Software Requirement Specification Document for Semi automated squash refereeing system using computer vision and machine learning

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Table 1: Document version history

Version	Date	Reason for Change
1.0	4-Jan-2024	SRS First version's specifications are defined.
1.1	8-Jan-2024	User Characteristics Functional Requirements Data Design
1.2	11-Jan-2024	Appendices section Overview and UML edited
1.3	14-Jan-2024	Scenario updated

GitHub: https://github.com/sa3eed-x/automated-squash-refereeing-system

Contents

Abstract

With 20 million players worldwide in over 185 countries, squash is considered one of the most famous sports in the world. In the dynamic and fast-paced world of squash, the need for an advanced refereeing system has emerged as more and more evident so as to reduce the human error as time passes.Our project aims to help fulfill this need by developing and implementing a functional squash system that is ready to transform the game of squash through artificial intelligence. Unlike traditional structures that rely completely on human sources, our answer harnesses modern computer vision like YOLO and openCV , data analytics and machine learning like RNN and use these technologies to autonomously and accurately officiate in real-time. In the end, this system hopes to ensure fair and consistent decisions and improve the overall squash experience for players and fans.In addition, it tries to revolutionize playing and watching squash by addressing the needs and expectations of players, referees, fans, and investors, thereby making squash a game that embraces technological innovation.

1 Introduction

1.1 Purpose of this document

The purpose of this Software Requirement Specification document is to illustrate and highlight the requirements needed for our project, Squash Video Assistant Referee (VAR) System.The project aims to develop an advanced system using computer vision and machine learning to serve as a virtual referee in squash. It will analyze video footage to make real-time, accurate decisions on ball in/out, player interference, and rule violations. This eliminates human error, speeds up the game, and provides valuable analytics. The goal is to revolutionize squash officiating with a semi-automated, fair, and accurate referee system.

1.2 Scope of this document

This document explores systems similar to our project, illustrates the overview, scope, and context of the Squash Video Assistant Referee (VAR) System design, and tackles the objectives of the system and the characteristics of it's potential users. Also, this document explains the needed functional and non-functional requirements, the design limitations, the data design and the system class diagram. Lastly, the document discusses the possible operational scenarios and presents an application time plan.

1.3 Business Context

Squash sport is getting popular and popular every year not only in Egypt but in the whole world. The number of playes is even getting bigger according to this article [1] number of players has increased to nearly the double in less than decade in the USA and Finland with rate of increase 82% for USA and 70% for Finland, also according to the Professional Squash Association (PSA) articles [2] they are evening increasing the prize pool for their tournaments, They will be interested in our project as it will assist their referees as it will detect ball double bounce, and insure transparency as it will detect any fouls during the game play

2 Similar Systems

2.1 Academic

1. In the paper entitled **Event-Based High-Speed Ball Detection in Sports Video** [3] written by **Nakabayashi, Takuya and Kondo, Akimasa and Higa, Kyota and Girbau, Andreu and Satoh, Shin'ichi and Saito, Hideo** it talks about detecting fast moving balls in sports, they are working on volleyball sport for applying their techniques, it introduced another approach for detecting fast moving balls by using another type of cameras that is called event camera that works in a different way than a normal camera, They contributed in the data-set and proposed two methods; using an event camera for generating a data-set and using events generated from the common camera, the methods they proposed showed an outstanding in the results compared to others, the paper has a new technique which is great but it faces a challenge in the data-set as it is limited and they are using YOLOV3(You Only Look Once) which is fine but YOLOV8 has more accuracy.

2. In the paper entitled **VARS: Video Assistant Referee System for Automated Soccer Decision Making from Multiple Views** [4] written by **Held, Jan and Cioppa, Anthony and Giancola, Silvio and Hamdi, Abdullah and Ghanem, Bernard and Van Droogenbroeck, Marc** the main goal is to automate the referee decisions based on multi-view video and be accurate and eliminate human error in order to ensure fairness, the authors collaborated to solve the problem of refereeing and contributed with their own multi-view data-set named SoccerNet-MVFouls, making the VAR system using multi-view for classifying and proposed in this paper how different camera can affect the performance of the system. The system showed great results with the different classifiers and transformers like ResNet, CNN R(2+1D), and MVit, The paper includes a challenge and has been solved in a good approach which is multi-view refereeing and it eliminated the human error by showing the fouls in different point of views it faced some challenges but managed to overcome it.

3. in the master thesis entitled **"Deep learning applied to detection, pose estimation, tracking, and birds-eye view in sport videos"**[5] it discusses different solutions for different data science processes problems, so the thesis contributed by providing a comprehensive analysis of different techniques used to develop detection models pose estimation, tracking, and bird's eye view in sports, it used YOLOv7 and MediaPipe for detection and put in consideration Faster R-CNN, SSD, and Mask R-CNN, For tracking it used different algorithms like SORT, DeepSORT, and ByteTrack also put in consideration other algorithms like MHT(MUltiple Hypothesis Tracking), Kernalized Correlation Filters(KCF) and Online Multi-Object Tracking (MOT), And for pose estimation it used YOLOv7-pose and suggested OpenPose, MediaPipe and HRNet, And for birds-eye view it used pre-trained model that uses two-GAN networks and suggested other methods like Direct Linear Transform(DLT) and Random sample consensus(RAN-SAC), The thesis used three different data-sets COCO data set, Basketball game and football game data-set, The results showed a successful achievement of it's objectives, The paper is full with different techniques but it needs to optimize the models for real-time processing and the difficulty of obtaining high-quality training data.

