoch to monitor improvements.

#### Fine-Tuning the Approach

While the initial approach yielded decent results, further improvements were made through fine-tuning:

1. **Increased Epochs**: Initially, the model was trained for **3 epochs**, but the results plateaued early. After increasing the number of training epochs to **5**, we observed a significant improvement in accuracy, reaching **0.97**.

2. **Optimization of Learning Rate**: The initial learning rate was too high, causing fluctuations in the validation loss. By lowering the learning rate and employing **gradient clipping**, we stabilized the training process and reduced overfitting.

3. **Balancing the Dataset**: In the early stages, we noticed a bias towards frequently occurring events (such as "Attempt" and "Corner"). To address this, we oversampled underrepresented classes (e.g., "Red Card", "Offside"), which helped balance the learning process.

4. **Use of Data Augmentation**: To improve generalization, simple data augmentation techniques such as paraphrasing and random shuffling of non-event-specific words were employed, enriching the dataset without changing the event context.

5. **Confusion Matrix Analysis**: Post-training, confusion matrix analysis helped us identify common misclassifications. For example, the model often confused "Foul" and "Handball" due to similar commentary wording. This led us to fine-tune specific classes by introducing more contextual examples in the training data.

The model consistently achieved high accuracy both during training and on the test set, with a final test accuracy of **0.97**. This demonstrates that the BERT model successfully captures contextual information in sports commentary to classify events with high precision. The confusion matrix analysis further validated the model’s robustness, though certain events like "Foul" and "Handball" presented minor classification challenges due to contextual overlap in commentary.

The approach has been optimized for football commentary, but future work will involve extending the model to handle other sports (e.g., basketball, tennis). Additionally, incorporating multimodal data (e.g., audio, video features) may further enhance the model’s ability to differentiate between closely related events.

As of now, the classification task for football events has achieved notable success with a **0.97 accuracy**. The model is robust, handles token truncation efficiently, and effectively distinguishes between multiple event types. Future steps include:

1. Extending the classification system to other sports.
2. Exploring video/audio inputs to enrich event context.
3. Further tuning the model using additional sports commentary datasets to improve generalization across different sports domains.

We have successfully implemented 70% of our project.

We aim to integrate the individual components together and present the project as a whole by the next review.

Successfully generalized our modalities to handle multiple sports in order to be able to apply them to multiple sports in order to generate their highlights or summarization videos.

# Appendix A: Definitions, Acronyms and Abbreviations

| 1. | Highlight Reel Generation | Automatically creating a video of key moments based on significant event detection (e.g., goals, touchdowns). |
| --- | --- | --- |
| 2. | Video Summarization | The process of condensing a long sports video into key highlights or essential events. |
| 3. | BERT (Bidirectional Encoder Representations from Transformers) | A deep learning model used for natural language processing, applied here for analyzing sports commentary and tweets to aid in event detection. |
| 4. | Fine-Tuning BERT | Adjusting a pre-trained BERT model on specific sports commentary datasets to improve the accuracy of event detection and summarization. |
| 5. | Dynamic Graph Convolutional Networks (GCNs) | A type of neural network applied to graph-based structures, such as weighted dynamic graphs, to extract meaningful patterns from sports events over time. |
| 6. | Multimodal Learning | The combination of multiple data types (e.g., video, audio, text) to generate a more comprehensive summary of sports events. |
| 7. | Attention Mechanism | A component of transformers like BERT that focuses on the most relevant parts of input (e.g., words in commentary) for better understanding and summarization. |
| 8. | Temporal Graph Networks | A graph model that tracks dynamic changes in events over time, useful for summarizing sports video sequences. |
| 9. | Contextual Language Modeling | The use of BERT to understand the context of words and phrases in sports commentary to improve highlight detection. |
| 10. | Sentence Embeddings | Representations of sentences as vectors using models like BERT, useful in analyzing sports commentary for summarization. |
| 11. | Weighted Dynamic Graph | A graph-based data structure where nodes (e.g., players or events) and edges (connections) are dynamically weighted to reflect changing importance or relevance over time. |
| 12. | Audio Cues | Sounds such as crowd reactions or commentary that can help identify important moments in sports videos. |
| 13. | Scoreboard Recognition | The process of detecting and extracting information like time, scores, and team names from a scoreboard in a video. |
| 14. | Annotation Tool | A software used to manually label regions in video frames (e.g., for training YOLOv4 to detect scoreboards). |
| 15. | Feature Extraction | The process of identifying key elements (e.g., text, objects) from video frames for summarization. |
| 16. | YOLOv4 (You Only Look Once Version 4) | An object detection model used for real-time detection tasks in video. |
| 17. | OCR (Optical Character Recognition) | Technology used to extract text, such as scores and team names, from images or video frames. |
| 18. | Region of Interest (ROI) | A selected area in a frame where important elements, like scoreboards, are located for further processing. |
| 19. | Darknet Framework | A lightweight neural network framework developed in C and CUDA. It is primarily used for training and deploying YOLO models for object detection tasks. |
| 20. | Thresholding | A preprocessing technique applied to images to enhance OCR accuracy by converting them to black and white. |

# Appendix B: References

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# Appendix C: Record of Change History

[This section describes the details of changes that have resulted in the current Low-Level Design document.]

| **#** | **Date** | **Document Version No.** | **Change Description** | **Reason for Change** |
| --- | --- | --- | --- | --- |
|  | 14/09/2024 | 1 | Changes in the models | Generalized the models and changed the algorithms extensively. |
|  | 16/09/2024 | 2 | Deployment diagram | Made changes to the deployment diagram |
|  | 18/09/2024 | 3 | Class Diagram | Thorough extension of class diagram |

# Appendix D: Traceability Matrix

| **Project Requirement Specification Reference Section No. and Name.** | **DESIGN / HLD Reference Section No. and Name.** | **LLD Reference Section No. Name** |
| --- | --- | --- |
| 3. User classes and Characteristics | 3.1.3 Class Diagram | 3.1 Module 1 |
| 3.1.1 User interfaces | 3.1.2 User Interface Diagram | 3.2.2 Use case diagram |
| 3.Hardware Requirements | 3.2.5 Packaging and Deployment Diagram | 3. Design Description |