2.2 Business Applications

1. Hawk-Eye [6], a cutting-edge tennis line-calling system, employs high-speed cameras strategically placed around the court to track the ball's movement. Using advanced algorithms, it predicts the ball's trajectory, comparing it to virtual court lines for precise in/out determinations. Instant replays, generated in real-time, aid chair umpires in making accurate decisions, improving the overall officiating accuracy in tennis matches.

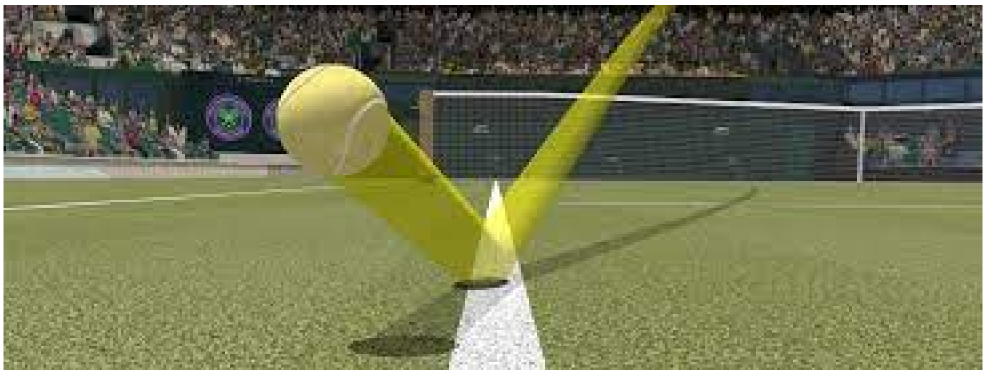


Figure 1: Hawk-eye Shot Spot

2. The video assistant referee (VAR) [7] system in football involves strategically placed cameras capturing match incidents. The centralized VAR Hub reviews key decisions, providing real-time input to the on-field referee via a headset. The referee can then choose to maintain or alter the decision based on VAR recommendations or personally review the footage using a sideline monitor. This collaborative process enhances the accuracy of critical decisions during football matches.In a study of 13 men's national leagues, using VAR was found to increase refereeing decision accuracy from 92.1% to 98.3% [8]

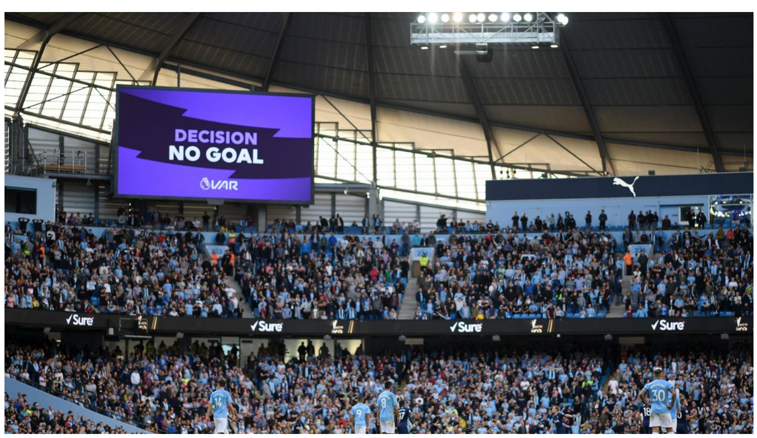


Figure 2: VAR

3 System Description

3.1 Problem Statement

- Manual refereeing in squash is prone to human error and subjectivity, leading to inaccurate decisions. The fast-paced nature of the game can cause difficulties in accurately tracking players' movements and the ball, resulting in missed calls or incorrect judgments. Personal biases and differing interpretations of rules can further inaccuracies, causing frustration and disputes among players. [9]

- Defining a ball's out of bounds, identifying fouls or interference, and accurately awarding points are also challenging for the referee.

- Referees must maintain control and ensure fair play in an intense, competitive sport, despite potential unsportsmanlike behavior. This can create frustration and impact the fairness and integrity of the game.

3.2 System Overview

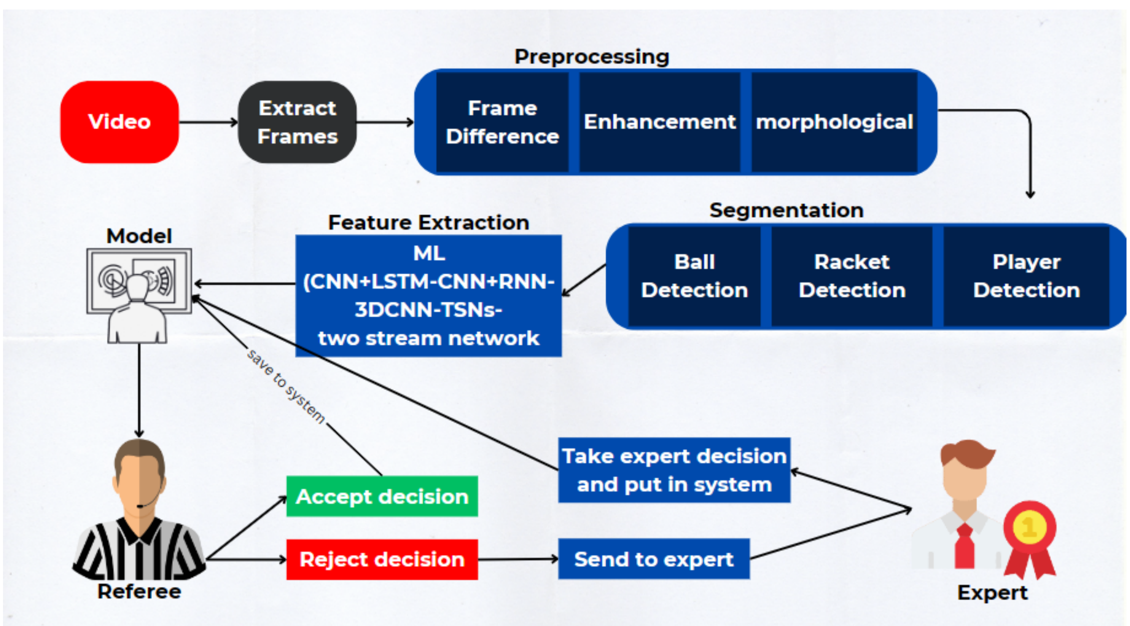


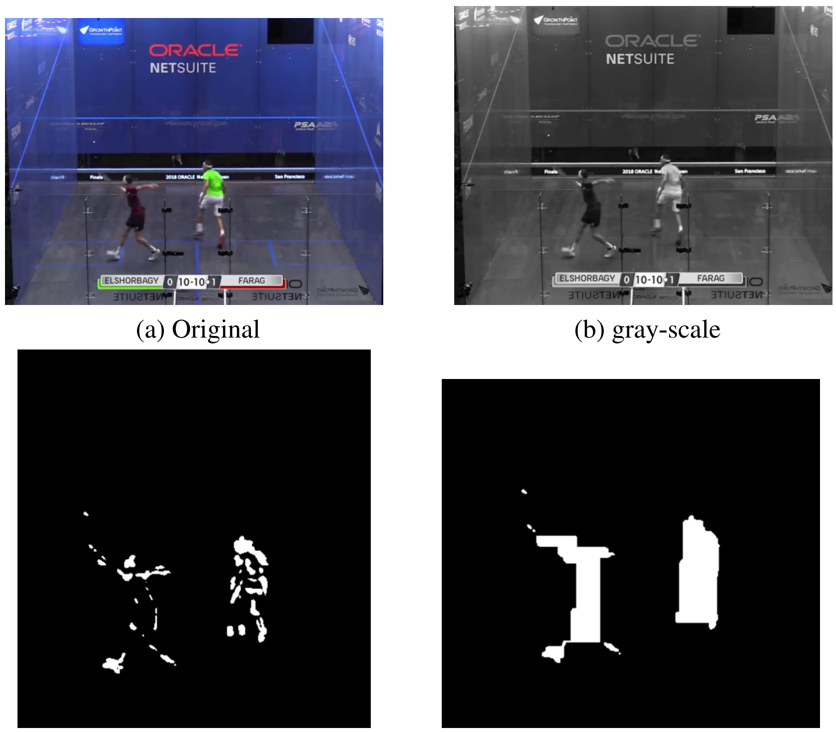
Figure 3: System OverView

Figure 2 shows the flowchart of the proposed project. It contains the following steps:

- **input :** A video will be required from a live ongoing match from multiple camera angels. Each camera acts as a single referee, All the cameras will be synchronized and aggregated in a voting system.

- **Data Gathering :** The model is trained on rally videos scraped manually from YouTube channel, The new live match captured by multiple cameras will be added to our database to be used after the match as new data.In addition to the data that came from the model itself, the clash video from the match with the system's decision.

- **Pre-Processing :** The main aim at this stage is to extract the foreground of the image frame by subtracting the background from the image.The process involves converting RGB image frames to gray-scale, filtering to reduce noise, combining frames using frame difference and Boolean operations, thresholding to form a binary image, and performing morphological operations like dilation and erosion to enhance objects and minimize discontinuity.



(a) Original (b) gray-scale

(c) frame difference (d) morphlogical operation

Figure 4: pre processing

- **Computer Vision & Deep Learning :** For detection and tracking, the effective ways are contouring, size, region, and velocity constraints. In addition, YOLO and Pytorch achieved a superb outcome. CNN, LSTM, transfer learning, GAN and transformers are commonly used models.The two methods, Kalman Filter & Holt's double-exponential smoothing were examined, but their accuracy cannot be accurately compared due to a lack of ground truth. (The exponential smoothing method results are smoother and more accurate)[10].

- **Decision-making & referee's monitoring :** The system developed a decision-making algorithm that fuses data from all cameras to make decisions like ball-out line and double bounce, but in critical decisions like fouls, the system shows the referee the percentage of the results, and he chooses the right one based on his POV plus the data the system offers. In some cases, if the player feels unfairly judged, the system retests the clash to confirm its decision.

- **model learning :** The model will always keep learning because every match video is reused as new data. And if the system's highest predicted decision doesn't match the referee's decision, this case will go to an expert to be checked, and the feedback will be returned to the model.

3.3 System Scope

Squash is an intensive very fast-paced sport that falls under the human error. making it hard for the referrers to give an accurate decisions.This system is mainly designed to help in the process of refereeing by real time both automated and semi automated ways, specifically in professional squash matches.The proposed system is capable of:

1. Help referees taking the right decision in fouls.
2. Providing a high degree of accuracy in double bounce and out decision.
3. Building trust with players and fans.
4. learning from it's own mistakes.

3.4 System Context

As illustrated in Figure 4, the context diagram of our project shows that the admin feeds the system with squash matches to train on.YOLO which is a real-time object detection algorithm, will detect and track balls and players from the video captured during the live match, automatically uploaded by the system using the CNN model and our own created dataset. Users (referees) will be offered three possible decisions by the system, and they will be able to respond to the system with one final decision.In addition, all the conflicting decisions between the referee and the system choice will be referred to squash experts to resolve the conflict and improve the system decisions.

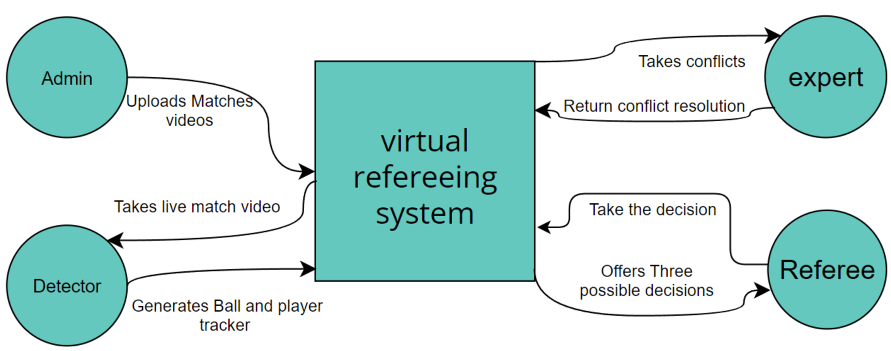


Figure 5: context diagram

3.5 Objectives

This project is meant to make the squash refereeing process unbiased and more accurate while reducing human error as much as possible. The system objective is to design, develop, and implement a solution that detect and track the players and ball throughout a live squash match and Make highly accurate decisions based on squash rules violations and help the referee in taking the critical foul decisions.To achieve this, the system will require proper gathering and creation of our own Data set of specifications of the fouls(Let, No Let, Stroke), Machine learning, and Deep learning.

- The system will enhance the overall refereeing experience and contribute to fair play in the sport of squash.
- The system will detect the players and ball by computer vision algorithms and track them with the suitable deep learning techniques.
- The system will use machine learning which provides it with foul detection and gives the referee the right decision.
- The system will have a communication line with the referee to help him make accurate decisions and learn from him.
- The system will have a fully automated notification network for both out-ball and double bounce detection ,and point giving.
- We will write the SRS document to meet with IEEE 830-1998 standard, which will be delivered by December 2024.

3.6 User Characteristics

our project targets specific users related to the Squash sport in order to be able to understand the system's purpose and mechanism

- Squash referee's who are familiar with the official rules of the game
- expert squash referee's who have 5+ years of experience and have seen multiple and different game fouls

4 Functional Requirements

The use case diagrams for this project are shown in the following figure. The Use Case diagram for users and admins using the app is shown in figure 5

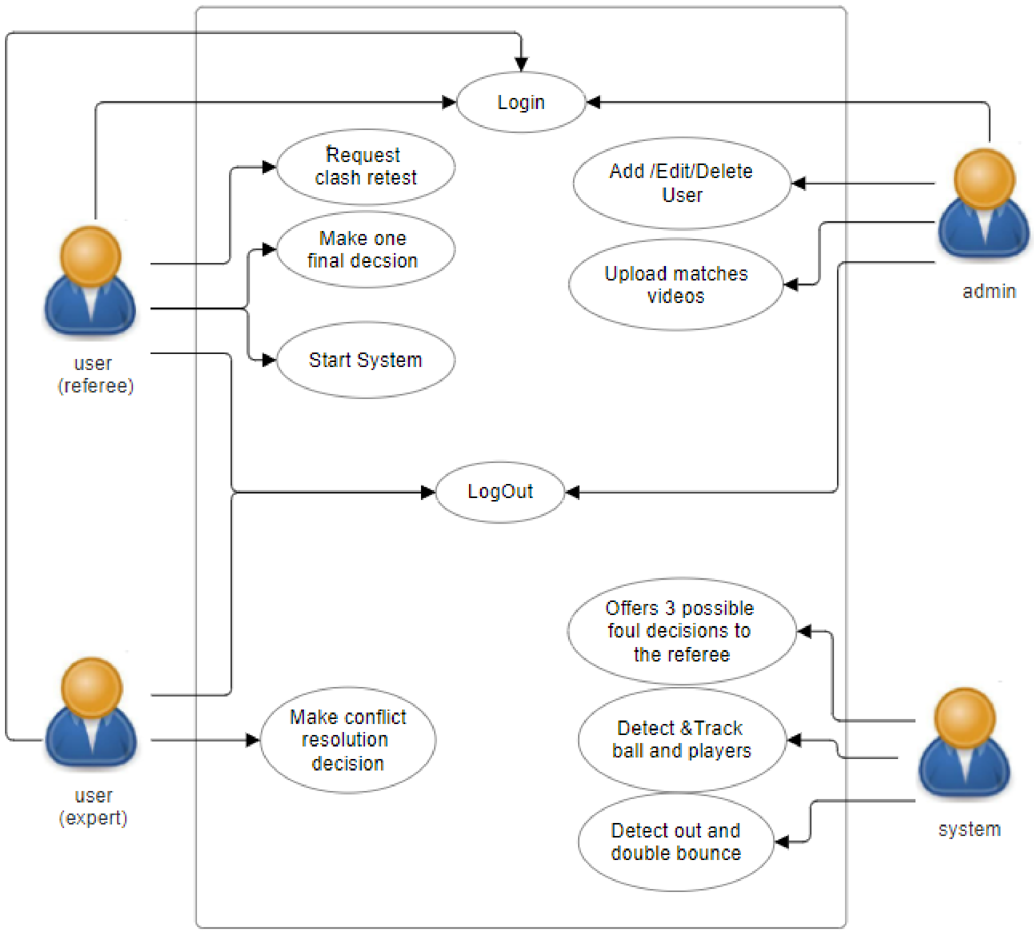


Figure 6: Use Case Diagram

4.1 System Functions

- System
  - The system Detects players & ball.
  - The system Tracks players & ball.
  - System shall acknowledge the referee about ball out and double bounce.
  - System shall detect a foul.
  - System shall make a decision(Let, No Let, Stroke).
  - System shall present to the referee three possible decisions along with the highest predicted decision.
  - The system shall save the chosen decision by the referee with the foul video.

- Admin
  - Admin shall add Users.
  - Admin shall edit Users.
  - Admin shall delete Users.
  - Admin shall add Match Videos.
- Users
  - User shall Login with an account.
  - User(referee) shall Make a decision.
  - User(referee) shall ask the system to retest the clash.
  - User(referee) shall Start the system.
  - User(expert) shall Make conflict resolution decision.

4.2 Detailed Functional Specification

Choose your main key functions (Minimum 3, Maximum 6).

Table 2: Login

Tasks	**Login**
code	Fn1
Priority	Extreme
Critical	The cell is necessary for the users to use the services assigned to them on the system
Description	It searches in a database for the entered username and password if it's valid or not
Input	Username and password
Output	Boolean(found or not found)
Pre-condition	User must already have a created account
post-condition	If found go to the page dedicated to him if not, say that the email or password is incorrect
Dependency	Fn2
Risk	None

Table 3: Add User

Tasks	Add User
code	Fn2
Priority	High
Critical	None
Description	It allows admin to create an account and add a user to the system, which could be a referee or an expert
Input	Username, Password, role(expert,referee)
Output	Boolean(User added or not)
Pre-condition	Admin must be signed in
post-condition	If there is no error while creating the account ,the user will be added to the database
Dependency	None
Risk	None

Table 4: Detector

Tasks	Detector
code	Fn3
Priority	Extreme
Critical	None
Description	It Detects and tracks the ball and players from the input live match
Input	Live match video captured
Output	Accurate location for the ball and the two players
Pre-condition	Referee starts the system
post-condition	None
Dependency	Fn1
Risk	None

Table 5: Referee Decision

Tasks	Referee Decision
code	Fn4
Priority	Extreme
Critical	None
Description	When a player asks for a "Let Ball",the system checks the clash and predicts the decision that helps the referee, He has the full power to choose his own decision from his POV
Input	one of the three decisions (Let,No Let,Stroke)
Output	The referee's decision and the system's highest predicted decision
Pre-condition	The system must offer the three decisions with their percentage
post-condition	If the two decision were different, this case will be sent to an expert if not, it would be labeled and sent to the dataset to be reused
Dependency	Fn3
Risk	None

Table 6: Expert Decision

Tasks	Expert Decision
code	Fn5
Priority	Medium
Critical	None
Description	The expert will receive a short video of the players clashing to resolves the conflict in decisions between the referee's decision and the system's highest predicted decision
Input	one of the three decisions (Let,No Let,Stroke)
Output	A short video of the players clashing with the expert's decision
Pre-condition	A conflict in decision between the referee and the system should be made
post-condition	The Output will be sent to the dataset,so that the system can be retrained on it
Dependency	Fn4
Risk	None

5 Design Constraints

5.1 Standards Compliance

The squash virtual refereeing system desktop application works with the Windows operating system and a reliable internet connection.

5.2 Hardware Limitations

- Cameras with very high FPS to capture the fast-moving balls.

- A reliable RAM storage to store and retrieve historical game data for analysis.
- GPU specifications can limit the speed and complexity of real-time data processing, affecting the system's responsiveness.

5.3 Environmental Conditions

For the system to function properly, proper lighting, position and number of cameras are required.

6 Non-functional Requirements

6.1 Accuracy

For precise decisions, a very high level of accuracy for tracking the squash ball and players' movements must be reached.

6.2 Real-time Processing

The system must have the ability to process and analyze data in real-time to provide instant feedback during the game.

6.3 Feedback Mechanism

A feedback mechanism is implemented for experts to provide input on the system's performance and accuracy.

6.4 Compliance

The squash virtual refereeing system shall be compliant with all relevant regulations and standards.

6.5 Ease of Use

The system shall be simple to use and not complex at all, as it doesn't require a lot of steps from the user.

6.6 Reliability

Since the input is a live captured video, the system must maintain at least 99% uptime during matches.

6.7 Security

The system should have secure authentication mechanisms for users (referees and experts), and the administrator will create a special permit for them to access the system's data and features.

7 Data Design

- The data set consists of two types of data, images and videos with MP4 format for videos and JPG format for images, the data set is build using different sources SQUASHTV, COCO Dataset , Custom made data-sets for players, racket, squash ball with size of **8,000+** labeled images, and labeled videos with foul decisions.

Figure 7: sample of labeled ball

- The databse that we will be using is **MongoDB** it will contain the users credential’s and labeled dataset.

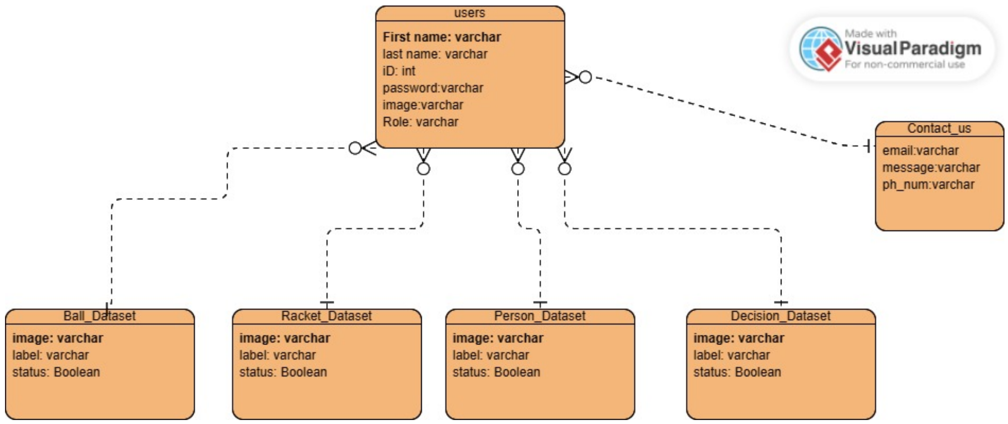


Figure 8: sample of the expected database schema

8 Preliminary Object-Oriented Domain Analysis

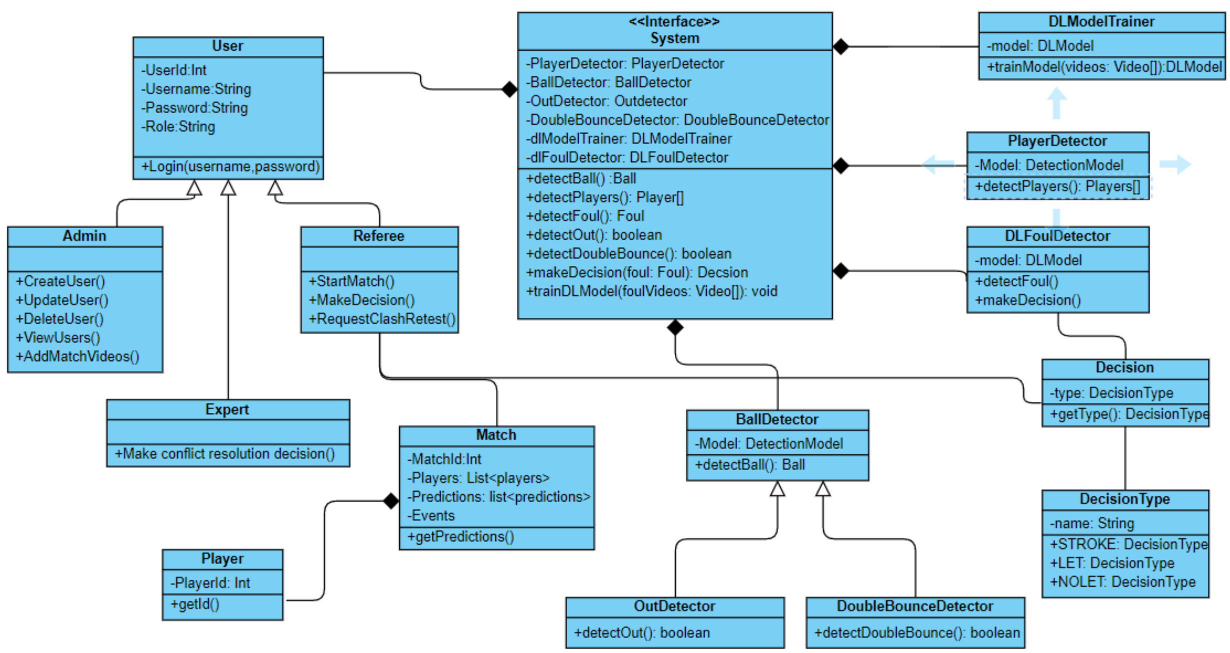


Figure 9: Class Diagram

9 Operational Scenarios

- **Scenario 1:**
  The admin has to log in to have access to the system and add, remove and edit users (referees). Also, admin can upload match videos to the dataset to train the model.
- **Scenario 2:**
  The system alerts the user (referee) if the ball made a double bounce and if the ball is out of the wall playing area when the ball hits the tin or the out. Also, the system detects interference between players and recommends to the referee three possible decisions with their percentage.
- **Scenario 3:**
  The User (referee) has to log in. First, he has to start the system.Then he can monitor the match and review the decisions offered by the system, and then he can make his own decision based on his perspective. Second, he can request that the system retest it's decision if the player asks for it. Moreover, he'll be required to add the points to show the score on the screen.
- **Scenario 4:**
  The user (expert) will browse a list of conflicts between the previous referee's decisions and the system's decisions to resolve them.The expert's decisions will be sent to the dataset to retrain the model.

10 Project Plan

The figures 10 and 11 below show the timeline of this project from the end of the proposal to SDD.

Tasks	Start Date	End Date	Duration	Team Member
Information Collection and Researches	22/09/2023	05/10/2023	13 days	All Team members
Survey and proposal Preparations	06/10/2023	29/10/2023	23 days	All Team Members
Preprocessing Stage	01/11/2023	14/11/2023	13 days	All Team Members
Proposal Presentation 10%	14/11/2023	20/11/2023	6 days	All Team Members
Classify dataset	26/11/2023	11/12/2023	16 days	All Team Members
Ball detection by Deep learning (YOLO)	29/11/2023	16/12/2023	17 days	Youssef Mohamed
Ball detection by computer vision	25/11/2023	07/12/2023	12 days	Ahmed said
Documentation of SRS	12/12/2023	14/01/2024	31 days	All Team members
Increaseing our YOLO custom-made Dataset	02/12/2023	14/12/2023	12 days	H,S,Y
Labeling ball images	02/12/2023	14/12/2023	12 days	H,S,Y
SRS presentation	10/01/2024	18/01/2024	8 days	All Team Members
Writing a research paper	10/02/2024	20/02/2024	10 days	All Team Members
Developing Desktop application	04/02/2024	20/03/2024	60 days	All Team Members
Documentation of SDD	04/02/2024	20/03/2024	45 days	All Team Members

Figure 10: Tasks and Time Plan

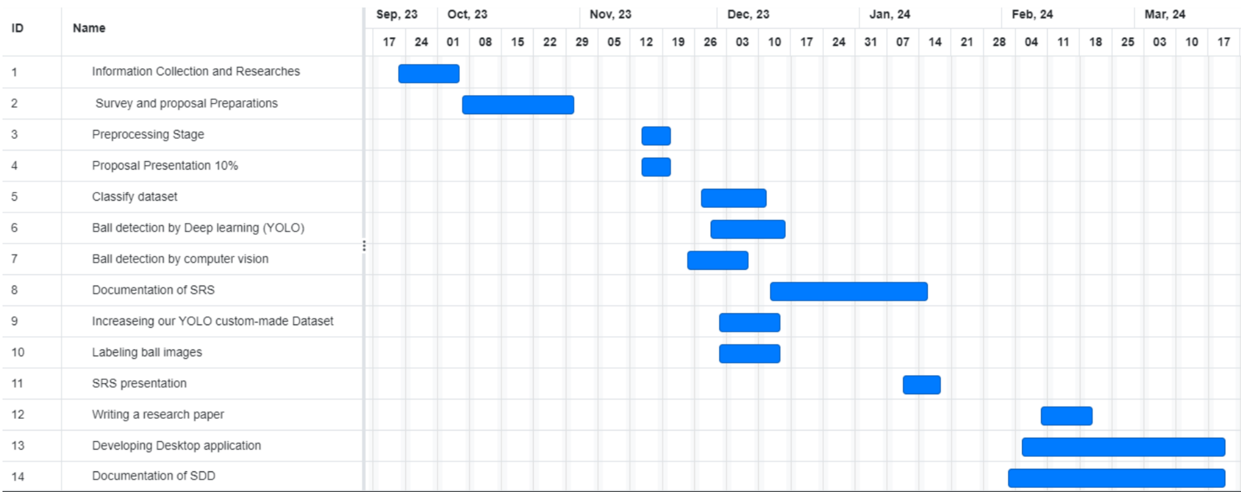


Figure 11: Gantt chart

11 Appendices

11.1 Definitions, Acronyms, Abbreviations

Abbreviation	Definition
SRS	Software Requirement Specification
CNN	convolutional neural network
YOLO	You only look once
POV	Point Of View
RNN	Recurrent neural network
LSTM	Long Short-Term Memory
VAR	Video assistant referee
GAN	Generative adversarial network
FPS	Frames Per Second
WSO	World Squash Officiating
PSA	Professional Squash Association

11.2 Contribution

No system comes close to squash as a refereeing system, as the two most similar systems show. But by combining what the contributors have achieved in high-speed ball detection and applying deep learning for human pose estimation and tracking, we seek to make our contribution an addition to automated refereeing through our system that detects high-speed ball double bounce, detects fouls, and predicts the correct decision.

11.3 Supportive Documents

- Dataset

1. SQUASHTV youtube channel
   In the proposed system, our dataset is scraped from (SQUASHTV youtube channel) which proved a generous amount of rallies as we want. Squash TV is the official live and video-on-demand website of online service exclusively for squash developed by the Professional Squash Association, the most important governing body for the men's and women's professional squash circuit.

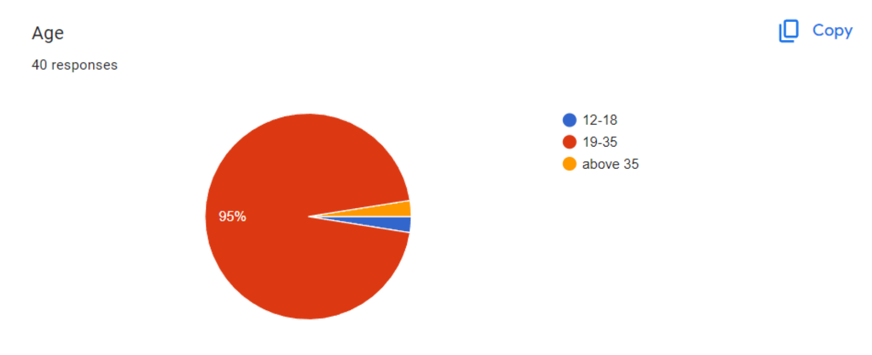
Figure 12: SQUASHTV Chanel Logo

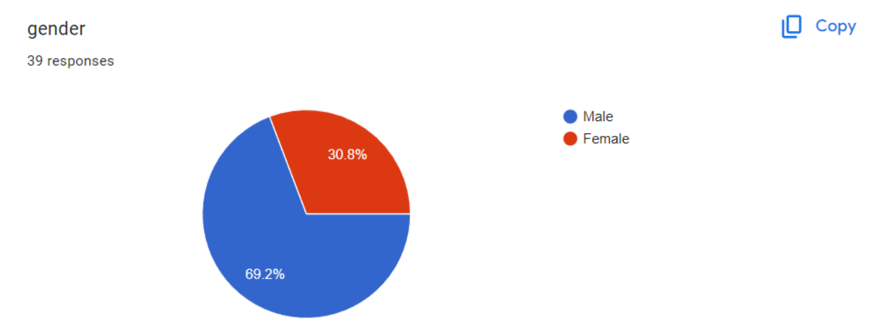
2. world squash officiating
   WSO is an organization consists of a team of highly skilled and trained individuals who play a pivotal role in ensuring fair play. The website offers videos of referees' incorrect decisions and their correction.

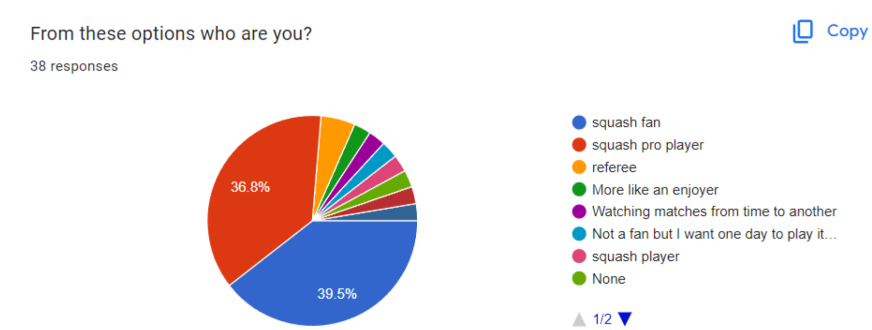
Figure 13: world squash officiating

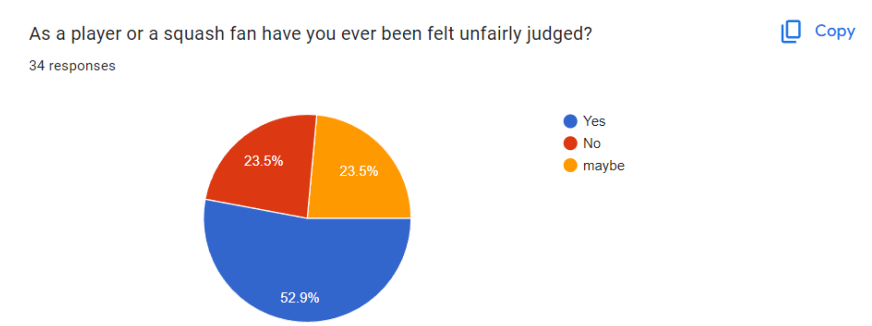
- Survey

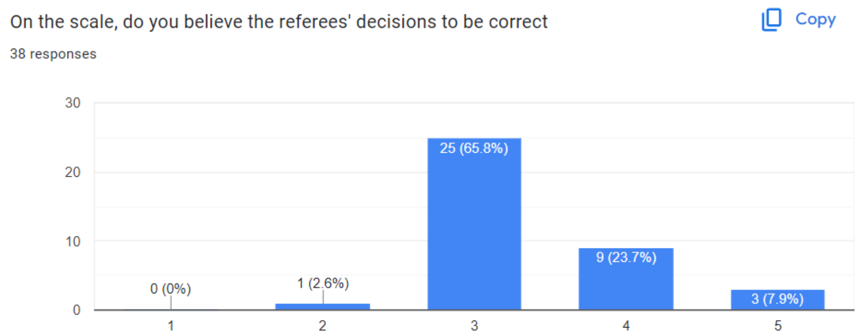
  A survey had been done to get a wider scope on the need for our project and expand our research. 15 Squash pro players , 2 referees , 1 Coach and 20 regular fans. The responses' niches varied from pro players niche, to various watchers including regular fans & from time to time watchers , coaches and referees. The results indicated how much our respondents were interested in squash and enthusiastic to see it applied in real matches.

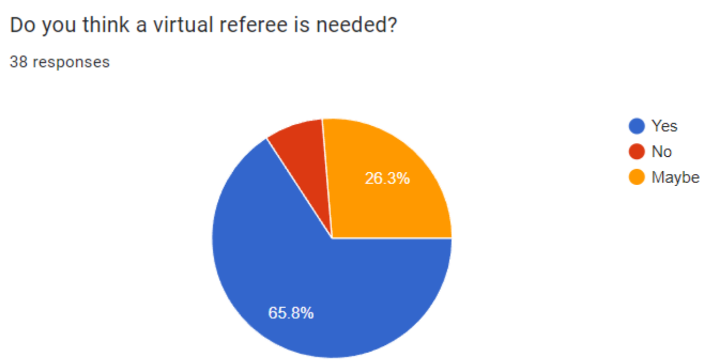












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